AGGREGATE EARNINGS, FORECASTS AND REVISIONS

Evaluation of the Information in, and Characteristics of, Aggregated Analysts' Forecasts

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Abstract

I INVESTIGATE THE information in aggregated US equity analysts' earnings forecasts. Despite a voluminous body of research evaluating the information in, and characteristics of, equity analysts' forecasts, relatively little is known regarding aggregated forecasts. However, Kothari, Lewellen and Warner (2006) demonstrate how estimated relationships between, for example, earnings and returns may differ markedly at the aggregate level compared with the individual stock level.

I generate time series of aggregated forecast earnings, aggregated forecast revisions and aggregated realized earnings for the period extending from the first quarter of 1979 through to the last quarter of 2009. These variables are employed in three examinations of aggregated earnings expectations. Firstly, prior research indicates significant information in analysts' forecasts for future realized earnings, and strong positive correlation between realized earnings and indicators of macroeconomic activity. I therefore hypothesize significant information in aggregated analysts' forecasts for future realized economic activity. Secondly, I investigate the informational efficiency of analysts' forecasts with respect to realized macroeconomic variables, and implications of earnings revision predictability for return predictability. Thirdly, I employ aggregated earnings revisions as proxies for market earnings surprise in tests of cash flow and discount rate effects in market returns.

I find evidence of statistically significant information for future US industrial production growth in aggregated analysts' forecasts, the magnitude of which is a partial function of earnings smoothing by management, firm size and earnings cyclicality. I also find evidence of systematic underreaction by analysts to realized macroeconomic factors, resulting in revision predictability which in turn is able to explain significant systematic variation in future industry returns.

In addition, my results suggest that the negative relationship between aggregated earnings surprise and contemporaneous returns identified by Kothari et al. (2006) is at least partially a product of the period they evaluate. In robustness tests employing both aggregated realized earnings and aggregated forecast revisions, I find evidence of positive (albeit insignificant) relationships between these proxies for earnings surprise and contemporaneous market returns. My results do not support the notion of a discount rate effect dominating a cash flow effect at the aggregate level.

For Lana, Georgia and Campbell

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1 Introduction

1.1 Introductory concepts

THIS RESEARCH FOCUSES on the information in aggregated analysts' earnings forecasts, and investigation of the relationship between aggregate forecast surprise and market returns. The analysis of analysts is a thoroughly established feature of the accounting and finance literature.[1] This is because the primary outputs of stock analysts (recommendations and earnings forecasts) represent key sources of estimates for market expectations. Researchers essentially have two choices for estimating market expectations for earnings: prediction with time series models based on earnings realizations and/or other realized factors, or the surveyed expectations of market participants. The latter arguably represent better proxies

[1] Comprehensive reviews of the literature are provided by Brown, Foster and Noreen (1985), Brown (1993) and Ramnath, Rock and Shane (2008).

for true market expectations,[2] and as Brown and Rozeff (1978) note, expectations are critical for a diverse range of issues of fundamental importance in the accounting and finance literature:[3] "Accurate measurement of earnings expectations is essential for studies of firm valuation, cost of capital and the relationship between unanticipated earnings and stock price changes" (p. 1). Analysts' expectations have also been employed in evaluations of such core issues as market efficiency[4] and behavioural theories,[5] with this list by no means being exhaustive. Consequently, analysts' earnings forecasts are amongst the most important data sources in the accounting and finance researcher's tool chest.

However, to date there has been little in the way of time series investigations of analysts' earnings forecasts for aggregated portfolios. In particular, there has been only limited investigation of the relationships between aggregated analysts' forecasts and macroeconomic variables. As Basu, Markov and Shivakumar (2010) observe:

> Despite the fact that half of the variation in firms' earnings (for example, Brown and Ball (1967)) is driven by macroeconomic factors, and analysts often discuss the relation between inflation and future earnings in their research reports, prior literature on analysts' forecasts has largely ignored these issues, limiting our understanding of how earnings expectations are formed. (p. 405)

This study adds to the literature through the investigation of three aspects of aggregated forecasts: firstly, whether aggregated forecasts contain information for future economic state variables; secondly, whether aggregated analysts' forecasts are efficient with respect to past realized economic state variables, and the

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[2] Analysts presumably incorporate far more information into their earnings forecasts than just past realized earnings.

[3] As Brown and Rozeff (1978) further note, evaluation of Muth's (1961) rational expectations hypothesis requires the best possible proxy for earnings expectations.

[4] Examples include Frankel and Lee (1998), Gleason and Lee (2003) and Livnat and Mendenhall (2006).

[5] Examples include Löffler (1998), Chen and Jiang (2006) and Friesen and Weller (2006).

relationship between earnings revision predictability and future returns; and thirdly, decomposition of the return response to aggregated earnings revisions into cash flow and discount rate effects.

In Chapter 5 I report evidence of statistically significant information in aggregated forecast earnings changes for future US industrial production growth (up to six quarters ahead). I find evidence of three forms of systematic variation in the magnitude of information in aggregated forecast changes in earnings: variation related to earnings smoothing by firm management, size-related variation and variation related to the historic cyclicality of realized earnings. On the first point, earnings smoothing by management reduces earnings volatility. I hypothesize that if smoothing reduces the strength of the relationship between macroeconomic activity and realized earnings, then smoothing will also reduce the magnitude of information in aggregated forecasts for future economic activity.[6] I also find evidence of a relationship between firm size and the magnitude of information in aggregated analysts' forecasts (greater information in small firms' forecasts relative to large firms), that is partially attributable to a positive relationship between firm size and smoothing.[7] Systematic variation in the informativeness of aggregated forecasts for future industrial production growth is employed to illustrate significant *marginal* information in the forecasts of small cyclical firms, relative to a range of additional economic state variables.

[6] One mechanism by which smoothing may be incorporated into analysts' forecasts is heavy analyst reliance on guidance from firm management. For evidence based on content analysis of analysts' reports see Previts, Bricker, Robinson and Young (1994). Cotter, Tuna and Wysocki (2006) report evidence of rapid analyst responses to management guidance events. Further, Feng and McVay (2010) illustrate how analysts may overweight management guidance at the expense of forecast accuracy in response to incentives such as investment banking opportunities.

[7] Moses (1987) reports evidence of a statistically significant positive relationship between firm size and income smoothing. An alternative explanation is that small firm analysts can more accurately (and more quickly) incorporate macroeconomic information and views relative to large firm analysts as a result of size-related forecast complexity. Cohen and Lou (2010) report evidence "that analysts are affected by similar information processing complications as investors and thus update their forecasts for simple standalone firms before these more complicated conglomerate firms" (p. 20).

With regard to the efficiency of analysts' forecasts, in Chapter 6 I report evidence of analyst underreaction to past values of economic state variables. Underreaction is particularly pronounced for the Institute of Supply Management's Purchasing Managers' Index (ISM PMI), despite long run evidence of the importance of this measure of business sentiment as a leading indicator of US economic activity.[8] This results in predictable errors in analysts' earnings forecasts. For example, I obtain an adjusted R^2 of 0.342 in a regression of aggregated one year revisions in annual earnings forecasts (deflated by lagged forecasts) on the lagged ISM PMI, lagged credit spreads, lagged revisions and lagged realized earnings growth.[9] Variation in the predictability of aggregated revisions across Fama and French (1997) industries is employed to form industry decile portfolios on the basis of predicted revisions. I find evidence of predicted revisions explaining significant systematic variation in *future* industry returns. For example, quarterly future excess returns are obtained for a portfolio long decile 10 industries (high predicted revisions) less decile 1 industries (low predicted revisions). In regressions of these excess returns on the Fama French three factor model, I obtain an average equally-weighted risk-adjusted (and statistically significant) quarterly excess return of 2.861% (2.575% value-weighted).[10]

The analysis presented in Chapters 5 and 6 not only has implications for academic researchers, but is also of practical utility. Macroeconomic forecasting models are a pervasive element of investment banking, fund management and monetary/fiscal authority research efforts. Evidence of statistically significant information in the aggregated earnings forecasts of stocks represents a finding of potential benefit to

[8] Kauffman (1999) summarizes research providing evidence of a lead relationship between the ISM PMI and measures of US aggregate economic activity.

[9] All explanatory variables are lagged to values available to analysts when their initial forecasts were published at the start of the one year revision period.

[10] Unless specified otherwise, statistical significance in all analysis refers to significance at the 10% level in a two tailed test.

practitioners. In addition, the predictability of a large proportion of aggregated analyst revision activity, with well-publicized economic state variables, points to considerable potential for further investigation of implications for portfolio construction (at the aggregate market level for asset allocation and in terms of portfolio trading strategies for subsets of stocks).

In Chapter 7 I reassess the conclusions of Kothari, Lewellen and Warner (2006), employing a more recent dataset, and a proxy for earnings surprise more closely aligned with their research aims. The results of Kothari et al. provide a stark illustration of the potential for significantly different results from cross-sectional analysis at the individual stock level compared with time series analysis at the aggregate market level. In short, they identify evidence of a statistically significant negative relationship between market returns and contemporaneous aggregated earnings growth, compared with evidence of a positive and statistically significant relationship at the individual stock level. However, they acknowledge their use of aggregated changes in realized earnings (and related time series models) as a proxy for earnings surprise constrains their analysis. I instead employ aggregated revisions in earnings forecasts in tests, emulating their methodology, of the relationship between earnings surprise and returns. I find no evidence of a significant negative relationship between aggregated earnings revisions and contemporaneous aggregate returns. Further, I find evidence suggesting the negative relationship between aggregate earnings and contemporaneous returns identified by Kothari et al. is largely a feature of the time period they focus on. It is not evident in more recent data, and its presence in earlier data is questionable. Further, I find no evidence of a statistically significant discount effect in the impact of aggregate earnings revisions on contemporaneous returns, but I do find evidence of a significant cash flow effect. My results are therefore not consistent with the notion that discount rate effects are the dominant feature of aggregate returns while cash flow effects are the dominant feature of stock-level returns.

1.2 Motivation and contribution

MOTIVATION FOR THIS research is threefold. Firstly, there has been little research into the relationship between aggregated analysts' earnings forecasts and economic state variables. Shivakumar (2010) observes "Prior studies note that aggregate earnings news is probably related to market returns because it provides information about the macroeconomy, but little is known about the macroeconomic content of such earnings" (p. 338). Similarly, in reference to Anilowski, Feng and Skinner (2007), Shivakumar (2007) notes that "A natural extension of this study is to examine whether aggregation of analysts' forecasts provides timely information about the macroeconomy" (p. 72).

At the individual firm level it is reasonable to expect that idiosyncratic characteristics will dominate earnings forecasts. However, it is hypothesized that, when aggregated, a diversification effect will increase the relative magnitude and significance of the consensus expectation for the outlook for macroeconomic activity; in other words, the component common to all stocks. This study evaluates not just the contemporaneous relationship between aggregate earnings forecasts and macroeconomic measures of business activity, but importantly whether there is predictive power. If analysts' forecasts of earnings for individual stocks contain significant information for future earnings then, by the diversification argument mentioned above, it should be reasonable to expect that aggregated earnings forecasts contain statistically significant information for measures of macroeconomic activity (such as industrial production and gross national product growth).[11]

Secondly, there is a growing body of research in recent years which attempts to identify and explain the mechanisms employed by analysts for generating their forecasts. The general process employed by analysts is often colloquially referred to as a “black box”, being unobservable to an external spectator. As such it has increasingly become a focus of attention for academic research.[12] Popular textbooks commonly include analysis of the overall business environment (which includes the macroeconomic backdrop) as the first stage in the forecasting process for firm earnings.[13] I investigate the informational efficiency of aggregated analysts' forecasts with respect to a range of economic state variables. In particular, I focus on the efficiency of forecasts with respect to a measure of business sentiment, the ISM PMI. Further, I extend this analysis to investigate the implications of earnings revision predictability for return predictability.

Thirdly, this research provides an additional perspective on the debate relating to the relationship between aggregate earnings and stock returns sparked by Kothari, Lewellen and Warner (2006). They find evidence of a statistically significant negative relationship between aggregate earnings and concurrent returns for US stocks. Stock returns are a function of cash flow news and expected return news (the discount rate), and the relationship between cash flow news and stock returns

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[11] This also implies the assumption of a positive relationship between realized earnings growth and macroeconomic growth. Supporting evidence for this assumption is plentiful, and discussed in Chapter 2. In addition, Howe, Unlu and Yan (2009) provide a useful precedent for the investigation of information in aggregated analyst data, in their case aggregated analyst recommendations.

[12] Examples include Previts, Bricker, Robinson and Young (1994), Rogers and Grant (1997), Abdolmohammadi, Simnett, Thibodeau and Wright (2006), De Zwart and Van Dijk (2008) and Lambert, Matolscy and Wyatt (2009) and Basu, Markov and Shivakumar (2010).

[13] Examples include Narayanan and Fahey (2001), Penman (2001), Palepu, Healy and Bernard (2004), Koller, Goedhart and Wessels (2005) and Lundholm and Sloan (2007).

is necessarily positive. Hence, the negative relationship between aggregate earnings and returns must be driven by the discount rate effect dominating the cash flow effect. That is, at the aggregate level, higher earnings are associated with an *increase* in the discount rate. As Kothari et al. observe, this is contentious because the result is at odds with the predictions of a range of theoretical models.[14] Consequently, several studies have attempted to provide theoretical explanations for this finding, supported by further empirical analysis.[15] My research adds to the debate by employing aggregated analysts' earnings forecasts (as opposed to Kothari et al.'s use of actual earnings outcomes) in tests related to Kothari et al.'s empirical methodology. By evaluating the relationship between aggregated earnings revisions and a range of cash flow and discount rate proxies this paper provides an additional viewpoint on the relative significance of, and sign of, cash flow and discount rate effects in stock returns at the aggregate level. While questions remain over the nature of these relationships, my research highlights weaknesses in the robustness of Kothari et al.'s results and provides evidence in conflict with a number of recent analyses.

1.3 Aggregated time series variables

A KEY UNIFYING feature of my empirical analysis is the utilization of consistent time series of aggregated changes in realized earnings, aggregated forecast changes in earnings and aggregated earnings revisions. These variables represent one of the unique features of this study. I extend the general framework employed by Kothari, Lewellen and Warner (2006) for realized earnings to I/B/E/S[16] forecasts for US stocks. This requires a range of modifications to their aggregation process. Specifically, I apply a time-weighting process to realized

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[14] Examples include Campbell and Cochrane (1999) and Chan and Kogan (2002).

[15] Examples include Patatoukas and Yan (2009) and Sadka and Sadka (2009).

[16] Institutional Brokers' Estimate System, commonly abbreviated to I/B/E/S.

earnings and I/B/E/S first and second fiscal year forecasts (FY1 and FY2) to derive measures of changes in forecasts and forecast revisions over standardized one year periods. I am not aware of any previous research which incorporates standardized and aggregated time series measures of realized earnings growth, forecast growth and forecast revisions for a consistent sample of stocks.[17]

For robustness purposes, nine variations on each of aggregated changes in realized earnings, aggregated forecast changes in earnings and aggregated earnings revisions are calculated (reflecting a range of aggregation techniques and choices for deflators). In addition, having developed an aggregation process for analysts' forecasts, I am able to apply this same process to sub-portfolios to investigate cross-sectional variation in identified effects.

The principal constraint on analysis is the length of the time period over which there is sufficient depth in I/B/E/S forecasts. Core variables are constructed from annual changes in annual earnings data (realized and forecast), on a rolling quarterly basis, from the quarter ending March 1979 through to December 2009.[18] Robustness tests on data for individual analysts are further constrained to the period from March 1984 through to December 2009. I explore the robustness of the dataset by employing a range of alternative construction methods for aggregate variables, combined with sub-period analysis and sub-portfolio analysis. In addition, there are a number of known issues with I/B/E/S forecasts that can cause problems for researchers.[19] These are discussed in the Appendix to Chapter 3, along with features of variable construction designed to alleviate concerns.

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[17] This also represents an evaluation of the information in analysts' multi-year forecasts. Academic research more typically focuses on the most recent current forecast period alone.

[18] Newey-West standard errors are employed to take into account serial correlation arising from the use of overlapping data.

[19] Notably, the revision of historic data (Ljungqvist, Malloy and Marston (2009)), incorrect earnings announcement dates (Acker and Duck (2009) and Berkman and Truong (2009)),

1.4 *Thesis structure*

CHAPTER 2 PROVIDES a literature review for the three empirical chapters in this study. Areas of focus for research presented in Chapters 5 and 6 are evidence of the informational content of analysts' earnings forecasts, the informational efficiency of analysts' forecasts and the relationship between economic activity and firm profits. Discussion of literature relevant to Chapter 7 focuses on the decomposition of returns into cash flow and discount rate effects within the framework provided by Campbell (1991). In addition, in the context of Kothari et al.'s (2006) evidence of pro-cyclicality in discount rates, I outline a selection of theoretical models that predict either discount rate pro-cyclicality or counter-cyclicality. I also review recent literature that expands on Kothari et al.'s findings.

Chapter 3 details the construction of variables measuring changes in aggregate earnings, aggregate forecast earnings and aggregate forecast revisions. This includes the aforementioned appendix outlining problems with I/B/E/S earnings forecasts identified in the literature, and how each of those issues have been addressed for the purposes of this study. Summary data for key variables are provided and discussed in Chapter 4.

Chapter 5, the first analytical chapter, evaluates the relationship between aggregate realized earnings growth and contemporaneous economic state variables, the information in aggregated forecast earnings for future realized earnings, and the information in aggregated forecast earnings for future realized values of economic state variables.

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differences between I/B/E/S and Compustat realized earnings per share data (Abarbanell and Lehavy (2000) and Livnat and Mendenhall (2006)) and, most critically, rounding errors (Payne and Thomas (2003)).

In Chapter 6 I investigate the informational efficiency of aggregated forecasts with respect to a range of economic state variables, focusing in particular on the ISM PMI, and implications for return predictability.

In Chapter 7 I employ measures of aggregated earnings revisions as proxies for earnings surprise in an investigation of the relationship between aggregate market surprise and returns. I perform the same analysis for changes in aggregated realized earnings and compare results, thus evaluating the robustness of Kothari et al.'s (2006) findings. I also estimate the magnitude and sign of cash flow and discount effects in the impact of aggregated annual earnings revisions on annual returns. Research summaries and conclusions are provided in Chapter 8.

2 Literature survey

2.1 Key concepts

IN THE PREVIOUS chapter it was noted that if realized earnings and macroeconomic activity are positively correlated, and if analysts forecast earnings with a significant degree of accuracy, it should be reasonable to expect that analysts' earnings forecasts contain information for future macroeconomic activity. As part of the forecasting process, analysts may also explicitly form a view on the outlook for the macroeconomy. In addition, if analysts' forecasts are informationally efficient with respect to historic and forecast macroeconomic indicators, their forecasts will incorporate the expected impact of realized economic activity on future earnings and the relationship between forecast macroeconomic activity and future earnings. In this chapter I provide arguments and empirical evidence relating to each of the above aspects of realized and forecast earnings.

Specifically, I focus on four branches of the literature relevant to my empirical investigations. Firstly, literature relating to the informational content of analysts' earnings forecasts (with particular emphasis on forecast accuracy) is reviewed to more broadly understand what is known about analysts' forecasts and the utility of these forecasts to investors. A range of studies find evidence of statistically significant information in forecast earnings and earnings growth for future realized earnings. Assuming realized earnings and macroeconomic activity are significantly related, this suggests the presence of significant information in aggregated earnings forecasts for measures of economic activity. The empirical investigation of this notion is the focus of Chapter 5.

Secondly, research evaluating linkages between the business cycle and company profits is discussed. Studies which provide evidence of a common market or business cycle component in realized earnings, and its variation through time, assist understanding of how earnings forecasts may share similar features. This provides further impetus for the focus of empirical investigations in Chapter 5.

Thirdly, literature discussing the processes employed by analysts for forecasting is reviewed. A number of studies discuss and evaluate "textbook" approaches to forecasting. That is, the processes outlined by popular business texts for training analysts. These typically advise incorporating expectations for business cycle factors into the earnings forecasting process. Some go further to recommend analysts develop a macroeconomic view as the first step in generating a firm's earnings outlook. If analysts do indeed follow this general approach then a significant business cycle component in aggregated earnings forecasts should be expected (although this needs to be related back to the issue of forecast accuracy to be able to infer the presence of information in forecasts for future realized economic activity). Whether or not analysts do indeed incorporate such an approach (either explicitly or implicitly) may be partially evaluated via investigation of the informational efficiency of their forecasts. Such tests can be employed to determine whether analysts recognize the implications of realized macroeconomic information for future realized earnings. Hence, a discussion of literature related to analyst forecast efficiency is provided (in particular with respect to macroeconomic factors). This literature provides the background for the focus of Chapter 6 – the informational efficiency of aggregated analysts' forecasts with respect to a range of macroeconomic factors.

Finally, the literature sparked by Kothari, Lewellen and Warner (2006) regarding the relationship between aggregate earnings and the discount rate is discussed. Kothari et al. find evidence of a positive relationship between earnings surprise and the discount rate, and observe this is at odds with the predictions of a range of theoretical models. Chapter 7 provides an empirical investigation of Kothari et al.'s findings employing alternative proxies for earnings surprise. In Section 2.5 I provide an overview of theoretical models which predict discount rate pro-cyclicality and counter-cyclicality, evidence in support of those theories and recent empirical findings which call into question the validity of popular theoretical approaches. It is clear from these discussions that the nature of cyclicality in discount rates is far from being conclusively resolved.

2.2 Information in earnings forecasts

2.2.1 Forecast earnings accuracy

THE QUANTITY OF academic research published over the last few decades investigating security analysts' forecasts is voluminous. Ramnath, Rock and Shane (2008) identify around 250 related papers published in just 11 journals from 1993 to June 2006. Similarly, Brown (1993) cites 171 papers in his evaluation of research into earnings forecasts up to that point and Brown, Foster and Noreen

(1985) refer to well in excess of 200 papers in their evaluation of the characteristics of analysts' earnings forecasts. It is not unreasonable to assume the typical equity analyst providing the forecasts that are being assessed in these studies will be tertiary educated. It is therefore interesting that these individuals can go from being taught their analytical skills and processes by academic institutions to, upon graduation and acceptance of employment, becoming inscrutable to their former teachers.

Much of the early research on earnings and/or analysts' forecasts focused on assessing their time series properties: Do earnings follow a random walk?[20] Can earnings be accurately modelled, and in turn predicted, with statistical methods (and are these techniques superior to analysts' forecasts)?[21]

This focus gradually changed to incorporate such features as the processes employed by analysts to forecast (with particular emphasis on forecast efficiency),[22] the characteristics of analysts and their forecasts and recommendations,[23] and behavioural aspects of analysts' research (including a considerable body of research evaluating incentive processes, biases and herding).[24] The research focus of Chapter 5 is the identification of information in analysts' earnings forecasts for the macroeconomy. Discussion in this section is therefore limited to two key related features of earnings forecasts: analyst forecast accuracy and forecast bias.

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[20] Examples include Little (1962), Ball and Brown (1968) and Ball and Watts (1972).

[21] Examples include Fried and Givoly (1982) and Brown, Hagerman, Griffin and Zmijewski (1987a, 1987b).

[22] Examples include Lys and Sohn (1990), Stickel (1990), Abarbanell (1991), Lang and Lundholm (1996), Rogers and Grant (1997) and Frankel and Lee (1998).

[23] Examples include Clement (1999), Hirst, Hopkins and Wahlen (2004) and Clement and Tse (2005).

[24] Examples include Francis and Philbrick (1993), Dugar and Nathan (1995), Calegari and Fargher (1997), Clement and Tse (2005) and Libby, Tan and Hunton (2006).

Forecast bias is important to consider given it has the potential for obfuscating the relationship between earnings forecasts and economic activity. Forecast accuracy is critical to this study's key hypotheses given the link between actual realized earnings and economic activity (discussed in Section 2.3). If these are positively correlated, and empirical evidence suggests this is the case,[25] then evidence of significant forecast accuracy would suggest the presence of information in those forecasts for economic activity in the forecast period.

Taking a textbook approach to the value of the firm, and assuming full market efficiency, a company's stock price should equal the present value of the expected stream of future dividends. Analysts' earnings forecasts provide one potential source for values of expected cash flows accruing to an investor in the stock (after applying an expected dividend pay-out ratio or earnings retention ratio).[26] In addition, any assessment of unanticipated shocks to earnings requires a proxy for earnings expectations to in turn estimate the magnitude of the unanticipated component. Hence, a good proxy for earnings expectations (which are ultimately unobservable) is required for key aspects of accounting and finance research. Brown and Rozeff (1978), in discussing motivations for their analysis of forecast accuracy, note that the rational expectations hypothesis (as outlined by Muth (1961)) requires that "market earnings expectations should be measured by the best available earnings forecasts" (p. 1).

A consequent focus of many early studies of analysts' forecasts was the usefulness of this source of expectations. In particular, the 1970s and 1980s saw a

[25] For example, see Brown and Ball (1967), Gonedes (1973), Magee (1974) and O'Brien (1994).

[26] However, for many stocks within public databases of analysts' forecasts (including the Institutional Brokers' Earnings System, I/B/E/S), forecasts are limited to a view on earnings over the 1–2 years following the last realized earnings announced. A subset of analysts will publish a forecast for earnings 3 years out, and some will also publish a long term earnings growth expectation, which is generally interpreted as an average earnings growth forecast for the 3–5 years following the explicit year 1, 2 and 3 earnings forecasts.

considerable number of articles published comparing the accuracy of analysts' forecasts with those of statistical models. Brown, Foster and Noreen (1985), Brown (1993) and Schipper (1991) provide detailed reviews of this research. The general conclusion is that analysts provide superior forecasting ability relative to statistical models.[27] While there have been results published which conflict with this conclusion, a common feature of early dissenting studies was the use of very small sample sets.[28] Since publication of these studies, the quantity and availability of analyst forecast data has progressively improved with the launch of electronic databases in the mid to late 1970s, and their subsequent growth in stock coverage and number of contributing analysts.

However, while empirical evidence points to the superior accuracy of security analysts' forecasts relative to statistical models, this does not necessarily mean that analysts' forecasts are the *best* measure of market earnings expectations. For example, a range of studies develop techniques combining analysts' forecasts with the predictions of time series models to generate significant increases in forecast accuracy. Consequently, Schipper (1991) notes the possibility of true investor expectations differing markedly from published analysts' earnings forecasts:

> While accounting researchers use earnings forecasts without adjustment and often without other measures to measure or proxy for market expectations of earnings, there is no compelling reason to believe that

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[27] For example, Brown and Rozeff (1978) found that analysts' forecasts were superior to a selection of simple time series models. Fried and Givoly (1982) similarly found evidence of analyst superiority relative to two univariate time series models – a result they largely attribute to the informational advantage of analysts relative to simple univariate models. Brown, Hagerman, Griffin and Zmijewski (1987b) present further evidence to support this result, and find evidence suggesting analyst superiority is a result of informational advantages including greater forecast efficiency relative to the time series models evaluated. In addition, a number of commentators have observed that the continued existence of the vast cost base that security analysts represent *should* imply the accuracy of those analysts' forecasts exceeds that of mechanical models.

[28] Examples include Cragg and Malkiel (1968), Elton and Gruber (1972) and Imhoff and Paré (1982). Cragg and Malkiel (1968) evaluate expected earnings per share growth for 185 firms at the end of 1962 and 1963, Elton and Gruber (1972) studied 180 companies from 1964–1966 with analyst data from 3 forecasting firms, and Imhoff and Paré (1982) evaluated just 46 forecasts from 1971 to 1974.

> market participants use such forecasts the same way. Investors may, for example, adjust the reported forecasts in some way to take account of other information about either the firm in question or the forecasting process itself. (p. 108)

Analyst accuracy may also vary widely depending upon such issues as the range of firms covered, the nature of the employing firm, analyst experience and myriad other factors.[29] Despite this, Mikhail, Walther and Willis (1999) and Hong and Kubik (2003) present evidence that analysts are incentivized to issue accurate earnings forecasts due to the imperatives of job security and career advancement.

A number of studies also find evidence of forecast accuracy being dependent upon the information environment. That is, accuracy improves with the availability and quality of information. This suggests the potential for a relationship between forecast accuracy and the business cycle. Notably, Higgins (2002), analyzing US firms in the I/B/E/S dataset from 1990 to 1992, found evidence to support the hypothesis that earnings forecasting becomes more difficult during recessions (as reflected in increased forecast errors and greater forecast dispersion). Further, the effect is greater for more cyclical firms and those with relatively higher leverage. This notion is investigated in Chapter 5 by estimating the information in analysts' earnings forecasts for future macroeconomic activity conditional on relative earnings cyclicality and economic regimes.

There is also a considerable body of research evaluating forecast efficiency (select examples are discussed in Section 2.4) reporting evidence of publicly available information that has not been fully incorporated into analysts' forecasts. Such issues raise problems for the capital markets researcher seeking the optimum proxy for market expectations. However, aggregation of analysts' forecasts across firms and analysts should reduce unsystematic firm- and analyst-specific biases.

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[29] See Brown, Richardson and Schwager (1987) and Clement (1999) for analysis of a range of these issues and Ramnath, Rock and Shane (2008) for an overview of this literature.

2.2.2 Multi-period forecasts

WHILE THE BODY of literature evaluating the information content of analysts' earnings forecasts is large there is, relatively speaking, surprisingly little analysis that considers the multiple periods of forecasts issued by analysts. A considerable proportion of analysis that does consists of accounting research incorporating analysts' multi-year forecasts in discounted valuation models.[30] A number of papers also evaluate analysts' long term growth forecasts (a three to five year forecast rate of growth collected by I/B/E/S).[31] However, there appears to be a gap in the literature. There is little in the way of published time series analysis evaluating the informational content of analysts' multi-year forecasts.[32]

Frankel and Lee (1998) and Cheng (2005) present evidence that models explaining the cross-section of price to book ratios can be significantly improved by incorporating not just earnings expectations for the next fiscal period, but also expectations for the following fiscal period and longer term forecast earnings growth. Similarly, Liu and Thomas (2000) find large and statistically significant increases in R^2 values for regressions estimating earnings response coefficients when forecast revisions for the next 1 and 2 years are included as explanatory variables. These results suggest the presence of additional information in analysts' earnings forecasts for periods beyond the next company announcement date.

To maximize the length of the time period that may be evaluated, the research design of this thesis incorporates a combination of the current forecast year and next forecast year (I/B/E/S FY1 and FY2 forecast years) to generate a standardized

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[30] Examples include Claus and Thomas (2001), Gebhardt, Lee and Swaminathan (2001) and Botosan and Plumlee (2005).

[31] Examples include Frankel and Lee (1998), Liu and Thomas (2000) and Jung, Shane and Yang (2009).

[32] A notable exception to this statement is Brown, Foster and Noreen (1985). This paper includes analysis of the relationship between multi-year earnings forecast revisions and security returns, but covers only the years 1977 through to 1980.

12 month-ahead forecast. Therefore, my analysis represents an investigation of the time-weighted information in analysts' multi-year forecasts. Variable construction is discussed in Chapter 3.

2.2.3 Forecast bias

FORECAST BIAS IS a phenomenon with the potential to distort the results of analysis. Forecast bias is a generic term applied to a wide range of prejudicial features of analysts' forecasts, most notably a positive bias in earnings forecasts.[33] Other reported features include herding (whereby analyst forecasts exhibit tight grouping, avoiding bold forecasts),[34] analyst incentives which foster bias in forecasts (for example, investment banking relationships, the analyst's relationship with firm management and trading commissions)[35] and behavioural/cognitive biases (including evidence suggesting analysts fail to update forecasts in a manner consistent with Bayes' theorem).[36]

These characteristics of analysts' forecasts could distort the results of empirical tests if their respective effects are sufficiently large, and hence research design and analysis of empirical results need to recognize this risk (although, as mentioned above, aggregation of forecasts should have a mitigating effect on some forms of forecast bias). My empirical analysis focuses on time series investigations of changes in analysts' earnings forecasts. Therefore, consistent systematic bias in forecasts will be manifest in the estimated intercepts in regression analysis, but will not impact estimated slope coefficients – the latter being the focus of research

[33] Evidence of a positive bias in analysts' forecasts is presented in Fried and Givoly (1982), Biddle and Ricks (1988), Affleck-Graves, Davis and Mendenhall (1990), Stickel (1990), Abarbanell (1991) and Butler and Lang (1991).

[34] See Graham (1999), Hong, Kubik and Solomon (2000) and Clarke and Subramanian (2006) for examples.

[35] See Dugar and Nathan (1995), Lim (2001), Irvine (2004) and Libby, Tan and Hunton (2006) for examples.

[36] See Maines and Hand (1996), Calegari and Fargher (1997) and Friesen and Weller (2006) for examples.

hypotheses. However, I do not explicitly investigate time variation in forecast bias, which could impact estimated slope coefficients. I do nonetheless evaluate variation in coefficients conditional on economic regimes. Hence, forecast bias that is correlated with the variable employed to define regimes will be reflected in a difference between estimated slope coefficients for different regimes. Other forms of time variation in forecast bias are left for future research. Note that forecast bias may also arise from the use of stale forecasts. I/B/E/S aggregation techniques for determining consensus earnings expectations result in the amalgamation of forecasts that may have been published months apart.[37] I employ robustness tests in all empirical chapters on a dataset comprised only of forecasts submitted to I/B/E/S within a narrow window. Any change in conclusions from the use of this dataset, compared with the full dataset, may be partially the result of forecast bias. In actuality I find all research conclusions are unchanged.

In this section I have discussed analysis of the information content of analysts' earnings forecasts for future earnings, i.e. forecast accuracy. Evidence of statistically significant forecasting prowess, combined with knowledge of a positive relationship between realized earnings and realized economic activity, provide a basis for hypothesis development relating forecast earnings to future economic activity. A second component is the relationship between realized earnings and economic activity. This is discussed in the following section.

[37] Guttman (2010) presents a model of the timing of forecast issuance in which "analysts with a high precision of initial private information tend to forecast earlier, and analysts with a higher learning ability tend to forecast later" (p. 513). More generally, Crichfield, Dyckman and Lakonishok (1978), O'Brien (1988b) and Brown (1991) provide evidence of a positive relationship between forecast accuracy and forecast timeliness.

2.3 Earnings and the business cycle

THE FOCUS OF Chapter 5 is the identification of information in analysts' earnings forecasts for economic activity. A key condition underlying the expectation of a statistically significant relationship between these variables is a statistically significant relationship between realized earnings and contemporaneous realized economic activity. Positive correlation between earnings and economic activity would provide motivation for analysts to incorporate this relationship in the forecasting process. The precepts of rationality require that analysts recognize this relationship.

In sub-section 2.3.1 the concept of business cycles is addressed and evidence for a positive relationship between economic activity and firm profits is presented. There is widespread agreement across studies that earnings do vary pro-cyclically. Secondly, the concept of a market component in earnings is investigated. Earnings may be decomposed into a stock specific component and common market component. The common market component reflects the exposure of all stocks to the business cycle. When earnings are aggregated across firms it should be expected, by a simple diversification argument, that the business cycle component of earnings will be a statistically significant proportion of total earnings. Applying the same argument, it is reasonable to expect to see a similar phenomenon for forecast earnings. A large common component in realized earnings provides further empirical support for hypothesizing the presence of information in earnings forecasts for economic activity.

2.3.1 Earnings and cycles

LUCAS (1977) PROVIDES a discussion of business cycle theory, and notes the following key features of business cycles:

> (i) Output movements across broadly defined sectors move together […]. (ii) Production of producer and consumer durables exhibits much greater amplitude than does the production of nondurables. (iii) Production and prices of agricultural goods and natural resources have lower than average conformity. *(iv) Business profits show high conformity and much greater amplitude than other series.* (v) Prices generally are procyclical. (vi) Short-term interest rates are procyclical; long term rates slightly so. (vii) Monetary aggregates and velocity measures are procyclical. (p. 9)[38]

Lucas further notes that "The features of economic time series listed here are, curiously, both 'well known' and expensive to document in any careful and comprehensive way" (p. 9). Nonetheless, in this section I provide a selection of illustrative examples of research finding a significant relationship between earnings and aggregate economic activity.

Gomme and Greenwood (1995) develop a general equilibrium real business cycle model in which entrepreneurs (shareholders) insure workers against cyclical risk with labour contracts. This results in the counter-cyclicality of labour's share of income and the pro-cyclicality of capital's share of income. Corporate profits represent a key component of the capital share of income. Hence, their model provides a theoretical framework for the observed pro-cyclicality of corporate profits. Their empirical work supports this implication of their model for the US and seven additional OECD countries.

Bernstein and Arnott (2003) highlight the close long term relationship between GDP and corporate profits in the US. With the exception of the Great Depression, corporate profits have remained around 8 to 12 percent of GDP since 1929. Bernstein and Arnott also note that per capita GDP is a measure of productivity

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[38] Emphasis added.

growth and productivity growth is an important driver of both earnings per share and dividends. Hence, we should expect to see a positive relationship between per capita GDP and earnings per share.

Longstaff and Piazzesi (2004) similarly note the high correlation between US aggregate consumption and the "corporate fraction" (a measure of dividends defined as corporate profits multiplied by a constant pay-out ratio of 50%) between 1929 and 2001. They also obtain supportive results employing a range of alternative datasets and definitions for their dividend measure, including earnings data for the S&P Composite Stock Price Index, UK data and Canadian data. In addition, they note the high volatility of the corporate fraction. This is consistent with Lucas's (1977) comments regarding the amplitude of the cycle in business profits, and highlights the sensitivity of earnings to economic shocks.

O'Brien (1994) evaluates the impact of macroeconomic news on earnings and earnings forecasts for US firms from 1976 through to 1988. The earnings yield is regressed on growth in industrial production, unexpected inflation, the 11 month change in bond yields and unexpected 11 month market returns (measured as the market return less the average annual corporate bond yield at the start of the 11 month period, adjusted to an 11 month basis). O'Brien concludes that "macroeconomic shocks to industrial production, inflation, interest rates and stocks returns have significant descriptive power over industry earnings/price ratios" (p. 19). Similarly, Kothari, Lewellen and Warner (2006) report strong positive correlations between a range of measures of changes in aggregate earnings and contemporaneous annual growth in US GDP, industrial production and aggregate consumption (correlation coefficients ranging from 0.363 to 0.670 depending upon the measure of aggregate earnings and measure of economic activity).

De Zwart and Van Dijk (2008) regress firm earnings growth (deflated by price) on real GDP growth and a selection of other macroeconomic and firm-specific variables for 29 emerging markets.[39] They find a statistically significant positive coefficient on GDP growth, further supporting the link between realized earnings and economic activity. However, they note that the R^2 on this regression is only 7.53%, signalling "that the relationship between earnings growth and macroeconomic developments in emerging markets is not particularly strong" (p. 16). This seems a somewhat surprising result given the common perception amongst market practitioners of the presence of high cyclicality in emerging markets. It may be that greater explanatory power is achieved with a measure of global economic activity, rather than local GDP for the countries corresponding to the stock domiciles (the latter is used by De Zwart and Van Dijk). It is also possible that significant heterogeneity in the relationship between economic activity and earnings growth across countries impacts the results. While De Zwart and Van Dijk do not report results of individual country regressions for realized earnings and realized economic activity, substantial country heterogeneity is evident in reported individual country regressions of forecast error on forecasts for macroeconomic variables, including GDP growth. The estimated coefficient on forecast GDP growth is positive and significant for 5 countries, negative and significant for 5 countries and statistically insignificant at the 10%, 5% and 1% levels for the remaining 17 countries. In contrast, my research investigates the relationship between realized (and forecast) earnings and macroeconomic variables at the aggregate market level and for a range of sub-portfolios. I employ a range of robustness tests to evaluate realized and forecast earnings at individual stock, sector, aggregate market and other portfolio groupings. Hence, research

[39] De Zwart and Van Dijk (2008) also include consumer price inflation, a political risk score, the change in earnings in the prior year, market capitalization, stock coverage and the price-to-book ratio as explanatory variables.

methodology is designed to evaluate the robustness of aggregate market results across a wide range of sub-groups.

Overall, the academic evidence supports the hypothesis of a statistically significant relationship between company earnings and contemporaneous economic activity, albeit with variation in estimates of the degree to which they are interlinked.

2.3.2 Systematic variation in earnings

AN ALTERNATIVE PERSPECTIVE on the relationship between earnings and the business cycle is provided by a branch of the literature which evaluates the extent to which earnings and earnings forecast errors are driven by a common market component, as opposed to firm-specific factors. These studies generally conform to one of three approaches: an earnings version of the market model in which firm or industry earnings are regressed on an aggregate market earnings measure or macroeconomic measure of activity[40], studies which investigate the presence of a common market component in analyst forecast errors[41], and studies of stock price synchronicity.[42] Examples of each of these approaches are provided below.

Brown and Ball (1967) regress earnings of US firms on average earnings for the full sample of firms for a period extending from 1947 through to 1965. Employing six different definitions of firm earnings, they find on average that 35% to 40% of the variation in a firm's annual earnings is accounted for by average earnings across the sample. The R^2 of their regressions increases by an average 10 to 15 percentage points when the residual from a regression of the firm's average industry earnings on average market earnings is added as an explanatory variable.

[40] Examples inlcude Brown and Ball (1967), Gonedes (1973), Magee (1974), Lev (1980), Foster (1986) and Chordia and Shivakumar (2005).

[41] Examples include Elton, Gruber and Gultekin (1984) and O'Brien (1994).

[42] Examples include Piotroski and Roulstone (2004) and Chan and Hameed (2006).

Foster (1986) applies the same approach to the net income of a sample of firms from 1964 through to 1983 and reports an average R^2 of 17%. Gonedes (1973) performs a similar study for 1947–1968 with two earnings measures (net sales deflated by common equity and net income deflated by common equity), two aggregation techniques to generate market earnings (simple average and a common equity-weighted sum) and two models (a market model in which the level of the accounting series in question is regressed on the level of the relevant market average, and a model employing the same structure but in which the factors are in first-differenced form). The value of the R^2 is in excess of 20% for all regressions with the exception of regressions employing the simple average of net sales deflated by common equity (levels and first-differenced). Magee (1974) also tests the size of the market component in earnings using a first-differenced version of the above market model for US firms from 1960 through to 1967 and reports an average R^2 of 18.5%.

Lev (1980) experiments with models of similar form, but for the market factor replaces sample averages of the accounting variables in question with macroeconomic indices – GNP and Total Corporate Profits After Taxes. The average R^2 for regressions of firm operating income on GNP for the period 1949–1967 was 49.7%, and for regressions employing first differences of the same variable Lev reported an average R^2 of 14.1%. Chordia and Shivakumar (2005) take a slightly different approach to estimating this relationship, by first generating decile portfolios sorted on standardized unexpected earnings (SUE) for each quarter from Q1 1972 through to Q4 2001. The next quarter's SUE is then regressed on three month growth in GDP, real GDP, industrial production and CPI inflation. They report that "earnings vary monotonically with the business cycle, as measured by growth in the nominal GDP" (p. 528).

The question of to what extent analysts' forecast errors are driven by a common market component is addressed by Elton, Gruber and Gultekin (1984) and O'Brien (1994). The former decompose mean squared forecast errors into economic, industry and stock-specific components. They report that the average error in forecasting the level of market earnings per share represents less than 3% of the total forecasting error, while the company-specific error represents in excess of 60% of the total error. This suggests that analysts are relatively successful at forecasting the market component of earnings.[43] However, in a regression of forecast errors on growth in industrial production, unexpected inflation, interest rate changes and unexpected market returns for the period 1976–1988, O'Brien (1994) reports "that common shocks are reflected in the cross-section of earnings forecast errors" (p. 4). Hence, there is some uncertainty around the issue of the proportion of forecast errors driven by a common market component, as opposed to industry- and stock-specific components.

A third perspective on market-wide information in analysts' work may be obtained from select studies of stock price synchronicity. Stock price synchronicity is typically derived from the R^2 of a simple market model regression of stock returns on market returns, and is calculated as the log of the ratio of R^2 to $1\text{-}R^2$.[44] Hence, synchronicity is employed to measure the degree to which stock prices move together. Piotroski and Roulstone (2004) find a statistically significant positive cross-sectional relationship between analyst forecasting activity (frequency of earnings revisions) and synchronicity for US firms from 1984–2000. They comment that this is "consistent with analysts contributing industry- or market-level expertise to the price formation process" (p. 1130). Chan and Hameed (2006) extend this analysis to emerging markets and similarly find a positive relationship

[43] However, some caution is warranted given Elton, Gruber and Gultekin (1984) evaluate forecast errors for only 414 companies over 3 years (1976–1978).

[44] See Morck, Yeung and Yu (2000).

between stock price synchronicity and analyst coverage, again consistent with the notion of analysts producing market-wide information. Chan and Hameed also generate three portfolios based on sorting by analyst coverage. They report the following:

> We find that the aggregate change in earnings forecasts in a high analyst-following stock portfolio affects aggregate returns of the portfolio itself as well as the aggregate returns of the low analyst-following stock portfolio. In contrast, the aggregate change in earnings forecasts in the low analyst-following stock portfolio does not provide information about the returns on either of the two portfolios. Overall, our evidence is consistent with the explanation that the information produced by security analysts has more market-wide content. (p. 117)

In summary, the academic evidence provides strong support for the notion of pro-cyclicality in company earnings, and the common market component of earnings on average represents a substantial and statistically significant proportion of company earnings. However, it is not clear to what extent forecast errors in this market component of earnings drive forecast errors in company earnings. Finally, it is helpful to note that analysis of synchronicity in stock returns also supports the notion of a significant market-wide component in the information provided by analysts.

Separately, a number of researchers have attempted to address the processes employed by analysts to generate their forecasts. If it can be shown that analysts explicitly incorporate a view on the macroeconomy in their earnings forecasts then, if forecast accuracy is significant, there is further motivation for evaluating the relationship between earnings forecasts and future economic activity. The following section discusses forecast process issues and evidence for analyst use of macroeconomic factors in the formation of their earnings expectations.

2.4 The forecasting process

UNDERSTANDING HOW ANALYSTS generate their forecasts is clearly important for developing an understanding of how those forecasts may be employed for portfolio analysis and risk management. In this section two branches of the literature that relate to forecast process are discussed. Firstly, there is growing academic interest in determining the precise tools and techniques employed by analysts to forecast earnings. Secondly, there is a large body of literature which evaluates forecast efficiency – investigating wide-ranging sources of information and to what extent analysts incorporate that information in their forecasts. Recent work has included tests of whether past economic data is incorporated into analysts' forecasts. Measuring the informational efficiency of analysts' forecasts with respect to historic economic data represents an indirect test of whether analysts take a view on future economic activity. In other words, it represents a test of whether analysts either explicitly or implicitly recognize the impact of the business cycle on a firm's earnings. Estimating the informational efficiency of aggregated analysts' forecasts with respect to a range of macroeconomic factors is the focus of empirical analysis in Chapter 6.

2.4.1 Macroeconomic views

LAMBERT, MATOLCSY AND Wyatt (2009) observe that a range of popular business texts refer to analysis of the business cycle as the first step in the forecasting process for individual companies.[45] If analysts do indeed incorporate historic macroeconomic data in their earnings forecasts this suggests they likely incorporate macroeconomic expectations in those earnings forecasts, providing further motivation for evaluating imputed macroeconomic information.

[45] Examples of such texts include Narayanan and Fahey (2001), Palepu, Healy and Bernard (2004), Koller, Goedhart and Wessels (2005), Lundholm and Sloan (2007) and Penman (2001).

Nonetheless, there appears to have been little analysis of the relationship between analysts' earnings forecasts and the macroeconomy. As noted by Brown (1993):

> Several studies have examined the relation between analysts' earnings forecasts and firm-specific factors, such as stock prices, changes in consensus earnings estimates, deviation from the consensus and forecast errors. However, with limited exceptions [Stone (1977), Fildes and Lam (1990)], *the macroeconomic and industry factors asserted by analysts to be important cues to their decisions have been ignored*. (p. 313)[46]

It appears that this observation remains largely correct today, 17 years after it was made. Hence, not only is there an obvious gap in knowledge of the processes employed by analysts to forecast earnings, but there is little understanding of the accuracy and effectiveness of analysts' forecasts with respect to the macroeconomic outlook. In this section textbook approaches to security analysis and business strategy are discussed to obtain guidance on the framework recommended by accounting and finance text authors to practitioners.

Lundholm and Sloan (2007) devote the bulk of a chapter to a discussion of the importance and use of macroeconomic factors in security analysis. This includes discussion of sector sensitivities to select macroeconomic factors, with a focus on GDP, interest rates, inflation, foreign exchange, oil and other commodity prices. They believe such analysis should be the first step in the overall evaluation process, recommending that "First, you should consider the general macroeconomic conditions. This will help you understand how the current economic climate affects the performance of each of the industries in which the business operates" (p. 38). Similarly, Palepu, Healy and Bernard (2004) believe that "a good analyst understands what economics scenarios could plausibly be reflected in the observed price" (p. 9-8). Further, Koller, Goedhart and Wessels (2005) discuss cyclicality in company earnings in some detail and the importance of understanding earnings cyclicality.

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[46] Emphasis added.

Narayanan and Fahey (2001) provide a framework for management to employ in an assessment of the implications of the macroeconomy for business strategy and performance. They argue that "an ongoing analysis of the macroenvironment is essential for crafting and executing sound strategy" (p. 189). They observe that many critical long term structural changes in drivers of business performance have been features of macroeconomic developments, including rapid growth in technological development and demographic changes. They highlight six key components of the macroenvironment which they label social, economic, political, technological, ecological and institutional. The economic component is the key focus of my research, which Narayanan and Fahey further split into a structural component and a cyclical component.[47] My research is focused on identifying links between analysts' forecasts and macroeconomic factors. There is no attempt to separately identify structural and cyclical components of a macroeconomic view. Nonetheless, the possibility exists of structural change which distorts analysis of cycle relationships. Research design can to an extent alleviate concerns regarding the impact of such effects by, for example, comparing results across sub-periods.

Importantly, Narayanan and Fahey believe that management analysis of the macroeconomy is not performed with the aim of predicting the business cycle. Instead, they argue the aim is to focus more on an understanding of the ways in which macroeconomic change can impact the business. They do acknowledge that the "benefits of macroenvironmental analysis, however, are only realized when those doing the analysis are willing to assume the difficult but necessary task of making judgements about the effects of the change" (p. 191). Similarly, Lundholm

[47] Narayanan and Fahey (2001) define structural change as referring to "change within and across sectors of the economy such as movements in economic activity from some types of industries to others […] and movements in the relationships among key economic variables such as the relative levels of imports and exports as a percentage of gross national product (GNP)" (pp. 194–195). Cyclical change is defined as referring to "upswings and downswings in the general level of economic activity such as the movement in GNP, interest rates, inflation, consumer prices, housing starts and industrial development"(p. 195).

and Sloan (2007) suggest what is critical is an understanding of the relevant relationships and sensitivities, rather than explicit macroeconomic forecasts. They advise the following:

> Your goal should be to understand the general consensus about major macroeconomic factors. You don't need to develop your own independent forecasts of future GDP or interest rate movements, but you should understand what the experts are saying about these factors and how they might influence your firm's performance in the future. (p. 42)

However, what these two sets of authors do not explicitly note is that if businesses (and forecasting analysts) act upon their analysis of the macroeconomy, their actions (forecasts) will contain information about their expectations for the business cycle (the focus of empirical analysis in Chapter 5). In addition, the recommendations of these authors raise awareness of the need for analysts' forecasts to, at a minimum, efficiently incorporate all past economic information in their earnings forecasts (the focus of empirical analysis in Chapter 6).

Penman (2001) provides an example of sensitivity analysis for company accounts by linking key revenue statement variables to GDP and testing a range of scenarios. Supporting and extending Narayanan and Fahey's view, Penman comments:

> Understanding both business conditions and the firm's strategy is a prerequisite for sound forecasting and valuation. When forecasting, the analyst asks how business conditions might change and how management's strategy might change – perhaps in reaction to changes in business conditions. (p. 500)

Hence, an equity analyst mimicking firm management's analysis of business strategy will consequently incorporate a business cycle outlook in their earnings expectations.

This recommended approach is also not a recent development. From the first edition of Reilly (1979), *Investment Analysis and Portfolio Management*, through to its latest co-authored eighth incarnation (Reilly and Brown (2006)), the text has recommended a first step of analyzing the relationships between macroeconomic factors and earnings for industry analysts embarking upon earnings forecasting.[48]

However, as noted above, there are textbooks which advise equity analysts avoid explicitly generating their own forecasts for macroeconomic activity, instead focusing on an understanding of, and appreciation for, the general issues. If this advice is indeed followed, it could limit the significance of information in analysts' forecasts for the business cycle. Further, it raises the possibility that analysts' earnings forecasts may merely represent noisy estimates of the consensus outlook for the macroeconomy.[49] My research investigates the marginal explanatory power of analysts' forecasts for macroeconomic activity over and above other potential drivers, including current market consensus on the state of the macroeconomy (as represented by, for example, surveys of business confidence). Hence, my research design seeks to control for this factor by including proxies for the consensus outlook for economic activity as explanatory variables in regressions.

In addition, there is considerable variation across the market in approaches taken by analysts. For example, Elton, Gruber and Gultekin (1984) make the following observation:

> Some institutions start with forecasts for the economy as a whole, then prepare industry studies, and finally prepare forecasts for individual firms (top-down approach). Other institutions start with the forecasts for individual firms and only after such forecasts are prepared, check with the economists' forecasts for macroeconomic consistency (bottom-up approach). (pp. 355–356)

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[48] Reilly (1979) provides recommended procedures for forecasting earnings, "the first of which is deriving an estimate of sales per share based upon an analysis of the relationship between sales of the given industry and aggregate sales for some relevant economic series" (p. 323). Similarly, Reilly and Brown (2006) recommend a first step of "macroanalysis of the industry to determine how this industry relates to the business cycle and what economic variables drive this industry" (p. 463).

[49] An early example of this concept is provided by Brown, Foster and Noreen (1985), who found evidence of stock prices leading analysts' earnings revisions, implying analysts' revisions could merely be a lagged indicator of the market.

It must therefore be recognized that modelling of analysts' forecasting processes (and indeed attempting to isolate key aspects of these processes) is clearly a complex problem. As observed by Ramnath, Rock and Shane (2008):

> The challenge is that analysts have a context-specific task that is very difficult to model, and, consistent with suggestions in Brown (1993) and Schipper (1991), in recent years we have seen relatively more studies using experimental and contextual approaches to questions about analysts' decision processes and incentives. (p. 38)

It is very difficult, for example, to distinguish between an explicit macroeconomic view and an implicit one. Nonetheless, a number of content analyses of analysts' research reports and analyst survey data suggest a macroeconomic view may be explicit. In a survey of 2000 US analysts Chugh and Meador (1984) found 39% of respondents reported their view on general economic conditions for the next quarter was of great importance in the analysis process (with 43% placing moderate importance on this driver). The numbers were 55% and 35%, respectively, for their view on general economic conditions over the next five years. In a content analysis of 479 financial analysts' reports Previts, Bricker, Robinson and Young (1994) found a large quantity of non-financial information which included analyst views on the macroeconomic environment. Similarly, in a content analysis of 187 financial analysts' reports Rogers and Grant (1997) found 144 of these contained some form of description of the firm's operating environment. Abdolmohammadi, Simnett, Thibodeau and Wright (2006) evaluate 64 analyst reports and find 326 references to industry and economic trends out of a total of 5,129 indentified information references. Hence, survey data and content analysis of research reports provide some evidence that an explicit view on the macroeconomic environment is a component of analysts' forecasting processes. However, the discussion of forecast efficiency research in the following section highlights far from conclusive results for the informational efficiency of analysts' forecasts with respect to macroeconomic variables. Therefore, while the results of

Chugh and Meador (1984) suggest a macroeconomic view is considered by analysts to be a key component of the stock analysis process, it is not clear that this macroeconomic view is formed and incorporated into earnings forecasts either efficiently or effectively.

This calls into question the potential for identifying a statistically significant positive relationship between aggregated forecast earnings growth and realized indicators of macroeconomic activity growth in the forecast period. That is, whether aggregated earnings forecasts contain information for future economic activity. Interestingly, while the results presented in Chapter 6 provide evidence of analysts underreacting to select macroeconomic factors, the results presented in Chapter 5 provide evidence of statistically significant information in aggregated forecasts for select measures of macroeconomic activity. Hence, while analysts' forecasts are inefficient with respect to a number of the economic factors tested, I find evidence they do react to economic news and, in aggregate, either implicitly or explicitly form a macroeconomic view.

2.4.2 Forecast efficiency

THE INFORMATIONAL EFFICIENCY of earnings forecasts refers to the notion of analysts incorporating all available information in their forecasts (stock-specific information and market-wide information). Given this study's aim of investigating the predictive power of earnings forecasts for economic activity, forecast efficiency literature is discussed in this section with respect to macroeconomic information. Evidence that analysts incorporate macroeconomic information in their forecasts would provide further support for a hypothesized link between earnings forecasts and future economic activity.

Tests of analyst efficiency generally involve the regression of forecast errors[50] on a range of variables reflecting information available to analysts prior to the publication of their forecasts.[51] Ackert and Hunter (1995) summarize the requirements for rationality (full information efficiency) in analysts' forecasts as "(1) the forecast errors, conditional on the available information set, have zero means, and (2) the forecast errors are uncorrelated with the values of all the variables in the information set and, therefore, with their own past values" (p. 429).[52] Numerous studies have examined these requirements for hypothesized members of the information set with considerable variation in results, including evidence of both analyst overreaction and underreaction to publicly available sources of information.[53]

Importantly, there has been growing focus in the literature on the role played by macroeconomic information, and to what extent this information is incorporated in analysts' forecasts. Hunter and Ackert (1993) provide one of the first analyses of the importance of macroeconomic information in tests of analyst rationality. They noted that earlier tests of analyst rationality generally assume that the forecasts of

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[50] Forecast errors are typically defined as the difference between earnings forecasts a specified number of months/quarters prior to the announcement date and realized earnings for the forecast period in question, often in turn deflated by price.

[51] Examples of analyst efficiency studies include Ackert and Hunter (1995), Frankel and Lee (1998) and Simpson (2010).

[52] These requirements are derived from the rational expectations hypothesis as outlined by Muth (1961).

[53] An oft-cited example is the work of Abarbanell and Bernard (1992). They find evidence of serial correlation in forecast errors, consistent with analyst underreaction to earnings announcements. More recently, Markov and Tamayo (2006) present a model in which serially-correlated forecast errors may still be consistent with a hypothesis of information efficiency. They introduce a learning process as a result of which serial correlation in forecast errors decreases over time as analysts develop an understanding of the time series properties of quarterly earnings. However, shocks re-start the learning process. In the last few years a number of studies have further investigated the revision of analysts' forecasts in response to earnings announcements, the revisions of other analysts and stock prices, emphasizing Bayesian characteristics in analyst behaviour. Examples include Yeung (2009) and Clement, Hales and Xue (2011). Zhang (2008) illustrates significant cross-sectional determinants of analyst responsiveness to earnings announcements including firm size. Consequently, robustness tests in Chapter 6 evaluate whether conclusions are conditional on this factor.

individual analysts are independent from those of other analysts, and that in turn analysts' forecast errors are independent. If this is not the case then rationality tests may be biased, and a key driver of correlation amongst forecast errors could be shocks to macroeconomic activity. They conclude that rationality tests need to incorporate the impact of business cycle effects. Doing so, they are unable to reject a hypothesis of rationality for quarterly forecasts from the I/B/E/S dataset from 1984 through to 1990. In Ackert and Hunter (1995) the same authors explicitly incorporate a range of macroeconomic variables as regressors, with forecast errors as the dependent variable. They find not only evidence of serial correlation in forecast errors but also a statistically significant relationship between values of unrevised changes in gross national product known by analysts on the forecast date and forecast errors for the period in question.[54]

Basu, Markov and Shivakumar (2010) generate a long/short portfolio based on relative inflation exposure. They find a selection of measures of expected inflation (including lagged inflation and survey data) is able to predict analysts' forecast errors for their portfolio. They conclude this implies that analysts fail to fully incorporate expected inflation information in earnings forecasts. Importantly, they find the same cannot be said of real output growth, which they proxy with industrial production. Hence, the hypothesis of analyst rationality with respect to this key measure of economic activity cannot be rejected (although their research design complicates comparison with other analyses of informational efficiency).

Rather than investigating whether or not analysts fully incorporate past macroeconomic data in their earnings forecasts, De Zwart and Van Dijk (2008) evaluate the relationship between earnings forecasts and forecasts of economic

[54] Although coefficients on changes in the consumer price index, the unemployment rate, oil prices, stock prices and aggregate corporate profits were insignificant, suggesting this information is fully incorporated in analysts' forecasts.

activity, including real GDP growth, in emerging markets. Notably, they find no significant relationship between economists' forecasts of GDP growth and firms' realized earnings for the period in question. Consequently, analysts should ignore the economists' forecasts. However, the authors in fact find evidence of a negative relationship between analysts' forecasts of earnings and economists' forecasts of output growth. Combined with evidence of a positive relationship between realized earnings and realized output growth, these results are remarkable and form an important component of the motivation for my research. Firstly, the results suggest that emerging market economists are poor forecasters and have little to offer emerging market stock analysts. Secondly, the negative reaction of analysts to economists' growth forecasts suggests there is recognition of this issue, but analysts go too far and overreact.

The study by De Zwart and Van Dijk evaluates analysts' earnings forecasts for 27 emerging markets from 1991 through to 2005. It may be that results differ for developed markets. In fact this possibility may be inferred from De Zwart and Van Dijk based upon their finding of greater analyst efficiency for more transparent stocks.[55] This implies results may be sensitive to the information environment.[56] These results indicate fertile ground for further evaluation of the relationship between analysts' earnings forecasts and macroeconomic activity. Importantly, these results also suggest not only evaluating what information can be derived from analysts' forecasts that may be of value to economists, but additional investigation of the information in economists' forecasts for analysts when forming their earnings expectations. This in turn provides an opportunity for a comparison

[55] De Zwart and Van Dijk (2008) include two proxies for informational transparency: whether a stock has an ADR listing (Lang, Lins and Miller (2003) find non-US stocks with a US cross listing on average have greater analyst coverage and higher forecast accuracy relative to non-US stocks without a US cross listing), and whether or not a stock has published its annual report within three months of the fiscal year end.

[56] Lim (2001) reports evidence of an inverse relationship between analyst forecast bias and proxies for the information environment including firm size and analyst coverage.

between the relative effectiveness of security analysts and economists, and is a component of empirical investigations in Chapter 5.

Note also that if analysts incorporate expectations for the business cycle in their forecasts, we should expect to see them revise their expectations in response to macroeconomic shocks. Hess and Kreutzmann (2009) address this issue in a study of the reactions of S&P 500 firms to a range of macroeconomic data announcements. They do indeed find evidence of a significant reaction by earnings forecasts to surprise in announcements of a selection of macroeconomic factors. In addition, they find evidence of asymmetry in the effect, with the reaction of earnings forecasts larger in recessions than in expansions. Similarly, Higgins (2002) finds evidence of increased forecast error and wider forecast dispersion during recessions. Within recessions the effect is greater for more cyclical firms and firms with higher leverage (although results are subject to the constraint of a sample consisting of only one recession).[57] I include analysis of regime variation in the information in aggregated forecasts for economic activity in Chapter 5 and regime variation in the efficiency of analysts' forecasts in Chapter 6.

Overall, evidence on the informational efficiency of analysts' forecasts with respect to macroeconomic factors is mixed. Analysts do appear to react to macroeconomic shocks, but it is unclear whether or not their forecasts fully reflect all available macroeconomic data. Complicating matters is evidence of time variation in the relationship between earnings forecasts and macroeconomic shocks.

[57] These results are also consistent with Zhang's (2006) evidence of a positive relationship between information uncertainty and the magnitude of reaction of forecast revisions to news (assuming economic contractions represent a poorer information environment, as indicated by Higgins's (2002) evidence of larger forecast errors and greater forecast dispersion).

2.5 Aggregate earnings, discount rate and cash flow effects

IN THE PREVIOUS sections I discuss research motivating an empirical evaluation of information for the macroeconomy in equity analysts' earnings forecasts. The dataset of aggregated forecasts, forecast revisions and realized earnings constructed for empirical tests of this notion can also provide a new perspective on the literature sparked by Kothari, Lewellen and Warner (2006) regarding the relationship between aggregate earnings and aggregate returns.

In short, Kothari et al. (2006) report evidence of a negative relationship between contemporaneous aggregate returns and aggregate earnings for US stocks from 1970 through to 2000. Given higher earnings also imply higher dividends, and the relationship between returns and dividend shocks is positive, Kothari et al.'s results suggest the negative relationship between earnings and returns is the result of a higher discount rate (an increase in expected returns). As Kothari et al. note, pro-cyclicality in the discount rate is a contentious result given the opposite is predicted by many theoretical models.

The framework Kothari et al. (2006) employ for this analysis is Campbell's (1991) return decomposition. Campbell's framework splits realized returns into cash flow and expected returns (discount rate) components.[58] The cash flow component represents the return response to a shock to expected earnings (or, more specifically expected dividends). Empirical analysis therefore requires a measure of earnings surprise. Kothari et al. employ changes in realized earnings and two simple time series models applied to realized earnings as proxies for earnings surprise. However, they comment that "In some tests we would ideally like to have an estimate of the market's earnings surprise, potentially different from the true surprise" (p. 549). My measures of aggregate market earnings revisions provide an

[58] In the presence of investor rationality, expected returns equal discount rates.

alternative measure of market surprise. In Chapter 7 I employ these measures to evaluate the robustness of Kothari et al.'s results. In the remainder of this section I provide the theoretical and empirical background to Kothari et al.'s research, along with an overview of more recent findings.

2.5.1 Decomposing returns

THERE IS A long history of research attempting to identify and explain the relationships between security prices, earnings and expected returns (discount rates). However, as Kothari et al. (2006) observe, "the importance of each remains poorly understood" (p. 538). There is, for example, substantial disparity in the literature with respect to the proportion of return variation explained by cash flow shocks versus discount rate (or expected return) shocks.[59]

The return decomposition provided by Campbell (1991) provides a useful starting point for discussion:

$$h_t = E_{t-1}(h_t) + \eta_{d,t} - \eta_{h,t} \tag{2.1}$$

h_t represents the log real return on a stock for the period from the end of t-1 to the end of t, $\mathrm{E}_{t-1}(h_t)$ denotes the expected value at the end of t-1 for h_t, $\eta_{d,t}$ denotes the impact on returns of the change from t-1 to t in expected future dividends and $\eta_{h,t}$

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[59] For example, Fama (1990) reports 30% of annual variance in NYSE returns is explained by expected return proxies and 43% is explained by a cash flow proxy (with combined explanatory power of 58%). Schwert (1990) reports similar results over a much longer time period. Kothari and Shanken (1992) report greater explanatory power for time series returns with additional cash flow proxies. However, the relationship between returns and cash flow proxies could be the result of a relationship between the cash flow proxies and expected returns, between the cash flow proxies and shocks to dividends and between the cash flow proxies and shocks to expected returns. Hecht and Vuolteenaho (2006) attempt to distinguish between these three components of returns. They find evidence that the high explanatory power for aggregate returns of a range of proxies for cash flow news is partially attributable to a negative relationship between the cash flow proxies and expected returns. Conversely, at the individual stock level the cash flow proxies and expected returns are positively correlated. As a result, returns are positively affected by cash flow news but the overall explanatory power of the earnings or cash flow proxy for returns is reduced by the increase in expected returns. Hecht and Vuolteenho (2006) therefore provide a useful illustration of the difficulties involved in any attempt to separately determine the contributions to returns from the three component drivers.

represents the impact on returns of the change in expected future returns.[60] Hence, returns are determined by expected returns, changes in expected dividends and changes in expected returns. It is therefore evident that a positive shock to dividends will, ceteris paribus, result in a positive impact on returns. However, a positive shock to future expected returns will negatively impact returns. This is because the stock price needs to be lower today to provide for an increase in the future expected return.

The relationship between earnings surprise and returns can be expressed as a function of the relationship between surprise and each of the three components of returns as follows (where "cov" refers to covariance and Δe_t denotes unexpected earnings):

$$\mathrm{cov}(\Delta e_t, h_t) = \mathrm{cov}(\Delta e_t, \mathrm{E}_{t-1}(h_t)) + \mathrm{cov}\big(\Delta e_t, \eta_{d,t}\big) - \mathrm{cov}\big(\Delta e_t, \eta_{h,t}\big) \tag{2.2}$$

Kothari et al. (2006) note that unexpected earnings and expected returns will be uncorrelated if a good proxy for unexpected earnings is employed, so $\mathrm{cov}(\Delta e_t, \mathrm{E}_{t-1}(h_t)) = 0$.[61] If we assume a positive relationship between earnings and dividends ($\mathrm{cov}\big(\Delta e_t, \eta_{d,t}\big) > 0$), then the cash flow effect of higher earnings should result in a positive relationship between earnings surprise and realized returns. In

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[60] Specifically, Campbell (1991) defines $\eta_{d,t}$ as $(\mathrm{E}_t - \mathrm{E}_{t-1})\sum_{j=0}^{\infty}\rho^j\,\Delta d_{t+j}$ where $(\mathrm{E}_t - \mathrm{E}_{t-1})$ denotes the change in expectations from the end of period t-1 to the end of period t, $\sum_{j=0}^{\infty}\rho^j\,\Delta d_{t+j}$ is the sum of one period future changes in log real dividends, and ρ is a discounting parameter close to (but less than) 1 (reflecting the lesser impact on returns today of a given increase in expected returns at a distant point in the future, relative to the impact on returns today of a given increase in expected returns in the immediate future). $\eta_{h,t}$ is defined as $(\mathrm{E}_t - \mathrm{E}_{t-1})\sum_{j=0}^{\infty}\rho^j\,\Delta h_{t+j}$. That is, the sum of the change in expected future one period returns.

[61] Expected returns are a function of expected dividends and the discount rate. Future unexpected earnings are not members of the information set employed to generate expected returns, and therefore there should be no relationship between expected returns and unexpected earnings.

other words, an increase in $\eta_{d,t}$ drives an increase in h_t and $\text{cov}(\Delta e_t, h_t) > 0$.[62] This is the result commonly reported by firm-level analyses.[63]

However, Kothari et al.'s (2006) reported result of a negative relationship between aggregate earnings and returns ($\text{cov}(\Delta e_t, h_t) < 0$) implies that there is an increase in expected returns ($\eta_{h,t}$) as well as an increase in expected dividends ($\eta_{d,t}$) in response to a positive earnings shock. In addition, the expected return effect is larger than the cash flow effect. In terms of covariances, $\text{cov}(\Delta e_t, \eta_{d,t}) > 0$, $\text{cov}(\Delta e_t, \eta_{h,t}) > 0$, and $\text{cov}(\Delta e_t, \eta_{h,t}) > \text{cov}(\Delta e_t, \eta_{d,t})$. In the presence of investor rationality, expected returns equal discount rates (the difference has been eliminated by trading activity). Hence, Kothari et al.'s results suggest the discount rate effect is larger than the cash flow effect and that the discount rate is positively correlated with earnings surprise. In other words, the discount rate is pro-cyclical.

2.5.2 Theory and evidence for discount rate counter-cyclicality

KOTHARI ET AL. (2006) observe that the implied positive relationship they identify between their proxies for earnings surprise and expected returns is at odds with the predictions of consumption smoothing models. Key examples include Merton (1973), Lucas (1978) and Breeden (1979). Fama and French (1989) provide a useful introduction to the implications for expected returns of these types of models. In essence, when current income is high investors save more in an effort to smooth future consumption. Without a commensurate increase in available investment opportunities, expected returns fall as a result of the increased demand

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[62] To proxy for cash flows I employ analysts' forecasts of earnings sourced from I/B/E/S. I do not use dividend forecasts given substantially fewer available data points. In addition, Ball, Sadka and Sadka (2009) provide a wide range of further rationales for preferring earnings over dividends, including: (1) many firms do not pay dividends; (2) dividends provide less information than earnings due to smoothing; and, (3) dividends are a lagged function of earnings (see Lintner (1956) and Fama and Babiak (1968) for early discussions of these phenomena).

[63] The literature on earnings response coefficients is vast. Key examples include Ball and Brown (1968), Beaver, Clarke and Wright (1979) and Teets and Wasley (1996).

for investment opportunities (security prices rise). Conversely, when income is low investors consume a greater proportion of their incomes and consequently save less. Without a drop in the supply of investment opportunities, expected returns increase.

For example, Campbell and Cochrane (1999) develop a consumption model in which there is time variation in economic agents' habits. "Habits" refers to the concept of "if good times lead people to acquire a 'taste for the good life', higher consumption in the past might raise rather than lower the marginal utility of consumption today" (Cochrane, 2008, p. 271). By introducing a time-varying habit component into agents' utility functions, the result is "as consumption declines relative to the 'trend' in a recession, people will become more risk-averse, stock prices will fall, expected returns will rise, and so on" (Cochrane, 2008, p. 276). In other words, investor risk aversion is pro-cyclical, resulting in counter-cyclical expected returns.[64]

Chan and Kogan (2002) obtain similar implications for expected returns in their model, despite (in contrast to Campbell and Cochrane (1999)) assuming constant risk aversion over time for individual economic agents. They assume that "individual utility is a power function of the ratio of individual consumption to the social standard of living" (p. 1258). That is, investor utility may be raised by increasing consumption relative to an aggregate endowment process.[65] The concept

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[64] Specifically, Campbell and Cochrane (1999) employ the following utility function for investor maximisation:

$$\mathrm{E}\sum_{t=0}^{\infty}\delta^t\frac{(C_t-X_t)^{1-\gamma}-1}{1-\gamma}$$

C denotes consumption, δ denotes a discount factor, γ reflects curvature in the utility function and X represents habit (in turn subject to a non-linear specification dependent upon past consumption).

[65] Specifically, in Chan and Kogan (2002) investors maximise the following utility function:

$$\mathrm{E}\int_0^{\infty}e^{-\delta t}\frac{1}{1-\gamma}\left(\frac{C_t}{X_t}\right)^{1-\gamma}dt$$

is more colloquially explained by the paper's title "Catching up with the Joneses". As a result, while individual investor risk aversion is constant through time, risk aversion does vary cross-sectionally. Chan and Kogan summarise the implications as follows:

> Relatively risk-tolerant agents hold a higher proportion of their wealth in stocks. Therefore, a decline in the stock market reduces the fraction of aggregate wealth controlled by such agents and hence their contribution to the aggregate risk aversion. Thus the equilibrium risk premium rises as a result of a fall in stock prices. (p. 1256)

The result is counter-cyclical expected returns.

There is also a lengthy record of empirical studies reporting evidence of counter-cyclicality in expected returns. Commonly cited examples include Fama and French (1989), Fama (1990) and Campbell (1991). Fama and French (1989) evaluate returns on NYSE value-weighted and equally-weighted portfolios from CRSP for 1927 through to 1987. They regress excess returns on a combination of dividend yields and the default spread, and dividend yields and the term spread.[66] The dividend yield captures both cash flow effects (through the numerator) and changes in expected returns (through the denominator). By adding the default spread as a regressor Fama and French incorporate an expected return proxy. They present evidence of positive correlation between dividend yields and the default spread, indicating both are capturing expected return effects. The default spread is counter-cyclical and the implication is therefore that expected returns (reflected in both dividend yields and the default spread) are counter-cyclical. Additional evidence is provided by results for the term spread, and further supporting results are reported by Fama (1990). Campbell (1991), in a study of data on the New York

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Parameters are as above for Campbell and Cochrane (1999) except for X, which in this instance denotes the standard of living in the economy.

[66] The default spread is defined as the yield difference between the year-end yield on the 100 corporate bonds in their analysis and the Moody's Aaa-rated yield. The term spread is defined as the yield difference between the Moody's Aaa-rated yield and the one month Treasury bill rate.

Stock Exchange from 1926 through to 1988, reports "increases in future expected cash flows tend to be associated with decreases in future expected returns" (p. 176).

Chen (1991) provides further supporting evidence by demonstrating that the dividend yield and default premium are both effective indicators of the current state of the macroeconomy, and that "the expected excess market return is negatively related to the recent growth of GNP (proxying for the current health of the economy)" (p. 553). Interestingly, Chen found that the dividend yield and default premium had no significant explanatory power for the quarterly growth rate in GNP more than one quarter ahead. They are only indicators of the current state of the economy. It is also worth noting that Chen finds a positive relationship between market excess returns and expected *future* economic growth.[67] This suggests the domination of a cash flow effect over a discount rate effect in expectations of future economic growth. However, it could also be the result of a positive relationship between the discount rate and expected future economic growth (i.e. higher future growth is perceived as more risky). This finding therefore provides an appropriate introduction to the following sub-section, in which evidence of pro-cyclicality in discount rates is addressed.

2.5.3 Theory and evidence for discount rate pro-cyclicality

IF KEY THEORETICAL models and a wealth of empirical evidence point to counter-cyclicality in expected returns and discount rates, then how is it that Kothari et al. (2006) find evidence of the reverse? What is different about their analysis? A key difference, from an empirical standpoint, is that they focus on aggregated earnings changes.

[67] Expected future economic growth is proxied by fitted values from a regression of GNP growth on a selection of lagged economic state variables.

As discussed above, the negative relationship they report between aggregate returns and aggregate earnings growth suggests expected returns are rising as earnings rise and expected returns fall as earnings fall. That is, pro-cyclicality in expected returns (discount rates). Kothari et al. (2006) comment that their results complement those of Lettau and Ludvigson (2005) who report evidence of positive covariation in expected returns and expected dividend growth for aggregate portfolios. More specifically, Lettau and Ludvigson report evidence “that there is important predictability of dividend growth over long horizons, and that predictable variation in dividend growth is correlated with that in excess returns” (p. 607). So, positive correlation between the predictable variation in dividend growth and the predictable variation in excess returns implies positive correlation between expected dividend growth (cash flows) and expected returns (discount rates). In comparison, Kothari et al. observe a negative relationship between aggregate earnings growth and contemporaneous returns, and from that infer a positive relationship between the discount effect and the cash flow effect. Shivakumar (2007) discusses one potential driver of such a relationship: inflation. He observes that “if higher earnings surprises imply higher future inflation, then both future cash flows as well as the discount rates could rise in line with inflation” (p. 67).

Further support for Kothari et al.’s (2006) findings is provided by Ball, Sadka and Sadka (2009). They too find evidence of a negative contemporaneous return-earnings relationship. However, direct comparisons between Kothari et al. and Ball et al. are complicated by the latter’s measure of aggregate earnings, derived from principal components analysis used to estimate common variation in earnings. In addition, their analysis also highlights the difficulties facing any attempt to separately identify cash flow and discount rate effects. They find evidence that “the common factors of earnings and returns are highly correlated, which implies that the information sets of returns and earnings are jointly determined and that it may not be possible to separately identify earnings/cash flow risk and return risk" (p. 1130).

Kothari et al. (2006) do note that differing results between studies of individual stocks and aggregate data are not necessarily inconsistent. For example, a diversification effect in aggregate data could increase the importance of the discount rate as a driver of returns given the impact of diversification on stock-specific cash flow effects.[68] However, Kothari et al. do not reconcile this result with any theoretical model. They go only so far as to suggest the possibility of rising interest rates as earnings increase, resulting in a negative impact on stock prices (and therefore higher expected returns).[69]

Sadka and Sadka (2009) report evidence of greater earnings predictability using returns for aggregated stocks compared with individual stocks, and as the number of stocks included in the portfolio increases the contemporaneous relationship between earnings and returns decreases from positive to negative. They partially

[68] For example, Vuolteenaho (2002) employs CRSP data for NYSE, AMEX and Nasdaq stocks from 1954 to 1996 to demonstrate both the dominance of cash flow news in individual stock returns and that cash flow news can be diversified away by aggregating stocks into portfolios. Notably, Vuolteenaho reports: "This finding suggests that cash-flow information is largely firm specific and that expected-return information is predominantly driven by systematic, market-wide components" (p. 259). This is consistent with the results of Campbell (1991) who finds evidence for the domination of expected return news over cash flow news in aggregate portfolios. However, Ball, Sadka and Sadka (2009) report evidence suggesting that cash flow news is not largely diversifiable. They find that "the systematic components of earnings and returns are similar in magnitude, seemingly inconsistent with the conclusion in prior literature that much of the cash-flow news (but not expected-return news) is idiosyncratic" (p. 3).

[69] Campbell and Vuolteenaho (2004) provide three variations on this explanation. Firstly, inflation could have a negative impact on the real economy, which in turn hurts earnings and may cause a drop in the long term expected growth rate of dividends. Thinking in terms of the simple Gordon growth model, this means an increase in inflation could drive an increase in the dividend yield. Secondly, a rise in inflation could spark greater risk aversion and hence a higher discount rate, again then increasing the dividend yield. Finally, they also refer to the hypothesis of Modigliani and Cohn (1979). In this story irrational investors fail to take into account the impact of changing inflation on the growth rate of dividends. Hence, when inflation rises investors use a higher discount rate (given investors react to higher interest rates), but fail to correctly adjust expectations for nominal dividend growth (which should be higher). Thus the dividend yield rises.

attribute this decline to the increase in earnings predictability. That is, as earnings predictability increases with higher levels of aggregation the amount of cash flow news in earnings decreases, in turn resulting in an increase in the importance of the discount rate effect. However, as Sadka and Sadka observe, this would only explain a reduction in the magnitude of the relationship between contemporaneous earnings and returns towards zero, not a negative relationship.[70] Hence, again returning to the Campbell (1991) return decomposition, this leaves us with "earnings changes at time *t* are either positively correlated with expected return news at time *t*, and/or negatively correlated with expected returns at time *t*-1" (Sadka and Sadka, 2009, p. 88). Kothari et al. (2006) favour the former explanation. Sadka and Sadka explore the latter and find "a high dividend-price ratio predicts both higher returns and lower earnings growth – which suggests expected returns and expected earnings are negatively correlated" (p. 88). However, they also report evidence that earnings changes fail to predict stock returns, which somewhat weakens their conclusions and leaves open the question of whether it is expected returns or expected return news which is driving the negative contemporaneous returns-earnings relationship. Critically, they note the sensitivity of results to the expectations model employed and provide the results of Chen and Zhao (2008) as a prime example. Chen and Zhao (2008) report a significant positive relationship between cash flow news and returns in a model which employs analysts' forecast errors to measure cash flow news.

Cready and Gurun (2010) perform an event study on aggregated earnings announcements, relating aggregate returns to aggregate earnings announced in a

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[70] Results presented in Chapter 7 suggest a key factor underlying Kothari et al.'s finding of a negative relationship between changes in aggregated realized earnings and contemporaneous returns is the choice of time period analyzed (1970–2000). It is important to recognize therefore that Sadka and Sadka (2009) employ data from the same source and over a very similar time period (1965–2000). Consequently, Sadka and Sadka's finding of a similar negative relationship should be of little surprise, and does not represent a robustness test of Kothari et al.'s results.

given month. They report "strong evidence of a negative earnings surprise effect that is most concentrated in the days immediately surrounding earnings releases" (p. 291). However, Shivakumar (2010) illustrates weaknesses in their methodology, for example, including Nasdaq stocks in the calculation of aggregate earnings but not in the calculation of aggregate returns.

Patatoukas and Yan (2009) seek to provide a theoretical framework for Kothari et al.'s (2006) results which allows for the dominance of a cash flow effect at the individual stock level and the dominance of the discount rate effect at the aggregate portfolio level. The key is the relationship between earnings news and the discount rate (applying the terminology of Campbell (1991), the magnitude of $\text{cov}(\Delta e_t, \eta_{h,t})$). Patatoukas and Yan suggest that the impact of earnings surprise in a single stock is unlikely to have much of an impact on growth rate expectations for the overall macroeconomy, and hence is unlikely to have much of an impact on the discount rate. So for a single stock the magnitude of $\text{cov}(\Delta e_t, \eta_{h,t})$ could be very small. However, earnings surprise for the stock market in aggregate could have significant implications for expectations of macroeconomic activity, and $\text{cov}(\Delta e_t, \eta_{h,t})$ is larger. Therefore, the cash flow effect dominates at the individual stock level and the discount rate effect dominates at the aggregate portfolio level, with respect to earnings news.[71] An interesting additional implication of Patatoukas and Yan's model is that the discount rate effect should be stronger for

[71] A further complication of the issue is provided by Hirshleifer, Hou and Teoh (2009) who report evidence suggesting that the negative relationship between aggregate earnings changes and contemporaneous growth observed by Kothari et al. is due to a negative relationship between changes in accruals and contemporaneous returns. Kang, Liu and Qi (2010) narrow this down to differential effects from discretionary accruals versus normal accruals. It should also be noted that while Hirshleifer et al. provide supporting evidence for Kothari et al.'s core result, direct comparison is complicated by the former's use of operating income after depreciation as a proxy for earnings. This measure is pre-tax and interest expenses. It may therefore represent a poorer proxy for cash flows. Indeed, when Hirshleifer et al. strip accruals out of their earnings measure to derive a proxy for aggregate cash flow changes they find a positive relationship between this variable and contemporaneous aggregate returns.

more cyclical stocks because cyclical stocks' earnings surprises are likely to be relatively closely correlated with aggregate market earnings surprises. Their empirical work provides evidence in support of this hypothesis.[72]

Overall, the precise nature of the relationship between earnings, discount rates and returns continues to be a conundrum for capital markets researchers. Further, while a selection of researchers have provided theoretical bases and supporting evidence for discount effects dominating aggregate market returns, the results presented in Chapter 7 suggest otherwise. I not only find evidence of a positive relationship between aggregate earnings revisions and contemporaneous market returns, sub-period analysis suggests much of the negative relationship between changes in aggregate realized earnings and returns identified by Kothari et al. (2006) is a product of the period analyzed. It is not evident in the data prior to, nor after, the period covered by their main dataset.

[72] However, my evaluation of variation in the relationship between earnings surprise and contemporaneous returns across sectors does not provide evidence of a clear relationship between the magnitude of discount rate effects and earnings cyclicality (Chapter 7).

3 Variable construction

3.1 Variable concepts

THE FOCUS OF this research is the evaluation of time series relationships between macroeconomic variables, returns, realized aggregate market changes in earnings, forecast changes in aggregate market earnings and aggregate revisions to forecast earnings. I build upon the aggregation framework employed by Kothari, Lewellen and Warner (2006) to construct key aggregate market earnings variables for US stocks. However, Kothari et al. investigate aggregate market measures of realized earnings alone. My research expands upon their approach to develop measures of aggregate market forecast earnings growth and revisions to forecast earnings.

In this chapter I provide a detailed description of the core aggregate market variables employed, along with construction techniques. This includes discussion of the idiosyncrasies of key data sources (I/B/E/S for analysts' earnings expectations and CRSP/Compustat for additional fundamental data and stock returns), and their impact on variable construction.

3.2 Methodology

I CONSTRUCT QUARTERLY rolling time series measures of changes in annual realized aggregate market earnings, annual forecast changes in aggregate market earnings one year ahead, and aggregated one year revisions to forecast earnings.[73] For robustness purposes, nine variations on each of these three variables of interest are constructed, representing a range of variable deflators and aggregation processes. Taking realized earnings as an example, the one year change in annual realized earnings is summed over all stocks in the sample each quarter and deflated by the sum of trailing earnings or market capitalization or book value. In addition, earnings per share measures of these variables are constructed and summed for each quarter with market value weights, equal weights or median values deflated by price or book value per share.[74] This same approach is applied to aggregated forecasts and aggregated forecast revisions.

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[73] Changes in forecast earnings (or earnings revision momentum) are equivalent to one year changes in forecast error. That is;

$$\left(\mathrm{E}_t^a - \mathrm{E}_{t-1}^f\right) - \left(\mathrm{E}_t^a - \mathrm{E}_t^f\right) = \mathrm{E}_t^f - \mathrm{E}_{t-1}^f$$

where E_t^a represents realized earnings for the year ending at time t, E_{t-1}^f represents forecast earnings as at time t-1 for the year ending at time t and E_t^f represents forecast earnings as at time t for the year ending at time t. Thus $\left(\mathrm{E}_t^a - \mathrm{E}_{t-1}^f\right)$ and $\left(\mathrm{E}_t^a - \mathrm{E}_t^f\right)$ represent forecast errors and $\mathrm{E}_t^f - \mathrm{E}_{t-1}^f$ represents forecast revisions. Hence, analysis of forecast revisions can be considered an evaluation of both aggregate revisions and aggregate changes in forecast error.

[74] Per share measures of earnings changes deflated by lagged earnings are excluded given problems arising with these variables when lagged earnings are negative.

Kothari et al. (2006) focus on seasonally-differenced quarterly earnings.[75] For realized earnings my research employs the sum of four quarters of earnings less the four quarter sum one year earlier. This provides greater comparability with I/B/E/S forecast earnings. While quarterly forecast data is available from I/B/E/S, this dataset is comparatively thin in the early years of the dataset relative to annual forecast earnings data and covers a significantly shorter time period, even for US stocks.[76] While Kothari et al. employ seasonally-differenced earnings and I employ annual changes in the four quarter sum of earnings, the two techniques are expected to result in strongly positively correlated series.[77] I explore the consistency of Kothari et al.'s results with my results in Chapter 7.

For a given quarterly observation, aggregate market realized earnings changes are calculated from the sum of four quarters of realized earnings up to that quarter end less the same measure four quarters prior (and then deflated by the sum of lagged earnings, market capitalization or book value). Earnings data represents rolling 12 month earnings per share from the merged CRSP/Compustat dataset (before extraordinary items and discontinued operations), multiplied by common shares on issue.[78]

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[75] Realized earnings for quarter t less realized earnings for quarter t-4.

[76] I/B/E/S began recording annual earnings per share forecast data for US companies from 1976, while quarterly forecast data starts in 1984. In addition, quarterly forecast data typically extends at most to three quarters beyond the date it is recorded for a given stock. Although four quarters may be included in the I/B/E/S database, the first quarter forecast will actually represent the previous quarter's earnings (which will not become realized earnings until the company announces its results 1–3 months later). Given this research focuses on an investigation of changes in expectations for aggregate earnings 12 months forward (and seeks the longest possible time series), quarterly I/B/E/S data is therefore of limited utility.

[77] In addition, the focus period for Kothari et al. runs from 1970 to 2000. My analysis focuses on the period from 1979 through to 2009. The starting point of the March quarter of 1979, rather than the I/B/E/S dataset start date of 1976, is selected to ensure a sufficiently deep forecast dataset for aggregation.

[78] The number of common shares on issue may be on a fully diluted basis or primary basis, depending upon the calculation method recorded by I/B/E/S for that period for earnings per share forecasts. When the recording method has changed over the period in question, the latest four quarter earnings per share measure is changed to the method employed one year

Denoting the change in aggregate realized annual earnings deflated by lagged aggregate annual earnings for quarter t as $\Delta\mathrm{EE}_t^{\mathrm{a}}$, $\mathrm{E}_{t,-4q\to t}^{i}$ as realized annual earnings at t for stock i for the period from t_{-4q} to t (where -4q refers to four quarters prior to t) and $\mathrm{E}_{-4q,-8q\to -4q}^{i}$ as realized annual earnings for stock i for the period from t_{-8q} to t_{-4q}, I define $\Delta\mathrm{EE}_t^{\mathrm{a}}$as:

$$\Delta\mathrm{EE}_t^{\mathrm{a}} = \frac{\sum_{i=1}^{n}\left(\mathrm{E}_{t,-4q\to t}^{i} - \mathrm{E}_{-4q,-8q\to -4q}^{i}\right)}{\sum_{i=1}^{n}\mathrm{E}_{-4q,-8q\to -4q}^{i}} \tag{3.1}$$

In addition, I define $\Delta\mathrm{EP}_t^{\mathrm{a}}$ and $\Delta\mathrm{EB}_t^{\mathrm{a}}$ as follows:

$$\Delta\mathrm{EP}_t^{\mathrm{a}} = \frac{\sum_{i=1}^{n}\left(\mathrm{E}_{t,-4q\to t}^{i} - \mathrm{E}_{-4q,-8q\to -4q}^{i}\right)}{\sum_{i=1}^{n}\mathrm{P}_{-4q}^{i}} \tag{3.2}$$

$$\Delta\mathrm{EB}_t^{\mathrm{a}} = \frac{\sum_{i=1}^{n}\left(\mathrm{E}_{t,-4q\to t}^{i} - \mathrm{E}_{-4q,-8q\to -4q}^{i}\right)}{\sum_{i=1}^{n}\mathrm{B}_{-4q}^{i}} \tag{3.3}$$

P_{-4q}^{i} and B_{-4q}^{i} refer to market capitalization and book value for stock i as at t_{-4q}.

For aggregate market changes in forecast earnings I require a standardized timeframe for earnings expectations to in turn compare with realized earnings and changes in macroeconomic factors. Given significant limitations on data availability for quarterly earnings forecasts relative to annual expectations, I calculate a proxy measure of one year ahead forecast annual earnings, calculated on a quarterly basis. An equivalent approach is applied to a combination of the last available reported earnings and the current period annual forecast to generate a proxy for estimated 12 month trailing earnings. These forecast proxies are discussed in more detail in Section 3.3.

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prior to ensure the earnings change is calculated using the same basis for each (and to ensure that the recorded basis for both realized and forecast earnings per share is the same for each stock).

Applying the notation employed above, with $\hat{\mathrm{E}}$ referring to 12 month earnings expectations and the superscript 'f' referring to changes in forecast aggregate earnings, then $\Delta \mathrm{EE}_t^{\mathrm{f}}$, $\Delta \mathrm{EP}_t^{\mathrm{f}}$ and $\Delta \mathrm{EB}_t^{\mathrm{f}}$ are calculated for each quarter as follows:

$$\Delta \mathrm{EE}_t^{\mathrm{f}} = \frac{\sum_{i=1}^{n}\left(\hat{\mathrm{E}}_{t,t\to+4q}^{i} - \hat{\mathrm{E}}_{t,-4q\to t}^{i}\right)}{\sum_{i=1}^{n} \mathrm{E}_{t,-4q\to t}^{i}} \tag{3.4}$$

$$\Delta \mathrm{EP}_t^{\mathrm{f}} = \frac{\sum_{i=1}^{n}\left(\hat{\mathrm{E}}_{t,t\to+4q}^{i} - \hat{\mathrm{E}}_{t,-4q\to t}^{i}\right)}{\sum_{i=1}^{n} \mathrm{P}_{t}^{i}} \tag{3.5}$$

$$\Delta \mathrm{EB}_t^{\mathrm{f}} = \frac{\sum_{i=1}^{n}\left(\hat{\mathrm{E}}_{t,t\to+4q}^{i} - \hat{\mathrm{E}}_{t,-4q\to t}^{i}\right)}{\sum_{i=1}^{n} \mathrm{B}_{t}^{i}} \tag{3.6}$$

Like realized earnings, forecast earnings are constructed from earnings per share forecasts multiplied by shares on issue, accounting for whether earnings per share forecasts were recorded on a primary or fully diluted basis (and accounting for changes in the recording basis).[79]

Similarly, annual aggregate forecast revisions are calculated each quarter as follows:[80]

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[79] There is no data available for forecast shares on issue for the full period under investigation. It is possible, for example, that some analysts may be expecting considerable dilution. It is also possible that analysts for the same company may differ regarding whether or not forecasts are submitted incorporating projected dilution. However, high correlations between aggregated forecast earnings measures and value-weighted forecast earnings per share measures suggest this is not a significant problem (correlation analysis is provided in Chapter 4).

[80] Analyst forecast error (as opposed to revision momentum or changes in forecast error) is not separately estimated given data limitations. Firstly, data limitations within the I/B/E/S database (combined with the time-weighting process employed to generate quarterly rolling series) mean that a significant number of data points would be lost if I/B/E/S was the source for realized earnings. Secondly, I/B/E/S forecast earnings are not directly comparable with CRSP/Compustat realized earnings. As discussed by Livnat and Mendenhall (2006), I/B/E/S earnings are typically "street" estimates (reflecting bottom-line earnings as reported by the company in question), while CRSP/Compustat earnings are recorded on a GAAP basis. Therefore, I cannot simply use CRSP/Compustat realized earnings less I/B/E/S forecasts as a measure of forecast error given the incompatible accounting treatments.

$$\Delta \mathrm{EE}_t^{\mathrm{r}} = \frac{\sum_{i=1}^{n} \left(\widehat{\mathrm{E}}_{t,-4q\to t}^{i} - \widehat{\mathrm{E}}_{-4q,-4q\to t}^{i} \right)}{\sum_{i=1}^{n} \widehat{\mathrm{E}}_{-4q,-4q\to t}^{i}} \tag{3.7}$$

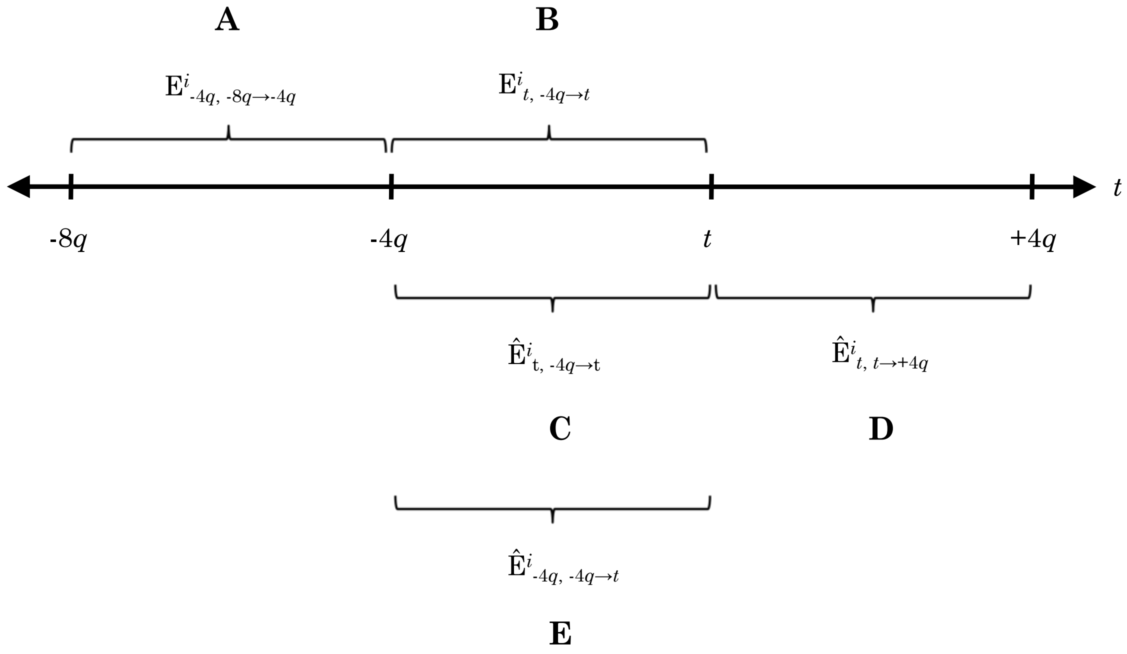
$$\Delta \mathrm{EP}_t^{\mathrm{r}} = \frac{\sum_{i=1}^{n} \left(\widehat{\mathrm{E}}_{t,-4q\to t}^{i} - \widehat{\mathrm{E}}_{-4q,-4q\to t}^{i} \right)}{\sum_{i=1}^{n} \mathrm{P}_{-4q}^{i}} \tag{3.8}$$

$$\Delta \mathrm{EB}_t^{\mathrm{r}} = \frac{\sum_{i=1}^{n} \left(\widehat{\mathrm{E}}_{t,-4q\to t}^{i} - \widehat{\mathrm{E}}_{-4q,-4q\to t}^{i} \right)}{\sum_{i=1}^{n} \mathrm{B}_{-4q}^{i}} \tag{3.9}$$

Figure 3.1 provides an illustration of the relative time periods employed for realized earnings and earnings expectations for a given quarter. The process is repeated each quarter to generate rolling quarterly time series for these variables. Per share values of the inputs are also used to generate equivalent per share factors. These are value-weighted or equally-weighted (with weights recalculated each quarter), or median values. They are denoted $\Delta \mathrm{epv}^x$, $\Delta \mathrm{ebv}^x$, $\Delta \mathrm{epeq}^x$, $\Delta \mathrm{ebeq}^x$, $\Delta \mathrm{epmed}^x$ and $\Delta \mathrm{ebmed}^x$ for changes in earnings per share deflated by price and value-weighted, changes in earnings per share deflated by book value per share and value-weighted, changes in earnings per share deflated by price and equally-weighted, changes in earnings per share deflated by book value per share and equally-weighted, and, median values of changes in earnings per share either deflated by price or book value per share, respectively (with x representing 'a' (changes in actuals), 'f' (forecast changes) or 'r' (forecast revisions)).

Figure 3.1 Construction of aggregate earnings variables – actuals, forecasts and forecast revisions

Time t on the timeline represents the calculation point for a given quarter end for aggregate earnings variables. $\mathrm{E}^{i}_{j,k\to j}$ represents the announced earnings per share result for stock i, multiplied by shares on issue, for the four quarters from the end of quarter k through to the end of quarter j from Compustat. $\hat{\mathrm{E}}^{i}_{j,k\to l}$ represents the I/B/E/S median expectation as at the end of period j for the four quarter forecast period extending from the end of period k through to the end of period l, for earnings per share for stock i, multiplied by shares on issue. Equations for each of $\Delta\mathrm{EE}^{\mathrm{a}}_{t}$, $\Delta\mathrm{EE}^{\mathrm{f}}_{t}$ and $\Delta\mathrm{EE}^{\mathrm{r}}_{t}$ for time t are provided below. Superscripts a, f and r refer to actuals, forecasts and forecast revisions, respectively. $\Delta\mathrm{EP}^{x}$and $\Delta\mathrm{EB}^{x}$ are calculated in the same manner, but with equivalent period values of market capitalization and book value as the denominators. $\Delta\mathrm{epv}^{x}$, $\Delta\mathrm{ebv}^{x}$, $\Delta\mathrm{epeq}^{x}$, $\Delta\mathrm{ebeq}^{x}$, $\Delta\mathrm{epmed}^{x}$and $\Delta\mathrm{ebmed}^{x}$are per share values of these variables, either value-weighted, equally-weighted or median values each quarter.



$$\Delta\mathrm{EE}^{\mathrm{a}}_{t} = \frac{\sum_{i=1}^{n}\left(\mathrm{E}^{i}_{t,-4q\to t} - \mathrm{E}^{i}_{-4q,-8q\to-4q}\right)}{\sum_{i=1}^{n}\mathrm{E}^{i}_{-4q,-8q\to-4q}} = \frac{\sum(\mathrm{B}-\mathrm{A})}{\sum\mathrm{A}}$$

$$\Delta\mathrm{EE}^{\mathrm{f}}_{t} = \frac{\sum_{i=1}^{n}\left(\hat{\mathrm{E}}^{i}_{t,t\to+4q} - \hat{\mathrm{E}}^{i}_{t,-4q\to t}\right)}{\sum_{i=1}^{n}\mathrm{E}^{i}_{t,-4q\to t}} = \frac{\sum(\mathrm{D}-\mathrm{C})}{\sum\mathrm{C}}$$

$$\Delta\mathrm{EE}^{\mathrm{r}}_{t} = \frac{\sum_{i=1}^{n}\left(\hat{\mathrm{E}}^{i}_{t,-4q\to t} - \hat{\mathrm{E}}^{i}_{-4q,-4q\to t}\right)}{\sum_{i=1}^{n}\hat{\mathrm{E}}^{i}_{-4q,-4q\to t}} = \frac{\sum(\mathrm{C}-\mathrm{E})}{\sum\mathrm{E}}$$

3.3 Time-weighting of earnings expectations

IN SECTION 3.2 I noted that limitations on the availability of quarterly earnings forecasts (combined with a desire for the longest time series of earnings possible) requires the calculation of a proxy for 12 month ahead earnings expectations. This study employs annual earnings forecasts combined with a time-weighting process to generate a measure of 12 month earnings expectations (and 12 month trailing earnings expectations) on a rolling quarterly basis. The approach taken is similar to that employed by I/B/E/S for the construction of aggregated forecast measures in their Global Aggregates data series.[81]

Specifically, in a given quarter, if a company's fiscal year end coincides with the forecast observation quarter, I employ the I/B/E/S second fiscal year (FY2) median earnings per share estimate as the 12 months ahead earnings per share forecast. The 12 month trailing earnings per share is the I/B/E/S FY1 median earnings per share estimate.[82] For example, a company with a December 2009 financial year end will, for the December 2009 quarter, be recorded as having a 12 month forward earnings per share forecast given by the I/B/E/S FY2 median estimate and a 12 month trailing earnings per share forecast given by the I/B/E/S FY1 median estimate (region A in Figure 3.2).[83]

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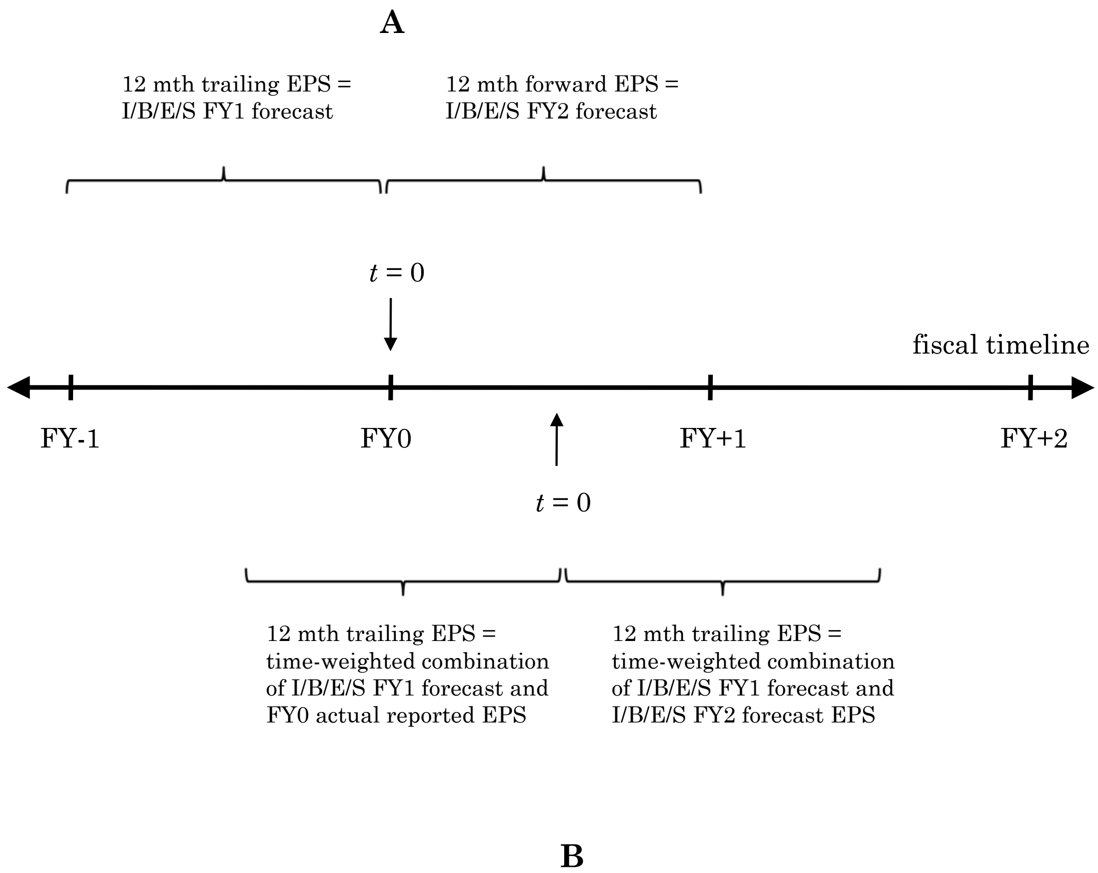
[81] More details on these series are available from *Thomson I/B/E/S Global Aggregates–User Guide*, Thomson Financial (2004).

[82] The FY1 and FY2 fiscal year classifications referred to here are those employed by I/B/E/S. The 12 month ahead period is represented by the FY2 forecast rather than the FY1 forecast because the company, while at the end of its financial year, will not yet have reported results and I/B/E/S continues to record a forecast as FY1 until the announcement date (at which point the FY1 year becomes the FY0 year).

[83] Median earnings per share data is obtained from the I/B/E/S unadjusted summary file. That is, the earnings per share forecasts have not been adjusted for stock splits. I perform the required stock split adjustment using the adjustment factor provided by CRSP/Compustat (checked for accuracy against stock split adjustment factors supplied by I/B/E/S). This approach is designed to avoid problems with rounding errors in the I/B/E/S adjusted summary file, discussed in more detail in the appendix to this chapter.

Figure 3.2 Time-weighting of forecast earnings

I/B/E/S annual estimates are time-weighted to generate rolling quarterly proxies for 12 month ahead earnings expectations and 12 month trailing earnings. Under scenario A, a company's current financial year end (FY0) coincides with the observation quarter (*t*=0). The I/B/E/S median estimate for the next fiscal year (denoted by I/B/E/S as FY2 earnings per share given the company has not yet announced FY1 earnings) is employed for the 12 months ahead earnings forecast and the FY1 forecast (as defined by I/B/E/S) is employed as the 12 months trailing earnings estimate. Under scenario B the observation quarter occurs between financial year ends. A time-weighted combination of I/B/E/S median FY1 and FY2 earnings per share forecasts is employed as a proxy for 12 month ahead earnings per share, with a time-weighted combination of the announced FY0 and forecast FY1 earnings per share as a proxy for 12 month trailing earnings per share.



When the observation quarter falls between a company's financial year ends, a time-weighted combination of FY1 and FY2 estimates is employed for the 12 month ahead earnings forecast. The 12 month trailing earnings are derived from a combination of FY0 and FY1 earnings per share values. The difference between the financial year end and the observation quarter is used as the time-weighting factor. Taking the previous example of a company with a December balance date for annual accounts, but this time an observation quarter of June 2010, the 12 month ahead earnings expectation is proxied by a 50/50 combination of FY2 and FY1 median earnings per share estimates, while the 12 month trailing expectation is proxied by a 50/50 combination of FY0 actual realized earnings and the median FY1 estimate (region B in Figure 3.2).[84]

A key complication for the time-weighting process is the potential for the accounting basis for earnings per share estimates to change from a primary basis to a fully diluted basis.[85] I/B/E/S provides a record of the basis for earnings per

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[84] It can be argued that the time-weighting process introduces noise for 12 month trailing earnings given it does not incorporate past quarterly observations of realized earnings. When quarter observations match a company's financial year-end, 12 month trailing earnings are proxied by the I/B/E/S FY1 forecast. This will incorporate the three previous realized quarters and analysts' expectations for the fourth and most recent quarter (the realized value of which will not at that point have been announced). When quarter observations do not line up with a company's financial year-end the time weighting of the last realized annual and FY1 forecast annual earnings ignores known information about realized quarterly earnings. The principal alternative is to sum three quarterly observations for realized earnings and one forecast quarter. However, Compustat and I/B/E/S realized earnings numbers are not compatible (for discussion see Abarbanell and Lehavy (2000)). This means I am restricted to the use of I/B/E/S data for quarterly realized earnings. However, up to around one quarter of the length of the time series currently employed would be lost given I/B/E/S did not begin publishing quarterly numbers until the mid-1980s. Given my focus on relating the aggregate forecast earnings measures to macroeconomic variables, I believe this would represent a major impediment to analysis. In addition, I do not find evidence of any systematic bias introduced by the time-weighting procedure (in, for example, robustness tests employing data restricted to annual December year observations for firms with end-December balance dates).

[85] In fact it should be recognized there is always a degree of ambiguity with respect to the precise definition of earnings per share recorded by I/B/E/S. The *Thomson Financial Estimates Glossary* (2008) defines earnings per share as "the EPS that the contributing analyst considers to be that with which to value a security. This figure may include or exclude certain items depending on the contributing analyst's specific model" (p. 13). Hence, it is possible that analysts may submit forecasts that represent differing definitions of

share, and dates when this basis changed. As a result, variable construction requires adjusting trailing earnings per share when a basis change has occurred to ensure that changes in earnings forecasts are calculated with compatible inputs.

Notably, in the first quarter of 1998, I/B/E/S changed the recorded basis for earnings per share calculation for a large proportion of stocks in the database. For the sample set employed by this analysis, the proportion of stocks recorded on a fully diluted basis in the December 1997 quarter was 2.3%. By the end of the March quarter of 1998 this had leapt to 60.2%.

The change was driven by the introduction of Statement of Financial Accounting Standards No. 128, which required companies to report *both* primary and fully diluted earnings per share. I/B/E/S then switched to recording a majority of companies on a fully diluted basis. However, for the purposes of this analysis changes in earnings per share forecasts require measures recorded on the same basis. Given there is no information on the appropriate fully diluted data in the December 2007 quarter for many of the stocks which saw their recorded basis change, these had to be removed from the dataset (before subsequently re-emerging over the following quarters as that data became available).[86] The result is a large (temporary) drop in stocks included in this analysis in the March 1998 quarter. Nonetheless, in robustness tests estimated coefficients on dummy variables added to regressions to capture this period were mostly insignificant. I find no evidence this phenomenon has any material impact on research conclusions.

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earnings per share for the same company. The use of median values of submitted forecasts for each company offers some reduction in risk of significant distortions.

[86] Some companies without fully diluted data in the December 2007 quarter have primary EPS data for both the December 2007 and March 2008 quarters, thus mitigating the negative impact on sample size.

Other key issues for the use of I/B/E/S forecast data for variable construction are discussed in Appendix 3A. These include evidence of changes made to historic data and the impact of rounding errors in stock split-adjusted data. Where relevant, measures have been taken to ensure that the variable construction methodology employed is robust to concerns raised in reviewed literature.

Overall, nine measures of each of aggregate realized earnings growth, aggregate forecast earnings growth and aggregate forecast earnings revisions are constructed. In Chapters 5, 6 and 7 I also provide results of analyses performed on these construction techniques applied to subsets of the full sample (including size and sector-based portfolios), I/B/E/S detail data (as opposed to summary data) and other variations in stock selection. The approach to variable construction outlined in this chapter remains consistent across all aggregate realized earnings, forecast earnings and earnings revision variables discussed. Chapter 4 provides more specific detail on data requirements for variable construction and discusses a range of summary characteristics.

Appendix 3A I/B/E/S data issues

3A.1 Key data issues

WHILE THE I/B/E/S consensus estimates dataset represents a critical source for analysts' earnings expectations, considerable caution is required when employing this data in empirical studies. The collection and data construction techniques employed by I/B/E/S are known to provide researchers with range of potential problems. Glushkov (2009) provides a useful overview of issues previously raised by academics. Key amongst these are the following:

1. Changes in historic data across different database update periods (Ljungqvist, Malloy and Marston (2009));
2. Incorrect earnings announcement dates (Acker and Duck (2009) and Berkman and Truong (2009));
3. Differences between I/B/E/S and Compustat actual historical results for earnings per share (Abarbanell and Lehavy (2000) and Livnat and Mendenhall (2006)); and,
4. Rounding errors (Payne and Thomas (2003)).

A brief discussion of each of these issues is provided here to outline their relevance and potential implications for this study's results.

3A.2 Changes in historic data

LJUNGQVIST, MALLOY AND Marston (2009) find substantial differences in historic analyst recommendations submitted to I/B/E/S across seven sampled periods between 2000 and 2007. Specifically, they find the proportion of historic recommendations subject to changes ranges from 1.6% to 21.7% from one sample period to the next. In addition, the changes were not random, but were related to analyst reputation, broker status and recommendation boldness.

My research does not employ analyst recommendations in any empirical analysis. However, the problems identified with recommendation data raise the question of whether or not similar anomalies exist in analysts' historic earnings forecasts recorded by I/B/E/S. Thomson Reuters contends this issue is a peculiarity specific to recommendations, and they have subsequently implemented remedial actions and procedures. Causal factors include variations in the wording of analysts' recommendations causing Thomson Reuters clerks to remove, add or modify existing database entries, and changes in broker rating scales.

Consequently, I believe the specific issues raised by Ljungvist, Malloy and Marston (2009) are not relevant for this study's empirical analysis. Although related problems for analysts' earnings per share forecasts cannot be ruled out, I am not aware of any research to date that provides evidence of rewriting of historic earnings per share forecasts.

3A.3 Incorrect earnings announcement dates

ACKER AND DUCK (2009) find evidence of different earnings announcement dates in the I/B/E/S dataset when compared with Worldscope data, despite both datasets being provided by Thomson Reuters. Acker and Duck (2009) also compared 1,874 hand-collected company announcement dates for UK companies from 1999 through to 2006 with announcement dates for those companies recorded by I/B/E/S. They found 24% were in error, with 97% of those in error having I/B/E/S announcement dates later than the true announcement date. In addition:

> About a quarter of these discrepancies were of either one or two days; a further quarter of them were between 3 and 10 days; and forty percent of them were between 11 and 50 days. A handful were over a year out. (p. 4)

Berkman and Truong (2009) similarly find evidence for US firms of significant differences in recorded announcement dates across datasets.

Despite my research not incorporating any form of event study based on earnings announcements, a high level of inaccuracy in I/B/E/S records for announcement dates may still be problematic. This is because I/B/E/S only changes the period deemed to be the first fiscal year forecast (FY1) to the most recent actual reported period (FY0) after a company has announced. As a result, FY1 represents a period which can in fact be not only historic, but also a period which ended some months in the past. The construction of time series of aggregate earnings forecasts for specific time periods (a key component of this analysis) requires knowledge of the correct periods represented by FY1 and FY2 forecasts and realized earnings.

To correct for what may be a significant issue for empirical results, this study employs a series of checks and specific requirements for I/B/E/S data. These include checks for anomalous announcement dates relative to I/B/E/S forecast dates. In particular, I require that the I/B/E/S announcement date falls within one quarter after the company's fiscal year end for that company to be included in the dataset. Given Acker and Duck (2009) identify 97% of the errors in the UK sample set are from I/B/E/S announcement dates later than true announcement dates, the one quarter limit on reporting should eliminate virtually all problematic dates. In other words, I am not concerned by I/B/E/S announcement dates that are later than true announcement dates. I am only concerned by announcement dates that are more than one quarter after the company's financial year end, and these are removed from the analysis.

3A.4 Differences in reported EPS across datasets

A RANGE OF potential explanations for differences in realized earnings reported by I/B/E/S and realized earnings reported by Compustat are provided by Livnat and Mendenhall (2006). They note, for example, that Compustat will modify reported earnings if they have been restated by, say, a revision by the auditors. I/B/E/S does not restate reported earnings, instead retaining the first value announced by the company. Livnat and Mendenhall (2006) also observe that "Compustat's earnings reflect generally accepted accounting principles (GAAP), while most analyst-tracking services report 'street' measures of earnings" (p. 179). Abarbanell and Lehavy (2000) provide examples of significant differences in results for investigations of, say, forecast rationality depending on the choice of data provider for the estimation of forecast errors, including data provided by I/B/E/S versus Compustat.

My research includes the construction of time series of aggregated earnings forecasts and aggregated historic earnings to generate a selection of measures of aggregate forecast earnings growth. To construct time-weighted forecast growth I employ I/B/E/S records for both earnings forecasts and actual reported values, rather than sourcing actual historic values from a different dataset. While this does not preclude the possibility of definitional differences between I/B/E/S forecasts and actuals, I/B/E/S endeavours to minimize such differences and this approach consequently avoids the additional risk of definitional differences across datasets. However, I calculate aggregate realized earnings growth from CRSP/Compustat data given the availability of rolling four quarter earnings. Hence, forecast growth and realized earnings growth, while closely related (and restricted to the same firm constituents), are not fully compatible. This is the key reason why time series of aggregate market forecast error are not generated in this study.

3A.5 Rounding errors

ROUNDING ERRORS IN I/B/E/S consensus summary data likely present the greatest potential problem for empirical analysis. I/B/E/S summary data (which provides a summary of earnings forecasts across analysts by company, including mean and median forecasts) is recorded to only two decimal places. As a result, when all historic summary earnings are adjusted for a stock split there is the potential for information loss as historic data is rounded – a problem which is more acute for stocks which split multiple times. Payne and Thomas (2003) provide a graphic illustration of this issue. They compare two hypothetical companies with forecast errors in year 1 of -0.31 and +0.31, respectively. If both companies undergo a series of splits over some subsequent time period resulting in an accumulated adjustment factor of 64-for-1, then the forecast error for both after rounding is zero.

Payne and Thomas (2003) report the average stock split adjustment factor as at the March 2001 summary (adjusted) data update was 1.939 for the 173,286 firm observations from 1984 through to 1999. The cut-off for the highest decile on the stock split adjustment was 3.71 and the highest value in the sample set was 288.

Payne and Thomas (2003) concede these values do not guarantee rounding errors. The presence of rounding errors is also dependent upon the levels of forecasts and reported earnings. Nonetheless, their results do highlight a risk for researchers.

One remedial approach is to employ I/B/E/S detail data, which is recorded to four decimal places, and from this employ an algorithm mimicking the I/B/E/S summary process to recreate the summary dataset with greater degrees of freedom. However, while the I/B/E/S summary dataset contains analysts' forecasts back to 1976 for US companies, the detail dataset begins in 1982. The focus of my research is time series analysis. Hence, the key issue is whether or not the informational benefits gained from employing the detail data outweigh a loss of data as a result of being restricted to a shorter sample period.

I instead use I/B/E/S summary data that has not been adjusted for stock splits and employ I/B/E/S and CRSP/Compustat stock split adjustment data files to perform my own adjustment of historic data. Hence, I generate stock split-adjusted data with a higher degree of precision than that provided by I/B/E/S. Sections of this thesis also analyze I/B/E/S unadjusted detail data, to which I apply the appropriate stock split adjustment, and employ to generate variations on I/B/E/S stock split-adjusted summary data.[87] As a result, the key concerns raised by Payne and Thomas (2003) have been accounted for in required datasets.

[87] This allows me, for example, to evaluate the relative benefits of analysts' forecasts restricted to forecasts submitted close to the end of the quarter, compared with summary data derived from forecasts which may be a number of months old (albeit subject to the limit of a shorter available time series for detail data).

4 Data

4.1 Summary data

FOR INCLUSION IN this analysis a stock must have both fiscal year 1 (FY1) and fiscal year 2 (FY2) median earnings per share forecasts available in the I/B/E/S unadjusted summary file. Following De Zwart and Van Dijk (2008), no lower limit is placed on the number of forecasts submitted to I/B/E/S for a stock in a given statistical period. At the individual firm level this means that I/B/E/S earnings may represent a poor proxy for market expectations for the company in question when, say, only one or two analysts have submitted forecasts. However, this research is focused on aggregate market time series relationships for measures of earnings growth, forecasts and forecast revisions. Therefore, the aim is to have the largest combination of forecasts available at each point in time. The inclusion of companies with only one or two submitted forecasts for a stock in a given statistical period is consistent with the intention of constructing the best possible proxy for aggregate market expectations, but may not be acceptable in cross-sectional studies of analysts' forecasts.

Pricing data, book value, 12 month rolling realized earnings per share and shares on issue data for matching periods must be available from the merged CRSP/Compustat file. All non-ADR NYSE, Amex and Nasdaq stocks reporting in US dollars with March, June, September or December balance dates, with required data on a quarterly basis, are eligible for inclusion.[88] For outlier reduction, a stock's price and book value per share must both be greater than $1. In addition, the top and bottom 0.5% of the sample each quarter ranked on the ratio of the forecast change in earnings per share to price are also excluded. Realized earnings from CRSP/Compustat are recorded before extraordinary items and discontinued operations. Forecast earnings from I/B/E/S may be before or after extraordinary items depending on standard practice for analysts of that stock. Therefore, caution is required comparing I/B/E/S forecasts with CRSP/Compustat realized earnings. This is also why the key variables constructed for this research do not include a direct comparison of the two (for example, forecast error calculated as I/B/E/S forecasts less Compustat reported earnings).[89] All stock data has been obtained from the Wharton Research Data Services (WRDS) web portal.

As discussed in Chapter 3, nine measures for each of aggregate market changes in realized earnings, forecast earnings and forecast revisions are constructed. I follow Kothari, Lewellen and Warner (2006) with aggregate earnings measures derived from cross-sectional sums of the earnings in question (realized or forecast), and value- and equal-weighted measures derived from weighted sums of per share

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[88]All conclusions derived from results presented in subsequent chapters remain unchanged when the sample is restricted to companies with December balance dates.

[89] See Appendix 3A.4 for more details regarding the differences between I/B/E/S and CRSP/Compustat reported earnings.

values for variables. I also include quarterly median values of per share variables. Aggregate earnings measures are denoted with capitalized descriptors and value-, equal-weighted and median per share measures with lower case descriptors. Hence, ΔEP refers to the changes in aggregate realized earnings (or forecast earnings or forecast revisions, depending upon appended superscript) deflated by lagged aggregate market capitalization, while Δepv refers to a value-weighted sum of changes in realized earnings per share (or similarly forecast earnings per share or forecast revisions per share) deflated by lagged market price. The equivalent equally-weighted and median variables are labelled Δepeq and Δepmed, respectively.[90]

I/B/E/S records for annual forecast earnings per share for US companies begin in 1976. However, to ensure a sufficiently robust dataset (incorporating all additional data required for each stock) the time series analyzed begin in March 1979 and run through to December 2009, providing 124 quarters for each series. Figure 4.1 illustrates the increase over time in sample size from a starting point of approximately 50% of total non-ADR NYSE/Amex/Nasdaq market capitalization to a sample period-end level of just under 90% of total market capitalization.[91]

Summary statistics (means and standard deviations across the 124 quarters) are provided in Table 4.1. All 27 aggregate market time series variables have an average sample size of 1,213 stocks each quarter. Across the full time series, the average market capitalization of stocks within each quarter is US$3,164 million, with a standard deviation of US$2,024 million.

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[90] All variable construction and empirical analysis is performed in *R: A Language and Environment for Statistical Computing* (2010).

[91] The temporary drop in sample size in 1998/99 is a result of a change in accounting regulations impacting I/B/E/S records. The change is discussed in more detail in Chapter 3. In robustness tests it is shown to have no material impact on research conclusions.

Figure 4.1 Sample size for earnings forecasts – number of stocks and proportion of non-ADR NYSE, Amex and Nasdaq market capitalization

The number of stocks in the full forecast growth sample is provided (LHS), along with the proportion these represent of total non-ADR NYSE/Amex/Nasdaq market capitalization. The dip in sample size in 1998/99 arises from the introduction of Statement of Financial Accounting Standards (SFAS) #128. This required companies report both basic and diluted earnings per share. Prior to this change less than 5% of stocks' earnings per share forecasts were recorded by I/B/E/S on a diluted basis. In the March 1998 quarter this jumped to close to 45%. Variable construction requires both current shares on issue and one quarter lagged shares on issue. However, a large number of the companies recorded on a diluted basis in March 1998 did not have diluted shares on issue available for the December 1997 quarter. This fall in the sample size is quickly reversed over the course of 1998 as the CRSP/Compustat dataset incorporates diluted shares data.

Table 4.1 Summary statistics for aggregate measures of changes in realized earnings, forecast earnings and forecast revisions, 1979–2009

Means and standard deviations for aggregate changes in realized earnings, forecast earnings and forecast revisions are presented, along with equivalent value-weighted, equal-weighted and median per share measures. ΔEE is deflated by the relevant lagged realized or forecast earnings measure. ΔEP and ΔEB are deflated by lagged aggregate market capitalization and book value, respectively. Similarly, Δepv and Δepeq are per share measures deflated by price ('v' refers to value-weighted, 'eq' refers to equal-weighted), while Δebv and Δebeq are per share measures deflated by book value. Δepmed and Δebmed represent median values of deflated per share measures. Summary data for firm size (in US$m) and number of firms per quarter (n) are also provided along with aggregate, value-weighted, equal-weighted and median book-to-market (BP, bpv, bpeq and bpmed). All variables are presented in percentage terms except for the number of firms, market capitalization and book-to-market values. For inclusion a firm must be a non-ADR NYSE, Amex or Nasdaq listed stock with a March, June, September or December financial year end. Realized and forecast earnings per share data for FY-1, FY0, FY1 and FY2 must be available in the I/B/E/S database. Realized earnings, book value, shares on issue and pricing data are also required from CRSP/Compustat. A stock's price and book value per share must both be greater than $1. The top and bottom 0.5% of the sample each quarter ranked on the ratio of forecast change in earnings per share to price are also excluded.

	n	Mkt. cap.	Aggregate				Value-weighted			Equally-weighted			Median		
			BP	ΔEE	ΔEP	ΔEB	bpv	Δepv	Δebv	bpeq	Δepeq	Δebeq	bpmed	Δepmed	Δebmed
A. Realized earnings															
Mean	1,213	3,164	0.48	6.90	0.39	0.82	0.48	0.34	1.49	0.63	0.41	1.20	0.57	0.60	1.26
Std.dev.	535	2,024	0.18	22.07	1.24	2.78	0.18	1.20	2.57	0.18	1.86	2.50	0.18	0.61	1.25
B. Forecast earnings															
Mean	-	-	-	16.23	1.13	2.44	-	1.11	3.21	-	1.73	3.35	-	1.12	2.33
Std.dev.	-	-	-	4.66	0.49	0.70	-	0.49	1.01	-	0.58	0.72	-	0.38	0.54
C. Forecast earnings revisions															
Mean	-	-	-	-6.66	-0.58	-1.17	-	-1.09	-2.89	-	-1.68	-3.03	-	0.86	-1.57
Std.dev.	-	-	-	8.75	0.85	1.52	-	0.85	1.93	-	1.08	1.29	-	0.68	1.01

The average aggregate book-to-market ratio for the full sample (Panel A of Table 4.1) is 0.48, with a standard deviation across the period analyzed of 0.18. The equally-weighted average book-to-market ratio is 0.63, and the median value is 0.58. The differences between the aggregate measure and both the equally-weighted and median book-to-market ratios highlight the presence of a large number of small stocks with relatively high book-to-market ratios.

Analyst forecast bias is clearly evident in Table 4.1. Panel B provides means and standard deviations for deflated measures of earnings expectations at time *t* for the next four quarters, relative to expected earnings at time *t* for the trailing four quarters. The average, when this is deflated by trailing four quarter earnings expectations (ΔEE), is 16.23%. That is, on average, analysts in aggregate forecast 12 month ahead earnings growth of 16.23%. This is a remarkably high number when compared with an average realized 12 month rolling rate of aggregate earnings growth of 6.90% (Panel A). Across the other measures of aggregate forecast earnings the expected change ranges from two to six times the actual historic change. Even considering the potential for definitional differences for earnings between realized and forecast measures, this is a large spread.

In addition, note that the volatility of realized earnings growth is much higher than the volatility of forecast earnings growth (22.07% versus 4.66%). A portion of this difference may be attributable to the fact that realized earnings here are represented by rolling 12 month earnings, while the forecast earnings are based on time-weighted annual values. Nonetheless, it appears that there is a considerable degree of stickiness in analysts' earnings expectations relative to realized earnings.[92]

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[92] While the construction of the aggregate realized earnings measures is slightly different to the methodology employed by Kothari, Lewellen and Warner (2006), similarities in summary statistics are evident. They report an average growth rate in seasonally-

One consequence of the large average difference between forecast earnings growth and realized earnings growth is that the average of one year forecast revisions is negative (Panel C of Table 4.1), at -6.66%. Another way of thinking of this is that analysts, on average, downgrade their expectations for market earnings growth by 6.66 percentage points over the course of the year after the forecasts for that four quarter period are first made. Interestingly, this still leaves a sizable gap at the end of a financial year between average forecast earnings growth and realized earnings growth. Some difference may be attributable to definitional conflicts between CRSP/Compustat earnings and I/B/E/S earnings. Nonetheless, it also indicates further considerable revision activity in the period between the end of a financial year and company reporting dates. This phenomenon is consistent across all measures of aggregate earnings activity presented here (regardless of deflator and/or aggregation technique). In Figures 4.2 through 4.4 it can be seen that these results appear relatively persistent through time. Forecast earnings changes (Figure 4.3) are generally considerably higher than realized earnings changes (Figure 4.2), resulting in negative forecast revisions (Figure 4.4). Forecast revisions rarely turn positive, regardless of variable deflator or aggregation methodology. While the impact of the late 2000s financial crisis is evident in all charts, the average forecast revision remains negative when this period is removed from the time series.

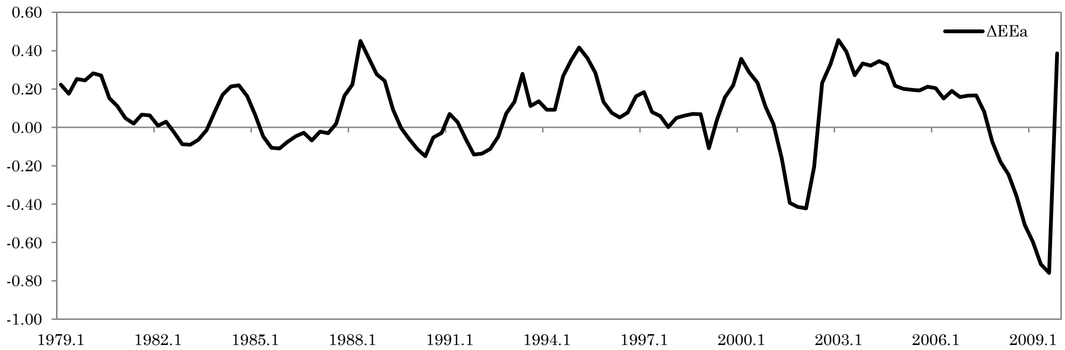
Note also in Table 4.1 the differences between equal- and value-weighted changes in forecast earnings and forecast revisions. On average, the value-weighted forecast earnings change is less than the equally-weighted forecast earnings change (1.11 versus 1.73 when deflated by price and 3.21 versus 3.35 when deflated by book value). This results in more negative average forecast revisions for the equal-

differenced quarterly earnings of 7.84% with a standard deviation of 17.77% for the period 1970 through to 2000. For the subset of this study's data running from 1979 through to 2000 the average growth rate in 12 month earnings relative to 12 month earnings a year prior is 9.14% with a standard deviation of 14.23%.

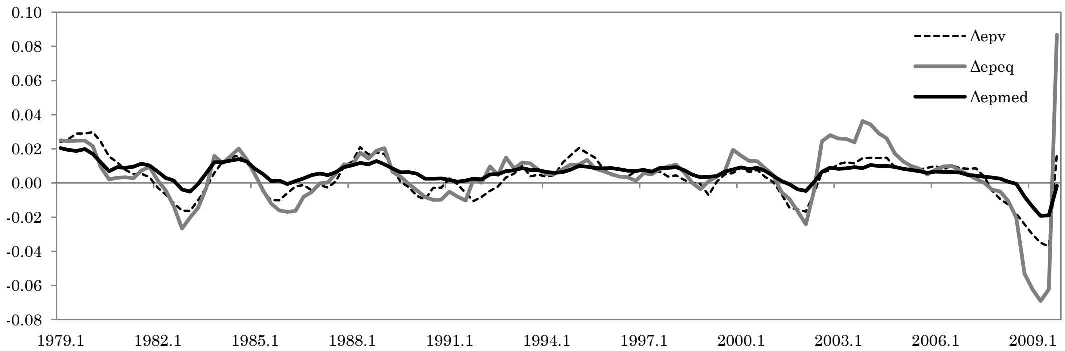
Figure 4.2 Aggregate measures of changes in realized earnings

ΔEE is deflated by lagged realized earnings. Δepv and Δepeq are per share measures deflated by price, while Δebv and Δebeq are per share measures deflated by book value per share. Δepmed and Δebmed are median values of per share measures.

A. Aggregate change in realized earnings deflated by lagged realized earnings



B. Value-weighted, equally-weighted and median changes in realized earnings deflated by lagged market price



C. Value-weighted, equally-weighted and median changes in realized earnings deflated by lagged book value

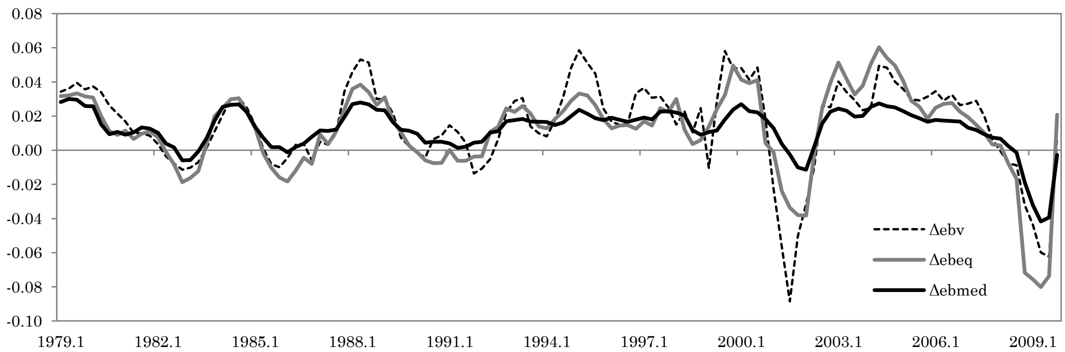
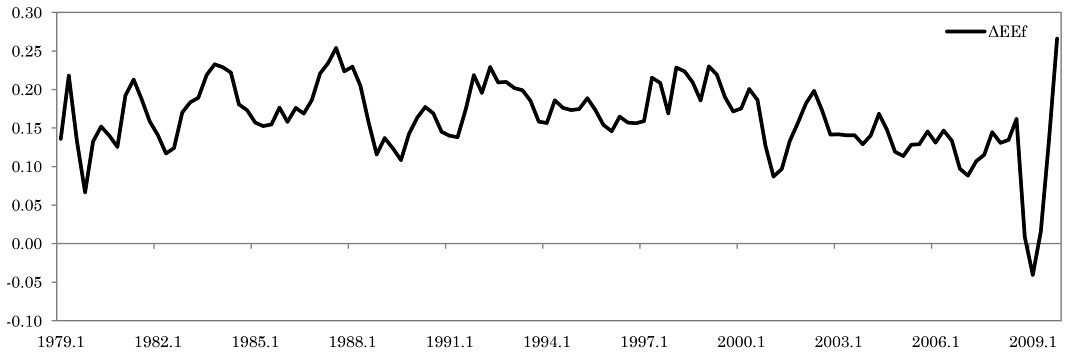


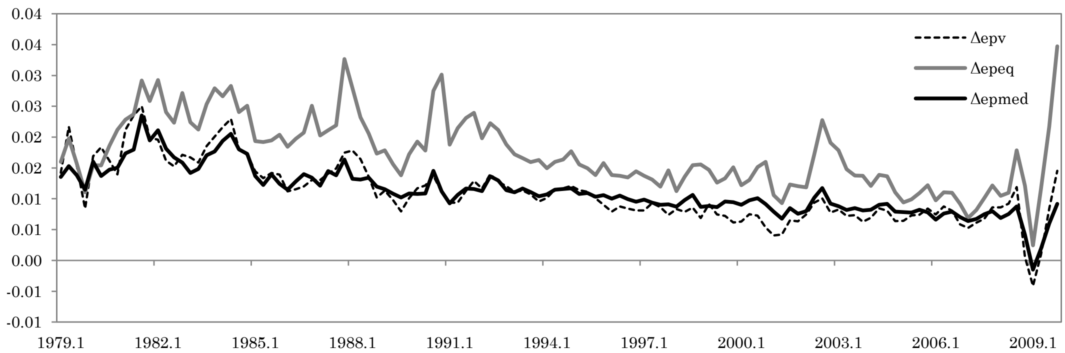
Figure 4.3 Aggregate measures of forecast earnings change

ΔEE is deflated by trailing 12 month estimated earnings. Δepv and Δepeq are per share measures deflated by price, while Δebv and Δebeq are per share measures deflated by book value per share. Δepmed and Δebmed are median values of per share measures.

A. Aggregate forecast earnings changes deflated by trailing earnings



B. Value-weighted, equally-weighted and median forecast changes in earnings deflated by lagged market price



C. Value-weighted, equally-weighted and median forecast changes in earnings deflated by lagged book value

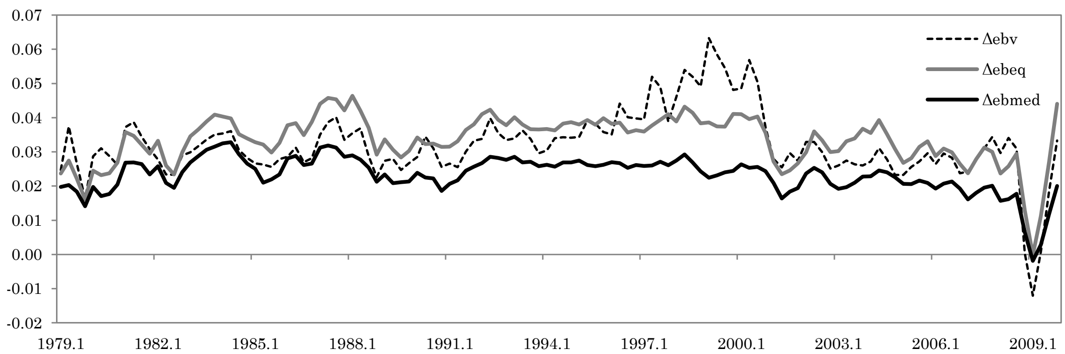
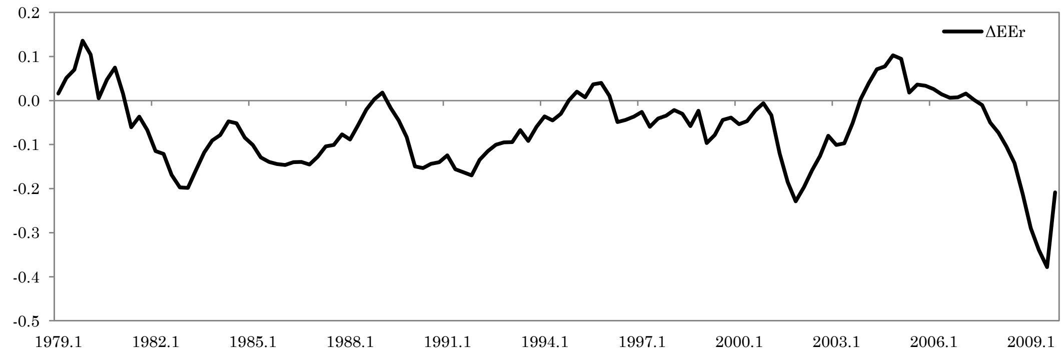


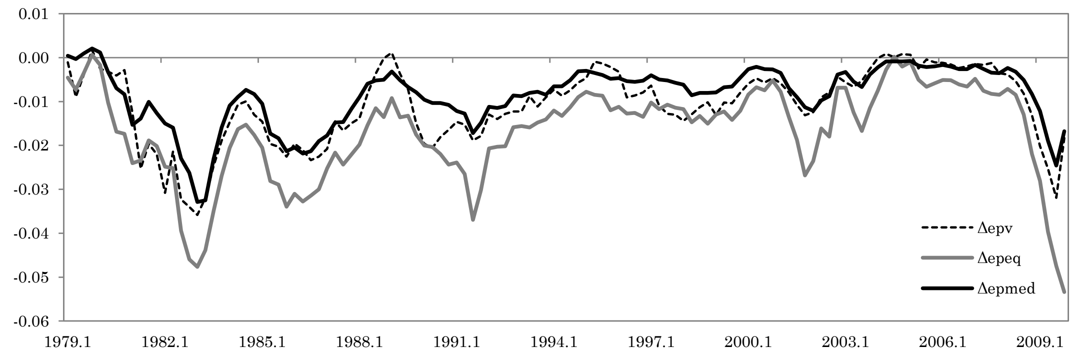
Figure 4.4 Aggregate measures of forecast revisions

ΔEE is deflated by the forecast made one year prior to the period ending in the data quarter. Δepv and Δepeq are per share measures deflated by price, while Δebv and Δebeq are per share measures deflated by book value per share. Δepmed and Δebmed are median values of per share measures.

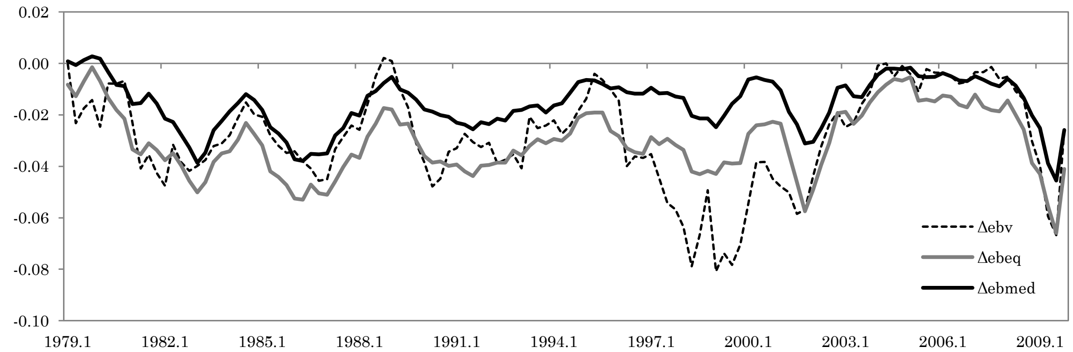
A. Aggregate forecast revisions deflated by lagged forecast earnings



B. Value-weighted, equally-weighted and median forecast revisions deflated by lagged market price



C. Value-weighted, equally-weighted and median forecast revisions deflated by lagged book value



weighted sample relative to the value-weighted sample (-1.68 versus -1.09 deflated by price and -3.03 versus -2.89 deflated by book value). This suggests a larger positive forecast bias for smaller companies relative to larger companies, across the period investigated. Simply, smaller companies receive a larger weighting in equal-weighted variables relative to value-weighted variables, thus driving differences between the two.[93]

Size differences are more clearly evident in Table 4.2. For each of realized earnings changes, forecast earnings changes and forecast revisions the full sample is split into tercile portfolios (rebalanced each quarter) ranked on either market capitalization (Panel A) or book-to-market ratios (Panel B). Aggregate earnings measures for the top and bottom tercile portfolios are presented. Focusing on change measures deflated by book value, ΔEB, the average change in realized earnings for large-cap stocks is 0.85 and 0.62 for small cap stocks. In addition, aggregate small cap realized earnings are more volatile, with a standard deviation of 3.23 relative to large caps at 2.84. However, for aggregate forecast earnings changes the large-cap average is 2.42, with 3.07 recorded for small caps. One consequence of this is that the average forecast revision for small companies is -2.34, compared with -1.10 for large companies. Given the well-known link between firm size and book-to-market ratios,[94] it is not surprising to see these differences mirrored (albeit to a lesser extent) in differences between low and high book-to-market portfolio average realized earnings changes, forecast changes and forecast revisions.

[93] Median values of forecast and forecast revision measures are smaller in absolute magnitude than both equally- and value-weighted measures, indicating some impact on variables from outliers. Similarly, median values of realized earnings measures are larger than equally- and value-weighted measures, suggesting average changes for the latter variables are pulled lower by a selection of large losses.

[94] For example, see Fama and French (1992).

Table 4.2 Summary statistics for aggregate measures of changes in realized earnings, forecast earnings and forecast revisions for size and book-to-market sorted portfolios, 1979–2009

For each aggregate earnings measure and each quarter stocks are ranked by market capitalization or book-to-market value and tercile portfolios formed. Aggregate earnings measures are then calculated for the tercile portfolios and summary statistics for terciles 1 and 3 reported. Means and standard deviations for aggregate changes in realized earnings, forecast earnings and forecast revisions are presented. ΔEE is deflated by the relevant lagged realized or forecast earnings measure. ΔEP and ΔEB are deflated by lagged aggregate market capitalization and book value, respectively. Summary data for firm size (in US$m) and number of firms per quarter (*n*) are also provided along with aggregate and equal-weighted book-to-market (BP and bpeq). All variables are presented in percentage terms except for the number of firms, market capitalization and book-to-market measures. For inclusion a firm must be a non-ADR NYSE, Amex or Nasdaq listed stock with a March, June, September or December financial year end. Realized and forecast earnings per share data for FY-1, FY0, FY1 and FY2 must be available in the I/B/E/S database. Realized earnings, book value, shares on issue and pricing data are also required from CRSP/Compustat. A stock's price and book value per share must both be greater than $1. The top and bottom 0.5% of the sample each quarter ranked on the ratio of forecast change in earnings per share to price are also excluded.

		n	Mkt. cap.	BP	bpeq	ΔEP^a	ΔEB^a	ΔEP^f	ΔEB^f	ΔEP^r	ΔEB^r
A. Terciles 1 and 3 by firm size											
Small	Mean	404	157	0.70	0.75	0.40	0.62	2.21	3.07	-1.67	-2.34
	Std.dev.	178	70	0.20	0.22	2.36	3.23	0.80	0.89	1.31	1.49
Large	Mean	405	8,651	0.47	0.54	0.40	0.85	1.08	2.42	-0.53	-1.10
	Std.dev.	178	5,743	0.18	0.18	1.23	2.84	0.48	0.75	0.85	1.57
B. Terciles 1 and 3 by book-to-market ratio											
Low Bk/Mkt	Mean	404	5,363	0.27	0.28	0.61	2.31	1.02	3.76	-0.33	-1.16
	Std.dev.	178	4,235	0.10	0.09	0.64	2.66	0.47	1.19	0.48	1.57
High Bk/Mkt	Mean	405	1,492	0.94	1.03	-0.03	-0.10	1.47	1.54	-1.25	-1.30
	Std.dev.	178	970	0.26	0.29	3.51	3.75	0.76	0.65	1.86	1.76

Figure 4.5 illustrates time series of tercile 1 and tercile 3 aggregate realized earnings changes (Panel A), forecast earnings changes (Panel B) and forecast revisions (Panel C). In Panel C of Figure 4.5 it is evident that size-related differences in forecast revisions are relatively persistent through time. Analyst forecast bias is on average greater for small companies than it is for large companies (and for high book-to-market companies versus low book-to-market companies). Das, Levine and Sivaramakrishnan (1998) also find evidence of greater forecast bias for small companies relative to large companies, as does Lim (2001).

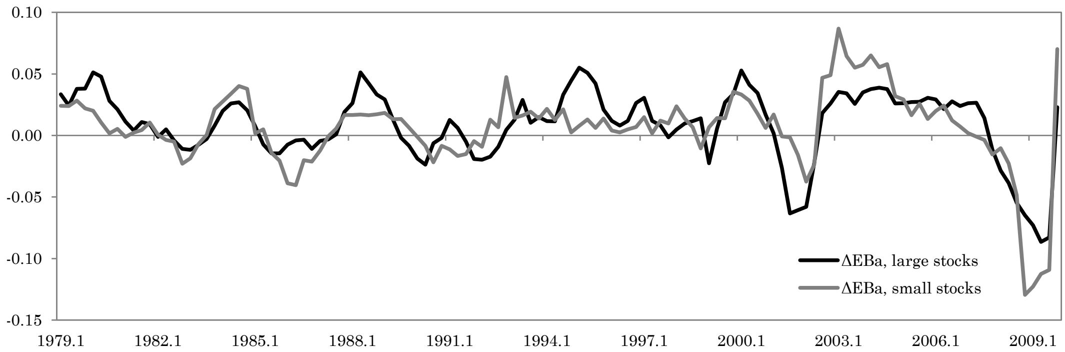
Table 4.3 provides Pearson correlation coefficients between measures of realized earnings changes, forecast changes and forecast revisions. Notably, aggregate earnings measures deflated by market capitalization and those deflated by aggregate book value are highly correlated with their per share value-weighted equivalents. For example the correlation between ΔEP^f and Δepv^f is 0.996 and correlation between ΔEB^f and Δebv^f is 0.936 for the period from 1979 through to 2009. Consequently, this study drops the value-weighted per share measures from most analysis, confirming in additional robustness tests (not shown) that the principal conclusions drawn from the aggregate measures may be extended to the value-weighted per share measures.

Table 4.4 takes the three versions of aggregate measures of realized earnings changes, forecast earnings changes and forecast revisions, and presents correlation coefficients. Forecast measures as at the start of the next 12 month forecast period are compared with realized and revision measures as at the end of each previous 12 month change period. Firstly, note forecast changes are positively correlated with realized earnings growth for the prior period. That is, stronger realized earnings growth for a given 12 month period is associated with higher forecast earnings growth for the subsequent 12 month period. However, some caution is warranted

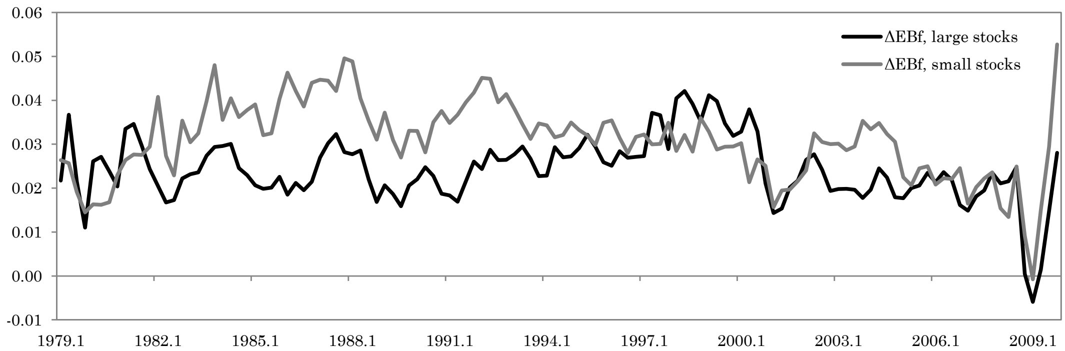
Figure 4.5 ΔEB for small and large capitalization stocks

For each aggregate earnings measure and each quarter stocks are ranked by market capitalization and tercile portfolios formed. Aggregate earnings measures are then calculated for the tercile portfolios and charts for terciles 1 and 3 are illustrated. ΔEB is deflated by lagged aggregate book value for the portfolio in question.

A. Realized earnings



B. Forecast earnings



C. Forecast revisions

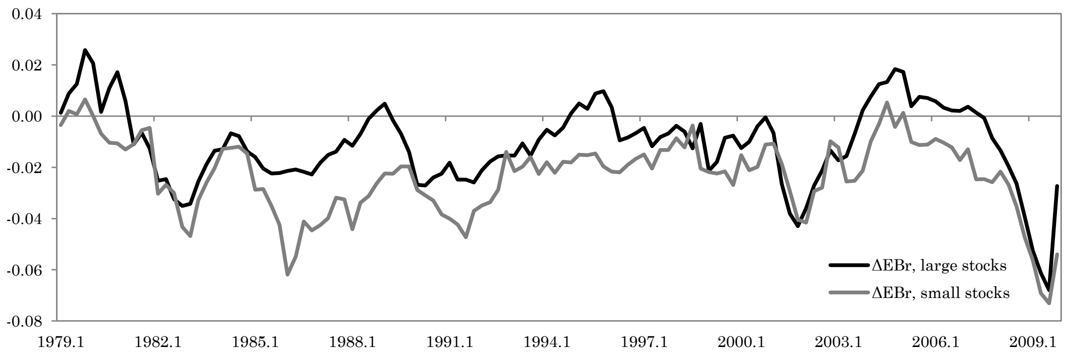


Table 4.3 Correlations amongst aggregate measures of changes in realized earnings, forecast earnings and forecast revisions, 1979–2009

Pearson correlation coefficients are presented for aggregate changes in realized earnings, forecast earnings and forecast errors, along with equivalent value-, equal-weighted and median per share measures. ΔEE is deflated by the relevant lagged realized or forecast earnings measure. ΔEP and ΔEB are deflated by lagged aggregate market capitalization and book value, respectively. Similarly, Δepv and Δepeq are per share measures deflated by price, while Δebv and Δebeq are per share measures deflated by book value, and Δepmed and Δebmed represent median values of deflated per share measures. For inclusion a firm must be a non-ADR NYSE, Amex or Nasdaq listed stock with a March, June, September or December financial year end. Realized and forecast earnings per share data for FY-1, FY0, FY1 and FY2 must be available in the I/B/E/S database. Realized earnings, book value, shares on issue and pricing data are also required from CRSP/Compustat. A stock's price and book value per share must both be greater than $1. The top and bottom 0.5% of the sample each quarter ranked on the ratio of forecast change in earnings per share to price are also excluded.

	ΔEE	ΔEP	ΔEB	Δepv	Δebv	Δepeq	Δebeq	Δepmed	Δebmed
A. Realized earnings									
ΔEE	1								
ΔEP	0.927	1							
ΔEB	0.985	0.941	1						
Δepv	0.911	0.985	0.923	1					
Δebv	0.893	0.835	0.916	0.840	1				
Δepeq	0.856	0.822	0.812	0.837	0.685	1			
Δebeq	0.923	0.855	0.916	0.861	0.883	0.878	1		
Δepmed	0.800	0.887	0.822	0.900	0.757	0.779	0.845	1	
Δebmed	0.877	0.865	0.885	0.877	0.839	0.817	0.940	0.938	1
B. Forecast earnings									
ΔEE	1								
ΔEP	0.574	1							
ΔEB	0.901	0.421	1						
Δepv	0.563	0.996	0.390	1					
Δebv	0.762	0.207	0.936	0.176	1				
Δepeq	0.533	0.773	0.260	0.796	0.073	1			
Δebeq	0.857	0.313	0.811	0.311	0.739	0.397	1		
Δepmed	0.493	0.930	0.362	0.936	0.196	0.782	0.326	1	
Δebmed	0.825	0.519	0.767	0.518	0.656	0.452	0.898	0.584	1
C. Forecast revisions									
ΔEE	1								
ΔEP	0.923	1							
ΔEB	0.994	0.908	1						
Δepv	0.770	0.889	0.756	1					
Δebv	0.534	0.446	0.571	0.584	1				
Δepeq	0.805	0.892	0.773	0.890	0.401	1			
Δebeq	0.846	0.805	0.840	0.818	0.732	0.819	1		
Δepmed	0.736	0.873	0.707	0.916	0.414	0.950	0.816	1	
Δebmed	0.861	0.868	0.842	0.849	0.580	0.887	0.947	0.909	1

here given realized earnings growth is not observable to analysts at the point at which these forecasts are made.[95] In addition, the positive correlation is principally due to the effects of the late 2000s financial crisis. For the period from 1979 through to the end of 2007 the correlation between realized earnings growth and future forecast earnings growth is negative. Secondly, observe the high correlation evident in Table 4.4 between aggregate realized earnings growth measures and forecast revisions for the period in question. Stronger realized earnings growth is associated with more positive (or typically less negative) forecast revisions. In other words, stronger realized earnings growth shrinks the gap between realized earnings growth and optimistic forecasts.

The relationship between forecast revisions and subsequent forecasts is mixed, depending upon the deflator chosen. For forecast changes in earnings deflated by either lagged earnings or market capitalization the correlations with matching earnings revisions measures are negative. Less negative earnings revisions tend to be associated with less optimistic subsequent forecasts. However, when deflated by lagged book value, less negative earnings revisions tend to be associated with more optimistic subsequent forecasts.

4.2 Autocorrelations

VARIABLE CONSTRUCTION METHODOLOGY, outlined in Chapter 3, is expected to result in statistically significant autocorrelation in all key time series variables. Employing 12 month realized earnings on a rolling quarterly basis to construct the realized earnings change measures, and annual forecasts (combined with the time-weighting of annual forecasts) for the forecast change and forecast revision variables, will produce autocorrelated final variables.

[95] Analysts will have access to three of the four previous quarters of realized earnings. The fourth, and most recent, will not have been announced when analysts' forecasts for the next 12 months are aggregated.

Table 4.4 Correlations across aggregate measures of changes in realized earnings, forecast earnings and forecast revisions, 1979–2009

Pearson correlation coefficients are presented across aggregate changes in realized earnings, forecast earnings and forecast revisions. ΔEE is deflated by the relevant lagged realized or forecast earnings measure. ΔEP and ΔEB are deflated by lagged aggregate market capitalization and book value, respectively. The superscripts "a", "f" and "r" refer to actuals, forecasts and forecast revisions, respectively. For inclusion a firm must be a non-ADR NYSE, Amex or Nasdaq listed stock with a March, June, September or December financial year end. Realized and forecast earnings per share data for FY-1, FY0, FY1 and FY2 must be available in the I/B/E/S database. Realized earnings, book value, shares on issue and pricing data are also required from CRSP/Compustat. A stock's price and book value per share must both be greater than $1. The top and bottom 0.5% of the sample each quarter ranked on the ratio of forecast change in earnings per share to price are also excluded.

	ΔEE^a	ΔEP^a	ΔEB^a	ΔEE^f	ΔEP^f	ΔEB^f	ΔEE^r	ΔEP^r	ΔEB^r
ΔEE^a	1								
ΔEP^a	0.927	1							
ΔEB^a	0.985	0.941	1						
ΔEE^f	0.244	0.187	0.229	1					
ΔEP^f	0.198	0.305	0.209	0.574	1				
ΔEB^f	0.343	0.292	0.358	0.901	0.421	1			
ΔEE^r	0.743	0.817	0.794	-0.018	0.055	0.214	1		
ΔEP^r	0.635	0.745	0.673	-0.061	-0.110	0.188	0.923	1	
ΔEB^r	0.770	0.836	0.817	0.021	0.091	0.220	0.994	0.908	1

Following Kothari, Lewellen and Warner (2006) I present in Table 4.5 results of univariate and multivariate investigations of autocorrelation for realized earnings growth, forecast earnings growth and forecast revisions. Each variable is regressed on a lagged series of itself with lags ranging from one to eight quarters, and separately regressed on all lags simultaneously. Results are presented only for variables with lagged earnings measures as denominators, but conclusions are consistent with those for variables with lagged market capitalization and lagged book value as denominators.

For the univariate realized earnings growth regressions (Panel A), autocorrelations are positive and statistically significant at the 10% level or higher out to three quarters, and negative and statistically significant at the 10% level or higher for lags of seven and eight quarters. In the multivariate regression the estimated slope coefficient on the one quarter lag variable is positive and statistically significant. The estimated coefficient for a lag of five quarters is also positive and statistically significant, while the four quarter lag variable is negative and significant. These results are broadly consistent with those reported by Kothari, Lewellen and Warner (2006). Depending upon the measure of aggregate changes in realized earnings employed, they find positive autocorrelations in single factor regressions out to three to four quarters, and positive autocorrelations for the first two quarter lags in multivariate regressions.

For forecast earnings growth, statistically significant (and positive) estimated slope coefficients are obtained for lags of 1, 2, 3, 7 and 8 quarters in univariate regressions. The estimated slope coefficients are positive for all lags investigated. This suggests persistence in forecast earnings growth – more than is evident in realized earnings growth. However, in the multivariate regression only the first and seventh quarter lags have positive and statistically significant estimated

Table 4.5 Autocorrelation estimations for changes in realized earnings, forecast earnings and forecast revisions, 1979–2009

Univariate and multivariate regression results are presented for aggregate changes in realized earnings, forecast earnings and forecast revisions (deflated by their respective lagged earnings measures) on lagged values of the same. Individual regression results for 1 to 8 quarter lags are illustrated, along with a regression of the dependent variable simultaneously on all 8 quarter lags. For inclusion a firm must be a non-ADR NYSE, Amex or Nasdaq listed stock with a March, June, September or December financial year end. Realized and forecast earnings per share data for FY-1, FY0, FY1 and FY2 must be available in the I/B/E/S database. Realized earnings, book value, shares on issue and pricing data are also required from CRSP/Compustat. A stock's price and book value per share must both be greater than $1. The top and bottom 0.5% of the sample each quarter ranked on the ratio of forecast change in earnings per share to price are also excluded. Estimated slope coefficients in bold are statistically significant at the 10% level.

	Lag	Univariate regressions			Multivariate regressions		
		Estimated slope coef.	t-statistic	Adj. R^2	Estimated slope coef.	t-statistic	Adj. R^2
A. Realized earnings	1	**0.805**	14.651	0.637	**1.184**	7.680	0.718
	2	**0.665**	8.690	0.381	-0.137	-0.531	
	3	**0.442**	4.604	0.144	-0.254	-0.987	
	4	0.169	1.549	0.012	**-0.590**	-2.422	
	5	-0.023	-0.201	-0.008	**0.624**	2.578	
	6	-0.168	-1.430	0.009	-0.031	-0.120	
	7	**-0.254**	-2.139	0.030	-0.167	-0.651	
	8	**-0.294**	-2.459	0.042	-0.093	-0.563	
B. Forecast earnings	1	**0.733**	11.373	0.513	**1.128**	11.168	0.635
	2	**0.382**	4.451	0.135	**-0.465**	-3.190	
	3	**0.220**	2.313	0.035	0.019	0.122	
	4	0.171	1.640	0.014	-0.040	-0.264	
	5	0.153	1.363	0.007	0.025	0.159	
	6	0.100	0.882	-0.002	-0.141	-0.848	
	7	**0.212**	1.881	0.021	**0.319**	2.080	
	8	**0.289**	2.582	0.047	-0.094	-0.850	
C. Forecast revisions	1	**0.918**	24.374	0.829	**1.241**	11.568	0.851
	2	**0.831**	13.917	0.614	**-0.347**	-1.963	
	3	**0.703**	9.076	0.404	0.012	0.072	
	4	**0.527**	5.838	0.218	-0.082	-0.484	
	5	**0.334**	3.404	0.082	-0.002	-0.011	
	6	0.164	1.603	0.013	-0.071	-0.427	
	7	0.019	0.180	-0.008	0.204	1.277	
	8	-0.120	-1.184	0.003	**-0.184**	-1.795	

coefficients. The second quarter lag has a negative and statistically significant slope coefficient (at the 1% level).

For forecast revisions, univariate lags of one through five quarters all have positive and statistically significant estimated slope coefficients (at the 10% level or better). Note also that the adjusted R^2 for the multivariate forecast revision regression (0.851) is higher than the adjusted R^2 for both realized earnings (0.718) and forecast earnings (0.635).

These results highlight the need for time series regressions to take autocorrelation into consideration to ensure consistent standard errors for hypothesis testing. I employ Newey and West (1987) heteroscedasticity and autocorrelation-consistent (HAC) standard errors for all subsequent regressions reported. I also use the Newey and West (1994) non-parametric automatic bandwidth selection procedure.[96]

4.3 Macroeconomic variables

THIS STUDY INCLUDES a range of economic state variables in investigations of the relationships between macroeconomic factors and aggregate market earnings growth, forecast earnings growth and forecast revisions. This section introduces the principal state variables employed. The choice of economic state variables is strongly influenced by a range of seminal works on the relationships between macroeconomic factors and stock market characteristics, including Chen, Roll and Ross (1986), Fama and French (1989), Fama (1990) and Chen (1991), as well as macroeconomic factors evaluated in the analyst efficiency literature (discussed in Chapter 6).

[96] In unreported robustness tests for analysis in Chapters 5, 6 and 7 I also run regressions setting the maximum bandwidth to a lag length of four quarters. There is no impact on research conclusions.

Industrial production

Unless specified otherwise, I employ seasonally unadjusted 12 month log changes in US industrial production calculated from the Federal Reserve non-seasonally adjusted index of industrial production. Seasonally unadjusted data is employed as an explanatory variable to avoid the impact of future data on the seasonal adjustment process, given a focus on information available at the time analysts' forecasts are made. The seasonally adjusted 12 month log change in industrial production is employed in Chapter 5 as a dependent variable.

Chen (1991) also employs this measure of industrial production growth, but acknowledges there is no formal theoretical basis for the choice of a 12 month growth period:

> Using a shorter period would imply that the measured growth rate reflects short-term production fluctuations rather than the health of the current economy relative to long-term growth. With a longer period, the growth rate might miss a business cycle altogether. (p. 531)

Like Chen (1991), I expect that the choice of a 12 month period provides an appropriate indication of current economic conditions. In addition, this will be a measure familiar to equity analysts (a relevant consideration when investigating the informational efficiency of analysts' forecasts).

Industrial production indices are published monthly and are available around the 15th day of the month following the statistical period in question.[97]

[97] The level of the industrial production index first reported after month end is a provisional value and is subject to revision over the following 5 months as additional source data becomes available. The US Federal Reserve estimates that 72% of source data is available (in value-added terms) when the first provisional value for industrial production is published, with 86%, 95% and 98% available over the subsequent 1, 2 and 3 months. The Federal Reserve calculates the absolute value of the average revision to the level of the total industrial production index from the first to the fourth estimate was 0.26% between 1987 and 2008. The absolute value of the average revision to the percentage change in industrial production across these four estimates was 0.21 of a percentage point between 1987 and 2008. Some comfort may be gained from the Federal Reserve's finding that the direction of change for one month industrial production remains the same for approximately 85% of final revised index values relative to the first provisional estimate. In

Business confidence

Both the level and 12 month log changes in the Institute of Supply Management's (ISM) Purchasing Managers' Index (PMI) for manufacturing companies are included in analysis. This measure of business confidence has received surprisingly little attention in the academic literature, despite being considered of great importance by financial market practitioners as an indicator of both the current health and future direction of US economic activity.[98] The history of, and academic perspective on, the ISM PMI are discussed in more detail in Chapter 6.

The published survey represents equally-weighted combinations of seasonally-adjusted component indices (new orders, production, employment, supplier deliveries and inventory indices). The index represents survey respondents' assessments of business conditions in the survey month relative to the previous month. A reading over 50 indicates generally improving business conditions, while a reading below 50 indicates respondents believe that business conditions are deteriorating. The distance of the index from 50 provides an indication of the strength of economic expansion or contraction. However, the index is not available in seasonally unadjusted form. Therefore, to avoid future information impacting the data via the seasonal adjustment process, I create a non-seasonally adjusted version of the PMI. Mimicking the ISM's index construction process I generate non-seasonally adjusted diffusions indices from the raw response data for new orders, production, employment, supplier deliveries and inventories. I then omit seasonal adjustment of the diffusion indices, and equally-weight the non-seasonally adjusted component indices.[99] The resulting series is divided by 100 for scaling purposes,

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addition, my use of 12 month changes in industrial production should reduce sensitivity of analysis to minor data revisions.

[98] Examples are provided in Chapter 6.

[99] Prior to January 1988 the index represents an equally-weighted combination of the new orders, production, employment and supplier deliveries indices. From January 1988

and represents a non-seasonally adjusted ISM index for manufacturing companies.[100] The PMI is available on the first business day of the month after the survey month.

Consumer confidence

A time series for US consumer confidence is provided by the University of Michigan's Index of Consumer Sentiment. The survey represents the results of a telephone poll of at least 500 individuals residing in the continental US, with the resulting index normalized to 100 in December 1964. Survey questions, from which the index is derived, incorporate assessment of historical change in consumer financial well-being, expected future change in financial well-being, future economy-wide business conditions and current consumer demand. The survey is dated by the month in which it is released (so a December 2009 survey is released in December 2009). Preliminary index values are published around the middle of the survey month, with final values published before month end. The index scale is altered by dividing levels by 100.

Inflation

I measure inflation with 12 month log changes in the US Consumer Price Index (CPI). CPI data is published around the middle of the month after the statistical period in question.

Real Treasury bill rate

As discussed by Fama and French (1989), bill rates tend to increase during economic expansions and fall during economic contractions. This paper employs

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onwards, data for the inventories diffusion index is available and included in the ISM index.

[100] The Non-Manufacturing Composite Index published by the ISM is only available from July 1997 and is therefore not included in this analysis.

month-end averages of daily 3 month Treasury bill yields, obtained from the US Federal Reserve, which are adjusted for CPI inflation to derive real yields. Aggregate market earnings measures developed in this research are in nominal terms. Real yields are therefore used, rather than nominal yields, to determine the relationships between these earnings measures and the inflation-adjusted component of interest rates, while relationships between earnings measures and consumer price inflation are separately estimated.

Real Treasury bond rate

Month-end averages of daily constant maturity 10 year Treasury bond yields are obtained from the US Federal Reserve and adjusted for CPI inflation to derive real yields.

Term structure

Chen (1991) outlines a consumption smoothing explanation for a relationship between the term structure and expected economic activity. Essentially an expectation of strong positive future economic growth leads consumption-smoothing individuals to borrow now to increase current consumption. This increase in borrowing raises longer term interest rates (as individuals match borrowing term with the timing of expected strengthening in the economic cycle) resulting in a steepening in the yield curve. Fama and French (1989) observe “a clear business cycle pattern” (p. 31) in the term spread (measured in their case as the difference between Aaa corporate bond yields and the one month bill rate). In this study I measure the term structure as the percentage point difference between the real 10 year Treasury bond rate and the real 3 month Treasury bill rate.

Default spread

Fama and French (1989) comment that "If bonds are priced rationally, the default spread, a spread of lower- over high-grade bond yields, is a measure of business conditions" (p. 28). They note a tendency for the default spread to be higher during recessions and lower during economic expansions. This research employs the percentage point difference between the Moody's seasoned Baa-rated corporate bond yield and the Moody's seasoned Aaa-rated corporate bond yield (month-end averages of daily yields) as a measure of the default spread.

Stock returns

I employ 12 month value-weighted returns (including distributions) on non-ADR NYSE, Amex and Nasdaq stocks as a measure of aggregate market stock returns.

Dividend yield

For the market dividend yield I employ the NYSE rolling 12 month dividend yield derived from CRSP NYSE returns with and without dividend returns, as per Fama and French (1988).

4.4 Concluding remarks

IN THIS CHAPTER I provide an overview of data characteristics for key earnings variables. The aggregate market realized earnings, forecast earnings and earnings revisions variables are internally consistent, and exhibit characteristics that are consistent with the findings of cross-sectional studies. The time series characteristics of the aggregate realized earnings variables are consistent with those presented by Kothari, Lewellen and Warner (2006). In addition, there is evidence of forecast bias, and the magnitude of bias is related to firm size. Demonstrating consistency between the characteristics exhibited by the aggregate time series variables and characteristics observed by other researchers in cross-sectional analyses is important given the aggregate market measures of forecast changes in earnings and earnings revisions are a distinguishing feature of my analysis. Therefore, the summary statistics presented in this chapter represent a form of robustness test on the variable construction methodology discussed in Chapter 3.

5 *Macroeconomic information in analysts' forecasts*

5.1 Introductory concepts

THIS CHAPTER PROVIDES an investigation of the information in equity analysts' forecasts for a selection of indicators of macroeconomic activity. As discussed in Chapter 1, statistically significant information in analysts' earnings forecasts for future realized earnings, and a strong positive relationship between realized earnings and contemporaneous macroeconomic growth, suggest analysts possess some degree of predictive power for the business cycle. This represents the central hypothesis of the research in this chapter.

The relationship between analysts' earnings forecasts and future measures of macroeconomic activity is poorly understood. Shivakumar (2010) observes "Prior studies note that aggregate earnings news is probably related to market returns because it provides information about the macroeconomy, but little is known about the macroeconomic content of such earnings" (p. 338). Similarly, Shivakumar (2007) comments on the potential value of an investigation into the macroeconomic information in aggregated analysts' forecasts.

In this chapter I estimate the information in aggregated earnings forecasts for a selection of economic state variables. In addition, I hypothesize less information for indicators of macroeconomic activity in the earnings forecasts of companies which engage in high levels of earnings smoothing relative to companies engaging in low levels of earnings smoothing. Smoothing by firm management has been shown to be a widespread feature of firms' earnings.[101] The effect of smoothing is to reduce variation in realized earnings through time. Hence, smoothing may reduce the magnitude of the relationship between realized earnings and measures of contemporaneous macroeconomic activity. If analysts incorporate expected smoothing in their forecasts, and there is supporting evidence for this in the literature, [102] then high levels of smoothing could reduce the explanatory power of analysts' forecasts for future macroeconomic activity.

I also hypothesize more information for future macroeconomic activity in the earnings forecasts of more cyclical firms, relative to less cyclical firms. That is, a relationship between the information in earnings forecasts for future

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[101] For example, see Beidleman (1973), Bhattacharya, Daouk and Welker (2003), Leuz, Nanda and Wysocki (2003), Tucker and Zarowin (2006), Cahan, Liu and Sun (2008) and Dechow, Ge and Schrand (2010).

[102] Examples include Burgstahler and Eames (2003), Liu (2005) and Gavious (2009). In addition, firm's managements provide earnings guidance to analysts. It is reasonable to assume that high smoothers incorporate more smoothing in their guidance for future earnings than low smoothers. A number of researchers have found that analysts are heavily reliant (or at least closely follow) management guidance on earnings. Examples include Previts, Bricker, Robinson and Young (1994) and Cotter, Tuna and Wysocki (2006). Feng and McVay (2010) find more than 80 per cent of management earnings guidance is incorporated into analysts' short term earnings revisions for a sample of 1,708 US firms from 1994 through to 2005. Therefore, management guidance could contribute to a relationship between the magnitude of information in analysts' forecasts for future economic activity and the extent of earnings smoothing.

macroeconomic activity and the sensitivity of firms' realized earnings to variation in macroeconomic activity. I therefore investigate variation in the information in aggregated earnings forecasts across portfolios determined by relative earnings cyclicality.[103]

I find evidence of statistically significant information in aggregated analysts' forecasts of year-ahead changes in earnings for future industrial production growth (up to six quarters ahead).

I find evidence of a negative relationship between relative smoothing and the magnitude of information in aggregated analysts' earnings forecasts for future industrial production. I also find evidence of a positive relationship between the extent of earnings smoothing and firm size, although size appears to be reflecting additional characteristics beyond just relative smoothing. In quintile portfolios formed on the basis of firm size I find the strongest predictive power in aggregated analysts' forecasts for future macroeconomic activity is amongst the smallest stocks.[104]

I find evidence of a positive relationship between relative stock cyclicality and the magnitude of information for future industrial production in analysts' earnings forecasts. I also find evidence of a size effect in the aggregated forecasts of firms with highly cyclical earnings. Specifically, I find weaker information in large cyclicals' earnings forecasts relative to small cyclicals.

[103] Relative cyclicality is determined by the magnitude of estimated coefficients and R^2s in regressions of realized earnings growth on contemporaneous macroeconomic growth. Details are provided in Section 5.6.

[104] In robustness tests for portfolios formed on double sorts of both size and relative smoothing I find that while firm size is a useful proxy for smoothing, size-based variation in the relationship between earnings forecasts and future macroeconomic activity is sufficiently large to suggest the presence of other size-related drivers.

In addition, I show evidence of regime-based variation in the predictive power of size-based portfolios for economic activity.[105] This is consistent with greater income smoothing by large companies, relative to small companies, as economic activity slows. That is, the forecasts of large companies' earnings react less to slowing in economic activity relative to the forecasts of small companies' earnings.[106] However, the result is also reflecting regime-based variation in the additional characteristics reflected in firm size.

Combining results for relative size and relative cyclicality, I propose that the magnitude of information in analysts' earnings forecasts for future macroeconomic activity is greatest for the aggregated forecasts of small cyclical firms. I find that the earnings forecasts of small cyclicals provide *marginal* explanatory power for future industrial production growth of sufficient magnitude (and sufficiently uncorrelated with other macroeconomic factors) to be significant even in combination with a range of additional economic state variables.

In Section 5.2 I investigate the two key precursors to an expectation of statistically significant information in aggregated analysts' forecasts for macroeconomic activity: (1) a positive and statistically significant relationship between aggregated realized earnings and contemporaneous measures of macroeconomic activity; and, (2) statistically significant information in aggregated earnings forecasts for future realized earnings. Section 5.3 evaluates the relationship between aggregated forecasts and measures of future economic activity. Section 5.4 investigates the

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[105] The aggregated earnings forecasts of small cyclicals are positively related to one year-ahead industrial production growth when future industrial production growth is both above and below long run average levels. However, the relationship between earnings forecasts for large cyclicals and future industrial production growth is positive only when future industrial production growth is stronger than average.

[106] Liu and Ryan (2006) report evidence of regime-dependent smoothing by commercial banks, derived from a comparison of the management of loss provisioning pre-1991 with loss provision management from 1991 through to 2000.

usefulness of more timely analyst forecasts[107], and Section 5.5 presents evidence of a relationship between earnings smoothing and the information in earnings forecasts for future macroeconomic growth. Section 5.6 develops and investigates the hypothesis of a relationship between the information in analysts' forecasts for macroeconomic growth, and the cyclicality of realized earnings. In Section 5.7 I investigate size effects in the forecasts of cyclical stocks, conditioned on business cycle regimes. Section 5.8 illustrates that, based on the results of the preceding sections, a portfolio of small highly cyclical firms has statistically significant explanatory power for future industrial production growth, even after including a range of economic state variables as additional regressors. Concluding remarks are provided in Section 5.9.

It should also be noted that while expectations for future macroeconomic activity form an *implicit* component of analysts' earnings forecasts, economists *explicitly* forecast macroeconomic activity. By formulating aggregated measures of earnings expectations I am able to compare the relative ability of analysts and economists to explain variation in macroeconomic activity. This analysis is provided in Appendix 5A. I report evidence that aggregated analysts' earnings forecasts provide more information for one year-ahead industrial production growth than consensus economists' forecasts for industrial production growth.

5.2 Antecedent hypotheses

THE CENTRAL HYPOTHESIS of this analysis is that there is statistically significant information in analysts' earnings forecasts for future macroeconomic activity. Underlying this hypothesis are two key hypothesized drivers: a positive

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[107] I/B/E/S summary forecasts, while considered by I/B/E/S to represent up-to-date analyst expectations, can include earnings forecasts that have been submitted several months earlier. I include tests on a more timely sample set, restricted to only those forecasts submitted within a narrow window prior to the end of each calendar quarter.

relationship between realized earnings and contemporaneous macroeconomic activity, and statistically significant information in analysts' earnings forecasts for future realized earnings. In this section I briefly examine these two components of the core hypothesis.

By simple diversification, the aggregation of earnings will reduce the unsystematic component of variation in earnings (relative to individual firm earnings) and highlight common variation. If the systematic component of variation in aggregated earnings represents a significant proportion of total variation, and the systematic component reflects the common exposure of firms to macroeconomic activity, then it is reasonable to expect a positive and statistically significant relationship between aggregated realized earnings and contemporaneous measures of macroeconomic growth.[108]

In Table 5.1 I provide Pearson correlation coefficients for four measures of macroeconomic growth in the US (annual growth in industrial production, GNP, GDP and Corporate profits after tax) [109] and seven measures of changes in aggregate realized earnings (changes in aggregated earnings deflated by lagged earnings, market capitalization or book value, equally-weighted sums of changes in earnings per share deflated by price or book value per share, as well as equivalent per share median values) from the March quarter of 1979 through to the December

[108] Conversely, the very different composition of the equity market relative to the aggregate economy (in particular, the different relative sizes of sectors) may weaken this relationship.

[109] The corporate profits measure employed here, from the National Income and Production Accounts, excludes inventory valuation and capital consumption adjustments. Results are similar for after-tax corporate profits including these adjustments. GDP, GNP, corporate profits and industrial production growth are all derived from seasonally-adjusted series in current dollars. GDP, GNP and corporate profits growth are annual changes in annual levels over rolling quarters. Industrial production growth is measured as annual changes in the quarterly average of the US Federal Reserve's monthly industrial production index.

Table 5.1 Correlations amongst macroeconomic growth measures and contemporaneous realized earnings growth measures, 1979–2009

Pearson correlation coefficients are presented for measures of macroeconomic growth (industrial production (ΔIP), ΔGNP, ΔGDP and ΔCorporate profits) and aggregated realized earnings changes. Earnings changes are calculated from the sum of four quarters of earnings less the sum of the prior four quarters of earnings, deflated by earnings (E), market capitalization (P) or book value (B). Lower case earnings measures refer to per-share aggregations. 'eq' refers to equally-weighted and 'med' to median.

	ΔIP	ΔGNP	ΔGDP	ΔCorp. profits	ΔEE[a]	ΔEP[a]	ΔEB[a]	Δepeq[a]	Δebeq[a]	Δepmed[a]	Δebmed[a]
ΔIP	1	0.603	0.603	0.441	0.610	0.562	0.629	0.565	0.699	0.694	0.783
ΔGNP		1	0.996	0.193	0.511	0.642	0.558	0.499	0.561	0.805	0.663
ΔGDP			1	0.177	0.497	0.626	0.547	0.475	0.541	0.788	0.645
ΔCorp. profits				1	0.501	0.417	0.448	0.626	0.545	0.338	0.435

quarter of 2009.[110] GDP and GNP are very highly correlated (a correlation coefficient of 0.996). Both exhibit correlations with changes in realized earnings variables ranging from approximately 50% up to 80%. Correlations between industrial production growth and changes in realized earnings are on average higher, and correlations between changes in realized earnings and corporate profits are lower, relative to GDP and GNP results. Nonetheless, all correlations suggest the presence of a strong relationship between these measures of economic activity and changes in aggregated realized earnings. Kothari, Lewellen and Warner (2006) similarly report large positive correlations between their various measures of aggregate earnings growth and both GDP and industrial production growth (ranging from a little under 50% up to 67%).[111]

Further, in Table 5.2 I present summary results for univariate regressions of aggregate changes in realized earnings on each measure of contemporaneous macroeconomic growth. Regressions are of the following form:

$$\Delta \mathrm{E}_t^{\mathrm{a}} = \alpha + \beta \mathrm{Y}_t + \varepsilon_t \tag{5.1}$$

Where, Y_t represents one year growth in the macroeconomic activity measure and $\Delta \mathrm{E}_t^{a}$ represents the one year change in the aggregated realized earnings measure, both in the period ending at time t. Reported results are estimated slope

[110] Realized earnings changes are derived from the sum of four consecutive quarters of earnings less the four quarter sum of earnings one year earlier, on a rolling quarterly basis. Data is sourced from Compustat. See Chapter 3 for more details on variable construction. Value-weighted per share variables are not included given the very high correlation reported in Chapter 4 between these and equivalent aggregated earnings variables (a correlation coefficient of 0.985 between realized measures of ΔEP and Δepv and 0.916 between realized measures of ΔEB and Δebv.

[111] Note that correlations are high despite large differences in the sector composition of the US equity market relative to the sector composition of the aggregate economy, and changes in relative sector composition over time (including, for example, the large increase in information technology companies as a proportion of total market capitalization in the late 1990s).

Table 5.2 Realized earnings growth regressed on contemporaneous macroeconomic growth, 1979–2009

Aggregated annual earnings changes are regressed on rolling quarters of annual macroeconomic growth measures. Earnings changes are calculated from the sum of four quarters of earnings less the sum of the prior four quarters of earnings, deflated by earnings (E), market capitalization (P) or book value (B). Lower case earnings measures refer to per-share aggregations. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$\Delta E_t^a = \alpha + \beta Y_t + \varepsilon_t$$

Y_t represents one year growth in the macroeconomic activity measure and ΔE_t^a represents the 1 year change in the aggregated realized earnings measure, both in the period ending at time t. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Dependent variable, ΔE_t^a						
Independent variable, Y_t	ΔEE^a	ΔEP^a	ΔEB^a	$\Delta epeq^a$	$\Delta ebeq^a$	$\Delta epmed^a$	$\Delta ebmed^a$
ΔGNP	**3.928**	**0.277**	**0.540**	**0.325**	**0.488**	**0.170**	**0.288**
	(2.185)	(3.064)	(2.175)	(2.194)	(1.983)	(4.007)	(2.120)
	0.261	0.412	0.311	0.249	0.315	0.647	0.439
ΔGDP	**3.838**	**0.271**	**0.532**	**0.310**	**0.472**	**0.167**	**0.281**
	(2.060)	(2.795)	(2.046)	(2.052)	(1.859)	(3.563)	(1.955)
	0.247	0.392	0.299	0.226	0.293	0.621	0.417
ΔCorporate profits	**0.587**	**0.027**	**0.066**	0.062	**0.072**	0.011	**0.029**
	(2.480)	(2.171)	(1.841)	(0.826)	(2.304)	(1.601)	(1.908)
	0.251	0.174	0.200	0.391	0.297	0.114	0.189
ΔIndustrial production	**3.247**	**0.168**	**0.422**	**0.254**	**0.421**	**0.101**	**0.235**
	(2.882)	(2.786)	(2.631)	(2.674)	(3.328)	(3.081)	(3.642)
	0.372	0.315	0.396	0.319	0.489	0.481	0.613

coefficients, t statistics (in parentheses) and R^2s.[112] Results in bold are statistically significant at the 10% level.

The estimated coefficients on the macroeconomic growth measures are significant at the 10% level or higher in all bar two regressions. There is evidence of a stronger relationship between realized earnings and industrial production growth relative to GDP and GNP (higher average R^2s), with corporate profits exhibiting the weakest (albeit in most instances still significant) relationship with realized earnings.[113] GDP and GNP results are sufficiently similar that only GNP is employed in subsequent analysis.[114] Note also that the regression R^2s for the median earnings per share measures are on average higher than all other variable R^2s, implying some impact on other aggregated earnings variables from outliers.

These results support the broad findings of other researchers to date – positive relationships between earnings and measures of macroeconomic activity. For regressions of first differences in operating income on first differences in GNP for the period 1949–1967 Lev (1980) reports an average R^2 of 14.1%. Chordia and Shivakumar (2005) report evidence of a positive and monotonic relationship

[112] The use of annual changes on a rolling quarterly basis induces significant autocorrelation in key time series variables. To account for this I employ Newey and West (1987) heteroscedasticity and autocorrelation-consistent (HAC) standard errors in all reported regressions, with the Newey and West (1994) non-parametric automatic bandwidth selection procedure.

[113] Corporates are defined in the national accounts as all entities required to file the Internal Revenue Service Form 1120. This not only includes the companies represented in the equity market sample analyzed here, but also a range of other organisations not represented in the equity market, including Federal Reserve Banks. In addition, corporate profits are estimated from such diverse sources as the International Transactions Accounts (imports/exports, receipts/payments and other transfers between the US and the rest of the world), the Quarterly Financial Report (a survey of businesses produced by the Census Bureau) and tabulations of tax returns. Notably, the national accounts measure of annual corporate profitability growth is substantially more volatile than annual GDP, GNP and industrial production growth. The combination of compositional issues, estimation techniques and greater relative volatility are sufficient to reduce the magnitude of the relationship between equity market reported profitability and the national accounts measure of corporate profits, relative to the other measures of macroeconomic activity evaluated.

[114] GNP is the preferred measure for investigating relationships with equity market variables. GDP measures total output produced within the US regardless of firm ownership, while GNP measures total output of US firms regardless of location.

between earnings and GDP growth. Similarly, Bernstein and Arnott (2003) and Longstaff and Piazzesi (2004) highlight strong positive correlation between measures of corporate profitability and measures of economic growth. Consequently, there is much supporting evidence for a strong and statistically significant relationship between macroeconomic growth and contemporaneous earnings growth.

Examining the second underlying driver of the core hypothesis, aggregated realized earnings changes are regressed on lagged forecast earnings changes to examine the information in analysts' forecasts for future realized earnings. Evaluations of the information in analysts' forecasts for future earnings commonly take the form of assessments of forecast error, compared with the results of statistical models.[115] I take a slightly different approach given I am less interested in forecast accuracy than the ability of variation in forecasts to explain variation in future realized earnings. That is, a significant permanent (and/or time varying) bias may be present in aggregated forecasts, but this does not preclude significant explanatory power in forecast variation for variation in future earnings. I am not aware of prior research performing an evaluation of the information in aggregated earnings forecasts for aggregated realized earnings.

Realized earnings changes are obtained from the same data used in the prior set of regressions. Forecast earnings changes are derived from a time-weighted combination of analysts' FY1 and FY2 earnings forecasts, to generate a proxy measure of 12 month forward forecast earnings. From this, a proxy measure of 12 month trailing earnings is subtracted, and the difference is deflated by trailing earnings, market capitalization or book value. Forecast earnings measures denoted

[115] Examples include Brown and Rozeff (1978), Fried and Givoly (1982), Brown, Hagerman, Griffin and Zmijewski (1987b) and Stickel (1993).

with lower caps represent earnings per share aggregations (value-weighted, equally-weighted and median).[116]

In Panel A of Table 5.3 I present the results of regressions of realized growth on forecast growth with a lag of four quarters.[117] These univariate regressions are of the following form:

$$\Delta \mathrm{E}_t^{\mathrm{a}} = \alpha + \beta \Delta \mathrm{E}_{t-4}^{\mathrm{f}} + \varepsilon_t \tag{5.2}$$

Where $\Delta \mathrm{E}_t^{\mathrm{a}}$ represents the one year change in aggregated realized earnings and $\Delta \mathrm{E}_{t-4}^{\mathrm{f}}$ represents the aggregated forecast one year change in earnings lagged four quarters. Estimated slope coefficients in bold are statistically significant at the 10% level or better.

Estimated slope coefficients are positive in all regressions, and statistically significant for aggregate forecast earnings growth (ΔEE) and all regressions where both realized earnings changes and forecast earnings changes are deflated by lagged book value. All of the market capitalization and price-deflated measures of aggregate forecast earnings changes are statistically insignificant. This appears to be a consequence of a strong downward trend in all price-deflated forecast earnings measures over the period evaluated, driven by a downward trend in earnings yields. The trend reduces the time series volatility of the price-deflated series relative to the book value-deflated series, rendering the price-deflated series insignificant. No such trend is evident in return on equity that could induce the same effect in forecast earnings changes deflated by book value.

[116] See Chapter 3 for more details on variable construction.

[117] A lag of four quarters is selected given this represents the closest available match with the forecast horizon of the aggregated forecast earnings measures.

Table 5.3 Realized earnings growth regressed on lagged forecast earnings growth (univariate regressions), 1979–2009

Rolling quarters of aggregated annual realized earnings changes are regressed on aggregated forecast annual earnings changes lagged four quarters. Realized earnings changes are calculated from the sum of four quarters of earnings less the sum of the prior four quarters of earnings, deflated by earnings (E), market capitalization (P) or book value (B). Lower case earnings measures refer to per-share aggregations. Forecast earnings changes are based on a proxy measure of four quarter forward earnings forecasts less four quarter trailing earnings. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$\Delta E_t^a = \alpha + \beta \Delta E_{t-4}^f + \varepsilon_t$$

ΔE_t^a represents the 1 year change in the aggregated realized earnings and ΔE_{t-4}^f represents the forecast 1 year change in earnings lagged 4 quarters. Panel A provides time series results for the aggregated earnings measures. Panel B provides the mean R^2 for the same regression form applied to individual stocks (with changes in earnings per share deflated either by price or book value per share). Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

A. Time series results

Realized growth (independent), ΔE_t^a, and forecast growth (dependent), ΔE_{t-4}^f , earnings measures

ΔEE	ΔEP	ΔEB	Δepeq	Δebeq	Δepmed	Δebmed
1.520	0.290	**1.109**	0.218	**1.275**	0.347	**1.229**
(1.735)	(0.597)	(1.795)	(0.241)	(1.737)	(0.449)	(1.908)
0.078	0.013	0.069	0.004	0.095	0.046	0.176

B. Cross-sectional results (four quarter forecast growth lag)

	Full sample		>10 obs.		>20 obs.		>50 obs.	
	No. stocks	Mean R^2	No. stocks	Mean R^2	No. stocks	Mean R^2	No. stocks	Mean R^2
Δep	4,462	0.255	2,943	0.184	2,015	0.163	655	0.128
Δeb	4,462	0.238	2,943	0.171	2,015	0.152	655	0.123

In the case of aggregate earnings growth (realized earnings changes deflated by lagged earnings), forecast growth explains 7.8% of the variation in one year-ahead realized earnings growth over the time period analyzed. Note that the R^2 for median earnings per share changes deflated by lagged book values, at 17.6%, is much higher than the R^2s for equivalent aggregate earnings and equally-weighted measures. This suggests a reduction in the explanatory power of aggregated forecasts arising from more idiosyncratic extreme forecasts that create measurable noise at the aggregate level.

In Panel B a selection of cross-sectional results are provided. Realized changes in earnings per share are regressed on forecast changes in earnings per share lagged four quarters (deflated by price (Δep) or book value per share (Δeb)). Time series regressions are run for each stock, and the resulting average R^2s across all individual stock regressions are presented. The mean R^2 lies between 23% and 26% for each of Δep and Δeb. However, many stocks have only a small number of observations. Hence, mean R^2s are also presented for data subsets requiring a minimum of 10, 20 and 50 quarters of observations for each stock. A tradeoff between robustness in terms of sample size and robustness in terms of observations for each stock is evident. As the minimum required number of quarter observations increases, the mean R^2 decreases towards the R^2 reported for the aggregate time series regressions (deflated by earnings and book value).

Interestingly, the results reported for both Δep and Δeb are very similar. This suggests the strong trend in aggregate market earnings yield does not materially impact cross-sectional results. Consequently, the insignificance of information in price-deflated forecast earnings changes for realized earnings is not an anomaly resulting from the dataset employed. Instead, the insignificance of estimated slope coefficients for price-deflated time series is a product of an effect which only becomes manifest as stocks are aggregated.[118] Given the insignificance of price-deflated forecast earnings in the aggregate time series regressions, the analysis in this chapter focuses on book value-deflated forecast earnings changes.

The results presented in Tables 5.1, 5.2 and 5.3 provide supporting evidence for both a significant relationship between realized earnings growth and contemporaneous macroeconomic growth, and, significant information in analysts' forecasts for future realized earnings.[119] Combining these two sets of results, I hypothesize a positive and statistically significant relationship between forecast earnings and future macroeconomic activity. This relationship is investigated in the following section.

5.3 *Macroeconomic information in analysts' forecasts*

TABLE 5.4 PRESENTS summary results from regressions of three measures of macroeconomic growth (GNP, corporate profits and industrial production) on four measures of lagged aggregate market forecast earnings changes (ΔEE^f, ΔEB^f, $\Delta ebeq^f$ and $\Delta ebmed^f$). The univariate regressions are of the following form:

$$\mathrm{Y}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{f}}_{t-l} + \varepsilon_t \tag{5.3}$$

Where Y_t represents one year growth in the macroeconomic activity measure and $\Delta \mathrm{E}^{\mathrm{f}}_{t-l}$ represents the forecast one year change in earnings lagged l quarters.[120]

[118] An effect which is particularly notable during periods such as the bull market in technology stocks in the late 1990s.

[119] This analysis was repeated for the subset of companies with December year-end balance dates. Conclusions do not change.

[120] At a lag of four quarters the one year-ahead period exactly matches the one year period over which macroeconomic growth is measured.

Although the principal focus of my analysis is the relationship between macroeconomic growth and forecast earnings changes lagged four quarters (given forecasts represent expectations for 12 months ahead), a range of lags are evaluated for robustness purposes. This provides some insight into the rate of deterioration in information in analysts' forecasts as the lag length increases.

Firstly, there is no evidence of significant predictive power in aggregated analysts' earnings forecasts for corporate profit growth. As observed in the previous section, the relationship between corporate profits and realized earnings growth is weaker than that observed for GNP and industrial production growth. This relationship is sufficiently weak that, when combined with error in analysts' forecasts, it results in insignificant information in all forecast measures, and across all lags, for the national accounts measure of corporate profits.

Analysts' forecast earnings changes contain statistically significant information for GNP growth out to a lag of three quarters for ΔEE^f and two quarters for ΔEB^f and $\Delta ebmed^f$. In addition, estimated slope coefficients and R^2s for all four measures of aggregate forecast changes in earnings decrease monotonically as the lag length increases out to five quarters. This is consistent with reduced information in analysts' forecasts as the lag length increases.

In regressions of macroeconomic growth on contemporaneous realized earnings growth, it is industrial production that exhibits the strongest relationship with earnings (Table 5.2). Reported R^2s for regressions of industrial production growth on lagged earnings forecasts are higher relative to regressions with GNP and corporate profits as dependent variables. In addition, all four measures of aggregate forecast changes contain statistically significant information for future industrial production growth out to a lag of four quarters, and ΔEE^f and $\Delta ebmed^f$ extend this to five quarters.

Table 5.4 Macroeconomic growth regressed on lagged aggregated forecast earnings growth (univariate regressions), 1979–2009

Rolling quarters of annual macroeconomic growth measures are regressed on aggregated forecast annual earnings changes lagged l quarters. Forecast earnings changes are based on a proxy measure of four quarter forward earnings forecasts less four quarter trailing earnings, and are deflated by earnings (E) or book value (B). Lower case earnings measures refer to per-share aggregations. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$\mathrm{Y}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{f}}_{t-l} + \varepsilon_t$$

Y_t represents one year growth in the macroeconomic activity measure and $\Delta \mathrm{E}^{\mathrm{f}}_{t-l}$ represents the forecast 1 year change in earnings lagged l quarters. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

Dependent variables:		ΔGNP				ΔCorporate profits				ΔIndustrial production			
Independent variables:		ΔEE^f	ΔEB^f	$\Delta ebeq^f$	$\Delta ebmed^f$	ΔEE^f	ΔEB^f	$\Delta ebeq^f$	$\Delta ebmed^f$	ΔEE^f	ΔEB^f	$\Delta ebeq^f$	$\Delta ebmed^f$
Lag, l	1	**0.283**	**1.773**	1.373	**2.784**	1.082	3.075	9.105	8.629	**0.627**	**4.128**	**4.449**	**6.066**
(qtrs)		(2.209)	(1.827)	(1.026)	(2.051)	(1.272)	(0.482)	(1.486)	(0.025)	(5.618)	(5.526)	(8.314)	(8.077)
		0.218	0.203	0.125	0.281	0.069	0.013	0.119	0.058	0.483	0.496	0.592	0.600
	2	**0.257**	**1.525**	1.264	**2.497**	0.495	-0.608	5.771	4.733	**0.568**	**3.561**	**4.107**	**5.649**
		(2.323)	(1.976)	(1.105)	(1.911)	(0.300)	(-0.149)	(0.218)	(0.121)	(5.793)	(5.650)	(7.154)	(3.852)
		0.186	0.153	0.109	0.224	0.014	0.001	0.048	0.017	0.395	0.364	0.502	0.500
	3	**0.198**	1.062	0.901	2.064	-0.054	-4.439	2.450	1.044	**0.459**	**2.688**	**3.489**	**5.044**
		(2.317)	(1.647)	(0.631)	(1.412)	(-0.058)	(-1.283)	(0.241)	(0.084)	(5.152)	(4.768)	(4.507)	(2.889)
		0.105	0.071	0.053	0.138	0.000	0.025	0.008	0.001	0.237	0.190	0.333	0.347
	4	0.129	0.476	0.448	1.634	-0.402	-7.524	1.945	0.095	**0.346**	**1.746**	**3.016**	**4.616**
		(0.875)	(0.423)	(0.205)	(0.580)	(-0.239)	(-0.815)	(0.181)	(0.005)	(3.279)	(2.270)	(2.861)	(2.294)
		0.038	0.012	0.011	0.068	0.007	0.060	0.004	0.000	0.111	0.067	0.199	0.224
	5	0.100	0.165	0.148	1.331	-0.025	-5.469	3.143	1.779	**0.242**	0.938	2.391	**3.993**
		(0.704)	(0.178)	(0.070)	(0.436)	(-0.034)	(-1.088)	(0.610)	(0.140)	(1.708)	(0.893)	(1.557)	(1.723)
		0.020	0.001	0.001	0.040	0.000	0.028	0.009	0.001	0.047	0.017	0.113	0.145
	6	0.112	0.164	0.042	1.267	-0.437	-7.408	0.468	-1.450	0.171	0.445	1.818	3.400
		(0.502)	(0.112)	(0.016)	(0.356)	(-0.470)	(-1.143)	(0.080)	(-0.116)	(0.959)	(0.338)	(1.129)	(1.474)
		0.026	0.001	0.000	0.036	0.007	0.051	0.000	0.001	0.024	0.004	0.066	0.104

Note also that the reported R^2s for regressions with $\Delta ebeq^f$ and $\Delta ebmed^f$ are, at all lag lengths, higher than those reported for ΔEE^f and ΔEB^f. At a lag length of four quarters, $\Delta ebeq^f$ explains 19.9% and $\Delta ebmed^f$ explains 22.4% of the variation in industrial production growth one year-ahead, compared with 11.1% and 6.7% for ΔEE^f and ΔEB^f, respectively. Large differences between results for aggregated earnings and equally-weighted (and median) earnings per share measures suggests the presence of size-related effects. This is explored in more detail in Section 5.5.

Table 5.5 presents results for these regressions repeated, with two additional independent variables: a lagged dependent variable and a dummy variable for the period from March 1998 through to September 1999. The dummy variable is included to identify any significant impact on regression results from the temporary decrease in sample size in 1998/99, as discussed in Chapter 4. I am also interested in any increase in explanatory power for future macroeconomic growth with the inclusion of the most recently announced value for that growth measure (testing whether the estimated coefficient on the forecast earnings change measure remains significant). Hence, I add a lagged dependent variable.

With only one exception, for all instances in which the estimated coefficient on the forecast earnings change measure is significant at the 10% level or higher in Table 5.4, that same measure and lag is significant in Table 5.5. There are also a number of additional instances of statistically significant estimated coefficients on forecast earnings in Table 5.5. The relationship between future industrial production growth and lagged forecast earnings changes remains stronger than that observed for GNP and corporate profit growth. In addition, for all GNP regressions and for the majority of industrial production regressions the adjusted R^2s are higher than the unadjusted R^2s reported in Table 5.4.[121] For example, median forecast changes

[121] The notable exceptions are regressions with ΔEE^f and ΔEB^f as independent variables for lag lengths of four quarters.

in earnings per share deflated by book value per share explain 26.1% of one year-ahead variation in annual industrial production growth when lagged industrial production growth is included as a regressor. Without lagged industrial production, the equivalent unadjusted R^2 reported in Table 5.4 is 22.4%. However, at a lag length of four quarters, the focus period for analysis, the estimated coefficient on the lagged dependent variable is statistically significant at the 10% level in only one regression. Therefore, lagged dependent variables are not included in most subsequent regression analysis in this chapter.

The dummy variable for March 1998 through to September 1999 is, in most instances evaluated, found to be statistically insignificant at the 10% level. In particular, in only one case is the estimated coefficient on the dummy variable found to be significant in a regression of one year-ahead macroeconomic growth on four quarter lagged forecast earnings changes – the lag length of particular interest in this analysis. Hence, the temporary decrease in sample size does not generally appear to have a material impact on results, and the dummy variable is excluded from all subsequent analysis.[122]

[122] Evaluation of the dummy variable in regressions employing subsets of the market similarly found no material impact on conclusions as a result of the temporary decrease in stock coverage. Note also, some caution is required interpreting any significant coefficients on the dummy variable given the risk it may capture macroeconomic dynamics at that point in time (for example, earnings recovery after the Asia crisis).

Table 5.5 Macroeconomic growth regressed on lagged aggregated forecast earnings growth (multivariate regressions), 1979–2009

Rolling quarters of annual macroeconomic growth measures are regressed on aggregated forecast annual earnings changes lagged l quarters, the last reported value of the dependent variable at time t-l and a dummy variable for the period from March 1998 through to September 1999. Forecast earnings changes are based on a proxy measure of four quarter forward earnings forecasts less four quarter trailing earnings, and are deflated by earnings (E) or book value (B). Lower case earnings measures refer to per-share aggregations. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2 for regressions of the following form:

$$\mathrm{Y}_t = \alpha + \beta_{\Delta \mathrm{E}} \Delta \mathrm{E}^{\mathrm{f}}_{t-l} + \beta_{\mathrm{Y}} \mathrm{Y}_{t-l} + \beta_{\mathrm{D}} \mathrm{D}_{t-l,98/99} + \varepsilon_t$$

Y_t represents one year growth in the macroeconomic activity measure (GNP in Panel A, Corporate Profits in Panel B and Industrial Production in Panel C), $\Delta \mathrm{E}^{\mathrm{f}}_{t-l}$ represents the forecast 1 year change in earnings lagged l quarters, Y_{t-l} represents the last reported value of the dependent variable at time t-l and $\mathrm{D}_{t-l,98/99}$ represents a dummy variable for the period from March 1998 through to September 1999. Four regressions are run for each macroeconomic growth measure and lag, with one of four measures of aggregate forecast earnings changes as an independent variable ($\Delta \mathrm{EE}^{\mathrm{f}}$ for regression (1), $\Delta \mathrm{EB}^{\mathrm{f}}$ for regression (2), $\Delta \mathrm{ebeq}^{\mathrm{f}}$ for regression (3) and $\Delta \mathrm{ebmed}^{\mathrm{f}}$ for regression (4)). Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Est. forecast growth coefficients, $\hat{\beta}_{\Delta \mathrm{E}}$				Est. lagged dependent coefficients, $\hat{\beta}_{\mathrm{Y}}$				Est. D98/99 coefficients, $\hat{\beta}_{\mathrm{D}}$				Adj. R^2			
Lag, l (qtrs)	(1) $\Delta \mathrm{EE}^{\mathrm{f}}$	(2) $\Delta \mathrm{EB}^{\mathrm{f}}$	(3) $\Delta \mathrm{ebeq}^{\mathrm{f}}$	(4) $\Delta \mathrm{ebmed}^{\mathrm{f}}$	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
A. GNP																
1	**0.184**	**1.220**	**1.078**	**1.653**	**0.658**	**0.643**	**0.705**	**0.633**	-0.007	**-0.014**	-0.003	0.000	0.632	0.618	0.626	0.640
	(3.166)	(2.975)	(3.300)	(3.482)	(7.016)	(8.079)	(9.455)	(6.842)	(-1.426)	(-1.961)	(-0.773)	(-0.061)				
2	**0.196**	**1.242**	**1.125**	**1.840**	**0.463**	**0.457**	**0.522**	**0.445**	-0.005	-0.012	-0.001	0.001	0.378	0.355	0.367	0.396
	(2.886)	(2.836)	(2.542)	(2.652)	(3.088)	(3.950)	(4.423)	(3.095)	(-0.951)	(-1.577)	(-0.316)	(0.285)				
3	**0.167**	**0.885**	0.901	**1.754**	0.304	0.310	**0.357**	0.288	0.000	-0.003	0.004	0.006	0.169	0.138	0.154	0.199
	(2.311)	(1.823)	(1.313)	(1.707)	(1.335)	(1.562)	(1.881)	(1.357)	(0.014)	(-0.411)	(0.687)	(0.756)				
4	0.116	0.293	0.604	1.564	0.209	0.223	0.247	0.198	0.004	0.006	0.006	0.007	0.055	0.030	0.045	0.090
	(0.983)	(0.224)	(0.359)	(0.843)	(0.719)	(0.376)	(0.855)	(0.779)	(0.351)	(0.598)	(0.972)	(0.867)				
5	0.088	-0.119	0.264	1.271	0.188	0.205	0.209	0.182	0.004	0.010	0.007	0.007	0.026	0.012	0.015	0.049
	(0.666)	(-0.139)	(0.140)	(0.597)	(0.610)	(0.750)	(0.708)	(0.679)	(0.452)	(1.111)	(1.031)	(0.761)				
6	0.103	-0.082	0.158	1.194	0.209	0.227	0.229	0.209	0.001	0.008	0.006	0.005	0.037	0.017	0.018	0.049
	(0.519)	(-0.070)	(0.102)	(0.636)	(0.710)	(1.043)	(0.788)	(1.025)	(0.170)	(0.758)	(0.822)	(0.735)				

Table continues overleaf

Table 5.5 Macroeconomic growth regressed on lagged aggregated forecast earnings growth (multivariate regressions), 1979–2009

Table continued from previous page

	Est. forecast growth coefficients, $\hat{\beta}_{\Delta E}$				Est. lagged dependent coefficients, $\hat{\beta}_{Y}$				Est. D98/99 coefficients, $\hat{\beta}_{D}$				Adj. R^2			
Lag, l (qtrs)	(1) ΔEE^f	(2) ΔEB^f	(3) $\Delta ebeq^f$	(4) $\Delta ebmed^f$	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
B. Corporate profits																
1	0.642	0.330	5.350	2.533	**0.496**	**0.550**	**0.456**	**0.524**	-0.064	-0.027	-0.068	-0.031	0.266	0.246	0.277	0.250
	(1.262)	(0.093)	(1.509)	(0.110)	(3.554)	(5.159)	(3.359)	(4.370)	(-0.691)	(-0.302)	(-0.718)	(-0.355)				
2	0.279	-2.618	4.311	1.700	0.269	0.329	0.216	0.275	-0.047	0.013	-0.065	-0.034	0.057	0.060	0.074	0.055
	(0.133)	(-0.491)	(0.685)	(0.081)	(0.406)	(1.374)	(0.654)	(0.659)	(-0.382)	(0.141)	(-0.522)	(-0.288)				
3	-0.014	-5.610	3.279	1.146	0.017	0.080	-0.039	0.004	-0.041	0.044	-0.069	-0.046	-0.023	0.005	-0.011	-0.022
	(-0.016)	(-1.314)	(0.571)	(0.145)	(0.045)	(0.362)	(-0.064)	(0.010)	(-0.349)	(0.473)	(-0.422)	(-0.421)				
4	-0.448	**-10.413**	2.234	-0.056	0.043	0.094	-0.007	0.021	0.008	0.134	-0.034	-0.017	-0.017	0.056	-0.021	-0.025
	(-0.488)	(-1.697)	(0.330)	(-0.005)	(0.109)	(0.320)	(-0.017)	(0.062)	(0.065)	(1.511)	(-0.296)	(-0.184)				
5	0.048	-6.836	3.809	1.849	-0.037	0.003	-0.077	-0.044	-0.051	0.048	-0.075	-0.053	-0.022	0.008	-0.010	-0.021
	(0.051)	(-1.150)	(0.594)	(0.144)	(-0.104)	(0.008)	(-0.186)	(-0.113)	(-0.362)	(0.366)	(-0.510)	(-0.397)				
6	-0.340	-8.841	1.363	-1.022	-0.079	-0.043	-0.108	-0.088	-0.053	0.054	-0.081	-0.069	-0.011	0.036	-0.013	-0.015
	(-0.355)	(-1.224)	(0.225)	(-0.080)	(-0.312)	(-0.180)	(-0.377)	(-0.294)	(-0.497)	(0.510)	(-0.661)	(-0.568)				
C. Industrial production																
1	**0.309**	**2.105**	**2.311**	**3.093**	**0.647**	**0.623**	**0.575**	**0.560**	-0.010	**-0.022**	-0.005	0.004	0.760	0.743	0.775	0.769
	(5.083)	(4.893)	(5.280)	(6.361)	(5.339)	(3.770)	(5.685)	(3.640)	(-1.666)	(-2.889)	(-0.979)	(0.622)				
2	**0.382**	**2.523**	**3.147**	**4.344**	**0.389**	**0.374**	**0.265**	0.252	-0.006	-0.021	-0.001	0.010	0.474	0.445	0.526	0.529
	(4.043)	(3.754)	(6.072)	(5.618)	(1.928)	(1.833)	(1.807)	(1.412)	(0.624)	(-1.420)	(-0.118)	(0.861)				
3	**0.393**	**2.384**	**3.527**	**5.180**	0.139	0.141	-0.026	-0.047	0.002	-0.010	0.007	0.019	0.229	0.184	0.318	0.342
	(3.134)	(2.253)	(5.511)	(5.414)	(0.667)	(0.639)	(-0.155)	(-0.306)	(0.168)	(-0.480)	(0.564)	(1.332)				
4	**0.357**	1.837	**3.772**	**5.855**	-0.076	-0.055	-0.265	**-0.298**	0.012	0.004	0.014	**0.027**	0.094	0.045	0.217	0.261
	(2.430)	(1.556)	(4.366)	(4.986)	(-0.308)	(-0.210)	(-1.582)	(-1.803)	(0.785)	(0.184)	(1.145)	(2.115)				
5	**0.287**	1.119	**3.457**	**5.745**	-0.199	-0.163	**-0.384**	**-0.425**	0.016	0.014	0.017	**0.029**	0.051	0.011	0.167	0.224
	(1.917)	(0.758)	(3.378)	(4.567)	(-0.765)	(-0.634)	(-2.135)	(-2.675)	(0.968)	(0.510)	(1.382)	(2.867)				
6	0.237	0.748	**2.923**	**5.206**	-0.231	-0.188	-0.388	**-0.437**	0.012	0.012	0.012	**0.023**	0.031	0.001	0.118	0.182
	(1.099)	(0.396)	(2.159)	(2.529)	(-0.725)	(-0.582)	(-1.279)	(-2.272)	(0.889)	(0.469)	(0.938)	(2.000)				

Overall it is evident there is a statistically significant relationship between aggregated analysts' earnings forecasts and future industrial production growth. The magnitude of information in earnings forecasts decreases monotonically with lag length out to at least six quarters ahead, and remains significant when lagged dependent variables are included as additional regressors.

In addition, the magnitude of information in analysts' earnings forecasts is a partial function of the strength of the relationship between the measure of macroeconomic activity in question and contemporaneous realized earnings growth, and, the relationship between forecast earnings growth and future realized earnings growth. Importantly, these results suggest that the predictive power of earnings forecasts for macroeconomic activity is a partial function of the cyclicality of realized earnings (a stronger relationship between changes in aggregate realized earnings and macroeconomic activity results in a stronger relationship between aggregate forecast changes in earnings and future macroeconomic activity). This is a notion investigated further in Section 5.6.

5.4 *Timely analyst forecasts*

THE PRECEDING ANALYSIS employs aggregated I/B/E/S summary forecasts (in this instance, median analyst earnings per share estimates for each stock) as proxies for consensus expectations as at the end of each calendar quarter. However, the survey date for I/B/E/S summary data is prior to the quarter end. In addition, many analysts' forecasts included in the calculation of consensus estimates may be a number of months old. This means earnings forecasts incorporate an information set that is older than that available to other economic agents forming expectations for future macroeconomic activity at the end of a quarter. In this section I investigate whether the explanatory power of analysts' earnings forecasts for future macroeconomic activity improves by restricting the I/B/E/S dataset to only forecasts submitted close to the end of the quarter. I find that while other researchers have noted evidence of improved forecast accuracy for more recent forecasts at the firm level,[123] the more recent forecasts evaluated in this research do not provide greater predictive power for future macroeconomic activity. Importantly, this does not represent evidence refuting the notion of improved information for future earnings in more recent forecast earnings. It could simply be a consequence of the restriction of qualifying I/B/E/S forecasts to only those submitted close to quarter end resulting in a sample biased towards larger firms (providing further motivation for the investigation of size-related variation in the predictive power of aggregated forecasts for future macroeconomic activity – a notion investigated in the next section).

The I/B/E/S detail dataset provides all individual analysts' forecasts for each company in question, and the dates these forecasts were submitted to I/B/E/S. I replicate the I/B/E/S methodology for constructing the summary forecast file. However, instead of each quarter including all eligible forecasts up to the Thursday before the third Friday of each month (what I/B/E/S refer to as the Statistical Period), I only accept eligible forecasts from the detail file between the last Statistical Period in the calendar quarter and the end of the quarter (an eligibility period of typically less than two weeks). The nine aggregate market earnings forecast measures are generated from the more timely set of earnings forecasts (referred to in this analysis as the month-end forecasts). However, the I/B/E/S detail file contains less historical data than the I/B/E/S summary file. The shorter dataset, combined with data requirements for construction of the aggregate forecast variables, restricts the length of the time series of aggregated forecasts

[123] Examples include Crichfield, Dyckman and Lakonishok (1978), O'Brien (1988a) and Brown (1991). Guttman (2010) presents a theoretical model in which "analysts with a higher precision of initial private information tend to forecast earlier" (p. 513).

from the March quarter of 1984 through to the December quarter of 2009 (representing a loss of 20 quarters, or nearly 20%, of the time series).

Table 5.6 provides summary results for three types of regressions comparing the full analyst data set with the month-end forecasts (representing the same regressions reported in Tables 5.2, 5.3 and 5.4 repeated for month-end forecast data). In Panel A the relationship between macroeconomic growth and realized earnings for the smaller dataset is investigated. Panel B evaluates the relationship between realized earnings and lagged forecasts, and Panel C evaluates the combination of Panel A and Panel B tests; the impact on information in analysts' forecasts for future macroeconomic activity resulting from the use of the more timely month-end forecast dataset.

Firstly, note that the R^2s for the first four regressions in Panel A are higher than those reported in Table 5.2 for the extended time series data. The move from a starting point of 1979 to 1984 sees an increase in the strength of the relationship between realized earnings and economic activity. However, then switching to only those companies that have month-end forecast data, the R^2s are lower relative to the full sample set, with only one exception. These reductions in R^2 should be expected to reduce the information in the forecasts of month-end data for future macroeconomic growth, albeit to a relatively modest degree. This is because of previous evidence suggesting that the strength of the relationship between earnings forecasts and future macroeconomic activity is a partial function of the strength of the relationship between realized earnings and contemporaneous macroeconomic activity. In other words, the predictive power of earnings forecasts for future economic activity is partially a function of the cyclicality of aggregated realized earnings.

Table 5.6 Evaluation of the informational advantage of month-end analysts' earnings forecasts, 1984–2009

Panel A provides results for aggregated annual earnings changes regressed on rolling quarters of annual macroeconomic growth measures for each of four measures of earnings changes. Regressions are run on the full sample set, and then repeated for the subset of stocks that have month-end forecast data available. Panel B provides summary results for regressions of realized earnings growth on forecast earnings growth lagged 4 quarters – firstly for all forecasts submitted by analysts, then for month-end forecasts. Panel C regressions replace realized earnings in Panel B regressions with macroeconomic growth measures as the dependent variables. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

A. Macroeconomic growth regressed on contemporaneous realized earnings growth

$$\Delta E_t^a = \alpha + \beta Y_t + \varepsilon_t$$

	Full sample (1984–2009)				Month-end forecasts				R^2 difference			
	ΔEE	ΔEB	Δebeq	Δebmed	ΔEE	ΔEB	Δebeq	Δebmed	ΔEE	ΔEB	Δebeq	Δebmed
GNP	**5.938**	**0.778**	**0.745**	**0.420**	**6.213**	**0.839**	**0.852**	**0.460**				
	(3.744)	(3.497)	(3.450)	(4.328)	(5.580)	(5.444)	(5.953)	(6.220)				
	0.357	0.395	0.448	0.606	0.366	0.364	0.426	0.526	+0.009	-0.031	-0.022	-0.080
Industrial	**4.113**	**0542**	**0.499**	**0.273**	**3.944**	**0.547**	**0.512**	**0.282**				
Production	(5.257)	(5.645)	(6.012)	(6.171)	(5.616)	(5.757)	(6.384)	(7.375)				
	0.481	0.540	0.565	0.721	0.415	0.435	0.433	0.553	-0.066	-0.105	-0.132	-0.168

B. Realized earnings growth regressed on forecast earnings growth lagged 4 quarters

$$\Delta E_t^a = \alpha + \beta \Delta E_{t-4}^f + \varepsilon_t$$

Realized	1.654	**1.233**	1.596	**1.446**	**0.875**	**0.751**	**0.466**	**1.764**				
earnings	(1.646)	(1.682)	(1.592)	(1.935)	(1.908)	(2.023)	(2.430)	(3.197)				
	0.080	0.080	0.117	0.208	0.040	0.049	0.052	0.269	-0.040	-0.031	-0.065	+0.061

C. Macroeconomic growth regressed on forecast earnings growth lagged 4 quarters

$$Y_t = \alpha + \beta \Delta E_{t-4}^f + \varepsilon_t$$

GNP	0.194	0.962	1.969	**2.827**	0.008	0.015	0.057	**2.002**				
	(1.113)	(0.741)	(1.562)	(2.075)	(0.200)	(0.047)	(0.180)	(2.163)				
	0.135	0.083	0.283	0.314	0.001	0.000	0.002	0.237	-0.134	-0.083	-0.281	-0.077
Industrial	**0.360**	**2.148**	**3.358**	**4.868**	0.067	0.409	0.353	**3.731**				
Production	(2.659)	(2.256)	(1.857)	(2.231)	(1.119)	(0.849)	(1.038)	(2.325)				
	0.145	0.128	0.255	0.289	0.013	0.013	0.020	0.255	-0.132	-0.115	-0.235	-0.034

Secondly, for three out of the four earnings forecast variables the relationship between realized earnings changes and forecast earnings changes lagged four quarters is weaker (lower R^2s) for the month-end data relative to the full set of forecasts for the full company dataset (Panel B). This result at first appears rather surprising given, for example, the results of Brown (1991) who found evidence of improved forecast accuracy with better forecast timeliness. In fact, when samples are matched not only in terms of the dates evaluated, but also in terms of company constituents, I do find evidence of higher explanatory power for future earnings using the month-end forecasts rather than the summary dataset forecasts. However, forecasts for the smaller month-end sample set generally exhibit less predictive power for realized earnings than forecasts for the full universe of forecasts.[124] Therefore, the more timely forecasts offer no advantage over the less timely full sample set.

Combining the findings presented in Panels A and B, it should therefore be of little surprise to see in Panel C that the month-end forecasts explain less of the variation in macroeconomic growth four quarters ahead than the full forecast dataset. At a lag length of four quarters, the more timely forecasts on average explain a smaller proportion of future realized earnings relative to the full forecast dataset. In addition, the relationship between realized earnings and economic activity is weaker for the smaller month-end dataset, driving the fall seen here in R^2s for predicted macroeconomic growth. This result may be partially due to a size bias as

[124] While Brown (1991) found evidence of improved forecast accuracy with more timely forecasts, it should be noted he also observed a tradeoff between forecast timeliness and the benefits of forecast aggregation. Specifically, he finds that the 30 day average of forecasts is more accurate than the most recent forecast for large companies, but the reverse is true for small companies. Hence, by using only the most timely forecasts, forecast accuracy will improve for small companies, but deteriorate for large companies. Interestingly, the results presented in Panel B of Table 5.6 provide some support for Brown's results. The median forecast growth measure, which is the variable least subject to size-related variation in forecast performance, sees an increase in the regression R^2 switching from the full forecast sample to month-end forecasts, compared with decreases in R^2 for all other forecast variables.

data timeliness requirements tighten. That is, more large stocks have forecasts submitted by analysts in the narrow window between the I/B/E/S Statistical Period and quarter-end than small stocks (the average market capitalization of stocks in the month-end sample is more than twice the average market capitalization of stocks in the full sample). Hence, this motivates investigating size-related differences in the predictive power of earnings forecasts for macroeconomic activity.

If the I/B/E/S detail file offered a deeper dataset (more stocks with month-end forecasts) then it is quite possible that month-end forecasts could offer greater explanatory power for future macroeconomic growth than the less timely full forecast dataset. However, given that is not the case with the data available, I employ the full forecast dataset for all subsequent analysis in this chapter.

5.5 Macroeconomic information and earnings smoothing

THE LITERATURE EVALUATING forms of earnings management, and consequent implications for earnings opacity, is vast. Dechow, Ge and Schrand (2010) provide a thorough review of this literature and highlight a range of common proxies for earnings quality, amongst which is earnings smoothness. Earnings smoothing by firm management represents an effort to reduce the volatility of realized earnings. Biedleman (1973) states that "Smoothing of reported earnings may be defined as the intentional dampening of fluctuations about some level of earnings that is considered to be normal for a firm" (p. 653).

Motivation for smoothing can be the reduction of the impact on earnings of random fluctuations in cash flows, thus increasing the persistence of earnings (and thereby potentially improving the informativeness of earnings). Conversely, motivation for smoothing could be manipulation of earnings to distort the underlying profitability of the firm, in which case the informativeness of earnings is adversely impacted.

Analyses of smoothing generally begin with an assumption of the latter motivation.[125] A notable exception is the work of Tucker and Zarowin (2006). They argue that smoothing improves earnings informativeness by increasing the information in current stock returns for future earnings.[126] However, distinguishing between smoothing of transitory cash flows and smoothing of permanent cash flows is a challenge for empirical analysis. Dechow, Ge and Schrand (2010) state that "It is difficult to disentangle smoothness of reported earnings that reflects smoothness of the (i) fundamental earnings process; (ii) accounting rules; and (iii) intentional earnings manipulation" (p. 351).

In this chapter I do not make any distinction between different forms of smoothing. I hypothesize, independent of the form of smoothing, that higher smoothing reduces the magnitude of information in analysts' earnings forecasts for future macroeconomic activity. Smoothing, by definition, is an attempt to reduce variation in earnings. A key source of variation in earnings is variation in macroeconomic activity (evidence for which is provided in Table 5.2). If smoothing reduces cyclical variation in realized earnings and analysts incorporate estimated smoothing in their forecasts, then higher smoothing should reduce the information in those forecasts for future economic activity. In support of that reasoning, Beidleman (1973) provides the following theoretical argument for smoothing: "Smoothing represents an attempt to counter the cyclical nature of reported earnings" (p. 654).

As noted above, the hypothesis of an inverse relationship between the extent of smoothing and the information in earnings forecasts for future macroeconomic activity requires that analysts incorporate anticipated smoothing in their earnings

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[125] Examples include Bhattacharya, Daouk and Welker (2003) and Leuz, Nanda and Wysocki (2003).

[126] In addition, a fundamental principle of accrual accounting "is that earnings smooth random fluctuations in the timing of cash payments and receipts, making earnings more informative about performance than cash flows" (Dechow, Ge and Schrand, 2010, p. 361).

expectations. There are two principal means by which anticipated smoothing can be incorporated into analysts' forecasts. Firstly, analysts have been shown to closely follow management earnings guidance.[127] It is reasonable to expect that firms intending to smooth earnings will incorporate expected smoothing in their earnings guidance. Analysts will then, by closely adhering to management guidance, incorporate expected smoothing in their forecasts. Secondly, analysts will be aware of past smoothing by companies and thus, if rational, incorporate an expectation for future smoothing in forecasts.

Burgstahler and Eames (2003) report evidence of analysts incorporating expected earnings management in forecasts (in particular, earnings management to avoid small losses). Liu (2005) finds evidence of a relationship between the tendency of firms to manage earnings and analysts' forecasts. Higher tendency to manage earnings lower (higher) is associated with analysts lowering (raising) their forecasts. In addition, Gavious (2009) provides evidence of a relationship between analysts' expectations (in the form of price targets) and the direction of earnings management. Therefore, there is empirical evidence of a link between earnings management and analysts' earnings forecasts.

To evaluate the implications of relative smoothing on the informativeness of forecast earnings for future macroeconomic activity, I follow Bhattacharya, Daouk and Welker (2003), Leuz, Nanda and Wysocki (2003) and Cahan, Liu and Sun (2008), measuring smoothing as the Spearman correlation between changes in accruals and changes in cash flows. Given I am not attempting to distinguish between competing forms of smoothing, I estimate total accruals (as opposed to discretionary accruals).

[127] For example see Previts, Bricker, Robinson and Young (1994), Cotter, Tuna and Wysocki (2006) and Feng and McVay (2010).

Accruals, scaled by total assets, are defined for each firm as follows:

$$\mathrm{ACC}_{it} = ((\Delta\mathrm{CA}_{it} - \Delta\mathrm{CASH}_{it}) - (\Delta\mathrm{CL}_{it} - \Delta\mathrm{CD}_{it} - \Delta\mathrm{TP}_{it}) - \mathrm{DA}_{it})/\mathrm{TA}_{it-1} \qquad (5.4)$$

ACC_{it} is scaled accruals for stock i in year t, $\Delta\mathrm{CA}_{it}$ is the annual change in current assets, $\Delta\mathrm{CASH}_{it}$ is the change in cash and cash equivalents, $\Delta\mathrm{CL}_{it}$ is the change in current liabilities, $\Delta\mathrm{CD}_{it}$ is the change in the current portion of debt included in current liabilities, $\Delta\mathrm{TP}_{it}$ is the change in taxes payable, DA_{it} is the depreciation and amortization expense and TA_{it-1} is lagged total assets. Data is sourced from Compustat. Following Leuz, Nanda and Wysocki (2003), if there is no data reported for $\Delta\mathrm{CD}_{it}$ or $\Delta\mathrm{TP}_{it}$ they are assumed to be zero. Cash flows are defined as reported earnings (before extraordinary items) less accruals, and are scaled by lagged total assets. Changes in scaled accruals and contemporaneous scaled cash flows are calculated for five consecutive years and firm smoothing is estimated as the correlation between changes in scaled accruals and scaled cash flows over that five year period. This process is repeated each year to generate time series of estimated smoothing for each stock. As noted by Bhattacharya, Daouk and Welker (2003):

> Because some degree of earnings smoothing is a natural outcome of any accrual accounting process, this measure is expected to be negative on average. However, the more negative this correlation, the more likely it is that earnings smoothing is obscuring the variability in underlying economic performance, and the greater is the earnings opacity. (p. 649)

I sort stocks each year on estimated smoothing, and to highlight differences in relative smoothing the sample is restricted to stocks which exhibit evidence of smoothing (negative correlation between scaled accruals and scaled cash flows). Stocks are then allocated to smoothing quintile portfolios which are rebalanced annually. I generate time series of aggregate forecast annual changes in earnings for each portfolio. I have not included results for lagged forecast earnings changes deflated by trailing earnings ($\Delta\mathrm{EE}^f$), given there are periods in which the sum of trailing earnings is negative for select subsets of the full sample.

I then regress one year-ahead industrial production on aggregated analysts' forecast earnings changes for each smoothing quintile. However, six consecutive years of fundamental data are required for each annual estimate of earnings smoothing. I am therefore estimating average smoothing over that time period. To best ensure that analysts' earnings forecasts are correctly sorted by smoothing I generate aggregate forecasts for each smoothing quintile as at the start of the middle year in the earnings smoothing estimation (designated Year 3), and for robustness one year either side of this (Years 2 and 4). Therefore, I can ensure that analysts' forecasts are on average correctly matched to periods in which firms were either smoothing more or less than the market average. This approach is presented diagrammatically in Figure 5.1.

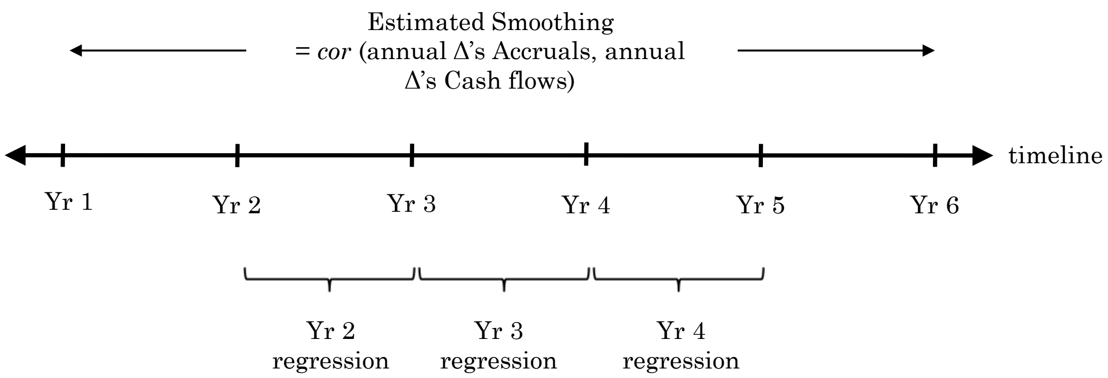
Data requirements result in some shrinkage in the sample. Matching time periods and averaging over December year annual data, the full sample employed in prior analysis averaged 1,204 firm observations per year, compared with 668 firm observations per year for the sample with smoothing data. The average stock size for the smoothing sample is US$3,418 million, compared with US$2,915 million for the full sample.

Table 5.7 summarizes results for regressions of industrial production growth on three measures of lagged Year 3 aggregated forecast changes in earnings for smoothing quintile 1 (high smoothing) through to quintile 5 (low smoothing). In all comparisons of quintile 1 and quintile 5 R^2s, the explanatory power of the aggregated earnings forecasts of low smoothing stocks is higher than the explanatory power of high smoothing stocks.[128] In robustness tests (not shown) of the same regressions performed for Year 2 and Year 4 forecast changes in earnings I similarly find quintile 5 R^2s are higher than quintile 1 R^2s for all three measures

[128] Results are similar, albeit with lower explanatory power overall, when GNP growth is employed as the dependent variable.

Figure 5.1 Regression of industrial production on lagged forecast changes in earnings for income smoothing-sorted portfolios

Earnings smoothing is estimated as the correlation between five consecutive years of annual changes in accruals and annual changes in cash flows for each stock for a given year. Portfolios are formed for quintiles of estimated smoothing. Aggregated forecast annual changes in earnings are calculated for each quintile (see Chapter 3 for details regarding the calculation of aggregated forecast changes) as at the start of the second year in the earnings smoothing estimation period, the third year and the fourth year, respectively. This process is repeated annually to generate time series of aggregated annual forecast changes in earnings for each of three measurement periods within the smoothing calculation periods and for each smoothing quintile. Annual industrial production growth as at the end of the periods matching the forecast horizons for earnings changes is then regressed on the forecast time series. This produces three sets of regression results for the information in aggregated analysts' forecasts for future industrial production growth for each smoothing quintile.



Yr 2 regression = Annual industrial production growth as at end of Yr 2 regressed on aggregated forecast changes in earnings as at start of Yr 2

Yr 3 regression = Annual industrial production growth as at end of Yr 3 regressed on aggregated forecast changes in earnings as at start of Yr 3

Yr 4 regression = Annual industrial production growth as at end of Yr 4 regressed on aggregated forecast changes in earnings as at start of Yr 4

Table 5.7 Industrial production growth regressed on lagged aggregated forecast earnings changes (smoothing quintile portfolios), annual data, 1979–2006

Rolling quarters of annual industrial production growth are regressed on aggregated forecast annual earnings changes for earnings smoothing-sorted quintile portfolios (lagged four quarters). Forecast earnings changes are based on a proxy measure of four quarter forward earnings forecasts less four quarter trailing earnings, and are deflated by book value (B). Lower case earnings measures refer to per-share aggregations. The estimation of relative smoothing requires five consecutive years of annual changes in accruals for each stock. Forecast changes in earnings are calculated for the middle year within this five year period (Year 3). Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2s for regressions of the following form:

$$\mathrm{Y}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{f}}_{t-4} + \varepsilon_t$$

Y_t represents one year growth in industrial production and $\Delta \mathrm{E}^{\mathrm{f}}_{t-4}$ represents the forecast 1 year change in earnings lagged four quarters. In addition, differences in quintile R^2s are provided. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

Independent variable	Q1 (high smoothing)	Q2	Q3	Q4	Q5 (low smoothing)	Q5 – Q1
$\Delta \mathrm{EB}^{\mathrm{f}}$	1.355	**2.258**	0.083	**1.282**	**1.397**	
	0.785	(2.265)	0.111	(3.935)	(4.469)	
	0.015	0.100	0.000	0.108	0.173	+0.158
$\Delta \mathrm{ebeq}^{\mathrm{f}}$	**3.074**	**2.531**	**1.948**	**1.549**	**1.250**	
	(3.948)	(2.039)	(6.515)	(4.520)	(4.342)	
	0.106	0.113	0.126	0.163	0.192	+0.086
$\Delta \mathrm{ebmed}^{\mathrm{f}}$	**3.432**	**3.999**	**2.730**	**2.626**	**1.618**	
	(3.465)	(6.378)	(8.398)	(5.757)	(2.917)	
	0.062	0.158	0.138	0.157	0.132	+0.070

of aggregated forecast changes in earnings. In most cases I do not find evidence of a monotonic relationship between smoothing and the information in aggregated forecasts. Nonetheless, there is evidence of a substantial difference in the information in aggregated analysts' forecasts of higher smoothers versus low smoothers, for future industrial production growth.

One difficulty with the prior analysis is that it requires ex post estimation of earnings smoothing. While providing fresh insights into the informativeness of analysts' forecasts, it is not useful for forecasting industrial production growth given estimated smoothing, as defined here, is not known when analysts' forecasts are aggregated. For forecasting purposes I require an ex ante estimate of smoothing. One option indicated by smoothing literature is firm size. Moses (1987) provides evidence that large companies engage in more income smoothing than small companies. Nelson, Elliott and Tarpley (2002) provide evidence that auditors are less likely to object to attempts by large clients to manage earnings. However, Dechow, Ge and Schrand (2010), summarizing literature on the relationship between firm size and earnings management, highlight the evidence is mixed as "more recent studies predict and find that size is positively associated with earnings quality" (p. 380).

In Sections 5.2 and 5.3 I noted preliminary evidence of a size effect in the strength of the relationship between industrial production growth and lagged aggregated earnings forecasts. For example, in Table 5.4 the R^2 from a regression of industrial production growth on ΔEB^f lagged four quarters is 0.111, compared with 0.199 when ΔEB^f is replaced with $\Delta ebeq^f$ as the independent variable. ΔEB^f is constructed from aggregated forecast changes in earnings, while the latter measure is constructed from an equally-weighted combination of forecast changes in earnings per share. The difference in respective regression R^2s suggests greater explanatory power for future industrial production growth in the forecasts of small companies relative to large companies. The lower predictive power of the month-end forecasts for macroeconomic activity, discussed in the previous section, also points to size-related effects (given the month-end data sample is on average comprised of much larger companies than the full dataset).

To explore the relationship between firm size and the information in aggregated forecasts for future macroeconomic activity I generate time series of aggregated forecast changes in earnings for quarterly rebalanced size quintile portfolios.[129] One year-ahead annual industrial production growth is then regressed on the aggregated forecasts for each portfolio. Results are summarized in Table 5.8.

It is evident there are large differences between quintile 1 earnings forecasts (large stocks) and quintile 5 earnings forecasts (small stocks) in terms of predictive power for future industrial production growth. A statistically significant coefficient on quintile 5 earnings forecasts and a R^2 of 0.188 for the ΔEB^f regression (0.225 for $\Delta ebeq^f$ and 0.235 for $\Delta ebmed^f$) compares with insignificant coefficients on quintile 1 earnings forecasts and R^2s of less than 0.040. I find results are also similar, albeit with lower R^2s, when industrial production growth is replaced with GNP growth as the dependent variable.

[129] By employing size rather than smoothing as the sorting factor I am able to utilize the full dataset and generate quarterly observations for the independent variables.

Table 5.8 Industrial production growth regressed on lagged aggregated forecast earnings changes (size quintile portfolios), 1979–2009

Rolling quarters of annual industrial production growth are regressed on aggregated forecast annual earnings changes lagged four quarters for size-sorted quintile portfolios. Forecast earnings changes are based on a proxy measure of four quarter forward earnings forecasts less four quarter trailing earnings, and are deflated by book value (B). Lower case earnings measures refer to per-share aggregations. Results provided are estimated slope coefficients, $\hat{\beta}$, *t* ratios (in parentheses) and R^2 for regressions of the following form:

$$\mathrm{Y}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{f}}_{t-4} + \varepsilon_t$$

$\Delta \mathrm{E}^{\mathrm{f}}_{t-4}$ represents the forecast 1 year change in earnings lagged four quarters. Average estimated smoothing for each size quintile is provided at the bottom of the table. Newey-West standard errors with automatic bandwidth selection are employed to calculate *t* ratios. Results in bold are statistically significant at the 10% level.

Independent variable	Q1 (large)	Q2	Q3	Q4	Q5 (small)	Q5 – Q1
$\Delta \mathrm{EB}^{\mathrm{f}}$	0.994	**2.716**	**2.943**	**2.217**	**1.793**	
	(1.429)	(3.020)	(2.789)	(1.972)	(2.258)	
	0.029	0.136	0.180	0.169	0.188	+0.159
$\Delta \mathrm{ebeq}^{\mathrm{f}}$	0.869	**2.213**	**2.639**	**2.668**	**2.144**	
	(0.983)	(2.611)	(2.312)	(2.418)	(2.639)	
	0.022	0.116	0.176	0.213	0.225	+0.203
$\Delta \mathrm{ebmed}^{\mathrm{f}}$	1.609	**3.434**	3.434	**3.607**	**2.759**	
	(1.029)	(2.606)	(1.607)	(2.229)	(1.968)	
	0.035	0.135	0.139	0.219	0.235	+0.200
Earnings Smoothing	-0.774	-0.680	-0.677	-0.666	-0.618	+0.157

Bhattacharya, Daouk and Welker (2003) estimate relative smoothing for countries by calculating the correlation between accruals and cash flows across stocks in a given year for a given country, and then averaging correlations across time for each country. Applying this approach to the size quintiles reported in Table 5.8, I obtain an average smoothing estimate of -0.774 for the largest stocks and -0.618 for the smallest stocks. The difference between these two smoothing estimates is statistically significant at the 1% level in a two-tailed test. Hence, my results provide evidence of a positive relationship between size and smoothing.

As a robustness check on results I repeat these regressions for 25 portfolios formed jointly on size and estimated smoothing.[130] Results are provided in Table 5.9 for ΔEB^f and $\Delta ebeq^f$. Within size quintiles it is evident that lower smoothing is generally associated with higher R^2s for regressions of industrial production growth on lagged aggregated earnings forecasts. However, there is also evidence of a size effect within smoothing quintiles. Results are supportive of the hypothesis of an inverse relationship between smoothing and the information in analysts' forecasts for future macroeconomic activity, and provide evidence of a positive relationship between size and smoothing. But results presented in Table 5.9 indicate an additional unknown driver(s) of a relationship between size and the predictive power of aggregated earnings forecasts for future industrial production growth.

From the perspective of the information environment, it should be expected that more information-rich companies (companies for which there are relatively greater numbers of analysts publishing forecasts) would have better quality forecasts (greater forecast accuracy) than information-poor companies. Analyst coverage has

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[130] To sort on estimated smoothing requires reverting to annual observations. Stocks exhibiting both positive and negative correlation between scaled accruals and scaled cash flows are included. Conclusions are unchanged if the sample is restricted to stocks exhibiting evidence of smoothing (negative correlation between scaled accruals and scaled cash flows).

Table 5.9 Industrial production growth regressed on lagged aggregated forecast earnings changes (portfolios formed jointly on size and smoothing), annual data, 1979–2006

Rolling quarters of annual macroeconomic growth measures are regressed on aggregated forecast annual earnings changes lagged 4 quarters for portfolios formed jointly on firm size and estimated smoothing for each stock submitted by analysts to I/B/E/S. Forecast earnings changes are based on a proxy measure of four quarter forward earnings forecasts less four quarter trailing earnings, and are deflated by book value (B). Lower case earnings measures refer to per-share aggregations. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$Y_t = \alpha + \beta \Delta E^f_{t-4} + \varepsilon_t$$

Y_t represents one year growth in industrial production and ΔE^f_{t-4} represents the forecast 1 year change in earnings lagged 4 quarters. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

A. ΔEB^f as independent variable						
	Size quintiles					
Smoothing	Q1 (large)	Q2	Q3	Q4	Q5 (small)	Q5 – Q1
Q1 (high)	0.674	0.580	-1.503	-0.052	0.772	
	(0.404)	(0.314)	(-1.501)	(-0.088)	(1.671)	
	0.008	0.004	0.041	0.000	0.051	+0.044
Q2	1.377	1.988	**1.411**	**2.081**	**2.195**	
	(1.414)	(1.207)	(2.888)	(4.659)	(5.369)	
	0.052	0.083	0.064	0.187	0.293	+0.242
Q3	0.315	1.000	**1.339**	-0.237	0.689	
	(0.554)	(1.001)	(2.385)	(-0.709)	(1.103)	
	0.008	0.031	0.063	0.005	0.044	+0.035
Q4	**0.825**	0.571	**1.054**	**1.065**	**0.862**	
	(2.573)	(1.263)	(3.784)	(3.702)	(2.258)	
	0.051	0.040	0.100	0.208	0.174	+0.123
Q5 (low)	0.678	**1.125**	0.517	**0.942**	**1.399**	
	(1.074)	(4.411)	(1.319)	(4.289)	(3.570)	
	0.058	0.200	0.052	0.147	0.381	+0.323
Q5 – Q1	+0.051	+0.196	+0.011	+0.147	+0.330	
B. $\Delta ebeq^f$ as independent variable						
	Size quintiles					
Smoothing	Q1 (large)	Q2	Q3	Q4	Q5 (small)	Q5 – Q1
Q1 (high)	**1.859**	1.862	-0.214	**1.480**	1.660	
	(2.060)	(1.212)	(-0.460)	(2.065)	(1.606)	
	0.068	0.106	0.002	0.102	0.078	+0.010
Q2	-0.439	1.329	**0.801**	**1.826**	**1.814**	
	(-0.793)	(1.203)	(2.105)	(3.172)	(4.453)	
	0.011	0.066	0.041	0.158	0.299	+0.288
Q3	0.750	**1.046**	0.657	-0.286	0.746	
	(1.572)	(1.740)	(1.191)	(-0.828)	(1.596)	
	0.040	0.052	0.039	0.008	0.075	+0.035
Q4	0.548	0.773	**0.913**	**0.986**	**0.467**	
	(0.959)	(1.597)	(4.999)	(2.353)	(1.743)	
	0.018	0.074	0.158	0.149	0.070	+0.052
Q5 (low)	0.539	**0.883**	0.497	0.410	**0.711**	
	(1.328)	(2.730)	(1.600)	(1.562)	(2.796)	
	0.047	0.142	0.061	0.047	0.169	+0.122
Q5 – Q1	-0.021	+0.036	+0.059	-0.054	+0.091	

been shown to exhibit a positive and statistically significant relationship with firm size.[131] Therefore, contrary to results in Tables 5.8 and 5.9, one would expect that the forecasts of large stocks would have relatively greater predictive power for realized earnings, and consequently greater predictive power for future macroeconomic growth relative to the earnings forecasts of small stocks, ceteris paribus.[132] However, I aggregate analysts' forecasts, and the resulting diversification of unsystematic forecast errors should mitigate the impact of relative information environments for small and large firms. Nonetheless, it is possible that lower levels of analyst coverage for smaller stocks may result in some form of systematic bias.

To examine the robustness of results in Tables 5.8 and 5.9 to analyst coverage, two forecast earnings variables (ΔEB^f, $\Delta ebeq^f$) are generated for 25 portfolios formed jointly on firm size quintiles and quintiles based on the number of forecasts submitted by analysts to I/B/E/S for each stock.[133] In Table 5.10 I provide estimated slope coefficients, *t* statistics and adjusted R^2s for separate regressions of industrial production growth on these measures of forecast earnings changes lagged four quarters.

[131] For example Bhushan (1989) and Brennan and Hughes (1991) find evidence for a positive and statistically significant relationship between firm size and the level of analyst coverage.

[132] Brown, Richardson and Schwager (1987) report evidence of a positive relationship between firm size and the superiority of analysts' forecasts over time series models. Kross, Ro and Schroeder (1990) find evidence of a positive relationship between forecast accuracy and the amount of coverage received by a stock in *The Wall Street Journal*. Lang, Lins and Miller (2003) report evidence of an information effect from cross-listing correlated with increased analyst coverage, and in turn associated with improved forecast accuracy.

[133] Analyst coverage portfolio splits are determined by relative coverage within size quintiles. Hence, on average, analyst coverage will be higher across all analyst coverage portfolios within the largest size quintile, relative to analyst coverage within the smallest size quintile. Although an absolute basis for determining analyst coverage portfolios may be preferable, sizable gaps in the resulting time series for either quintile 1 or quintile 5 (or both) emerge depending upon the coverage cut-off points selected.

Table 5.10 Macroeconomic growth regressed on lagged aggregated forecast earnings changes (portfolios formed jointly on stock size and the number of submitted forecasts), 1979–2009

Rolling quarters of annual macroeconomic growth measures are regressed on aggregated forecast annual earnings changes lagged 4 quarters for portfolios formed jointly on firm size and the number of forecasts for each stock submitted by analysts to I/B/E/S. Forecast earnings changes are based on a proxy measure of four quarter forward earnings forecasts less four quarter trailing earnings, and are deflated by book value (B). Lower case earnings measures refer to per-share aggregations. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$\mathrm{Y}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{f}}_{t-4} + \varepsilon_t$$

Y_t represents one year growth in industrial production and $\Delta \mathrm{E}^{\mathrm{f}}_{t-4}$ represents the forecast 1 year change in earnings lagged 4 quarters. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

A. ΔEB$^{\mathrm{f}}$ as independent variable						
	Size quintiles					
Number of analysts	Q1 (large)	Q2	Q3	Q4	Q5 (small)	Avg R^2
Q1 (high)	0.231	0.435	**1.079**	1.150	0.942	
	(0.383)	(0.667)	(1.871)	(1.647)	(1.291)	
	0.004	0.008	0.105	0.101	0.088	0.061
Q2	0.399	**0.934**	**1.843**	0.837	**1.335**	
	(0.748)	(2.178)	(2.723)	(1.344)	(2.171)	
	0.008	0.040	0.125	0.076	0.161	0.082
Q3	**1.024**	**2.336**	**1.826**	**1.773**	**1.254**	
	(2.180)	(2.840)	(1.797)	(2.095)	(2.028)	
	0.030	0.160	0.090	0.135	0.117	0.107
Q4	**1.376**	**2.041**	**1.597**	**1.713**	**1.324**	
	(4.347)	(3.110)	(1.893)	(2.008)	(3.405)	
	0.102	0.153	0.073	0.119	0.122	0.114
Q5 (low)	0.788	1.366	0.324	**1.554**	**1.583**	
	(0.438)	(1.415)	(0.370)	(1.746)	(2.457)	
	0.021	0.084	0.005	0.091	0.209	0.082
Avg R^2	0.033	0.089	0.080	0.104	0.139	
B. Δebeq$^{\mathrm{f}}$ as independent variable						
	Size quintiles					
Number of analysts	Q1 (large)	Q2	Q3	Q4	Q5 (small)	Avg R^2
Q1 (high)	-0.071	0.598	**1.387**	**1.347**	1.165	
	(-0.150)	(1.280)	(2.141)	(2.349)	(1.437)	
	0.000	0.016	0.146	0.130	0.098	0.078
Q2	0.311	**0.944**	**1.514**	**1.640**	**1.619**	
	(0.468)	(1.880)	(2.329)	(2.249)	(2.785)	
	0.003	0.039	0.109	0.148	0.170	0.094
Q3	0.873	**1.060**	**1.346**	**1.391**	**1.170**	
	(1.469)	(1.807)	(2.087)	(2.074)	(2.111)	
	0.030	0.046	0.080	0.105	0.119	0.076
Q4	**1.024**	**1.217**	**1.497**	**1.603**	**1.247**	
	(2.810)	(2.154)	(2.236)	(1.882)	(2.756)	
	0.048	0.085	0.089	0.134	0.121	0.095
Q5 (low)	0.797	**1.504**	0.432	0.917	**1.607**	
	(0.935)	(2.031)	(0.527)	(1.598)	(2.801)	
	0.039	0.134	0.009	0.046	0.255	0.096
Avg R^2	0.024	0.064	0.087	0.113	0.153	

I find size quintile 5 (small) R^2s are higher than size quintile 1 (large) R^2s within all analyst coverage quintiles. Averaging regression R^2s across analyst coverage quintiles, there are large differences between size quintile 1 R^2s and size quintile 5 R^2s for both measures of aggregate forecast earnings changes. There is no such large increase in average R^2s across size quintiles between analyst coverage quintile 1 stocks and quintile 5 stocks. There is no evidence of a relationship between analyst coverage and the magnitude of information in aggregated earnings forecasts for future industrial production growth. Therefore, the size effect evident in Tables 5.8 and 5.9 is robust to conditioning on analyst coverage. It is not an effect resulting from sample bias driven by differences in analyst coverage for small versus large firms. Thus, consistent with the notion of size-based variation in income smoothing, I find evidence of size-based variation in the magnitude of information in aggregated analysts' earnings forecasts for measures of future macroeconomic activity. This variation is not the product of a systematic bias resulting from lower analyst coverage for small stocks.

Overall, results support the hypothesis of differential information for future macroeconomic activity in aggregated forecasts conditioned on earnings smoothing. Smoothing reduces the informativeness of forecasts for future industrial production growth. I also find evidence of a positive relationship between size and smoothing. However, relative size appears to be capturing additional characteristics not reflected by smoothing alone. In the next section I extend this analysis to the relationship between the informativeness of analysts' earnings forecasts for future macroeconomic activity and the cyclicality of earnings.

5.6 Macroeconomic information and earnings cyclicality

INTUITIVELY, THE EARNINGS of certain groups of stocks are likely to be more closely related to measures of contemporaneous macroeconomic activity than others. For example, it is reasonable to expect that the relationship between realized earnings and contemporaneous industrial production growth is stronger for basic materials companies than it is for, say, utilities. If there is significant variation in the relationship between realized earnings and macroeconomic activity (significant variation in earnings cyclicality), it is reasonable to expect this would also result in significant variation in the magnitude of information in analysts' earnings forecasts for future macroeconomic activity.

To evaluate the relationship between earnings cyclicality and the information in earnings forecasts for future macroeconomic growth, I firstly form sector portfolios based on the 10 sectors comprising level 1 of the Global Industry Classification Standards. All aggregated forecast and realized earnings variables previously discussed are generated for each sector portfolio. I regress GNP growth and industrial production growth on the time series of contemporaneous realized earnings for each sector to provide estimates of relative earnings cyclicality. Results are provided in Table 5.11. If relative cyclicality is defined by a combination of the ranking of sectors by average R^2 in these regressions and the magnitude of the average estimated coefficient on realized earnings changes, then the most cyclical sectors are Consumer Discretionary, Industrials, Materials and Information Technology.[134]

[134] These remain the four most cyclical sectors if cyclicality is defined by average R^2 rankings alone, or if cyclicality is defined relative to the relationship between realized earnings and GDP alone or the relationship between realized earnings and industrial production growth alone.

Table 5.11 Realized earnings growth for sector portfolios regressed on contemporaneous macroeconomic growth, 1979–2009

Aggregated annual earnings changes for sector portfolios are regressed on rolling quarters of annual macroeconomic growth measures. Earnings changes are calculated from the sum of four quarters of earnings less the sum of the prior four quarters of earnings, deflated by book value (B). Lower case earnings measures refer to per-share aggregations. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$\Delta \mathrm{E}_t^a = \alpha + \beta \mathrm{Y}_t + \varepsilon_t$$

Y_t represents one year growth in the macroeconomic activity measure and $\Delta \mathrm{E}_t^a$ represents the 1 year change in the aggregated realized earnings measure, both in the period ending at time t. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Estimated coef., $\hat{\beta}$			t statistic			R^2			R^2 rank		
	ΔEB^a	$\Delta ebeq^a$	$\Delta ebmed^a$	ΔEB^a	$\Delta ebeq^a$	$\Delta ebmed^a$	ΔEB^a	$\Delta ebeq^a$	$\Delta ebmed^a$	ΔEB^a	$\Delta ebeq^a$	$\Delta ebmed^a$
A. GNP growth as dependent variable												
Energy	**0.849**	0.670	0.413	(1.673)	(1.538)	(1.420)	0.133	0.057	0.048	4	6	9
Materials	**0.962**	**0.719**	**0.562**	(2.176)	(2.888)	(2.454)	0.223	0.174	0.296	2	4	3
Industrials	**0.547**	**0.622**	**0.391**	(3.215)	(2.748)	(2.573)	0.347	0.393	0.348	1	1	2
Consumer Discretionary	0.690	0.591	**0.432**	(1.108)	(1.510)	(2.004)	0.148	0.269	0.432	3	2	1
Consumer Staples	0.088	**0.214**	**0.137**	(0.535)	(1.969)	(2.365)	0.011	0.047	0.140	8	7	6
Health Care	0.013	0.090	0.058	(0.113)	(0.792)	(0.920)	0.000	0.008	0.034	10	10	10
Financials	0.427	0.345	0.257	(0.681)	(0.767)	(0.816)	0.104	0.171	0.263	5	5	4
Information Technology	0.773	**0.770**	**0.537**	(1.429)	(1.885)	(1.739)	0.101	0.185	0.230	6	3	5
Telecommunication Services	-0.114	0.422	0.239	(-0.243)	(0.888)	(1.417)	0.003	0.027	0.082	9	8	8
Utilities	**0.173**	**0.084**	**0.073**	(3.388)	(1.837)	(1.823)	0.078	0.026	0.097	7	9	7
B. Industrial production growth as dependent variable												
Energy	0.375	0.251	0.057	(0.978)	(0.660)	(0.206)	0.054	0.017	0.002	6	10	10
Materials	**0.799**	**0.717**	**0.516**	(2.423)	(4.726)	(4.992)	0.322	0.360	0.522	2	3	3
Industrials	**0.407**	**0.520**	**0.336**	(6.147)	(5.185)	(5.079)	0.401	0.571	0.536	1	1	2
Consumer Discretionary	**0.580**	**0.528**	**0.367**	(2.139)	(3.007)	(4.189)	0.219	0.448	0.651	3	2	1
Consumer Staples	0.133	**0.170**	**0.092**	(1.449)	(2.424)	(2.097)	0.051	0.062	0.133	7	6	7
Health Care	0.114	0.104	**0.077**	(1.494)	(0.887)	(2.190)	0.032	0.023	0.125	8	9	8
Financials	0.405	0.287	0.207	(1.035)	(1.129)	(1.064)	0.196	0.247	0.353	5	5	5
Information Technology	**0.759**	**0.732**	**0.513**	(1.836)	(3.282)	(3.637)	0.204	0.348	0.439	4	4	4
Telecommunication Services	0.026	0.266	**0.220**	(0.061)	(1.150)	(1.952)	0.000	0.024	0.154	10	8	6
Utilities	0.075	**0.073**	0.043	(1.283)	(2.063)	(1.132)	0.030	0.040	0.071	9	7	9

The least cyclical are Consumer Staples, Health Care, Telecommunication Services and Utilities.

I group sectors into 3 categories based on the combined rankings of R^2s and estimated slope coefficients in Table 5.11: a high cyclicality group, a mid-cyclicality group and a low cyclicality group. In the high cyclicality group are the Consumer Discretionary, Industrials, Materials and Information Technology sectors. In the mid cyclicality group are the Energy and Financials sectors. In the low cyclicality group are the Consumer Staples, Health Care, Telecommunication Services and Utilities sectors. Time series of aggregated earnings forecast changes and realized earnings changes are constructed for each of the sector groupings, and for size quintile portfolios within each grouping. Industrial production growth is then regressed on forecast earnings changes for each of these groupings, lagged four quarters. Results are presented in Table 5.12.

In Panel A the estimated coefficients and, in particular, the regression R^2s for the high cyclicality grouping are substantially higher than those reported for the mid and low cyclicality groupings. The adjusted R^2 for the regression of future industrial production on ΔEB^f is 0.138, 0.261 for $\Delta ebeq^f$ and 0.246 for $\Delta ebmed^f$ in the case of the high cyclicality grouping, compared with 0.009, 0.013 and -0.004, respectively, for the low cyclicality grouping. This provides support for the hypothesis of a positive relationship between the cyclicality of realized earnings and the magnitude of explanatory power in earnings forecasts for future macroeconomic activity.

Given this evidence of a relationship between the magnitude of information in earnings forecasts for future macroeconomic activity and earnings cyclicality, combined with evidence presented in the previous section of size-based variation in

Table 5.12 Industrial Production growth regressed on lagged aggregated forecast earnings growth (sector groupings formed on relative cyclicality), 1979–2009

Rolling quarters of annual industrial production growth are regressed on aggregated forecast annual earnings changes lagged 4 quarters for portfolios formed on the basis of relative sector cyclicality. Forecast earnings changes are based on a proxy measure of four quarter forward earnings forecasts less four quarter trailing earnings, and are deflated by book value (B). Lower case earnings measures refer to per-share aggregations. Results provided are estimated slope coefficients, $\hat{\beta}_{\Delta E}$, t ratios (in parentheses) and adjusted R^2 for regressions of the following form:

$$Y_t = \alpha + \beta_{\Delta E}\Delta E^f_{t-4} + \beta_Y Y_{t-4} + \varepsilon_t$$

Y_t represents one year growth in industrial production, ΔE^f_{t-4} represents the forecast 1 year change in earnings lagged 4 quarters and Y_{t-4} represents the last reported value of the dependent variable at time t-4. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

A. Sector groupings									
	Estimated coef., $\hat{\beta}_{\Delta E}$			t statistic			R^2		
	ΔEB^f	$\Delta ebeq^f$	$\Delta ebmed^f$	ΔEB^f	$\Delta ebeq^f$	$\Delta ebmed^f$	ΔEB^f	$\Delta ebeq^f$	$\Delta ebmed^f$
High cyclicality	**1.926**	**2.820**	**3.774**	(2.720)	(5.832)	(2.983)	0.138	0.261	0.246
Mid cyclicality	0.250	1.267	3.255	(0.395)	(1.095)	(1.438)	-0.004	0.027	0.099
Low cyclicality	**0.640**	0.690	-0.247	(1.813)	(0.931)	(-0.199)	0.009	0.013	-0.004

B. High cyclicality sectors by size quintiles					
Independent variable	Q1 (large)	Q2	Q3	Q4	Q5 (small)
ΔEB^f	**1.292**	**1.871**	**2.137**	**1.854**	**1.708**
	(1.926)	(3.486)	(3.671)	(3.128)	(3.019)
	0.069	0.195	0.258	0.211	0.189
$\Delta ebeq^f$	1.191	**2.131**	**2.090**	**2.074**	**1.825**
	(0.922)	(3.917)	(4.016)	(3.545)	(4.007)
	0.054	0.226	0.224	0.214	0.175
$\Delta ebmed^f$	1.704	**2.866**	**2.871**	**2.779**	**2.834**
	(0.931)	(2.303)	(2.224)	(2.318)	(3.386)
	0.052	0.193	0.208	0.190	0.223
C. Mid cyclicality sectors by size quintiles					
ΔEB^f	-0.035	0.698	0.285	0.278	0.548
	(-0.074)	(0.887)	(0.723)	(0.383)	(0.726)
	-0.005	0.024	-0.002	-0.001	0.021
$\Delta ebeq^f$	0.242	0.420	0.433	0.877	0.888
	(0.387)	(0.329)	(0.510)	(0.939)	(1.329)
	-0.003	0.001	0.001	0.015	0.054
$\Delta ebmed^f$	1.006	**2.995**	2.464	**2.943**	1.628
	(0.857)	(1.846)	(1.547)	(1.754)	(1.126)
	0.010	0.104	0.074	0.108	0.072
D. Low cyclicality sectors by size quintiles					
ΔEB^f	**0.450**	-0.363	-0.419	**1.060**	0.442
	(1.943)	(-0.378)	(-0.461)	(1.779)	(1.166)
	0.008	-0.004	-0.003	0.030	0.014
$\Delta ebeq^f$	-0.163	-0.391	0.435	0.672	0.584
	(-0.244)	(-0.584)	(0.551)	(1.577)	(0.999)
	-0.004	0.002	0.002	0.039	0.039
$\Delta ebmed^f$	-0.811	-0.990	-1.359	0.156	**1.568**
	(-1.050)	(-1.015)	(-1.422)	(0.173)	(1.719)
	0.014	0.012	0.025	-0.005	0.089

the informativeness of forecasts, it is reasonable to expect a significant size effect in the predictive power of the earnings forecasts of the high cyclicality group for macroeconomic activity. However, the impact of relative size should be smaller for mid and low cyclicality firms given their forecasts already exhibit relatively weaker (and insignificant) explanatory power for variation in future macroeconomic activity. In Panels B, C and D of Table 5.12, I provide estimated coefficients on aggregate forecast earnings changes for the high, mid and low cyclicality groupings respectively, each further divided into size quintiles.

For the high cyclicality grouping (Panel B) there is no evidence of a monotonic relationship between firm size and the magnitude of explanatory power in earnings forecasts for industrial production growth. But it is evident that the explanatory power of forecasts within quintile 1 (the largest stocks) is much lower than all other quintiles (which exhibit roughly similar R^2s). In addition, the differences between the quintile 1 and quintile 5 estimated coefficients on earnings forecasts for all three forecast earnings measures are statistically significant.[135]

In Panels C and D, splitting the mid and low cyclicality groupings into size quintiles, the results on average display less in the way of a size effect. There are few significant coefficients on the forecast earnings variables and, while quintile 5 R^2s are higher than quintile 1 R^2s, the lack of statistically significant coefficients argues against the presence of a robust size effect.

Overall, these results provide evidence supporting the hypothesis of variation in the informativeness of aggregated analysts' forecasts for future macroeconomic activity resulting from the relative cyclicality of realized earnings. In addition,

[135] Repeating the methodology employed to estimate smoothing for size quintile portfolios in the previous section, I find a smoothing value of -0.743 for the portfolio comprised of the largest cyclical stocks, compared with -0.623 for the smallest cyclical stocks. The difference between these estimates is statistically significant at the 10% level in a two tailed test. Hence, a portion of the size effect evident may be attributable to size-related differences in relative smoothing.

results for size quintiles within the high cyclicality group are consistent with the smoothing hypothesis evaluated in the previous section. However, the size effect evident here is unlikely to be solely a smoothing phenomenon.

5.7 *Earnings forecasts and business cycle regimes*

MOSES (1987) REPORTS evidence of a statistically significant positive relationship between income smoothing and firm size. In addition, his results suggest income smoothing increases as the gap between earnings and expectations widens. Importantly, he also finds that the relationship between smoothing and size increases for a sub-sample of cases where the gap between pre-smoothed earnings and expectations is larger. This implies that not only do large companies tend to smooth earnings more than small companies, but that the difference between large and small company smoothing increases when there is greater need (from management's perspective) to smooth. Consequently, this suggests a difference, that is conditional on economic activity over the forecast horizon, between large and small company forecasts in terms of the information those forecasts contain for future economic activity. Specifically, as economic activity slows, requiring downward revisions in earnings expectations, large companies smooth earnings more than small companies, thus reducing information in forecasts for future macroeconomic growth in large stocks relative to small stocks.[136]

[136] Note also that Beidleman (1973) discusses the use of earnings smoothing to reduce earnings cyclicality. Assuming an asymmetric response by management to the impact of the economic cycle on earnings, this is consistent with the notion of increased smoothing as economic activity slows. Interestingly, Anilowski, Feng and Skinner (2007) find evidence of increased company earnings guidance for quarters in which aggregate market returns are negative, relative to quarters in which market returns are positive.

To test this idea I run regressions of the following form:

$$\mathrm{Y}_t = \alpha_1 + \alpha_2 \mathrm{D}_t + \beta_1 \mathrm{D}_t \Delta \mathrm{E}^{\mathrm{f}}_{t-4} + \beta_2 (1 - \mathrm{D}_t) \Delta \mathrm{E}^{\mathrm{f}}_{t-4} + \varepsilon_t \tag{5.5}$$

Where Y_t represents one year growth in industrial production, $\Delta \mathrm{E}^{\mathrm{f}}_{t-4}$ represents the forecast one year change in earnings lagged four quarters and D_t represents a two-state regime dummy variable. Three regime determinants are evaluated: the National Bureau of Economic research (NBER) expansion or contraction regime as at the start of the forecast period, the NBER regime as at the end of the forecast period and whether annual industrial production growth at the end of the forecast period is either above or below the average level of growth over the full sample period.

Panel A in Table 5.13 provides results for this regression for quintile 1 and quintile 5 of high cyclicality companies sorted on market capitalization, in turn for each of ΔEB^f, $\Delta ebeq^f$ and $\Delta ebmed^f$. The first regime determinant is the NBER assessment of the economic phase as at the end of the quarter from which earnings forecasts are collected. Earnings forecasts for small stocks provide statistically significant information for future industrial production growth in expansions across all earnings measures. However, the estimated coefficient on large cyclicals' earnings forecasts is statistically significant only for ΔEB^f in economic expansions. For large cyclicals, the estimated coefficients on $\Delta ebeq^f$ and $\Delta ebmed^f$ are negative and statistically significant in economic contractions (and negative but insignificant for ΔEB^f). Therefore, for two out of the three measures of aggregate forecast earnings changes for large cyclicals there is no significant information for future industrial production growth in economic expansions. In addition, for two out of the three measures of aggregate forecast earnings changes for large cyclicals the analysts' forecasts do exhibit significant predictive power for industrial production growth in economic contractions, but the relationship is negative.

Table 5.13 Industrial production growth regressed on lagged aggregated forecast earnings growth with regime shifts (size quintiles 1 and 5 of cyclical stocks), 1979–2009

Rolling quarters of annual industrial production growth are regressed on aggregated forecast annual earnings changes lagged 4 quarters for size quintiles 1 and 5 of portfolios of cyclical stocks. A regime dummy variable is included to identify change in estimated parameters across regimes. Forecast earnings changes are based on a proxy measure of four quarter forward earnings forecasts less four quarter trailing earnings, and are deflated by book value (B). Lower case earnings measures refer to per-share aggregations. In Panel A results provided are estimated slope coefficients, $\hat{\beta}_{1,2}$, t ratios (in parentheses) and adjusted R^2 for regressions of the following form:

$$\mathrm{Y}_t = \alpha_1 + \alpha_2 \mathrm{D}_t + \beta_{1,\Delta \mathrm{E}} \mathrm{D}_t \Delta \mathrm{E}^{\mathrm{f}}_{t-4} + \beta_{2,\Delta \mathrm{E}} (1 - \mathrm{D}_t) \Delta \mathrm{E}^{\mathrm{f}}_{t-4} + \varepsilon_t$$

Y_t represents one year growth in industrial production, $\Delta \mathrm{E}^{\mathrm{f}}_{t-4}$ represents the forecast 1 year change in earnings lagged 4 quarters and D_t represents a two-state regime dummy variable. Wald test statistics are provided, evaluating the statistical significance of the difference between estimated coefficients on the earnings forecast variables across regimes. In Panel B adjusted R^2s are provided for industrial production growth regressed on 4 quarter lagged earnings forecasts of cyclical stocks by size quintile, with separate regressions for each of two states of future industrial production growth. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

A. Forecast earnings parameter estimates for regime regressions

Regime	Condition	ΔEB^f		Δebeq^f		Δebmed^f	
		Q1 (large)	Q5 (small)	Q1 (large)	Q5 (small)	Q1 (large)	Q5 (small)
NBER = expansion	False	-1.667	0.598	**-2.173**	-0.427	**-3.024**	0.816
		(-1.306)	(0.341)	(-1.836)	(-0.240)	(-1.983)	(0.363)
	True	**0.848**	**1.351**	0.710	**1.473**	1.087	**2.150**
		(1.941)	(2.551)	(1.019)	(3.160)	(0.726)	(2.806)
	Adj. R^2	0.235	0.282	0.242	0.271	0.233	0.294
	Wald test	**4.131**	0.166	**6.329**	1.178	**7.221**	0.320
NBER fwd 4 qtrs = expansion	False	**-1.406**	-0.258	**-1.417**	-0.978	**-1.911**	0.116
		(-2.256)	(-0.169)	(-2.250)	(-1.199)	(-2.874)	(0.062)
	True	0.592	**0.881**	0.634	**0.965**	0.984	**1.640**
		(1.129)	(1.724)	(0.894)	(2.072)	(0.755)	(2.069)
	Adj. R^2	0.479	0.484	0.488	0.486	0.479	0.509
	Wald test	**5.895**	0.466	**4.288**	**4.294**	**3.341**	0.558
IP fwd 4 qtrs > LR avg	False	-0.328	**1.395**	-0.370	**1.337**	-0.292	**1.853**
		(-0.971)	(2.386)	(-1.046)	(2.565)	(-0.520)	(2.038)
	True	**0.680**	0.516	**0.612**	0.265	**1.332**	**0.881**
		(2.712)	(1.657)	(2.290)	(0.911)	(2.454)	(1.671)
	Adj. R^2	0.580	0.627	0.579	0.602	0.585	0.617
	Wald test	**4.487**	1.792	**3.864**	**3.239**	**3.085**	0.827

B. Regression adjusted R^2s for size quintiles of cyclical stocks conditioned on future industrial production growth

Regime	Forecast measure	Q1 (large)	Q2	Q3	Q4	Q5 (small)
IP fwd 4 qtrs > LR avg	ΔEB^f	0.086	0.191	0.137	0.109	0.062
	Δebeq^f	0.069	0.102	0.083	0.112	0.013
	Δebmed^f	0.130	0.207	0.195	0.173	0.081
IP fwd 4 qtrs ≤ LR avg	ΔEB^f	0.012	0.003	0.096	0.127	0.196
	Δebeq^f	0.018	0.000	0.044	0.089	0.133
	Δebmed^f	0.005	0.006	0.021	0.088	0.147

In economic contractions, the higher the forecast change in earnings for large cyclicals, the lower the predicted level of future industrial production growth. Wald tests of the differences in the estimated coefficients on forecast earnings changes in economic expansions versus economic contractions are all significant for large cyclicals, but insignificant for small cyclicals. These results are consistent with greater income smoothing by large cyclicals in economic downturns, relative to small cyclicals.[137] Further, these results suggest that the degree of smoothing amongst large cyclicals is sufficient to induce a significant negative relationship between forecast changes in earnings and future industrial production growth.

Switching to assessment of the NBER expansion/contraction phase as at the end of the forecast period (one year after the forecast date), results are similar. All estimated coefficients on large cyclicals' earnings forecasts are negative and significant in economic contractions. Two out of three estimated coefficients are also negative for small cyclicals, but these are not significant at the 10% level.

The third regime variable investigated is industrial production growth. Specifically, whether industrial production growth over the forecast horizon is greater or less than the long term average rate of growth over the period evaluated. The estimated coefficients on the earnings forecasts of small cyclicals are positive and statistically significant when industrial production growth is below its long run average. For $\Delta ebmed^f$, the earnings forecasts of small cyclicals provide statistically significant information for future industrial production growth in *both* stronger-than-average growth periods and weaker-than-average growth periods. Conversely, the earnings forecast variables for large cyclicals provide statistically significant explanatory power in periods of stronger-than-average growth only.

[137] However, results presented in Section 5.5 suggest that relative smoothing is unlikely to be the sole cause of regime-based variation in the observed size effect.

In Panel B I report the adjusted R^2s for regressions of industrial production growth on four quarter lagged earnings forecasts (and lagged industrial production growth) for size quintiles within the high cyclicality group of sectors. Regressions are run separately for periods when four quarter forward industrial production growth is above the long term average, and when it is below the long term average. When future industrial production growth is above average, the size effect in regression R^2s disappears for ΔEB^f, $\Delta ebeq^f$ and $\Delta ebmed^f$. When future industrial production is below the long term average, the regression R^2s for quintile 5 cyclicals are at least seven times larger than those reported for quintile 1 cyclicals. These results represent indirect evidence of greater income smoothing by large cyclicals relative to small cyclicals as economic activity slows.

Reviewing results, in Section 5.5 I provide evidence of inverse relationships between the informativeness of analysts' earnings forecasts for future macroeconomic activity, and the extent of earnings smoothing and relative firm size. These relationships are shown in Section 5.6 to be more prominent amongst high cyclicality firms given the starting point for the earnings forecasts for these firms is higher explanatory power for future macroeconomic activity. Taking this one step further, results presented in Table 5.13 suggest not just a greater size effect for cyclicals, but also that the size effect in the informativeness of aggregated forecasts is principally a feature of periods in which the pace of economic growth is slowing.

5.8 Marginal information in analysts' forecasts

THE PREVIOUS SECTIONS investigate the explanatory power of aggregated earnings forecasts for future macroeconomic activity. In this section I investigate the *marginal* explanatory power of aggregated earnings forecasts for future macroeconomic activity, when these forecasts are combined with a range of economic state variables. The additional variables evaluated are the Institute of Supply Management's (ISM) Purchasing Managers' Index (PMI) for manufacturing companies (level and 12 month log change), the University of Michigan's Index of Consumer Sentiment (level and 12 month log change), the 12 month log change in the US Consumer Price Index, the term structure (the percentage point difference between the 10 year Treasury bond rate and the 3 month Treasury bill rate), the default spread (the percentage point difference between the Moody's seasoned Baa-rated corporate bond yield and the Moody's seasoned Aaa-rated corporate bond yield), the 12 month market return (the value-weighted return on non-ADR NYSE, Amex and Nasdaq stocks) and the NYSE dividend yield.[138] Values of all independent variables in each quarter are from the most recent published release of that variable as at the close of business on the last day of the quarter in question. This represents the dataset available to an investor at quarter end for the purpose of forming expectations for macroeconomic growth. All of these variables essentially act as proxies for expectations for macroeconomic growth. Hence, I am evaluating whether or not analysts' earnings forecasts, when added to the available information set, provide any significant marginal predictive power for macroeconomic growth.

Evidence is provided in previous sections for significant predictive power in analysts' earnings forecasts for future industrial production growth. However, there is no a priori reason to believe that analysts' forecasts should have significant explanatory power over and above what is provided by the selected range of economic state variables. Firstly, bond and equity markets are likely relatively efficient processors of macroeconomic information and can therefore incorporate all

[138] See Chapter 4 for more details on selected economic state variables.

of the macroeconomic information imputed in analysts' earnings forecasts.[139] Secondly, analysts' forecasts from the I/B/E/S summary file reflect published earnings estimates up to the Thursday before the third Friday of each month. The estimates combined to generate the consensus expectations may in fact date from some months prior. Hence, analysts' summary consensus earnings forecasts suffer from a substantial timing disadvantage with respect to a number of the economic state variables I have selected for this analysis.

Table 5.14 provides univariate and multivariate results for annual industrial production growth regressed on lagged economic state variables. In the univariate regressions, business confidence (ISM PMI and ISM PMI changes) are statistically significant at all lags evaluated. The same is true of the 12 month change in consumer sentiment and 12 month market returns. These latter two factors provide the largest R^2s for variation in industrial production growth four quarters out (25.1% for consumer sentiment changes and 20.7% for market returns). However, when all variables are combined in the multivariate regressions in Panel B, it is the default spread which provides the most consistent statistically significant explanatory power. Note that the magnitude of the R^2s in Panel B, combined with few significant t statistics, points to an issue with multicollinearity. This statistical issue has the potential to further decrease the likelihood of finding significant coefficients on measures of aggregated earnings forecasts.

To test the marginal explanatory power of aggregated forecasts for future macroeconomic activity annual industrial production growth is regressed on lagged

[139] Chen (1991) reports evidence of statistically significant relationships between a range of economic state variables and stock returns. Similarly, Fama and French (1989) find evidence for a relationship between credit spreads, term spreads, dividend yields and expected stock returns. Vassalou (2003) finds evidence that the cross-section of stock returns contains information for future GDP growth.

Table 5.14 Industrial production growth regressed on lagged economic state variables, 1979–2009

Rolling quarters of annual industrial production growth are regressed on a range of economic state variables lagged l quarters. Panel A contains results of univariate regressions. Panel B reports results of multivariate regressions in which all listed state variables are included as independent variables. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2 for regressions of the following form:

$$Y_t = \alpha + \beta S_{t-l} + \varepsilon_t$$

Y_t represents one year growth in industrial production and S_{t-l} represents an economic state variable (or vector of economic state variables in Panel B) lagged l quarters. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

Lag, l (qtrs)	ISM PMI	ISM PMI, 12m%	Cons. Sent.	Cons. Sent., 12m%	CPI, 12m%	Term structure	Default spread	Market return, 12m%	Dividend yield	Adj. R^2 (multivariate only)
A. Univariate regressions										
1	**0.487**	**0.115**	**0.210**	**0.165**	-0.282	-0.083	**-5.039**	**0.110**	-0.044	-
	(5.895)	(3.439)	(3.039)	(6.225)	(-0.525)	(-0.092)	(-4.053)	(1.972)	(-0.040)	
	0.514	0.264	0.425	0.243	0.032	-0.008	0.381	0.242	-0.008	
2	**0.449**	**0.121**	**0.200**	**0.200**	-0.431	0.272	**-4.427**	**0.130**	0.146	-
	(6.133)	(3.379)	(3.081)	(4.929)	(-1.012)	(0.369)	(-2.661)	(2.918)	(0.128)	
	0.436	0.296	0.381	0.357	0.083	0.000	0.292	0.344	-0.005	
3	**0.340**	**0.111**	**0.175**	**0.207**	-0.533	0.533	-3.331	**0.127**	0.253	-
	(5.443)	(3.624)	(2.435)	(3.677)	(-1.525)	(1.119)	(-1.464)	(3.105)	(0.210)	
	0.245	0.246	0.286	0.372	0.127	0.022	0.159	0.312	0.002	
4	**0.149**	**0.071**	0.138	**0.172**	-0.558	**0.881**	-2.102	**0.108**	0.300	-
	(1.711)	(2.262)	(1.414)	(2.665)	(-1.446)	(2.291)	(-0.667)	(3.260)	(0.218)	
	0.038	0.094	0.167	0.251	0.138	0.074	0.051	0.207	0.006	
B. Multivariate regressions										
1	**0.185**	**0.034**	**0.125**	0.028	0.250	0.171	**-2.694**	0.007	0.291	0.739
	(1.810)	(1.828)	(2.542)	(0.823)	(1.306)	(0.587)	(-2.989)	(0.208)	(0.643)	
2	0.130	0.025	**0.066**	**0.060**	-0.112	0.299	**-2.604**	0.038	0.500	0.727
	(1.281)	(1.069)	(1.692)	(1.694)	(-0.674)	(0.880)	(-2.565)	(1.107)	(0.940)	
3	0.007	0.032	0.041	0.068	-0.447	0.260	**-2.340**	0.037	0.836	0.608
	(0.058)	(1.127)	(0.621)	(1.108)	(-1.219)	(0.809)	(-2.087)	(1.307)	(1.375)	
4	-0.170	0.024	0.036	0.069	-0.545	**0.559**	**-2.474**	0.038	1.021	0.478
	(-1.399)	(0.902)	(0.399)	(1.133)	(-1.095)	(1.645)	(-2.186)	(1.140)	(1.306)	

forecast earnings, a selection of lagged economic state variables and a lagged dependent variable.[140] Regressions are therefore of the following form:

$$\mathrm{Y}_t = \alpha + \beta_{\Delta\mathrm{E}}\Delta\mathrm{E}^{\mathrm{f}}_{t-l} + \boldsymbol{\beta}_{\mathrm{S}}\mathbf{S}_{t-l} + \beta_{\mathrm{Y}}\mathrm{Y}_{t-l} + \varepsilon_t \tag{5.6}$$

Where Y_t represents one year growth in industrial production, $\Delta\mathrm{E}^{\mathrm{f}}_{t-l}$ represents the forecast one year change in earnings lagged *l* quarters, $\mathbf{S}_{t-l}$ represents a vector of economic state variables lagged *l* quarters and Y_{t-l} represents the last reported value of the dependent variable at time *t-l*. The lagged economic state variables and lagged dependent variable represent the last published values of these variables available at the end of the quarter in question. Results are reported in Table 5.15.

None of the estimated coefficients on $\Delta\mathrm{EE}^{\mathrm{f}}$, $\Delta\mathrm{EB}^{\mathrm{f}}$ and $\Delta\mathrm{ebeq}^{\mathrm{f}}$ are significant predictors of annual industrial production growth when combined with the economic state variables. Similarly, when GNP growth is employed as the independent variable (results not reported here), none of the forecast earnings measures are found to be statistically significant.[141]

Therefore, aggregated across the full sample set, analysts' forecasts for annual changes in earnings do not exhibit significant information for future industrial production growth nor GNP growth. However, in Section 5.5 I document a relationship between firm size (which may be partially attributed to relative smoothing) and the magnitude of information in analysts' forecasts for future macroeconomic activity. In Section 5.6 I document a relationship between earnings

[140] The selection of economic state variables is identical to that employed in Table 5.14, with the exception of CPI and Dividend Yield. All estimated coefficients on these two variables reported in Table 5.14 were statistically insignificant at the 10% level (in both univariate and multivariate regressions). I have therefore not included these two variables as independent variables in the regressions reported in Tables 5.15 and 5.16.

[141] Results are similar when $\Delta\mathrm{ebmed}^{\mathrm{f}}$ is employed as the forecast earnings measure.

Table 5.15 Industrial production growth regressed on lagged economic state variables and lagged aggregated forecast earnings growth, 1979–2009

Rolling quarters of annual industrial production growth are regressed on a range of economic state variables lagged l quarters. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2 for regressions of the following form:

$$\mathrm{Y}_t = \alpha + \beta_{\Delta\mathrm{E}}\Delta\mathrm{E}^{\mathrm{f}}_{t-l} + \boldsymbol{\beta}_{\mathrm{S}}\mathbf{S}_{t-l} + \beta_{\mathrm{Y}}\mathrm{Y}_{t-l} + \varepsilon_t$$

Y_t represents one year growth in industrial production, $\Delta\mathrm{E}^{\mathrm{f}}_{t-l}$ represents the forecast 1 year change in earnings lagged l quarters, $\mathbf{S}_{t-l}$ represents a vector of economic state variables lagged l quarters and Y_{t-l} represents the last reported value of the dependent variable at time t-l. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

Lag, l (qtrs)	$\Delta\mathrm{EE}^{\mathrm{f}}$	$\Delta\mathrm{EB}^{\mathrm{f}}$	$\Delta\mathrm{ebeq}^{\mathrm{f}}$	ISM PMI	ISM PMI, 12m%	Cons. Sent.	Cons. Sent., 12m%	Term structure	Default spread	Market return, 12m%	Lagged dep.	Adj. R^2
1	0.091	-	-	0.027	**0.038**	0.016	**0.061**	0.060	**-1.187**	**0.022**	**0.560**	0.912
	(1.540)			(0.537)	(4.228)	(1.035)	(3.614)	(0.478)	(-2.943)	(1.950)	(9.029)	
		0.402	-	0.028	**0.042**	0.014	**0.059**	0.137	**-1.146**	**0.024**	**0.578**	0.909
		(1.315)		(0.512)	(5.185)	(0.866)	(3.182)	(1.231)	(-2.702)	(2.219)	(9.265)	
	-	-	0.477	0.025	**0.041**	0.011	**0.060**	0.079	**-1.097**	**0.023**	**0.578**	0.909
			(1.061)	(0.453)	(4.334)	(0.728)	(3.570)	(0.580)	(-2.404)	(2.141)	(7.806)	
2	0.089		-	0.051	0.025	0.031	**0.078**	0.367	**-1.461**	**0.057**	**0.251**	0.765
	(0.960)			(0.461)	(0.904)	(1.127)	(2.398)	(1.500)	(-2.337)	(2.832)	(2.127)	
	-	0.424	-	0.051	0.028	0.029	**0.076**	**0.441**	**-1.409**	**0.059**	**0.267**	0.763
		(0.843)		(0.441)	(1.010)	(1.066)	(2.257)	(2.088)	(-2.237)	(2.912)	(2.207)	
	-	-	0.564	0.050	0.027	0.025	**0.077**	0.372	**-1.351**	**0.057**	**0.262**	0.764
			(0.713)	(0.410)	(0.852)	(0.919)	(2.392)	(1.435)	(-1.924)	(3.047)	(1.768)	
3	0.053		-	0.013	0.030	0.062	0.071	0.546	-1.416	**0.070**	-0.024	0.575
	(0.313)			(0.088)	(0.969)	(1.187)	(1.326)	(1.287)	(-1.457)	(3.213)	(-0.145)	
	-	0.139	-	0.010	0.034	0.062	0.070	**0.590**	-1.393	**0.072**	-0.003	0.574
		(0.165)		(0.065)	(1.091)	(1.159)	(1.267)	(1.736)	(-1.389)	(3.024)	(-0.018)	
	-	-	0.488	0.017	0.029	0.057	0.071	0.529	-1.331	**0.069**	-0.031	0.576
			(0.442)	(0.106)	(0.898)	(1.125)	(1.306)	(1.257)	(-1.228)	(2.997)	(-0.178)	
4	0.052		-	-0.128	0.018	0.067	0.077	**0.898**	-1.624	**0.078**	-0.120	0.431
	(0.367)			(-1.088)	(0.573)	(0.981)	(1.208)	(2.049)	(-1.448)	(3.726)	(-0.752)	
	-	0.051	-	-0.134	0.022	0.068	0.075	**0.942**	-1.584	**0.080**	-0.092	0.430
		(0.061)		(-1.209)	(0.874)	(1.032)	(1.180)	(2.696)	(-1.368)	(3.626)	(-0.670)	
	-	-	0.845	-0.118	0.013	0.057	0.078	**0.837**	-1.516	**0.074**	-0.154	0.436
			(0.827)	(-1.047)	(0.453)	(0.933)	(1.225)	(1.908)	(-1.273)	(3.627)	(-1.025)	

cyclicality and the magnitude of information in analysts' forecasts for future macroeconomic activity. Combining these results, I provide evidence that the aggregated forecast changes in earnings for small cyclical firms contain more information for future macroeconomic activity than the aggregated forecast changes in earnings for large cyclical firms.

Repeating regressions based on equation 5.6 for the aggregated forecast changes in earnings for size quintiles of the high cyclicality firms (as defined in Section 5.6) I find evidence of statistically significant *marginal* information for small cyclical firms. In Table 5.16, for all three earnings forecast measures, the estimated coefficients on forecast earnings for the smallest stocks (quintile 5) are statistically significant at the 10% level or higher.

Thus, having established links between the predictive power of earnings forecasts for future macroeconomic activity and cyclicality (and size portfolios within cyclicals), I highlight a portfolio with statistically significant *marginal* explanatory power for one year-ahead industrial production growth, even in combination with a range of economic state variables. While the increases in regression R^2s over those for regressions with economic state variables alone is rather small, this research indicates that aggregated analysts' forecasts contain new information for the prediction of future industrial production growth.

Table 5.16 Industrial production growth regressed on lagged aggregated forecast earnings (size quintiles of cyclical stocks) and economic state variables, 1979–2009

Rolling quarters of annual industrial production growth are regressed on 4 quarter lagged earnings forecasts for cyclical stocks in size quintiles, and a range of economic state variables. Results provided are estimated slope coefficients, β_t, t ratios (in parentheses) and adjusted R^2 for univariate regressions of the following form:

$$\mathrm{Y}_t = \alpha + \beta_{\Delta\mathrm{E}}\Delta\mathrm{E}^{\mathrm{f}}_{t-4} + \boldsymbol{\beta}_{\mathrm{S}}\mathbf{S}_{t-4} + \beta_{\mathrm{Y}}\mathrm{Y}_{t-4} + \varepsilon_t$$

Y_t represents one year growth in industrial production, $\Delta\mathrm{E}^{\mathrm{f}}_{t-4}$ represents the forecast 1 year change in earnings lagged 4 quarters, $\mathbf{S}_{t-4}$ represents a vector of economic state variables lagged 4 quarters and Y_{t-4} represents the last reported value of the dependent variable at time t-4. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

Q1 (large)	Q2	Q3	Q4	Q5 (small)	ISM PMI	ISM PMI, 12m%	Cons. Sent.	Cons. Sent., 12m%	Term structure	Default spread	Market return, 12m%	Lagged dep.	Adj. R^2
A. Regressions for ΔEB^f for size quintiles of cyclical stocks													
0.006	-	-	-	-	-0.147	0.023	0.075	0.079	**0.957**	-1.582	**0.078**	-0.105	0.435
(0.008)					(-1.146)	(0.813)	(1.008)	(1.064)	(2.310)	(-1.369)	(3.654)	(-0.565)	
-	0.437	-	-	-	-0.140	0.014	0.072	0.076	0.833	**-1.724**	**0.073**	-0.161	0.439
	(0.504)				(-1.115)	(0.514)	(0.883)	(1.000)	(1.603)	(-1.679)	(3.451)	(-0.820)	
-	-	**0.966**	-	-	-0.127	0.004	0.075	0.064	**0.721**	-1.499	**0.068**	-0.202	0.464
		(1.664)			(-0.986)	(0.129)	(1.009)	(1.015)	(1.703)	(-1.258)	(3.321)	(-1.216)	
-	-	-	0.806	-	-0.124	0.009	0.081	0.071	0.680	-1.703	**0.065**	-0.221	0.458
			(1.506)		(-1.056)	(0.294)	(1.024)	(1.040)	(1.535)	(-1.398)	(2.939)	(-1.203)	
-	-	-	-	**1.034**	-0.149	0.002	0.045	0.091	**0.680**	**-2.374**	**0.069**	-0.181	0.479
				(2.171)	(-1.274)	(0.070)	(0.751)	(1.449)	(1.973)	(-1.886)	(3.719)	(-1.139)	
B. Regressions for $\Delta ebeq^f$ for size quintiles of cyclical stocks													
-0.713	-	-	-	-	-0.161	0.036	0.088	0.075	**1.005**	-1.512	**0.090**	0.029	0.449
(-0.664)					(-1.304)	(1.307)	(1.314)	(1.115)	(2.859)	(-1.273)	(3.477)	(0.129)	
-	0.506	-	-	-	-0.125	0.012	0.069	0.079	0.829	-1.551	**0.070**	-0.180	0.442
	(0.639)				(-0.969)	(0.445)	(0.883)	(1.105)	(1.588)	(-1.385)	(3.246)	(-0.915)	
-	-	0.696	-	-	-0.133	0.010	0.067	0.073	**0.834**	-1.524	**0.072**	-0.184	0.450
		(1.235)			(-1.062)	(0.323)	(0.919)	(1.110)	(1.906)	(-1.329)	(3.596)	(-1.165)	
-	-	-	0.695	-	-0.127	0.011	0.075	0.075	**0.769**	-1.558	**0.068**	-0.188	0.450
			(1.553)		(-1.072)	(0.403)	(1.043)	(1.106)	(1.883)	(-1.301)	(3.239)	(-1.180)	
-	-	-	-	**0.889**	-0.163	0.005	0.045	0.094	**0.761**	-1.809	**0.074**	-0.123	0.458
				(1.805)	(-1.346)	(0.171)	(0.724)	(1.404)	(2.304)	(-1.521)	(3.812)	(-0.869)	

Table continues overleaf

Table 5.16 Industrial production growth regressed on lagged aggregated forecast earnings (size quintiles of cyclical stocks) and economic state variables, 1979–2009

Table continued from previous page

C. Regressions for $\Delta ebmed^f$ for size quintiles of cyclical stocks

Q1 (large)	Q2	Q3	Q4	Q5 (small)	ISM PMI	ISM PMI, 12m%	Cons. Sent.	Cons. Sent., 12m%	Term structure	Default spread	Market return, 12m%	Lagged dep.	Adj. R^2
-0.438	-	-	-	-	-0.149	0.029	0.083	0.079	**0.961**	-1.403	**0.081**	-0.056	0.437
(-0.277)					(-1.170)	(1.001)	(1.197)	(1.100)	(2.536)	(-1.300)	(3.816)	(-0.259)	
-	0.653	-	-	-	-0.120	0.013	0.069	0.071	**0.908**	-1.679	**0.074**	-0.182	0.440
	(0.698)				(-0.940)	(0.485)	(0.916)	(0.952)	(2.074)	(-1.614)	(3.662)	(-1.012)	
-	-	1.072	-	-	-0.112	0.007	0.072	0.062	**0.907**	-1.731	**0.069**	-0.230	0.450
		(1.246)			(-0.923)	(0.265)	(0.978)	(0.955)	(2.384)	(-1.563)	(3.425)	(-1.455)	
-	-	-	0.975	-	-0.119	0.015	0.083	0.059	**0.797**	-1.664	**0.071**	-0.213	0.448
			(0.142)		(-0.973)	(0.469)	(0.996)	(0.882)	(1.759)	(-1.406)	(3.317)	(-1.058)	
-	-	-	-	**1.642**	-0.159	0.009	0.053	0.068	**0.734**	**-2.393**	**0.068**	-0.220	0.480
				(2.980)	(-1.380)	(0.328)	(0.815)	(1.022)	(2.181)	(-1.946)	(3.489)	(-1.332)	

5.9 Concluding remarks

THE PRINCIPAL FOCUS of this chapter is the investigation of information in aggregated analysts' earnings forecasts for measures of future macroeconomic growth (in particular, future industrial production growth). Firstly, I provide evidence supporting the two key precursors to an expectation of significant macroeconomic information in analysts' forecasts. That is, I provide evidence of a statistically significant positive relationship between aggregated realized earnings and contemporaneous macroeconomic growth, and, evidence of information in aggregated forecasts for future realized earnings. Combined, these results drive the core hypothesis of significant information in aggregated forecasts for future macroeconomic growth. Indeed, for a selection of measures of aggregated earnings forecasts I find statistically significant information for annual industrial production growth up to six quarters ahead.

I also hypothesize that the stronger the relationship between realized earnings and contemporaneous macroeconomic growth, the stronger the relationship between analysts' earnings forecasts and future macroeconomic growth. By grouping stocks into portfolios based on the relative cyclicality of realized earnings I provide evidence supporting this hypothesis. In addition, I hypothesize variation in the information in aggregated forecasts for future macroeconomic activity across portfolios conditioned on income smoothing. I find evidence supporting the notion of reduced macroeconomic information in the earnings forecasts of high smoothers relative to low smoothers. I also provide evidence of a positive relationship between firm size and smoothing, although results suggest size may also be proxying for additional drivers of systematic variation in the informativeness of aggregated analysts' forecasts.

Combining these effects, I find evidence of significantly less macroeconomic information in the forecasts of large cyclicals relative to small cyclicals. I also provide evidence of regime-dependent differences in this effect, including results consistent with greater income smoothing by large cyclicals in economic downturns, relative to small cyclicals. Further, reported results suggest that income smoothing by large cyclicals in economic downturns is of sufficient magnitude to result in a significant *negative* relationship between forecast changes in earnings and future industrial production growth. However, relative smoothing is only a partial explanation for size-related differences in the informativeness of aggregated forecasts for future industrial production growth.

When a range of lagged macroeconomic state factors are included as additional independent variables in regressions estimating the information in aggregated forecasts for future macroeconomic activity, analysts' earnings forecasts do not exhibit significant marginal explanatory power. However, analysts' earnings forecasts are at an informational disadvantage to economic state variables available to economic agents at the end of each quarter. Consequently, it should not be surprising to see that, for the aggregate market, I do not find evidence of statistically significant marginal information in analysts' earnings forecasts for future macroeconomic growth.[142]

Nonetheless, employing results presented in Sections 5.5 (for the hypothesis that the magnitude of macroeconomic information in analysts' forecasts is related to income smoothing and firm size) and 5.6 (for the hypothesis that the magnitude of macroeconomic information is related to the cyclicality of realized earnings), I find that the aggregated forecasts of small cyclical companies do have statistically

[142] Although it is interesting to note that the outlook for future macroeconomic growth implicit in analysts' earnings forecasts appears to provide more information than economists' explicit forecasts for macroeconomic growth (see Appendix 5A).

significant marginal explanatory power for one year-ahead industrial production growth, even in combination with a selection of economic state variables.

Evidence of statistically significant information in aggregated analysts' earnings forecasts for future GNP and industrial production growth highlights the important (albeit often implicit) role of macroeconomic views as components of analysts' forecasts. In Chapter 6 I investigate the extent to which available macroeconomic information is incorporated in earnings forecasts, and consequently the extent to which forecast revisions are predictable with a selection of economic state variables.

Appendix 5A Analysts versus economists

EQUITY ANALYSTS' EARNINGS forecasts contain an imputed assessment of the macroeconomic outlook over the forecast horizon, and analysts' views on the impact of the macroeconomic outlook on firm profitability. The macroeconomic outlook therefore represents an *implicit* component of the overall forecasting process (one I attempt to elucidate by aggregating forecasts). Conversely, economists *explicitly* forecast each of the three measures of macroeconomic activity employed in this chapter. The formulation of aggregated analysts' earnings forecasts provides an opportunity to compare the relative ability of analysts and economists to explain variation in macroeconomic activity.

Employing consensus forecasts from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters, evaluations of the forecast accuracy of economists commonly focus on the root mean square error for point predictions. A recent example is provided by Stark (2010), who notes that estimation of forecast accuracy is made problematic by large revisions to historic series of realized economic data. I use the four quarter change in median economists' point predictions for the economic variable in question, starting from the prediction for the end of the survey quarter. This means the start and end points for the measurement of forecast change are based upon the same start and end points for the economic variable. In addition, with a final data point for the realized macroeconomic variables of December 2009, I can be confident of little change to annual growth results from revisions dated after publication of this research.

Stark (2010), evaluating quarter-on-quarter real GNP/GDP growth[143] from 1985 through to 2007, finds that economists' forecast accuracy deteriorates rapidly

[143] Consensus economists' forecasts for GNP/GDP undergo definitional changes during the period evaluated. Prior to 1992 the time series of economists' forecasts reflects expectations

moving beyond one quarter ahead forecasts.[144] McNees (1992) compares nine sources of consensus economists' forecasts, and a wide range of economic variables, and similarly finds evidence of a general trend towards deteriorating accuracy as the forecast horizon lengthens. However, McNees (1992) also notes that this trend can reverse for very long forecast time periods given long term mean reversion in many indicators of economic growth.

The focus of my research is not specifically forecast accuracy, but rather the ability of analysts' forecasts to explain future variation in macroeconomic activity. Baghestani and Kianian (1993) provide a related evaluation of economists' GNP forecasts from the Survey of Professional Forecasters for the 10 years to June 1991. In a regression of the level of realized GNP on four-quarter-ahead forecast GNP, lagged four quarters, they report a strongly significant slope coefficient. I perform a similar regression for four quarter growth in GNP (and forecast growth in GNP), combined with equity analysts' earnings forecasts. This is then repeated for economists' forecasts for growth in industrial production and corporate profits.

Table 5A.1 provides summary results of four regressions for each of the four measures of economic activity from March 1979 through to December 2009. Each macroeconomic growth indicator is regressed on the combination of a measure of

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for GNP growth. After this date survey responses reflect expectations for GDP growth. Similarly, surveyed expectations for corporate profits undergo definitional change from corporate profits after tax *excluding* inventory valuation adjustments and capital consumption adjustments to corporate profits after tax *including* valuation adjustments and capital consumption adjustments.

[144] Stark (2010) reports a root mean squared forecast error of 1.40% for quarter on quarter GNP/GDP growth for the current quarter forecast, increasing to 1.65%, 1.76% and 1.81% for one, two and three quarters-ahead forecasts, respectively.

Table 5A.1 Macroeconomic growth regressed on 4 quarter lagged aggregated earnings growth forecasts and 4 quarter lagged macroeconomic growth forecasts, 1979–2009

Rolling quarters of annual macroeconomic growth measures are regressed on aggregated forecast annual earnings changes lagged 4 quarters and the last reported consensus economists' forecast for the macroeconomic variable in question at time *t*-4. Forecast earnings changes are based on a proxy measure of four quarter forward earnings forecasts less four quarter trailing earnings, and are deflated by earnings (E) or book value (B). Lower case earnings measures refer to per-share aggregations. Results provided are estimated slope coefficients, $\hat{\beta}$, *t* ratios (in parentheses) and adjusted R^2 for regressions of the following form:

$$\mathrm{Y}_t = \alpha + \beta_{\Delta\mathrm{E}}\Delta\mathrm{E}^{\mathrm{f}}_{t-4} + \beta_{\mathrm{Y}}\hat{\mathrm{Y}}_{t-4} + \varepsilon_t$$

Y_t represents one year growth in a macroeconomic activity variable, $\Delta\mathrm{E}^{\mathrm{f}}_{t-4}$ represents the forecast 1 year change in earnings lagged 4 quarters and $\hat{\mathrm{Y}}_{t-4}$ represents the most recent consensus economists' one year-ahead forecast for the macroeconomic variable in question as at time *t*-4. Newey-West standard errors with automatic bandwidth selection are employed to calculate *t* ratios. Results in bold are statistically significant at the 10% level.

Independent variable	Analysts' forecasts, $\hat{\beta}_{\Delta\mathrm{E}}$				Economists' forecasts, $\hat{\beta}_{\mathrm{Y}}$				Adj. R^2			
	(1) $\Delta\mathrm{EE}^{\mathrm{f}}$	(2) $\Delta\mathrm{EB}^{\mathrm{f}}$	(3) $\Delta\mathrm{ebeq}^{\mathrm{f}}$	(4) $\Delta\mathrm{ebmed}^{\mathrm{f}}$	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
GNP*	0.105	0.589	0.763	1.202	0.634	0.663	0.688	0.610	0.247	0.241	0.254	0.259
	(1.168)	(0.853)	(0.813)	(0.732)	(1.028)	(1.054)	(1.149)	(1.068)				
Profits*	-0.198	-4.843	3.152	0.751	0.651	0.587	0.619	0.626	0.036	0.065	0.047	0.034
	(-0.183)	(-0.938)	(0.487)	(0.060)	(1.071)	(1.014)	(1.005)	(0.982)				
IP	**0.296**	**1.614**	**2.719**	**4.208**	0.513	0.625	0.422	0.261	0.138	0.118	0.214	0.220
	(3.105)	(2.024)	(2.400)	(2.387)	(0.755)	(0.865)	(0.635)	(0.389)				

* Consensus economists' forecasts for these variables undergo definitional changes during the period evaluated. Prior to 1992 the time series of economists' forecasts reflected expectations for GNP growth. After this date survey responses reflect expectations for GDP growth. Similarly, prior to the first quarter of 2006 economists' forecasts for corporate profits represent expectations for corporate profits excluding inventory valuation and capital consumption adjustments. After this date survey expectations are for corporate profits including inventory valuation and capital consumption adjustments. The time series for realized GNP and corporate profits have been adjusted accordingly so that they represent the variable being forecast by economists at each point in time.

aggregated analysts' earnings forecasts, and economists' forecasts for that macroeconomic variable.[145] Regressions are hence of the following form:

$$\mathrm{Y}_t = \alpha + \beta_{\Delta\mathrm{E}}\Delta\mathrm{E}^{\mathrm{f}}_{t-4} + \beta_{\mathrm{Y}}\widehat{\mathrm{Y}}_{t-4} + \varepsilon_t \tag{5A.1}$$

Where Y_t represents one year growth in a macroeconomic activity variable, $\Delta\mathrm{E}^{\mathrm{f}}_{t-4}$ represents the forecast one year change in earnings lagged four quarters and $\widehat{\mathrm{Y}}_{t-4}$ represents the most recent consensus economists' one year-ahead forecast for the macroeconomic variable in question as at time t-4. Importantly, the dependent variable exactly matches the definition of the variable forecast by economists. This necessitates changes in the definition of GNP and corporate profits during the time period evaluated due to definitional changes in economists' forecasts in the Survey of Professional Forecasters. Consequently, this test of relative explanatory power is designed to be as fair as possible to economists. On that point, economists are surveyed by the Federal Reserve Bank of Philadelphia in the middle of each calendar quarter. However, equity analysts' forecasts date from the Thursday before the third Friday of each month. Hence, in terms of sampling data, analysts have a roughly four to five week advantage over economists. In reality the information sets available to economists and equity analysts will be more similar than the survey dates suggest. This is because consensus analysts' earnings forecasts represent the combination of individual analysts' submissions to I/B/E/S over a period encompassing multiple months prior to the survey date.

In Table 5A.1 I report no evidence of statistically significant explanatory power in equity analysts' earnings forecasts, nor in economists' forecasts, for GNP and corporate profit growth (four quarters ahead). However, the estimated coefficients on $\Delta\mathrm{EE}^{\mathrm{f}}$, $\Delta\mathrm{EB}^{\mathrm{f}}$, $\Delta\mathrm{ebeq}^{\mathrm{f}}$ and $\Delta\mathrm{ebmed}^{\mathrm{f}}$ are all significant, while estimated coefficients

[145] Median economists' forecasts for the current quarter and four quarters ahead are employed to generate annual growth forecasts, on a rolling quarterly basis, for the economic variable in question.

on economists' forecasts are all insignificant, for future industrial production growth.

Hence, these results provide evidence that the *implicit* forecasts of industrial production growth in aggregated equity analysts' earnings forecasts provide *more* information for future industrial production growth than economists' *explicit* forecasts of industrial production growth.

6 The efficiency of aggregated earnings revisions

6.1 Introductory concepts

IN CHAPTER 5 I evaluate relationships between analysts' earnings forecasts and a range of future economic state variables. Underlying the central hypothesis of the chapter is an expectation that analysts either explicitly or implicitly incorporate macroeconomic forecasts in their published earnings expectations. Those macroeconomic forecasts (and analysts' expectations of their impact on company profits) should incorporate information in historic realized macroeconomic variables. If historic macroeconomic conditions are fully reflected in analysts' earnings expectations, then their forecast errors will be uncorrelated with past macroeconomic variables. Conversely, if analysts' earnings forecasts are not fully efficient with respect to historic macroeconomic variables then systematic errors in earnings forecasts will be evident, resulting in predictable earnings revisions. However, the extent to which analysts incorporate macroeconomic information in earnings forecasts is poorly understood. Basu, Markov and Shivakumar (2010) support that observation:

> Despite the fact that half of the variation in firms' earnings (for example, Brown and Ball (1967)) is driven by macroeconomic factors, and analysts often discuss the relation between inflation and future earnings in their research reports, prior literature on analysts' forecasts has largely ignored these issues, limiting our understanding of how earnings expectations are formed. (p. 405)

The focus of this chapter is analysis of the efficiency of aggregated analysts' forecasts with respect to a range of economic state variables, and identification of implications of earnings revision predictability for return predictability. In particular, I investigate in detail the efficiency of analysts' earnings forecasts with respect to the Institute of Supply Management's (ISM) Purchasing Managers' Index (PMI) – an important leading indicator of US economic activity, but one which has received little attention from academic researchers evaluating analyst efficiency.[146]

Anecdotally, the ISM PMI is considered a key variable by market practitioners as not only an indicator of manufacturing activity, but as a lead indicator for the direction of economic output for the wider macroeconomy. A number of academic researchers have reported findings consistent with the ISM PMI as a lead indicator.[147] Others have consequently evaluated the use of the ISM PMI as a

[146] Key examples of analyses of relationships between analysts' forecasts and macroeconomic variables are Hunter and Ackert (1993), Ackert and Hunter (1995), De Zwart and Van Dijk (2008), Hess and Kreutzmann (2009) and Basu, Markov and Shivakumar (2010). Of these, only one (Hess and Kreutzmann (2009)) includes evaluation of the relationship between earnings revisions and the ISM PMI. Hess and Kreutzmann perform an event study analyzing the response of forecast revisions to surprise in macroeconomic announcements.

[147] Examples include Klein and Moore (1988), Harris (1991) and Koenig (2002).

valuable tool for management in the strategic planning process.[148] Hence, there is considerable motivation for expecting that analysts should recognize the importance of the ISM PMI as an indicator of economic activity, and will incorporate an assessment of its impact on company profitability into the earnings forecasting process.

I regress time series of aggregated four quarter earnings revisions on lagged values of macroeconomic variables.[149] Given the importance placed on the ISM PMI by practitioners in particular (discussed in Section 6.4) it is therefore surprising to find evidence of systematic underreaction by analysts to the ISM PMI. More surprising still, the R^2s for simple univariate regressions of aggregated annual earnings revisions on lagged values of the ISM PMI (values available to analysts prior to the start of the revision periods) are high: ranging from 0.208 to 0.311 for the period 1979–2009, depending on aggregation methodology and variable deflator. Underreaction to the ISM PMI is robust to portfolio formation on the basis of firm size, book-to market ratios and analyst coverage. I also find evidence of systematic underreaction by analysts to lagged values of the default spread (defined as the difference between the Mooody's seasoned Baa-rated corporate bond yield and the Moody's seasoned Aaa-rated corporate bond yield).

I find evidence of significant variation in the efficiency of analysts' forecasts with respect to the ISM PMI across Global Industry Classification Standards (GICS) sectors and the Fama-French 49 industries.[150] Evidence is also presented of a significant relationship between aggregate earnings revisions and future market returns (in particular, over a return horizon of three to six months). I combine systematic variation in the relationship between industry earnings revisions and

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[148] Examples include Kauffman (1999) and Lindsey and Pavur (2005).

[149] Construction of the aggregated earnings revision variables is as per the methodology outlined in Chapter 3, with summary statistics provided in Chapter 4.

[150] The Fama-French industry classification is derived from Fama and French (1997).

select lagged macroeconomic and earnings variables, with a significant relationship between revisions and future three month returns, to analyze aggregate industry return predictability with aggregated industry predicted earnings revisions. Lagged values of macroeconomic and earnings variables are employed to generate fitted earnings revisions for Fama-French industries. Industries are then divided into deciles on the basis of ranked predicted revisions. Decile portfolio returns are measured over the following quarter, and the process repeated each quarter for new predicted revisions and re-balanced portfolios. I find evidence of a statistically significant positive return (both in terms of simple-average and risk-adjusted returns) for decile 10 returns (high predicted revisions) less decile 1 returns (low predicted revisions). I obtain an average quarterly equally-weighted return of 2.645% (2.333% value-weighted) for portfolios long decile 10 and short decile 1 for the period 1979–2009. The average quarterly equally-weighted risk-adjusted return (from the Fama-French three factor model) for this long-short strategy is 2.861% (2.575% value-weighted).

In Section 6.2 I provide an overview of related research on analyst efficiency. In Section 6.3 I outline the research framework and implications for interpretation of results from an evaluation of efficiency at the aggregate market level, compared with the stock or individual analyst level. In Section 6.4 I discuss the history, derivation and importance of the ISM PMI as an indicator of economic activity. Section 6.5 provides results from regressions of aggregated earnings revisions on economic state variables. Robustness tests evaluating the consistency of the relationship between earnings revisions and the ISM PMI are provided in Section 6.6, including investigation of efficiency for size-based portfolios, book-to-market portfolios, relative analyst coverage, economic regimes, sectors and industries. Section 6.7 investigates the relationship between aggregated revisions (and predicted revisions) and returns, resulting in a long-short strategy based on predicted industry-level revisions, and concluding remarks are provided in Section 6.8. In the appendix to the chapter I investigate whether results may be adversely impacted by I/B/E/S summary data collation procedures.

6.2 Analyst efficiency

AS OUTLINED IN Chapter 2, evaluations of the efficiency of analysts' earnings forecasts typically involve the regression of forecast errors on variables representing members of the information set available to analysts when forecasts are made. The null hypothesis of forecast efficiency is evaluated with tests of the statistical significance of the estimated coefficients on the variables in the information set.

My focus is the efficiency of analysts' forecasts with respect to macroeconomic variables. Examples of related research on this issue include Hunter and Ackert (1993), Ackert and Hunter (1995), Hughes, Liu and Su (2008), De Zwart and Van Dijk (2008), Hess and Kreutzmann (2009), Aiolfi, Rodriguez and Timmermann (2010) and Basu, Markov and Shivakumar (2010).

Hunter and Ackert (1993) find evidence of time series dependence in the residuals from regressions of forecast errors on lagged forecast errors. They note that this may be the result of business cycle effects, but the explanation remains untested until Ackert and Hunter (1995). They regress quarterly I/B/E/S consensus forecast errors (1984–1990) on lagged forecast errors, lagged realized earnings and a set of realized macroeconomic variables published prior to the sampling date for analysts' forecasts. Amongst the macroeconomic variables examined, they find evidence against analyst efficiency only in respect of quarterly percentage changes in GNP. Basu, Markov and Shivakumar (2010) apply a portfolio approach to the question of analyst forecast efficiency, almost exclusively devoted to efficiency with respect to inflation. They find evidence of cross-sectional variation in the reaction of earnings to inflation which is not fully accounted for by analysts in their earnings forecasts. Consequently, Basu et al. find evidence of predictability in analysts' forecast errors and evidence of a relationship between predicted forecast errors and stock returns.[151]

Despite reporting evidence of predictability of forecast errors, Hughes, Liu and Su (2008) find evidence that "the predictability of analysts' forecast errors does not directly translate into profitable trading strategies; rather the predictable component of analysts' forecast errors is largely unrelated to future abnormal returns" (p. 268). Hughes et al. regress forecast errors on factors including firm size, analyst coverage, accruals, long term growth forecasts, changes in assets, lagged earnings surprise and past stock returns. They find statistically significant relationships between forecast errors and a number of these variables, thus identifying forms of analyst inefficiency. However, upon forming quintile portfolios based on sorts of predicted revisions they report no evidence of a statistically significant difference between quintile 1 and quintile 5 portfolio average returns (for returns both 4 and 13 months after portfolio formation). They conclude their result implies "that the independent element in the predictable component of analyst forecast errors is large relative to the common element, and since this independent element has little to do with the predictable component of market returns, it becomes a source of noise that biases the test toward the null"[152] (p.

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[151] However, they do not employ lagged inflation to predict forecast errors and then investigate the relationship between predicted errors and future stock returns. Instead they note that the ability of expected inflation proxies to explain future returns decreases when forecast errors for a portfolio long in stocks with high positive exposure of earnings to inflation and short in stocks with low negative exposure to inflation are included as additional explanatory variables. They conclude this implies that the inflation-based errors made by investors are partially the result of relying on analysts' forecasts that contain inflation-based errors.

[152] Hughes, Liu and Su (2008) present a framework in which both analysts and the market form earnings expectations. The common element refers to the error common to both

287). This notion suggests an explanation for the difference between their results and my own. By generating value-weighted aggregate revisions and returns across industries I may be decreasing the independent element in the predictable component of revisions, relative to the common element, through diversification.

De Zwart and Van Dijk (2008) regress six month forecast errors on consensus economists' forecasts of GDP growth and inflation growth (matched to the earnings forecast period), within emerging market economies. However, by employing economists' forecasts rather than realized macroeconomic data their work raises two problematic issues. Firstly, it is not clear from their variable construction techniques that the economists' forecasts represent a dataset available to analysts at the date that they publish their earnings forecasts. Hence, a significant estimated coefficient on a macroeconomic forecast may not represent evidence of analyst forecast inefficiency. It may be a result of variation in the information sets available to economists and financial analysts when their respective forecasts are recorded. Secondly, De Zwart and Van Dijk (2008) do acknowledge the problem of macroeconomic forecast accuracy. If macroeconomic forecasts contain no useful information there would be no reason for analysts to incorporate the data in their earnings forecasts.[153] De Zwart and Van Dijk (2008) provide evidence of strong and statistically significant relationships between macroeconomic forecasts and consequent macroeconomic variable realizations. They therefore state that "From this we conclude that the quality of the macroeconomic forecast is good enough to use in our analysis" (p. 12). However, this nonetheless introduces an additional

analysts and the market, while independent errors are also made by analysts and the market.

[153] In the appendix to Chapter 5, investigating the information in both aggregated analysts' earnings forecasts and consensus economists' forecasts for GNP growth, industrial production growth and corporate profit growth, I provide evidence of no statistically significant information in US consensus economists' year-ahead forecasts.

error source and complicates the process of drawing conclusions from regression results.

Hess and Kreutzmann (2009) provide an event study, measuring the relationship between analysts' earnings forecast revisions and announcement surprise for key macroeconomic variables.[154] They find evidence of a significant relationship between earnings revisions and macroeconomic news (as measured by the difference between economists' expectations and actual realized values) for industrial production, consumer confidence and the ISM PMI. The significant result for the ISM PMI is particularly important in light of results presented in this chapter. It provides evidence of analysts' explicitly recognizing and reacting to this variable (or at least reacting to information correlated with the ISM PMI). Aiolfi, Rodriguez and Timmermann (2010) also investigate the relationship between earnings revisions and select economic state variables (stock returns, return volatility and Treasury bill yields), but do so in a three-state regime switching time series model. Some caution is warranted interpreting their results given they limit their analysis to stocks in the Dow Jones 30 index. Nonetheless, they report evidence of predictability of the direction of revisions with lagged Treasury bill yields.

In comparison with previous research I add to the body of knowledge regarding the efficiency of analysts' forecasts in the following manner:

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[154] Their dataset comprises S&P 500 firms, a sample period extending from March 1982 through to December 2007 and results summarized for an event window ranging from two to eight weeks after the macroeconomic announcement. They note that by restricting the sample set to S&P 500 firms they may be biasing expected results in favour of finding a significant relationship between macroeconomic announcements and earnings revisions given evidence of size-related asymmetry in the reaction of stock returns to macroeconomic news (for example, Cenesizoglu (2008) reports evidence of large growth stock returns reacting more to certain forms of economic news than small value stocks). Note that, in the interests of consistency with empirical analysis in Chapters 5 and 6, I employ time series analysis rather than an event study (in contrast with the approach adopted by Hess and Kreutzmann (2009)). Having reported in an event study evidence of analysts revising earnings in response to macroeconomic news, Hess and Kreutzmann's results are employed here as motivation for investigating whether analysts *efficiently* process macroeconomic information.

1. This research provides the first evaluation of analyst efficiency at the aggregate market level. Kothari, Lewellen and Warner (2006) provide results demonstrating the potential for stock-level relationships to differ markedly at the aggregate level.
2. This research provides time series analysis of the relationship between aggregate earnings revisions and a wide range of macroeconomic variables available to analysts when compiling their forecasts.
3. This research represents the first examination of forecast efficiency with respect to macroeconomic data over annual timeframes. Previous studies commonly evaluate quarterly periods. This research therefore evaluates whether analysts are able to fully incorporate the implications of longer term trend information in macroeconomic data, rather than shorter term variation.
4. Some aspects of methodology are similar to those employed by De Zwart and Van Dijk (2008). However, I employ US data (rather than emerging markets data) and realized macroeconomic data (rather than economists' forecasts). By ensuring that the macroeconomic data was available to analysts prior to the submission of their earnings forecasts, I can confidently evaluate efficiency with respect to that data, and avoid the additional ambiguities presented by economists' forecasts.
5. I also investigate the ability of industry-based variation in the predictability of earnings revisions to explain future stock returns.

6.3 Research framework

INVESTIGATION OF AGGREGATE, rather than stock- or analyst-level, efficiency has important implications for the interpretation of results. It can be shown that rejection of the null hypothesis of forecast efficiency at the aggregate market level also provides strong evidence against the null hypothesis of forecast efficiency at the individual stock and individual analyst levels. Conversely, the methodology employed does not impose an expectation of forecast efficiency at the stock and analyst level in order to evaluate the null hypothesis of forecast efficiency at the aggregate market level.

Specifically, I evaluate forecast efficiency with respect to members of the information set available to analysts prior to forecast submission in regressions of the following general form:

$$\Delta \mathrm{E}^{\mathrm{r}}_{t-1\to t} = \alpha + \boldsymbol{\beta}' \boldsymbol{\Phi}_{t-1} + \varepsilon_t \tag{6.1}$$

Where $\Delta \mathrm{E}^{\mathrm{r}}_{t-1\to t}$ represents the revision of earnings from period t-1 to t and $\boldsymbol{\Phi}_{t-1}$ represents a vector of variables comprising the information set available to analysts at time t-1.[155]

The null hypothesis of forecast efficiency requires $\mathrm{E}(\varepsilon_t | \boldsymbol{\Phi}_{t-1}) = 0$, and therefore testing the statistical significance of $\boldsymbol{\beta}$. Applying this to individual analysts, i, a stock-level version of equation 6.1 can be constructed from a weighted sum over analysts, with some weighting scheme, w_i:

$$\sum_{i=1}^{N_i} w_i \Delta \mathrm{E}^{\mathrm{r}}_{i,t-1\to t} = \sum_{i=1}^{N_i} w_i \alpha_i + \sum_{i=1}^{N_i} w_i\, \boldsymbol{\beta}'_{\boldsymbol{i}} \boldsymbol{\Phi}_{t-1} + \sum_{i=1}^{N_i} w_i \varepsilon_{i,t} \tag{6.2}$$

N_i represents the number of eligible analyst forecasts for the stock in question. Assuming $\mathrm{E}(\varepsilon_{i,t} | \boldsymbol{\Phi}_{t-1}) = 0$, then $\sum_{i=1}^{N_i} w_{\boldsymbol{i}}\, \mathrm{E}(\varepsilon_{i,t} | \boldsymbol{\Phi}_{t-1}) = 0$ for all potential w_i.

[155] For simplicity it is assumed that analysts do not have private information. Ackert and Hunter (1995) demonstrate how relaxation of this assumption does not change the evaluation procedure. It is also assumed that all analysts have access to the same information set, which requires all analysts submit forecasts at the same time. In practice this is clearly not the case. Nonetheless, the sensitivity of research conclusions to this assumption is investigated in robustness tests on the length of the eligibility period for submitted forecasts (Appendix 6A). I do not find evidence that the conclusions of this research are materially impacted by differences in forecast submission dates. However, there is presumably a threshold point past which widening of the eligibility period for forecasts means that the information sets available to analysts are unacceptably different.

However, assuming $\sum_{i=1}^{N_i} w_i \, \mathrm{E}(\varepsilon_{i,t}|\boldsymbol{\Phi}_{t-1}) = 0$ does not necessarily imply $\mathrm{E}(\varepsilon_{i,t}|\boldsymbol{\Phi}_{t-1}) = 0$. That is, an evaluation of forecast efficiency at the stock level represents a test of efficiency conditional on the selected analyst weighting scheme, and does not require forecast efficiency at the individual analyst level.[156] Equation 6.2 can be further aggregated across companies, with weighting scheme w_j, to evaluate the efficiency of analysts' earnings forecasts at the aggregate market level:

$$\sum_{j=1}^{N_j}\sum_{i=1}^{N_i} w_j \, w_i \Delta \mathrm{E}^{\mathrm{r}}_{ij,t-1\to t} = \sum_{j=1}^{N_j}\sum_{i=1}^{N_i} w_j \, w_i \alpha_{ij} + \sum_{j=1}^{N_j}\sum_{i=1}^{N_i} w_j \, w_i \, \boldsymbol{\beta}'_{\boldsymbol{ij}} \boldsymbol{\Phi}_{t-1} + \sum_{j=1}^{N_j}\sum_{i=1}^{N_i} w_j \, w_i \varepsilon_{ij,t} \tag{6.3}$$

Where N_j represents the number of stocks. Therefore, extending the null hypothesis of analyst efficiency to the aggregate market level represents the following expectation:

$$\mathrm{E}\left(\sum_{j=1}^{N_j}\sum_{i=1}^{N_i} w_j \, w_i \varepsilon_{ij,t} \, |\boldsymbol{\Phi}_{t-1}\right) = 0 \tag{6.4}$$

As before with the stock-level case, this assumption does not require $\sum_{i=1}^{N_i} w_i \, \mathrm{E}(\varepsilon_{i,t}|\boldsymbol{\Phi}_{t-1}) = 0$ nor $\mathrm{E}(\varepsilon_{i,t}|\boldsymbol{\Phi}_{t-1}) = 0$. Consequently, evidence supporting the null hypothesis at the aggregate market level does not necessarily imply stock-level nor analyst-level forecast efficiency. However, rejection of the null hypothesis of efficiency at the aggregate market level implies rejection of the null hypothesis of efficiency at both stock and analyst levels, given the aggregate market regression

[156] Evidence of forecast efficiency at the stock level with a reasonable weighting scheme (such as a mean or median approach to the construction of a consensus measure of forecasts) would provide some supporting evidence for efficiency at the individual analyst level.

errors are weighted averages of the stock and analyst regression errors.[157] As a result, by evaluating analyst forecast efficiency at the aggregate market level this research provides a broader assessment of efficiency, with implications for aggregate market, stock and individual analyst efficiency.

In addition, with respect to the research framework employed, in Section 6.7 evidence of systematic inefficiency is used in tests of the relationship between predicted earnings revisions for industries and future returns. It should be noted that my analysis represents an in-sample assessment of industry return predictability with predicted earnings revisions; in-sample given the full history of the relationship between revisions and macroeconomic variables is employed to generate the time series of predicted revisions. Nonetheless, my results suggest this approach offers benefits for investors seeking an alternative perspective on forming return expectations for these industries going forward. Results also suggest potential for further investigation of earnings revision predictability and its relationship with return predictability.

6.4 The ISM Purchasing Managers' Index

IN THIS CHAPTER the efficiency of aggregated analysts' forecasts is investigated with respect to a range of macroeconomic variables. In particular, I provide more detailed assessment of forecast efficiency with respect to the ISM PMI. While a macroeconomic variable generally considered by finance practitioners to be of importance, the PMI has received little attention in academic research compared with many other economic state variables (for example, industrial

[157] In comparison, Basu, Markov and Shivakumar (2010) perform stock level analysis. They note that "Inefficiencies at the firm level, as we document in this study, do not imply inefficient use at the aggregate level of inflation data by analysts. […] Similarly, evidence of forecast efficiency at the aggregate market level does not imply forecast efficiency at the firm level" (p. 407). These statements are correct, but I demonstrate in this section that evidence of forecast *inefficiency* at the aggregate level does imply inefficiency at the firm level.

production, the term structure of interest rates, default spreads, and stock returns).[158] Hence, in this section I provide an introduction to the ISM PMI, its construction and evidence for its utility as an indicator of future economic activity.

Since 1931 the ISM has published the results of surveys of purchasing and supply executives amongst US manufacturing companies in its monthly Manufacturing Report on Business.[159] In the early 1980s survey results were employed to construct a composite measure of business sentiment, the Manufacturing ISM PMI. Survey data was employed to back-fill the PMI to January 1948.

Each month around 300–400 purchasing managers[160] are asked whether the components of key aspects of business conditions are better, the same or worse than business conditions one month prior. Participants are selected from sectors in an effort to match the sector composition of manufacturing output. The specific components incorporated in the calculation of the ISM PMI are managers' assessments of new orders, production, employment (higher/same/lower), supplier deliveries (slower/same/faster) and inventories (higher/same/lower). Survey responses are never revised. To construct the diffusion index the percentage of positive responses is added to half the percentage of "same" responses, and the index is then seasonally-adjusted (with all survey respondents considered equal in terms of weighting of responses). The five diffusion indices are then equally-

[158] On the ISM's website, www.ism.ws, Alan Greenspan, former Chairman of the US Federal Reserve Board, is quoted as saying "I find the surveys conducted by the purchasing and supply managers to be an excellent supplement to the data supplied by various departments and agencies of government." On the same website Nobel laureate Joseph Stiglitz, formerly Chief Economist at the World Bank and Chair of President Clinton's Council of Economic Advisors, is quoted as having said "The ISM Manufacturing Report On Business has one of the shortest reporting lags of any macroeconomic series and gives an important early look at the economy. It also measures some concepts (such as lead times and delivery lags) that can be found nowhere else. It makes an important contribution to the American statistical system and to economic policy."

[159] Albeit with a four year gap in survey data during World War II.

[160] Purchasing managers represent executives within firms who are members of the ISM's Business Survey Committee.

weighted and summed to form the PMI.[161] The impact of the seasonal adjustment process is relatively small. I generate a non-seasonally adjusted measure of the PMI from the raw responses for the period from January 1975 through to July 2010. The correlation between the seasonally-adjusted PMI and non-seasonally-adjusted PMI is 0.933.

One of the attractions of the PMI is its timeliness. Respondents are surveyed in the middle of a given month, with results published on the first business day of the following month. The PMI is therefore released three months in advance of the final GDP release for the corresponding period and a number of weeks in advance of many other monthly economic indicators. The fact that the ISM is largely not subject to revisions also makes it a very useful variable for researchers seeking to model business expectations and economic activity as understood when the data was first released.[162] More important, from the perspective of this chapter's focus, is the view of many market participants and researchers that the PMI is a leading indicator for aggregate economic activity.

As noted in Chapter 3, the ISM considers a PMI level over 50 to be generally indicative of improving manufacturing activity, while a level below 50 is indicative of deteriorating manufacturing activity. A level below 42 is considered to be indicative of deteriorating GDP. These levels are closely watched by market participants. In addition, there is supporting evidence in the academic literature

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[161] In 2008 an equal-weighting approach was taken, and back-dated in the published PMI series to January 2001. Prior to this date a 30% weight was applied to the new orders diffusion index, 25% to production, 20% to employment, 15% to supplier deliveries and 10% to inventories. The change was implemented to increase the correlation between the ISM and US GDP. The change in methodology has no implications for research presented in this chapter. The correlation between PMI indices from January 1948 through to July 2010 generated in the first instance from equally-weighted diffusion indices and in the second instance from the alternative weighting scheme outlined above is 0.989.

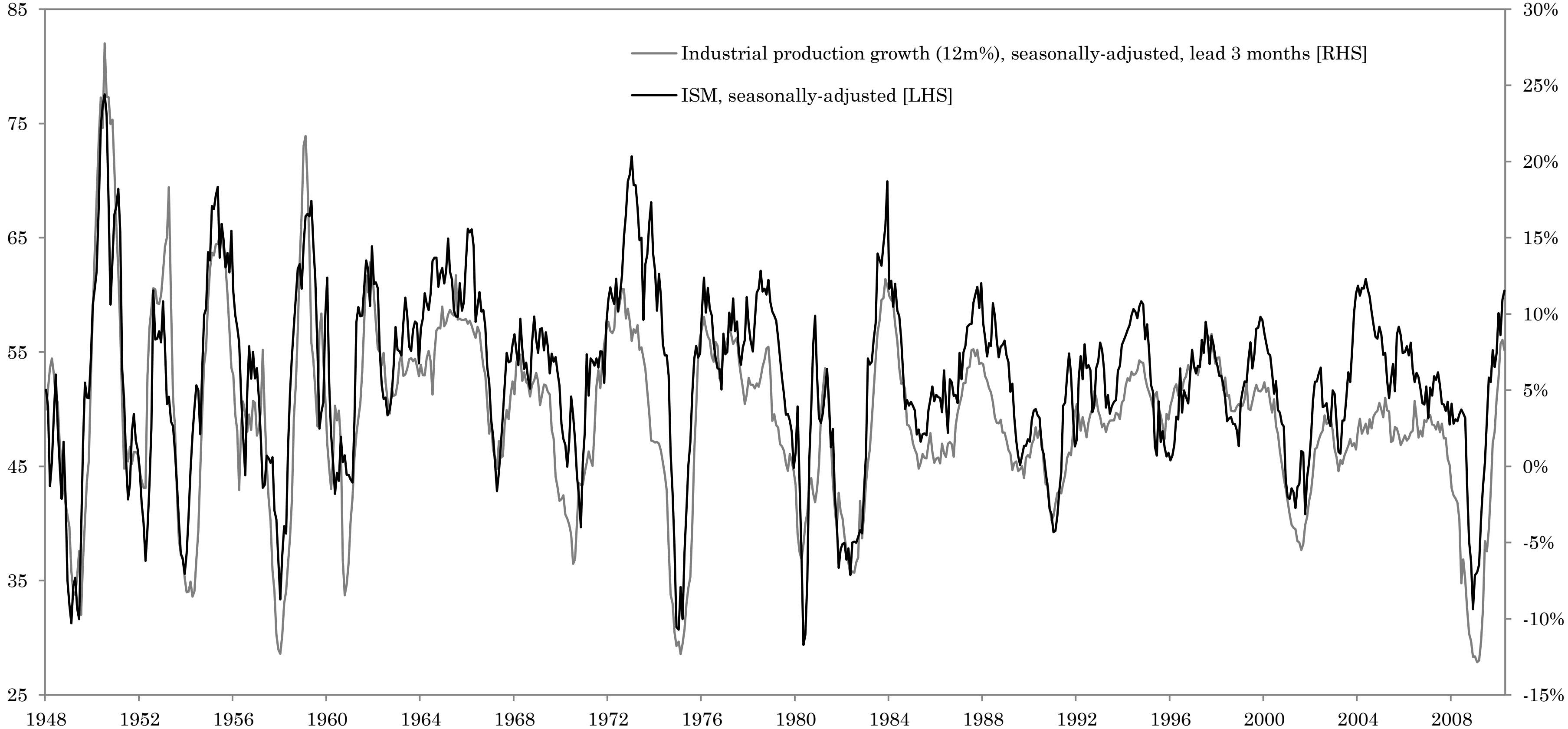
[162] However, given the PMI is a weighted average of a set of diffusion indices it merely represents the proportion of survey respondents with a positive outlook relative to those with a negative outlook. Hence, it does not measure any change in the magnitude of the expected improvement or deterioration. Conversely, the simplicity of the survey questions may be viewed as a strength given the lack of potential for ambiguity.

for a lead relationship between the PMI and measures of aggregate economic activity. A range of examples are summarized by Kauffman (1999). Notably, Klein and Moore (1988) find a composite index comprised of the prices paid, new orders, inventories and supplier deliveries surveys has led turning points in the business cycle by an average of three months from 1948 through to 1987. In regressions of US industrial production growth on the contemporaneous level of the ISM PMI, Harris (1991) reports a R^2 of 0.250 using monthly industrial production growth, 0.556 for quarterly growth and 0.669 for annual growth (1959–1991). For the same regressions applied to real GNP, Harris reports quarterly and annual R^2s of 0.393 and 0.713, respectively. Harris also finds evidence of statistically significant information in the ISM PMI for future industrial production and real GNP growth.[163] Figure 6.1 illustrates the ISM PMI index from January 1948 through to July 2010, compared with rolling 12 month growth in the US seasonally-adjusted index of industrial production, lagged three months. The Pearson correlation coefficient for the ISM PMI and lagged industrial production growth over this period is 0.797, highlighting the close relationship between these variables.

Koenig (2002) expresses the concern that the ISM PMI may have become less relevant over time as an indicator of aggregate economic activity as the manufacturing sector has become a smaller component of the overall economy. Koenig compares results from regressions of annualized quarterly growth in real GDP (and manufacturing output) on the ISM PMI and changes in the PMI for two sample periods: 1948 through to 2002 and 1983 through to 2002. He reports that "The long-run impact of a 1-point increase in the PMI is also essentially the same as before: 0.61 percentage points for manufacturing output growth and 0.27 percentage points for real GDP growth" (p. 6). Similarly, Bretz (1990) notes that

[163] However, Harris (1991) reports irregularity in the lead time between ISM turning points and aggregate economic activity. Wide variation in the duration of the lead time means the use of the ISM for turning point prediction may be problematic.

Figure 6.1 ISM PMI and 12 month % changes in seasonally-adjusted US industrial production (3 months ahead)



variation in manufacturing sector activity represents a large proportion of variation in aggregate economic activity and that manufacturers are significant purchasers of services. Combined, these factors suggest that the PMI may retain a significant relationship with measures of aggregate economic activity, despite the decline over time in the proportion of the aggregate economy represented by manufacturers.[164]

Like Harris (1991), Koenig also reports evidence of statistically significant information in the ISM PMI for future GDP growth. In terms of prediction, Koenig finds that "If the index is considered in isolation, its level is what matters. […] If the index is considered in conjunction with recent jobs, sales and factory output data, its change embodies useful information" (p. 9). In empirical tests I evaluate both level and change in the ISM PMI.

Koenig also goes further to present evidence of a statistically significant relationship between the PMI and US Federal Reserve monetary policy settings. He concludes the following:

> Federal Reserve officials draw on information from a wide variety of sources to gauge the health of the manufacturing sector, which – because of its interest-rate sensitivity – is an important factor influencing policy decisions. The PMI is highly correlated with trends in factory output growth, and policy changes, in turn, are highly correlated with contemporaneous values of the PMI. A forecasting model that draws on the most recent PMI – along with real-time inflation, unemployment, and jobs-growth data – does a good job of predicting the general thrust of Federal Reserve Policy over the past 15 years. (p. 13)

Evidence of a lead relationship between the PMI and the aggregate business cycle has led researchers in the business management literature to evaluate the use of the PMI within strategic business management and planning. Examples include Kauffman (1999) and Lindsey and Pavur (2005). The former article argues that the

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[164] A non-manufacturing index (NMI) is published monthly by the ISM. However, the Non-Manufacturing Report on Business was first published in June 1998 and the first data point for the composite NMI is dated January 2008, meaning there is insufficient history for the NMI to be included in this analysis.

PMI (and its component diffusion indices) can be an important component of strategic planning given its indications of business cycle trends and potential turning points. Lindsey and Pavur develop a time series model of the PMI with a view to incorporating the PMI and expectations for the PMI into management planning processes. As an example, Lindsey and Pavur state that:

> If the regression cycle model indicates that a peak in the PMI will not occur for another year or longer, then a manager can use this information to prepare for various contingencies, such as increased customer orders, delays in supplier deliveries, a reduction in inventories, and possibly an increase in hiring to meet higher production numbers. (p. 37)

The reverse occurs when the PMI appears to be peaking. If indeed, as Kauffman (1999) and Lindsey and Pavur (2005) suggest, managers do employ the PMI as a key component of the strategic planning process, then the predictive power of the PMI for future economic activity may become a self-fulfilling process. In addition, the PMI represents management sentiment for the average company. Presumably that sentiment will impact management decisions. Therefore, even if managers do not explicitly incorporate the PMI into the decision-making process, firms' strategic planning will on average be impacted by a correlated factor – firm-specific sentiment.

From the perspective of security analysts, there are consequently three potential drivers of a relationship between their earnings forecasts and the PMI. Firstly, there is evidence in the academic literature of a lead relationship between the PMI and measures of aggregate economic activity (and in Chapter 5 evidence was presented of a statistically significant relationship between realized earnings growth and contemporaneous macroeconomic activity, and evidence was presented of statistically significant information in analysts' forecasts for future realized earnings).[165] Secondly, for the aggregate market, strategic planning by firm

[165] Kauffman (1991) summarizes the findings of academic research on the ISM indices (known as the NAPM indices at the time) as follows:

management will likely be either implicitly or explicitly affected by the PMI. The effect will be explicit when firm management includes the PMI as part of the strategic planning process, and implicit for the aggregate market given the PMI represents net management sentiment (albeit for manufacturers alone). Thirdly (and somewhat anecdotally), the considerable emphasis placed on the ISM PMI by market practitioners and the media may impact analyst expectations. Consequently, I believe it is important to evaluate not only the relationship between the PMI and analysts' earnings forecasts, but also the efficiency of analysts' forecasts with respect to the PMI.

6.5 *Earnings revisions and economic state variables*

TO EVALUATE THE efficiency of analysts' earnings forecasts with respect to macroeconomic factors I employ earnings revisions (rather than forecast errors) as dependent variables in regressions on economic state variables.[166] Aggregate market measures of four quarter earnings revisions are constructed, as per the methodology discussed in Chapter 3. Summary results from univariate time series

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- "NAPM indexes, as indicators of manufacturing business activity, are more representative than the manufacturing part of GDP.
- Because manufacturing activity is more sensitive to general economic conditions than overall measures, NAPM indexes are good indicators of change in general economic conditions.
- NAPM indexes have advantages of timeliness, high proportions of trend and cyclical components, non-revision of data, and leading indicator and single index number properties of diffusion indexes.
- NAPM indexes on average generally lead business cycle turning points and with a greater lead at peaks than at troughs.
- NAPM PMI, Production, and New Orders Indexes correlate well with general economic indicators.
- NAPM indexes, while they often lead at turning points, usually coincide or lag general economic indicators, but have the advantage of earlier availability.
- NAPM indexes on average lead most of the peaks and troughs of most comparable indicator series." (p. 35).

[166] By using four quarter earnings revisions, the dependent variables will be highly correlated with forecast errors for one year-ahead annual earnings expectations relative to realized annual earnings. In addition, evaluating forecast revisions is equivalent to evaluating changes in forecast errors. Regardless of whether forecast revisions or forecast errors are employed as dependent variables, the methodology employed represents a test of the efficiency of earnings forecasts.

regressions of aggregate earnings revisions on each of 10 lagged economic state variables are presented in Panel A of Table 6.1. Regressions are of the following functional form:

$$\Delta \mathrm{E}_t^{\mathrm{r}} = \alpha + \beta \mathrm{S}_{t-4} + \varepsilon_t \qquad (6.5)$$

Where $\Delta \mathrm{E}_t^{\mathrm{r}}$ represents aggregated earnings revisions from period t-4 to t and S_{t-4} represents an economic state variable.[167]

The economic variables represent the last month-end published value of the factor in question prior to the aggregation date for analysts' earnings forecasts at quarter t-4 (the Thursday before the third Friday of the last month of the quarter), and are defined in Chapter 4.[168]

Estimated slope coefficients are statistically significant for two of the state variables across all dependent variables examined: the level of the ISM PMI and the level of the default spread (as for regressions in Chapter 5, Newey-West standard errors with automatic bandwidth selection are employed for t statistics). The 12 month log change in industrial production is significant in five out of seven regressions and the 12 month log change in the ISM PMI is significant in only one. The three significant results for $\Delta \mathrm{EE}^{\mathrm{r}}$ may be interpreted as follows: a 1% point increase in annual industrial production growth is associated with a +0.79% point annual revision in aggregate earnings expectations for the year ahead relative to

[167] Earnings revisions represent four quarter changes in aggregated earnings forecasts deflated by lagged earnings forecasts ($\Delta \mathrm{EE}^{\mathrm{r}}$), market capitalization ($\Delta \mathrm{EP}^{\mathrm{r}}$) or book value ($\Delta \mathrm{EB}^{\mathrm{r}}$), or equally-weighted earnings per share revisions deflated by price ($\Delta \mathrm{epeq}^{\mathrm{r}}$) or book value per share ($\Delta \mathrm{ebeq}^{\mathrm{r}}$), or median earnings per share revisions deflated by price (Δepmed) or book value per share ($\Delta \mathrm{ebmed}^{\mathrm{r}}$).

[168] Analysts' forecasts may date from some months prior to the aggregation date, and therefore the value of the economic variable in question may not be a member of the information set available to analysts when forecasts were made. However, analysts have the ability to update their forecasts in response to the changing macroeconomic environment if they believe a new release significantly impacts existing forecasts, and the findings of Hess and Kreutzmann (2009) support the notion of analysts revising earnings in response to macroeconomic surprise. Nonetheless, recognizing the potential for different macroeconomic information sets for individual analyst forecasts, I perform robustness tests in the appendix to this chapter on the duration of the eligibility period for forecasts.

Table 6.1 Univariate regressions of aggregate earnings revisions on lagged economic state variables, 1979–2009

Measures of aggregate market 4 quarter earnings revisions, on a rolling quarterly basis, are regressed on economic state variables lagged to ensure the economic data in question was available to analysts prior to the submission of earnings forecasts at the start of the 4 quarter revision period. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$\Delta E_t^r = \alpha + \beta S_{t-4} + \varepsilon_t$$

ΔE_t^r represents the measure of aggregate 4 quarter earnings revisions and S_{t-4} represents the most recent month-end value of the economic state variable prior to the date at which analysts' earnings forecasts are aggregated. Panel B provides summary results for equivalent cross-sectional regressions employing two measures of individual stock 4 quarter earnings revisions and the lagged ISM PMI as independent variable. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

A. Univariate time series regressions

Dependent variable	Ind. Prod., 12m%	ISM PMI	ISM PMI, 12m%	Cons. Sent.	Cons. Sent., 12m%	CPI, 12m%	Term structure	Default spread	Market ret., 12m%	Dividend yield
	0.787	**0.673**	0.104	0.118	0.172	-0.027	0.234	**-7.301**	0.109	0.092
ΔEE^r	(1.872)	(3.535)	(1.246)	(0.379)	(0.976)	(-0.031)	(0.112)	(-2.877)	(0.824)	(0.033)
	0.102	0.223	0.048	0.030	0.075	0.000	0.001	0.148	0.042	0.000
	0.077	**0.068**	0.009	0.017	0.011	-0.040	-0.016	**-1.026**	0.010	-0.075
ΔEP^r	(1.782)	(2.718)	(1.322)	(0.637)	(0.820)	(-0.301)	(-0.116)	(-3.555)	(0.720)	(-0.301)
	0.104	0.237	0.042	0.068	0.030	0.019	0.001	0.310	0.037	0.021
	0.121	**0.113**	0.018	0.016	0.028	-0.007	0.104	**-1.129**	0.018	0.047
ΔEB^r	(1.927)	(3.538)	(1.543)	(0.363)	(0.997)	(-0.047)	(0.356)	(-2.388)	(0.834)	(0.117)
	0.080	0.208	0.048	0.019	0.067	0.000	0.008	0.117	0.037	0.003
	0.109	**0.098**	0.017	0.035	0.021	-0.120	-0.027	**-1.588**	0.015	-0.209
$\Delta epeq^r$	(0.933)	(2.980)	(0.961)	(0.421)	(0.728)	(-0.908)	(-0.068)	(-4.499)	(0.206)	(-0.397)
	0.128	0.311	0.088	0.173	0.072	0.102	0.001	0.461	0.053	0.104
	0.067	**0.102**	**0.018**	0.004	0.015	-0.024	0.044	**-0.892**	-0.002	-0.113
$\Delta ebeq^r$	(1.101)	(3.708)	(2.071)	(0.136)	(0.998)	(-0.196)	(0.157)	(-1.927)	(-0.114)	(-0.330)
	0.034	0.236	0.070	0.001	0.026	0.003	0.002	0.102	0.001	0.021
	0.068	**0.059**	0.010	0.019	0.008	-0.079	-0.026	**-0.984**	0.005	-0.163
$\Delta epmed^r$	(1.756)	(2.500)	(1.167)	(1.211)	(1.032)	(-0.867)	(-0.206)	(-3.678)	(0.411)	(-0.914)
	0.124	0.283	0.072	0.123	0.028	0.110	0.002	0.440	0.015	0.157
	0.080	**0.079**	0.013	0.011	0.013	-0.028	-0.041	**-0.984**	0.005	-0.111
$\Delta ebmed^r$	(1.720)	(3.636)	(1.530)	(0.500)	(0.964)	(-0.244)	(-0.190)	(-2.962)	(0.326)	(-0.388)
	0.080	0.231	0.057	0.021	0.031	0.006	0.003	0.203	0.006	0.034

B. Cross-sectional univariate regressions of forecast revisions on ISM

	Full sample		>10 obs.		>20 obs.		>50 obs.	
	No. stocks	Mean R^2	No. stocks	Mean R^2	No. stocks	Mean R^2	No. stocks	Mean R^2
Δep^r	5,539	0.220	3,578	0.128	2,437	0.092	828	0.060
Δeb^r	5,539	0.197	3,578	0.102	2,437	0.071	828	0.043

current expectations for the next year, ceteris paribus; a one point higher level in the ISM PMI (for example a reading of 51 versus 50) is associated with a +0.67% point revision in year-ahead aggregate earnings expectations; and, a 1% point wider default spread is associated with a -7.3% point revision in year-ahead earnings expectations.

The R^2s for ISM PMI regressions lie within a range of 0.208 to 0.311, with this single factor on average able to explain slightly less than one quarter of the variation in aggregate market earnings revisions over the following year. The R^2s for default spread regressions are higher than those for ISM PMI regressions when the earnings revisions are deflated by price (or market capitalization), but lower in all other cases. This result is partially a consequence of a downward trend in earnings yields and default spreads over much of the period investigated. Consequently, in subsequent discussion I focus principally on results for earnings revision variables not deflated by price or market capitalization.[169]

In Panel B of Table 6.1 I present cross-sectional results for regressions of earnings per share revisions on the lagged ISM PMI. Approximately 20% of one year-ahead earnings per share revisions are explained by variation in the ISM PMI, although this decreases as the minimum number of required observations per stock is increased.

I do not find evidence of analyst inefficiency at the aggregate market level with respect to consumer sentiment (levels and 12 month changes), the term structure of interest rates, aggregate market 12 month returns nor the NYSE dividend yield. In addition, none of the estimated slope coefficients on 12 month CPI inflation is statistically significant at the 10% level.

[169] See Chapter 5 for more discussion on trending price-deflated variables, and their causes.

Table 6.2 Multivariate regressions of aggregate earnings revisions on lagged economic state variables, 1979–2009

Measures of aggregate market 4 quarter earnings revisions are regressed on economic state variables lagged to ensure the economic data in question was available to analysts prior to the submission of earnings forecasts at the start of the 4 quarter revision period. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2 for regressions of the following form:

$$\Delta \mathrm{E}_t^r = \alpha + \boldsymbol{\beta}\mathbf{S}_{t-4} + \varepsilon_t$$

$\Delta \mathrm{E}_t^r$ represents the measure of aggregate 4 quarter earnings revisions and $\mathbf{S}_{t-4}$ represents a vector of the most recent month-end value of the economic state variable prior to the date at which analysts' earnings forecasts are aggregated. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

Dependent variable	Industrial production, 12m%	ISM PMI	ISM PMI, 12m%	Cons. Sent.	Cons. Sent., 12m%	CPI, 12m%	Term structure	Default spread	Market return, 12m%	Dividend yield	Adj. R^2
ΔEE^r	-0.112	**0.556**	**-0.098**	-0.051	0.149	**1.013**	1.569	-5.601	0.090	-1.104	0.249
	(-0.384)	(2.028)	(-2.039)	(-0.244)	(1.521)	(2.178)	(1.611)	(-1.561)	(1.083)	(-0.649)	
ΔEP^r	-0.030	**0.050**	-0.004	0.000	0.002	0.068	0.094	**-0.803**	0.009	-0.109	0.346
	(-1.333)	(2.351)	(-0.874)	(-0.028)	(0.239)	(1.364)	(1.359)	(-2.916)	(1.181)	(-0.920)	
ΔEB^r	-0.029	**0.099**	**-0.017**	-0.011	0.024	**0.139**	**0.304**	**-1.001**	0.012	-0.102	0.221
	(-0.576)	(1.997)	(-2.081)	(-0.293)	(1.390)	(1.762)	(1.755)	(-1.879)	(0.851)	(-0.352)	
$\Delta epeq^r$	**-0.055**	**0.070**	-0.005	-0.003	0.011	0.058	0.069	**-1.000**	0.015	-0.267	0.561
	(-2.049)	(2.050)	(-0.801)	(-0.129)	(1.265)	(1.101)	(0.817)	(-1.697)	(1.496)	(-1.302)	
$\Delta ebeq^r$	-0.072	**0.133**	-0.013	-0.034	0.024	0.072	0.061	-0.473	0.002	-0.329	0.300
	(-1.632)	(3.013)	(-1.354)	(-1.225)	(1.531)	(1.144)	(0.436)	(-0.912)	(0.144)	(-1.319)	
$\Delta epmed^r$	-0.021	**0.045**	-0.001	-0.009	0.003	0.010	-0.004	**-0.547**	0.008	**-0.195**	0.546
	(-1.368)	(2.642)	(-0.291)	(-0.892)	(0.407)	(0.284)	(-0.070)	(-3.957)	(1.468)	(-2.255)	
$\Delta ebmed^r$	-0.026	**0.076**	-0.006	-0.020	0.014	0.077	0.025	**-0.571**	0.007	-0.269	0.299
	(-0.819)	(2.409)	(-0.853)	(-0.810)	(1.000)	(1.277)	(0.209)	(-1.830)	(0.761)	(-1.479)	

In Table 6.2 summary results from multivariate regressions of aggregated earnings revisions on lagged values of all ten economic state variables are presented. Notably, estimated coefficients on the ISM PMI and default spreads are statistically significant in all regressions bar two. For the two exceptions the ISM PMI is significant but the default spread variable is not.

The estimated slope coefficient on the inflation variable is statistically significant in only two instances: for aggregate earnings revisions deflated by lagged earnings forecasts and aggregated earnings revisions deflated by lagged book value. An issue with multicollinearity is suggested by the fact that the estimated coefficient on the inflation variable is not significant in any of the univariate results summarized in Table 6.1. These simple aggregate regressions run counter to the firm-level conclusions of Basu, Markov and Shivakumar (2010), who report evidence against the notion of forecast efficiency with respect to inflation, but results are supportive of De Zwart and Van Dijk (2008) who find evidence supporting efficiency. However, as discussed in Section 6.3, evidence of forecast efficiency at the aggregate level is not necessarily inconsistent with evidence of forecast inefficiency at the firm level.[170]

[170] Basu, Markov and Shivakumar (2010) apply their analysis of the informational efficiency of analysts' forecasts with respect to inflation, to the notion of inflation-related errors by investors as drivers of post earnings announcement drift. Their results suggest that, at the firm level, inflation-related errors by analysts contribute to inflation-related errors by investors. My results in Table 6.1 represent evidence of analyst efficiency in terms of the relationship between earnings revisions and lagged inflation. Hence, my results represent evidence against extending Basu et al.'s findings to the aggregate market level, and consequently evidence against the notion of inflation-related errors by analysts as a driver of investor-related inflation errors at the aggregate level.

In Table 6.3 lagged values of the ISM PMI, credit spreads, realized earnings changes and earnings revisions are combined as independent variables in a regression of the following form:[171]

$$\Delta \mathrm{E}_t^{\mathrm{r}} = \alpha + \beta_{\Delta \mathrm{E}^{\mathrm{r}}} \Delta \mathrm{E}_{t-5}^{\mathrm{r}} + \beta_{\Delta \mathrm{E}^{\mathrm{a}}} \Delta \mathrm{E}_{t-5}^{\mathrm{a}} + \boldsymbol{\beta}_{\mathrm{S}} \mathbf{S}_{t-4} + \varepsilon_t \tag{6.6}$$

$\Delta \mathrm{E}_t^{\mathrm{r}}$ represents the measure of aggregate four quarter earnings revisions ending at time t and $\mathbf{S}_{t-4}$ represents a vector of the most recent month-end values of the economic state variables prior to the date at which analysts' earnings forecasts are aggregated. $\Delta \mathrm{E}_{t-5}^{\mathrm{r}}$ represents earnings revisions lagged five quarters and $\Delta \mathrm{E}_{t-5}^{\mathrm{a}}$ represents realized earnings changes lagged five quarters. The realized earnings changes and earnings revisions variables are lagged five quarters (back to one quarter prior to the start of the forecast revision period) to ensure analysts had access to this information when they submitted forecasts (or that they had access to the information but chose not to revise forecasts in response to it). Estimated coefficients on the ISM PMI are statistically significant in all regressions, while the default spread variable is significant only for price-deflated measures of earnings revisions. Estimated coefficients on lagged realized earnings changes are not significant, and there is only one instance of a significant estimated coefficient on lagged forecast revisions. Note also that the intercept term is significant and negative in all regressions, illustrating significant forecast bias (initial forecasts are too high and require downward revision). If I exclude the price-deflated measures of aggregate revisions, these simple regressions explain on average 28.5% of the variation in one year-ahead earnings revisions. Including the price-deflated measures raises that number to 37.1%. These results are therefore not consistent with analyst efficiency, and in particular provide evidence supporting rejection of the null hypothesis of analyst efficiency with respect to the ISM PMI.

[171] A lagged dependent variable is included as a regressor by Ackert and Hunter (1995) in their tests of analyst efficiency. Lagged changes in realized earnings are included as regressors by De Zwart and Van Dijk (2008) and Hess and Kreutzmann (2009).

Table 6.3 Multivariate regressions of aggregate earnings revisions on lagged economic state variables, lagged earnings revisions and lagged realized earnings, 1979–2009

Measures of aggregate market 4 quarter earnings revisions are regressed on economic state variables lagged to ensure the economic data in question was available to analysts prior to the submission of earnings forecasts at the start of the 4 quarter revision period, and lagged earnings revisions and lagged realized earnings. The latter two variables are lagged by 5 quarters to ensure availability for forecasting analysts. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2 for regressions of the following form:

$$\Delta\mathrm{E}_t^{\mathrm{r}} = \alpha + \beta_{\Delta\mathrm{E}^{\mathrm{r}}}\Delta\mathrm{E}_{t-5}^{\mathrm{r}} + \beta_{\Delta\mathrm{E}^{\mathrm{a}}}\Delta\mathrm{E}_{t-5}^{\mathrm{a}} + \boldsymbol{\beta}_{\mathrm{S}}\mathbf{S}_{t-4} + \varepsilon_t$$

$\Delta\mathrm{E}_t^{\mathrm{r}}$ represents the measure of aggregate 4 quarter earnings revisions and $\mathbf{S}_{t-4}$ represents a vector of the most recent month-end value of the economic state variable prior to the date at which analysts' earnings forecasts are aggregated. $\Delta\mathrm{E}_{t-5}^{\mathrm{r}}$ represents earnings revisions lagged 5 quarters. $\Delta\mathrm{E}_{t-5}^{\mathrm{a}}$ represents realized earnings changes lagged 5 quarters. The lagged realized earnings and earnings revisions measures are consistent with the construction of the dependent variable in terms of numerator (earnings or earnings per share) and deflator. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

Dependent variable	α	$\Delta\mathrm{E}_{t-5}^{\mathrm{r}}$	$\Delta\mathrm{E}_{t-5}^{\mathrm{a}}$	ISM PMI	Default spread	Adj. R^2
$\Delta\mathrm{EE}^{\mathrm{r}}$	**-0.276**	-0.049	0.200	**0.410**	-2.335	0.342
	(-2.717)	(-0.179)	(1.584)	(2.410)	(-0.976)	
$\Delta\mathrm{EP}^{\mathrm{r}}$	**-0.016**	0.009	0.170	**0.033**	**-0.711**	0.388
	(-1.730)	(0.038)	(0.871)	(2.125)	(-2.442)	
$\Delta\mathrm{EB}^{\mathrm{r}}$	**-0.052**	-0.116	0.258	**0.076**	-0.308	0.269
	(-2.823)	(-0.317)	(1.189)	(2.398)	(-0.734)	
$\Delta\mathrm{epeq}^{\mathrm{r}}$	**-0.032**	-0.013	0.129	**0.051**	**-1.158**	0.531
	(-3.042)	(-0.052)	(0.593)	(2.380)	(-3.477)	
$\Delta\mathrm{ebeq}^{\mathrm{r}}$	**-0.066**	0.146	0.107	**0.076**	-0.138	0.254
	(-4.743)	(0.731)	(0.584)	(2.995)	(-0.392)	
$\Delta\mathrm{epmed}^{\mathrm{r}}$	**-0.019**	**0.345**	-0.343	**0.041**	**-0.568**	0.538
	(-3.308)	(1.978)	(-1.611)	(3.450)	(-4.173)	
$\Delta\mathrm{ebmed}^{\mathrm{r}}$	**-0.038**	0.137	0.085	**0.053**	-0.476	0.274
	(-2.875)	(0.472)	(0.240)	(2.903)	(-1.412)	

The strong and consistent significance of estimated coefficients on the ISM PMI are particularly interesting when compared with the results of Hess and Kreutzmann (2009), who find evidence of analysts revising earnings in response to surprise in this variable. The results presented in Tables 6.1, 6.2 and 6.3 suggest that while analysts may indeed revise earnings in response to ISM PMI surprise, they underreact leading to predictable future revision activity.

In Table 6.4 I provide results for regressions of realized earnings changes on lagged realized earnings changes and the ISM PMI, and, forecast earnings changes on lagged forecast changes and the ISM PMI. Firstly, it is evident that lagged levels of the ISM PMI contain statistically significant information for future realized earnings changes. This means that analysts would be correct to revise earnings in response to surprise in the ISM, providing one explanation for the results of Hess and Kreutzmann (2009). Indeed, on the right-hand side of Table 6.4, regression results for forecast earnings changes provide evidence of a statistically significant relationship between the ISM PMI and analysts' expectations for earnings growth over the following year. However, comparing the estimated coefficient on the ISM PMI for each realized earnings change regression with its forecast earnings change counterpart, there is a key distinguishing characteristic: the forecast earnings change coefficients are much lower than the realized earnings change coefficients.[172] The ISM PMI does appear to have an impact on analysts' earnings expectations, but they underreact. The sensitivity of realized earnings to the ISM PMI is much larger. This accounts for the positive and statistically significant relationship between the ISM PMI and future earnings revisions.

[172] In addition, the adjusted R^2s for the forecast earnings change regressions are much larger than those reported for the realized earnings change regressions. This is partially a consequence of greater autocorrelation for aggregate forecast measures compared with aggregate realized earnings measures.

Table 6.4 Multivariate regressions of aggregate realized earnings changes (and forecast earnings changes) on the lagged ISM PMI and a lagged dependent variable, 1979–2009

Measures of aggregate market 4 quarter realized earnings changes (and forecast earnings changes) are regressed on the lagged ISM PMI and a lagged dependent variable. The lagged dependent variable is lagged by 5 quarters. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2 for regressions of the following form:

$$\Delta\mathrm{E}_t^{\mathrm{a}} = \alpha + \beta_{\Delta\mathrm{E}^{\mathrm{a}}}\Delta\mathrm{E}_{t-5}^{\mathrm{a}} + \beta_{\mathrm{S}}\mathrm{S}_{t-4} + \varepsilon_t$$

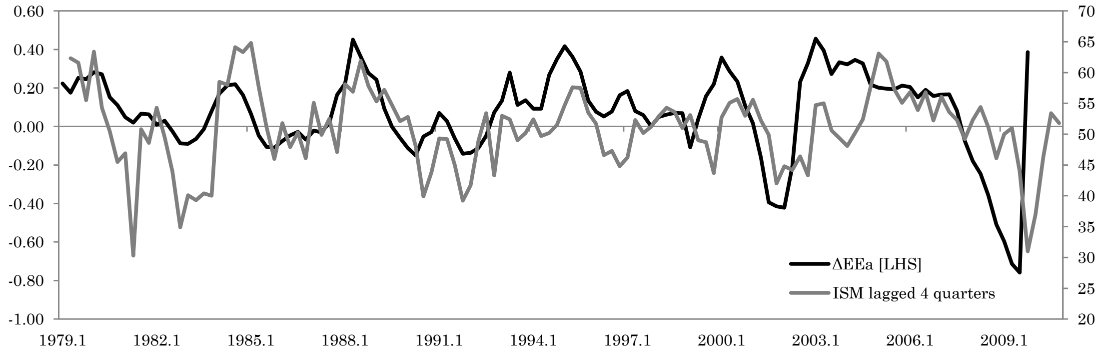
$$\Delta\mathrm{E}_t^{\mathrm{f}} = \alpha + \beta_{\Delta\mathrm{E}^{\mathrm{f}}}\Delta\mathrm{E}_{t-5}^{\mathrm{f}} + \beta_{\mathrm{S}}\mathrm{S}_{t-4} + \varepsilon_t$$

The superscripts "a" and "f" refer to actuals (realized earnings) and forecasts, respectively. S_{t-4} represents the most recent month-end value of the ISM PMI prior to the dependent variable start date for change measurement. The lagged realized earnings and forecast earnings measures are consistent with the construction of the dependent variable in terms of numerator (earnings or earnings per share) and deflator. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

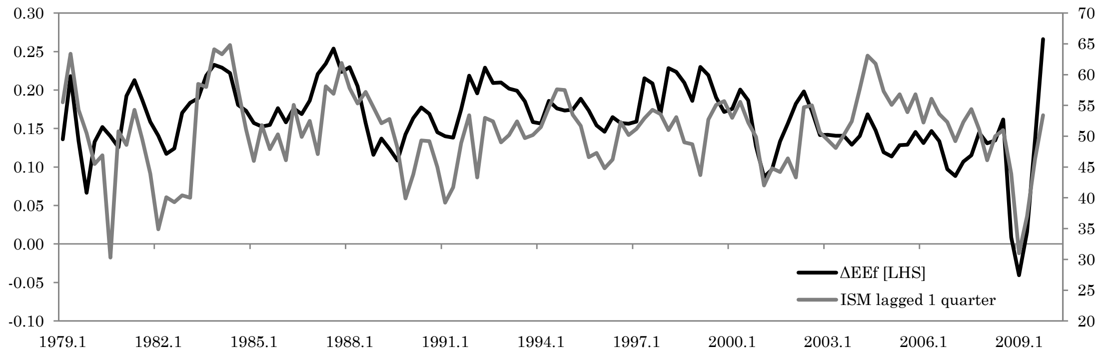
	Realized earnings regressed on lagged realized earnings and lagged PMI			*Forecast earnings* regressed on lagged forecast earnings and lagged PMI		
Dependent variable	$\Delta\mathrm{E}_{t-5}^{\mathrm{a}}$	ISM PMI	Adj. R^2	$\Delta\mathrm{E}_{t-5}^{\mathrm{f}}$	ISM PMI	Adj. R^2
ΔEE	-0.084	**1.054**	0.062	0.154	**0.364**	0.235
	(-0.346)	(2.586)		(0.936)	(2.590)	
ΔEB	-0.048	**0.142**	0.075	**0.368**	**0.053**	0.261
	(-0.218)	(3.022)		(2.158)	(2.902)	
Δebeq	-0.064	**0.126**	0.069	**0.276**	**0.063**	0.369
	(-0.239)	(3.224)		(2.144)	(3.543)	
Δebmed	-0.040	**0.078**	0.125	0.436	**0.042**	0.366
	(-0.139)	(4.403)		(1.627)	(2.626)	

Figure 6.2 Aggregate measures of realized earnings changes, forecast earnings changes and forecast revisions compared with lagged values of the ISM PMI

A. Aggregate realized earnings growth and lagged ISM PMI index



B. Aggregate forecast earnings growth and lagged ISM PMI index



C. Aggregate forecast revisions and lagged ISM PMI index

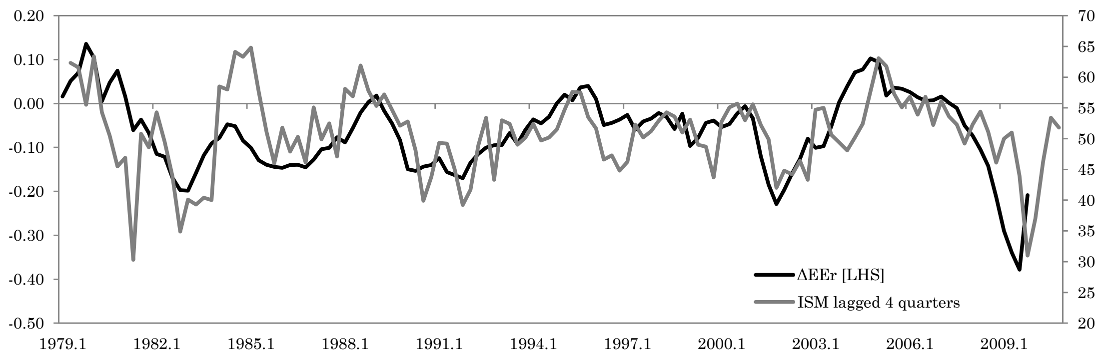


Figure 6.2 provides a graphical illustration of the relationships between lagged values of the ISM PMI and realized earnings changes, forecast earnings changes and forecast earnings revisions, highlighting the relative consistency of relationships through time.

6.6 Consistency in the relationship between revisions and the ISM

IN THIS SECTION I perform robustness tests on the relationship between aggregated earnings revisions and the ISM PMI to identify sources of systematic variation.

6.6.1 Size and Book-to-market

FIRSTLY, SIZE QUINTILE portfolios and book-to-market quintile portfolios are formed for each of three measures of aggregated earnings revisions (aggregate earnings revisions deflated by lagged book value, and equally-weighted and median earnings per share revisions deflated by lagged book value per share). The time series of aggregate earnings revisions for each quintile portfolio are regressed on values of the ISM PMI available to analysts at the start of the forecasting period. Slope coefficients, *t* statistics (derived from Newey-West standard errors) and regressions R^2s are reported in Table 6.5.

All estimated slope coefficients are statistically significant at the 10% level or better. In Panel A it is evident that quintile 5 (smallest stocks) R^2s are lower than R^2s for quintiles 1 through 4. In addition, there is a statistically significant difference between quintile 1 and quintile 5 estimated coefficients for ΔEB^r and $\Delta ebeq^r$, but not for $\Delta ebmed^r$. Nonetheless, there is no evidence of a monotonic relationship between the magnitude of the estimated slope coefficient (nor the magnitude of the R^2) and firm size. Similarly, in Panel B there is no evidence of a

Table 6.5 Univariate regressions of aggregate earnings revisions on the lagged ISM PMI by size quintile and book-to-market quintile, 1979–2009

The dataset is divided into size quintiles (Panel A) and book-to-market quintiles (Panel B) based on market capitalization and book-to-market ratios at the start of the forecast revision period. Select measures of aggregate market 4 quarter earnings revisions for each quintile portfolio are regressed on the ISM PMI, lagged to ensure this variable was available to analysts prior to the submission of earnings forecasts at the start of the 4 quarter revision period. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$\Delta \mathrm{E}_t^{\mathrm{r}} = \alpha + \beta \mathrm{S}_{t-4} + \varepsilon_t$$

$\Delta \mathrm{E}_t^{\mathrm{r}}$ represents the measure of aggregate 4 quarter earnings revisions and S_{t-4} represents the most recent month-end value of the economic state variable prior to the date at which analysts' earnings forecasts are aggregated. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

A. Size quintiles					
Dependent variable	Q1 (large)	Q2	Q3	Q4	Q5 (small)
ΔEB^r	**0.119**	**0.094**	**0.106**	**0.095**	**0.086**
	(3.577)	(2.709)	(3.339)	(3.262)	(2.344)
	0.202	0.179	0.218	0.175	0.102
$\Delta ebeq^r$	**0.116**	**0.112**	**0.105**	**0.103**	**0.076**
	(3.273)	(3.465)	(3.343)	(3.802)	(2.640)
	0.189	0.247	0.202	0.211	0.101
$\Delta ebmed^r$	**0.072**	**0.080**	**0.085**	**0.086**	**0.075**
	(3.048)	(3.548)	(3.648)	(4.416)	(2.355)
	0.193	0.264	0.208	0.217	0.126
B. Book-to-market quintiles					
Dependent variable	Q1 (low)	Q2	Q3	Q4	Q5 (high)
ΔEB^r	**0.067**	**0.132**	**0.115**	**0.100**	**0.140**
	(2.771)	(2.768)	(2.681)	(2.951)	(3.233)
	0.065	0.196	0.166	0.164	0.175
$\Delta ebeq^r$	**0.121**	**0.121**	**0.091**	**0.076**	**0.102**
	(3.828)	(3.443)	(3.005)	(2.836)	(3.080)
	0.127	0.244	0.163	0.163	0.183
$\Delta ebmed^r$	**0.150**	**0.107**	**0.067**	**0.053**	**0.073**
	(5.037)	(3.171)	(2.914)	(3.173)	(3.521)
	0.207	0.234	0.141	0.158	0.197

Table 6.6 Univariate regressions of aggregate earnings revisions on the lagged ISM PMI by both size quintile and book-to-market quintile combined, 1979–2009

The dataset is divided into size quintiles and each size quintile then divided into book-to-market quintiles, based on market capitalization and book-to-market ratios at the start of the forecast revision period. Select measures of aggregate market 4 quarter earnings revisions for the 25 portfolios are regressed on the ISM PMI, lagged to ensure this variable was available to analysts prior to the submission of earnings forecasts at the start of the 4 quarter revision period. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$\Delta \mathrm{E}_t^{\mathrm{r}} = \alpha + \beta \mathrm{S}_{t-4} + \varepsilon_t$$

$\Delta \mathrm{E}_t^{\mathrm{r}}$ represents the measure of aggregate 4 quarter earnings revisions and S_{t-4} represents the most recent month-end value of the economic state variable prior to the date at which analysts' earnings forecasts are aggregated. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

A. $\Delta \mathrm{EB}^{\mathrm{r}}$ as independent variable

	Size quintiles					
Book-to-market quintiles	Q1 (large)	Q2	Q3	Q4	Q5 (small)	Q5 - Q1
1 (low)	0.047	**0.097**	**0.110**	0.060	0.048	
	(1.509)	(1.892)	(2.912)	(1.175)	(1.160)	
	0.020	0.063	0.076	0.021	0.016	-0.004
2	**0.097**	**0.077**	**0.120**	**0.129**	**0.070**	
	(2.590)	(1.840)	(2.401)	(3.079)	(1.890)	
	0.095	0.080	0.153	0.169	0.052	-0.043
3	**0.156**	**0.124**	**0.098**	**0.102**	**0.091**	
	(2.869)	(3.705)	(2.990)	(2.768)	(2.525)	
	0.203	0.245	0.153	0.150	0.087	-0.117
4	**0.123**	**0.064**	**0.091**	**0.085**	**0.101**	
	(3.105)	(1.918)	(2.794)	(2.655)	(2.144)	
	0.167	0.091	0.167	0.124	0.103	-0.064
5 (high)	**0.137**	**0.102**	**0.114**	**0.093**	**0.090**	
	(3.538)	(2.846)	(3.149)	(3.047)	(2.028)	
	0.184	0.123	0.170	0.105	0.060	-0.124
Q5 - Q1	+0.164	+0.060	+0.094	+0.084	+0.043	

B. $\Delta \mathrm{ebeq}^{\mathrm{r}}$ as independent variable

	Size quintiles					
Book-to-market quintiles	Q1 (large)	Q2	Q3	Q4	Q5 (small)	Q5 - Q1
1 (low)	**0.150**	**0.192**	**0.140**	**0.109**	**0.069**	
	(2.449)	(4.390)	(3.493)	(2.203)	(2.691)	
	0.071	0.167	0.102	0.079	0.043	-0.028
2	**0.117**	**0.100**	**0.114**	**0.140**	**0.072**	
	(2.959)	(2.404)	(3.196)	(4.409)	(2.418)	
	0.134	0.145	0.172	0.182	0.051	-0.082
3	**0.148**	**0.098**	**0.090**	**0.094**	**0.066**	
	(3.358)	(2.876)	(2.584)	(3.405)	(2.352)	
	0.258	0.155	0.096	0.120	0.058	-0.201
4	**0.069**	**0.067**	**0.087**	**0.089**	**0.098**	
	(2.537)	(2.072)	(3.086)	(3.251)	(1.887)	
	0.083	0.108	0.147	0.149	0.110	+0.026
5 (high)	**0.095**	**0.101**	**0.094**	**0.082**	**0.075**	
	(4.072)	(3.060)	(3.030)	(3.359)	(1.868)	
	0.208	0.172	0.138	0.100	0.060	-0.148
Q5 - Q1	+0.137	+0.006	+0.036	+0.021	+0.017	

Table continues overleaf

Table 6.6 Univariate regressions of aggregate earnings revisions on the lagged ISM PMI by both size quintile and book-to-market quintile combined, 1979–2009

Table continued from previous page

C. $\Delta ebmed^r$ as independent variable						
	Size quintiles					
Book-to-market quintiles	Q1 (large)	Q2	Q3	Q4	Q5 (small)	Q5 - Q1
1 (low)	**0.120**	**0.198**	**0.161**	**0.147**	**0.085**	
	(2.602)	(4.755)	(4.603)	(3.789)	(2.764)	
	0.053	0.214	0.149	0.144	0.066	+0.014
2	**0.075**	**0.108**	**0.112**	**0.124**	**0.068**	
	(2.823)	(2.312)	(3.005)	(5.442)	(2.214)	
	0.100	0.187	0.178	0.217	0.071	-0.029
3	**0.106**	**0.066**	**0.063**	**0.075**	**0.050**	
	(3.350)	(3.413)	(2.671)	(3.516)	(1.829)	
	0.211	0.121	0.092	0.119	0.041	-0.171
4	0.030	**0.034**	**0.064**	**0.061**	0.068	
	(1.417)	(1.993)	(3.114)	(2.917)	(1.553)	
	0.027	0.063	0.142	0.117	0.084	+0.057
5 (high)	**0.054**	**0.071**	**0.063**	**0.060**	**0.062**	
	(3.928)	(3.429)	(3.880)	(3.241)	(1.939)	
	0.156	0.197	0.124	0.116	0.066	-0.090
Q5 - Q1	+0.104	-0.018	-0.025	-0.029	0.000	

monotonic relationship between the magnitude of the estimated slope coefficient (nor the magnitude of the R^2) and firm book-to-market ratios.

It is well known that firm size and book-to-market are correlated.[173] Therefore I repeat the above regressions for 25 portfolios formed from quintile sorts on size, and then on book-to-market ratios within size quintiles. Summary results are presented in Table 6.6. Estimated slope coefficients are statistically significant at the 10% level or better for almost all portfolios across each of the three measures of aggregated revisions. Consequently, it is evident that a significant relationship between the ISM PMI and subsequent earnings revisions is a pervasive feature of revision activity.

There is no evidence in Table 6.6 of systematic variation in the strength of the relationship between earnings revisions and the lagged ISM PMI across size and book-to-market portfolios. There are significant differences in estimated coefficients for low (quintile 1) versus high (quintile 5) book-to-market portfolios within some size quintiles, but not in others. Similarly, there are significant differences in estimated coefficients for large (quintile 1) versus small (quintile 5) size portfolios within some book-to-market quintiles, but not in others. There is no obvious consistent pattern in statistical significance. Nor is there evidence of consistent monotonic relationships between estimated slope coefficients (nor regressions R^2s) and size and book-to-market.

6.6.2 Analyst coverage

SMALLER STOCKS WILL on average have fewer analysts submitting earnings forecasts to I/B/E/S relative to larger stocks. Information asymmetry with respect to firm size has been shown in the literature to be associated with relatively poorer

[173] For example, see Fama and French (1992, 1993)

forecast accuracy for small stocks relative to large stocks.[174] In the context of this chapter's focus, it also raises the question of whether forecasts from analysts of smaller stocks exhibit any greater degree of inefficiency with respect to the ISM PMI, relative to forecasts from analysts of large stocks. Information asymmetry in this setting is typically a stock-level concept, not a market-level concept. The information asymmetry arises because of the relatively weaker information environment for an individual small stock. Macroeconomic information is available to all analysts. However, Basu, Markov and Shivakumar (2010) comment "We argue that the analyst's main challenge is to estimate the link between future inflation and earnings, that is, inflation exposure rather than forecasting inflation itself" (p. 408). A weaker information environment for small stocks may complicate an analyst's assessment of the impact of macroeconomic information on the firm's earnings.

To evaluate the relationship between the efficiency of aggregated analysts' forecasts with respect to the ISM PMI and the information environment I form time series of aggregate earnings revisions for 25 portfolios, formed firstly on size quintiles, and then split into quintiles based on the number of submitted forecasts within size quintiles.[175] Earnings revisions for each portfolio are then regressed on the lagged ISM PMI. Summary results are presented in Table 6.7.

Firstly, the estimated slope coefficients on the lagged ISM PMI are statistically significant at the 10% level or better in all analyst coverage portfolios within size quintiles 1 through 4. However, out of the 15 analyst coverage portfolios evaluated within the smallest size quintile, 10 are statistically significant. For all three

[174] For example, see Brown, Richardson and Schwager (1987).

[175] As per analysis of analyst coverage discussed in Chapter 5, portfolio splits are determined by relative coverage within size quintiles. Therefore, average analyst coverage will be higher across all analyst coverage portfolios within the largest size quintile, relative to analyst coverage within the smallest size quintile.

Table 6.7 Univariate regressions of aggregate earnings revisions on the lagged ISM PMI for portfolios formed jointly on firm size and the number of submitted forecasts, 1979–2009

The dataset is divided into size quintiles and each size quintile then divided into quintiles determined by the number of forecasts submitted to I/B/E/S in the forecasting period. Select measures of aggregate market 4 quarter earnings revisions for the 25 portfolios are regressed on the ISM PMI, lagged to ensure this variable was available to analysts prior to the submission of earnings forecasts at the start of the 4 quarter revision period. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$\Delta \mathrm{E}_t^r = \alpha + \beta \mathrm{S}_{t-4} + \varepsilon_t$$

$\Delta \mathrm{E}_t^r$ represents the measure of aggregate 4 quarter earnings revisions and S_{t-4} represents the most recent month-end value of the economic state variable prior to the date at which analysts' earnings forecasts are aggregated. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

A. ΔEB^r as independent variable						
	Size quintiles					
Number of analysts	Q1 (large)	Q2	Q3	Q4	Q5 (small)	Avg R^2
1 (high)	**0.124**	**0.094**	**0.135**	**0.096**	**0.067**	
	(3.942)	(2.039)	(2.694)	(2.222)	(1.764)	
	0.158	0.082	0.166	0.084	0.037	0.106
2	**0.143**	**0.089**	**0.117**	**0.088**	**0.117**	
	(3.341)	(2.969)	(3.370)	(2.586)	(2.378)	
	0.183	0.148	0.182	0.097	0.109	0.144
3	**0.112**	**0.086**	**0.071**	**0.092**	**0.084**	
	(3.806)	(2.300)	(2.339)	(2.964)	(2.213)	
	0.167	0.104	0.095	0.132	0.074	0.114
4	**0.074**	**0.102**	**0.085**	**0.102**	**0.095**	
	(2.691)	(2.947)	(3.091)	(4.128)	(2.277)	
	0.087	0.182	0.098	0.167	0.082	0.123
5 (low)	**0.096**	**0.101**	**0.107**	**0.082**	0.055	
	(2.528)	(3.317)	(2.780)	(2.708)	(1.096)	
	0.092	0.184	0.166	0.101	0.027	0.114
Avg R^2	0.137	0.140	0.141	0.116	0.066	

B. $\Delta ebeq^r$ as independent variable						
	Size quintiles					
Number of analysts	Q1 (large)	Q2	Q3	Q4	Q5 (small)	Avg R^2
1 (high)	**0.131**	**0.082**	**0.152**	**0.098**	**0.080**	
	(3.647)	(2.578)	(3.759)	(3.250)	(2.349)	
	0.119	0.089	0.211	0.109	0.075	0.120
2	**0.124**	**0.114**	**0.103**	**0.127**	**0.097**	
	(4.028)	(3.897)	(3.612)	(3.431)	(2.748)	
	0.150	0.220	0.149	0.167	0.115	0.160
3	**0.090**	**0.133**	**0.096**	**0.089**	**0.098**	
	(2.675)	(5.107)	(2.879)	(3.891)	(3.738)	
	0.140	0.231	0.113	0.128	0.105	0.143
4	**0.111**	**0.126**	**0.060**	**0.123**	**0.058**	
	(2.858)	(3.062)	(1.905)	(5.148)	(1.754)	
	0.168	0.175	0.039	0.180	0.033	0.119
5 (low)	**0.128**	**0.109**	**0.096**	**0.073**	0.041	
	(3.844)	(3.196)	(2.191)	(2.248)	(1.130)	
	0.138	0.136	0.095	0.053	0.015	0.087
Avg R^2	0.143	0.170	0.121	0.127	0.068	

Table continues overleaf

Table 6.7 Univariate regressions of aggregate earnings revisions on the lagged ISM PMI for portfolios formed jointly on firm size and the number of submitted forecasts, 1979–2009

Table continued from previous page

C. Δebmed^r as independent variable						
	Size quintiles					
Number of analysts	Q1 (large)	Q2	Q3	Q4	Q5 (small)	Avg R^2
1 (high)	**0.087**	**0.078**	**0.129**	**0.109**	0.063	
	(2.749)	(3.121)	(3.924)	(3.862)	(1.543)	
	0.083	0.137	0.249	0.179	0.058	0.141
2	**0.063**	**0.072**	**0.092**	**0.103**	**0.091**	
	(2.963)	(2.982)	(3.359)	(3.658)	(2.159)	
	0.080	0.188	0.170	0.168	0.114	0.144
3	**0.066**	**0.079**	**0.070**	**0.092**	**0.083**	
	(3.149)	(3.744)	(2.519)	(5.354)	(2.758)	
	0.146	0.170	0.104	0.192	0.093	0.141
4	**0.079**	**0.093**	**0.044**	**0.076**	0.039	
	(3.272)	(2.702)	(1.817)	(4.150)	(1.192)	
	0.172	0.227	0.045	0.132	0.027	0.121
5 (low)	**0.072**	**0.075**	**0.081**	**0.058**	0.014	
	(3.208)	(2.753)	(2.422)	(2.454)	(0.356)	
	0.099	0.139	0.159	0.075	0.002	0.095
Avg R^2	0.116	0.172	0.145	0.149	0.059	

measures of aggregate revisions, the estimated slope coefficient for the smallest firms/fewest forecasts portfolio is statistically insignificant.[176] Nonetheless, there is no evidence of a monotonic relationship between the number of submitted forecasts within size quintiles and estimated slope coefficients (nor regression R^2s). Results are consistent with the hypothesis of no significant relationship between analyst coverage and the informational efficiency of aggregated forecasts with respect to the ISM PMI.

Overall, the evidence suggests there is a relationship between the ISM PMI and subsequent aggregated earnings revisions that is robust across portfolios formed on combinations of firm size, book-to-market ratios and analyst coverage. There is no conclusive evidence of systematic variation in the relationship between the ISM PMI and earnings revisions across these conditioning variables. This analysis suggests the inefficiency of analysts' forecasts with respect to the ISM PMI is a pervasive characteristic of earnings forecasts.

6.6.3 Economic regimes

GIVEN THE FOCUS of this chapter is the relationship between earnings revisions and historic economic state variables, it is appropriate to evaluate time variation in this relationship related to macroeconomic cycles. Motivation for investigation of time-varying effects is provided by the results of Aiolfi, Rodriguez and Timmermann (2010) who, in a three regime model, report "strong evidence of asymmetries and persistence in the magnitude and signs of revisions to analysts' earnings expectations" (p. 306).

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[176] Some caution is warranted interpreting results for the smallest firms/fewest forecasts portfolio (Q5 size/Q5 number of analysts). Regressions for this portfolio are based on approximately 40% fewer data points given the use of relative criteria for portfolio selection. The Q5 size/Q4 number of analysts portfolio covers the full time series, and therefore arguably offers a more robust portfolio for comparison of results. Nonetheless, results for this portfolio have no material impact on general conclusions.

I employ National Bureau of Economic Research (NBER) specifications for economic expansions and contractions to generate a macroeconomic cycle dummy variable.[177] The dummy variable is employed to generate the following two-state version of equation 6.6:

$$\Delta \mathrm{E}_t^{\mathrm{r}} = \alpha_1 + \alpha_2 \mathrm{D}_t + \beta_{1,\Delta\mathrm{E}^{\mathrm{r}}}(1-\mathrm{D}_t)\Delta\mathrm{E}_{t-5}^{\mathrm{r}} + \beta_{2,\Delta\mathrm{E}^{\mathrm{r}}}\mathrm{D}_t\Delta\mathrm{E}_{t-5}^{\mathrm{r}} + \beta_{1,\Delta\mathrm{E}^{\mathrm{a}}}(1-\mathrm{D}_t)\Delta\mathrm{E}_{t-5}^{\mathrm{a}} + \beta_{2,\Delta\mathrm{E}^{\mathrm{a}}}\mathrm{D}_t\Delta\mathrm{E}_{t-5}^{\mathrm{a}} + \boldsymbol{\beta}_{1,\mathrm{S}}(1-\mathrm{D}_t)\mathbf{S}_{t-4} + \boldsymbol{\beta}_{2,\mathrm{S}}\mathrm{D}_t\mathbf{S}_{t-4} + \varepsilon_t \quad (6.7)$$

D_t is 1 in expansions and 0 in contractions. Regression results for four measures of aggregate market earnings revisions are presented in Table 6.8. Results are conditional on the NBER regime at the start of the four quarter revision period.

Firstly, there are no regressions with a statistically insignificant estimated coefficient on the ISM PMI in expansion phases, and all estimated coefficients on this variable are positive. Therefore, the evidence supports underreaction by analysts to the ISM PMI in economic expansions. However, all estimated coefficients on the ISM PMI are negative in contraction phases, and only one is statistically significant. In addition, the evidence is mixed regarding the statistical significance of the difference between estimated coefficients on the ISM PMI in expansion phases versus contraction phases. Two of the four Wald statistics are significant.[178]

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[177] NBER cycle peaks and troughs are determined several months after the event. Therefore, this test does not represent an evaluation of earnings revision predictability, but rather the stability of the relationship between earnings revisions and macroeconomic variables across phases of the cycle.

[178] Insignificant coefficients on the ISM PMI for contractions relative to expansions is partially the result of a much smaller number of contraction observations. Less than 13% of the quarters from March 1979 through to December 2009 are designated as contraction phases. However, note that estimated coefficients on the default spread for equally-weighted and median revision regressions are statistically significant in contraction phases. This is evidence of analysts' underreacting to the negative impact on earnings of higher default spreads in contraction phases.

Table 6.8 Multivariate regressions of aggregate earnings revisions on lagged economic state variables, lagged earnings revisions and lagged realized earnings with regime shifts, 1979–2009

Aggregated earnings revisions are regressed on lagged earnings revisions, lagged changes in realized earnings and two economic state variables: the lagged ISM PMI and lagged credit spreads. A regime dummy variable is included to identify change in estimated parameters across regimes. Regimes are determined by NBER classification of periods of expansion and contraction. Results are conditional on the NBER regime at the start of the 4 quarter revision period. Results provided are estimated coefficients, t ratios (in parentheses) and adjusted R^2 for regressions of the following form:

$$\Delta \mathrm{E}_t^{\mathrm{r}} = \alpha_1 + \alpha_2 \mathrm{D}_t + \beta_{1,\Delta\mathrm{E}^{\mathrm{r}}}(1-\mathrm{D}_t)\Delta \mathrm{E}_{t-5}^{\mathrm{r}} + \beta_{2,\Delta\mathrm{E}^{\mathrm{r}}}\mathrm{D}_t\Delta \mathrm{E}_{t-5}^{\mathrm{r}} + \beta_{1,\Delta\mathrm{E}^{\mathrm{a}}}(1-\mathrm{D}_t)\Delta \mathrm{E}_{t-5}^{\mathrm{a}} + \beta_{2,\Delta\mathrm{E}^{\mathrm{a}}}\mathrm{D}_t\Delta \mathrm{E}_{t-5}^{\mathrm{a}}$$

$$+\boldsymbol{\beta}_{1,\mathrm{S}}(1-\mathrm{D}_t)\mathbf{S}_{t-4} + \boldsymbol{\beta}_{2,\mathrm{S}}\mathrm{D}_t\mathbf{S}_{t-4} + \varepsilon_t$$

$\Delta \mathrm{E}_t^{\mathrm{r}}$ represents the measure of aggregate 4 quarter earnings revisions and $\mathbf{S}_{t-4}$ represents a vector of the most recent month-end values of the economic state variables prior to the date at which analysts' earnings forecasts are aggregated. $\Delta \mathrm{E}_{t-5}^{\mathrm{r}}$ represents earnings revisions lagged 5 quarters and $\Delta \mathrm{E}_{t-5}^{\mathrm{a}}$ represents realized earnings changes lagged 5 quarters. D_t represents a two-state regime dummy variable. The lagged realized earnings and earnings revisions measures are consistent with the construction of the dependent variable in terms of numerator (earnings or earnings per share) and deflator. Wald test statistics are included, investigating the significance of the differences in all estimated coefficients between regimes, and the significance of the difference between estimated coefficients on the ISM PMI in expansion and contraction phases. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

Coefficient	ΔEE$^{\mathrm{r}}$	ΔEB$^{\mathrm{r}}$	Δebeq$^{\mathrm{r}}$	Δebmed$^{\mathrm{r}}$
α_1	0.028	0.005	0.000	0.004
	(0.118)	(0.103)	(-0.007)	(0.245)
α_2	-0.305	-0.055	**-0.066**	**-0.040**
	(-1.026)	(-1.004)	(-2.635)	(-1.857)
$\beta_{1,\Delta\mathrm{E}^{\mathrm{r}}}$	-0.051	-0.151	0.026	0.025
	(-0.217)	(-0.564)	(0.126)	(0.073)
$\beta_{2,\Delta\mathrm{E}^{\mathrm{r}}}$	0.003	0.013	**0.336**	**0.356**
	(0.012)	(0.037)	(2.301)	(1.681)
$\beta_{1,\Delta\mathrm{E}^{\mathrm{a}}}$	**0.379**	**0.433**	0.040	0.288
	(2.960)	(2.817)	(0.195)	(0.576)
$\beta_{2,\Delta\mathrm{E}^{\mathrm{a}}}$	0.120	0.103	-0.011	-0.177
	(0.898)	(0.484)	(-0.058)	(-0.575)
ISM PMI (contraction, $\mathrm{D}_t = 0$)	-0.383	-0.071	-0.076	**-0.058**
	(-0.706)	(-0.693)	(-1.487)	(-2.261)
ISM PMI (expansion, $\mathrm{D}_t = 1$)	**0.456**	**0.084**	**0.094**	**0.066**
	(1.729)	(1.747)	(2.483)	(2.745)
Default spread (contraction, $\mathrm{D}_t = 0$)	-2.139	-0.297	**-0.609**	**-0.561**
	(-0.854)	(-0.646)	(-2.692)	(-2.138)
Default spread (expansion, $\mathrm{D}_t = 1$)	-2.914	-0.417	-0.170	-0.509
	(-1.021)	(-0.754)	(-0.267)	(-1.023)
Adjusted R^2	0.446	0.376	0.320	0.372
Wald statistic: Regime 1 coefficients = Regime 2 coefficients	**18.336**	**16.786**	**35.312**	**41.753**
Wald statistic: Regime 1 ISM PMI coefficient = Regime 2 ISM PMI coefficient	1.662	1.605	**8.735**	**10.857**

Overall, there is supporting evidence for analysts' earnings forecasts underreacting to the ISM PMI during expansion phases. However, the fewer available data points for contraction phases makes drawing firm conclusions difficult for periods of deteriorating macroeconomic growth.

6.6.4 Sectors and industries

IN CHAPTER 5 I provide evidence of significant variation in the relationships between aggregated realized earnings changes and a range of macroeconomic variables across sectors (variation in earnings cyclicality). If sector earnings display systematic variation in their sensitivity to macroeconomic factors it raises the question of whether analysts recognize this. By evaluating analyst efficiency with respect to macroeconomic information at the sector level it is possible to obtain stronger insights into the drivers of forecast inefficiency. For example, it is possible to obtain stronger insights regarding competing drivers of forecast inefficiency: analysts reacting systematically to economic information when realized earnings do not, and analysts underreacting to economic information relative to realized earnings' reactions.

I form GICS level 1 sector portfolios and generate time series for aggregate sector measures of four quarter earnings revisions, four quarter changes in realized earnings and four quarter forecast changes in earnings. Each of these is then regressed on lagged values of the ISM PMI. In the case of forecast revisions the values of the ISM PMI represents levels available to analysts prior to the start of the revision period. For realized earnings changes it is the value of the ISM PMI available prior to the start of the earnings period. For forecast earnings changes it is the value of the ISM PMI published prior to the submission date for analysts' four quarter earnings expectations. This enables comparison of the relationship between realized earnings and the lagged ISM PMI with analyst expectations for the reaction of realized earnings to the lagged ISM PMI, and any consequent relationship between earnings revisions and the lagged ISM PMI.

For example, the first sector in Table 6.9 is Energy. For aggregated forecast revisions deflated by book value I find a statistically significant slope coefficient. The same is true for realized earnings changes, but not for forecast earnings changes. Therefore, for this sector there is a statistically significant relationship between future realized earnings and the ISM PMI, but analysts fail to recognize this (hence the insignificant coefficient on forecast earnings changes). This contributes to a significant relationship between future revision activity for Energy sector earnings and the ISM PMI. Energy sector analysts on average underreact to the ISM PMI, so earnings forecasts are subject to later revision. This result is robust to the earnings aggregation methodology presented here (ΔEB, Δebeq and Δebmed).

Results for other sectors vary depending on the aggregation methodology employed for the earnings variable.[179] Nonetheless, in all regressions for which I find a statistically significant relationship between the ISM PMI and future realized

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[179] For example, for the Materials and Industrials sectors the estimated coefficients on forecast earnings measures are smaller than those on realized earnings measures (and the difference is statistically significant). Although there is a strong and statistically significant relationship between realized earnings and the lagged ISM PMI (with R^2s ranging from 0.191 to 0.285), the evidence suggests analysts fail to fully incorporate this relationship into their forecasts. However, unlike Energy sector analysts, the Materials and Industrials sector analysts at least appear to recognize there is a relationship between realized earnings and the ISM PMI (hence, the statistically significant estimated coefficient on forecast earnings for these two sectors). Conversely, aggregated realized earnings changes for the Financials and Telecommunication Services sectors show no evidence of a significant relationship with the lagged ISM PMI across any of the three aggregate earnings factors presented. Analysts' forecasts correctly display no evidence of a relationship with the lagged ISM PMI. Therefore, the evidence is consistent with analysts recognizing the ISM PMI should have no significant impact on their earnings expectations. Consequently, I find no evidence of a significant relationship between the ISM PMI and one year-ahead earnings revisions for these sectors. Results for the Consumer Discretionary sector provide a further variation. For two out of the three aggregate earnings methodologies the relationship between realized earnings changes and the lagged ISM PMI is not significant, but the relationship between forecast earnings changes and the lagged ISM PMI is. Therefore, analysts appear to react to the ISM PMI despite the lack of consistent evidence for a relationship between the ISM PMI and future realized earnings.

Table 6.9 Univariate regressions of aggregate revisions, realized earnings and forecasts on the lagged ISM PMI by sector, 1979–2009

The dataset is divided into GICS level 1 sectors. Select measures of aggregate market 4 quarter earnings revisions, realized earnings and forecast earnings changes are regressed on lagged values of the ISM PMI. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$\Delta E_t^x = \alpha + \beta S_{t-4} + \varepsilon_t$$

ΔE_t^x represents either forecast revisions, realized earnings or forecast earnings measures and S_{t-4} represents the most recent month-end value of the economic state variable prior to the start of the earnings change period. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

Sector	ΔEB			Δebeq			Δebmed		
	Forecast revisions	Realized earnings	Forecast earnings	Forecast revisions	Realized earnings	Forecast earnings	Forecast revisions	Realized earnings	Forecast earnings
	0.260	**0.372**	0.078	**0.214**	**0.421**	0.055	**0.161**	**0.301**	0.019
Energy	(2.367)	(2.730)	(1.139)	(2.152)	(2.716)	(1.043)	(2.456)	(2.713)	(0.409)
	0.142	0.117	0.058	0.118	0.104	0.028	0.107	0.117	0.005
	0.292	**0.417**	**0.201**	**0.240**	**0.378**	**0.161**	**0.170**	**0.251**	**0.088**
Materials	(3.409)	(3.479)	(4.158)	(3.433)	(3.166)	(4.471)	(3.234)	(4.768)	(4.496)
	0.248	0.191	0.395	0.292	0.219	0.397	0.276	0.269	0.380
	0.122	**0.232**	**0.089**	**0.134**	**0.212**	**0.088**	**0.149**	**0.166**	**0.068**
Industrials	(3.391)	(5.233)	(2.535)	(3.741)	(4.699)	(2.825)	(3.964)	(4.295)	(2.430)
	0.227	0.284	0.215	0.252	0.208	0.281	0.315	0.285	0.249
	0.090	0.102	**0.069**	**0.062**	0.041	**0.063**	**0.076**	**0.064**	**0.049**
Consumer Discretionary	(2.775)	(1.039)	(2.281)	(3.096)	(0.943)	(2.884)	(3.339)	(2.387)	(1.806)
	0.091	0.015	0.139	0.072	0.006	0.214	0.131	0.043	0.176
	0.010	0.075	0.020	**0.071**	0.055	0.028	**0.039**	0.019	0.014
Consumer Staples	(0.377)	(1.365)	(0.639)	(1.903)	(1.362)	(1.335)	(1.769)	(0.856)	(0.778)
	0.001	0.036	0.009	0.062	0.014	0.038	0.073	0.013	0.025
	0.026	0.028	0.001	**0.052**	-0.005	0.022	**0.046**	0.008	0.002
Health Care	(1.373)	(0.897)	(0.025)	(2.000)	(-0.163)	(0.911)	(2.106)	(0.510)	(0.063)
	0.021	0.004	0.000	0.044	0.000	0.012	0.062	0.003	0.000
	0.066	0.053	0.017	0.042	0.034	0.023	0.022	0.029	0.021
Financials	(1.340)	(0.955)	(0.485)	(1.051)	(0.865)	(1.011)	(0.766)	(0.888)	(1.487)
	0.031	0.007	0.008	0.031	0.007	0.029	0.016	0.015	0.066
	0.105	0.122	**0.096**	**0.167**	**0.173**	**0.098**	**0.175**	**0.178**	**0.066**
Information Technology	(1.561)	(0.914)	(2.232)	(4.112)	(2.253)	(2.599)	(3.867)	(2.212)	(1.897)
	0.052	0.012	0.114	0.161	0.042	0.156	0.215	0.115	0.111
	0.016	0.042	0.019	0.074	0.074	0.002	**0.066**	0.066	0.003
Telecommunication Services	(0.371)	(0.553)	(0.434)	(1.481)	(0.554)	(0.077)	(2.989)	(1.291)	(0.192)
	0.001	0.002	0.001	0.013	0.004	0.000	0.081	0.031	0.001
	0.017	-0.006	-0.009	0.029	0.015	-0.005	**0.024**	0.023	**-0.010**
Utilities	(0.609)	(-0.229)	(-1.283)	(1.636)	(0.805)	(-0.786)	(1.840)	(1.391)	(-2.219)
	0.022	0.000	0.022	0.080	0.004	0.009	0.106	0.044	0.068

Table 6.10 Univariate regressions of aggregate earnings revisions on the lagged ISM PMI by Fama-French industry, 1979–2009

The dataset is divided into the Fama-French 49 industries. Select measures of aggregate market 4 quarter earnings revisions for the industry portfolios are regressed on the ISM PMI, lagged to ensure this variable was available to analysts prior to the submission of earnings forecasts at the start of the 4 quarter revision period. Results provided are estimated slope coefficients, $\hat{\beta}_t$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$\Delta E_t^r = \alpha + \beta S_{t-4} + \varepsilon_t$$

ΔE_t^r represents the measure of aggregate 4 quarter earnings revisions and S_{t-4} represents the most recent month-end value of the economic state variable prior to the date at which analysts' earnings forecasts are aggregated. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

Industry		ΔEB^r			$\Delta ebeq^r$			$\Delta ebmed^r$		
	df	$\hat{\beta}$	t	R^2	$\hat{\beta}$	t	R^2	$\hat{\beta}$	t	R^2
Agriculture	43	0.243	(1.161)	0.033	-0.028	(-0.159)	0.000	-0.026	(-0.150)	0.000
Food Products	121	0.026	(0.566)	0.010	**0.099**	(2.269)	0.078	**0.063**	(1.700)	0.055
Candy & Soda	116	**0.056**	(1.798)	0.045	**0.126**	(1.717)	0.056	**0.096**	(2.154)	0.041
Beer & Liquor	117	-0.030	(-0.581)	0.002	-0.020	(-0.326)	0.001	-0.049	(-0.955)	0.027
Tobacco Products	122	0.077	(1.389)	0.018	**0.141**	(2.449)	0.044	-0.003	(-0.072)	0.000
Recreation	122	**0.104**	(1.843)	0.019	**0.115**	(1.696)	0.023	0.098	(1.442)	0.014
Entertainment	122	0.139	(1.573)	0.103	0.016	(0.158)	0.001	0.106	(1.418)	0.040
Printing and Publishing	122	0.068	(1.533)	0.038	**0.087**	(2.288)	0.067	0.056	(1.568)	0.041
Consumer Goods	122	-0.014	(-0.233)	0.001	0.015	(0.374)	0.002	0.029	(0.927)	0.018
Apparel	113	-0.036	(-0.802)	0.011	0.025	(0.501)	0.003	0.041	(0.981)	0.011
Healthcare	117	-0.076	(-0.925)	0.018	-0.074	(-0.885)	0.014	-0.029	(-0.370)	0.003
Medical Equipment	122	0.039	(0.971)	0.025	0.069	(1.432)	0.049	0.063	(1.209)	0.049
Pharmaceutical Products	122	0.013	(0.531)	0.003	0.069	(1.277)	0.031	**0.061**	(2.284)	0.060
Chemicals	122	**0.223**	(3.550)	0.210	**0.200**	(3.795)	0.283	**0.163**	(3.567)	0.241
Rubber and Plastic Products	120	**0.131**	(2.826)	0.109	**0.162**	(2.755)	0.126	**0.158**	(2.750)	0.125
Textiles	118	0.068	(1.283)	0.036	**0.114**	(2.360)	0.105	**0.117**	(2.807)	0.127
Construction Materials	122	**0.203**	(3.152)	0.218	**0.172**	(3.031)	0.205	**0.151**	(3.868)	0.251
Construction	122	-0.073	(-0.360)	0.009	-0.019	(-0.222)	0.001	0.019	(0.293)	0.002
Steel Works etc	122	**0.441**	(2.665)	0.268	**0.400**	(2.630)	0.262	**0.274**	(2.891)	0.249
Fabricated Products	115	**0.210**	(1.743)	0.041	**0.205**	(1.799)	0.060	0.133	(1.544)	0.030
Machinery	122	**0.254**	(1.777)	0.182	**0.203**	(3.211)	0.161	**0.211**	(3.473)	0.251

Table continues overleaf

Table 6.10 Univariate regressions of aggregate earnings revisions on the lagged ISM PMI by Fama-French industry, 1979–2009

Table continued from previous page

Industry		ΔEB^r			$\Delta ebeq^r$			$\Delta ebmed^r$		
	df	$\hat{\beta}$	t	R^2	$\hat{\beta}$	t	R^2	$\hat{\beta}$	t	R^2
Electrical Equipment	122	**0.107**	(2.763)	0.155	**0.121**	(2.799)	0.085	**0.100**	(2.189)	0.073
Automobiles and Trucks	122	0.007	(0.080)	0.000	**0.096**	(2.174)	0.041	**0.117**	(2.905)	0.061
Aircraft	122	**0.235**	(3.234)	0.122	**0.139**	(2.459)	0.106	**0.116**	(1.990)	0.081
Shipbuilding, Railroad Equipment	120	0.077	(1.266)	0.040	0.019	(0.323)	0.002	**0.068**	(1.831)	0.032
Defense	118	0.063	(0.925)	0.007	0.097	(0.707)	0.015	0.126	(0.844)	0.024
Precious Metals	120	0.073	(0.858)	0.013	-0.009	(-0.112)	0.000	0.036	(0.482)	0.004
Non-Metallic and Ind Met Mining	96	-0.133	(-0.616)	0.007	0.000	(0.001)	0.000	0.030	(0.132)	0.001
Coal	122	**0.557**	(3.028)	0.153	**0.274**	(2.612)	0.089	**0.242**	(1.828)	0.120
Petroleum and Natural Gas	110	0.182	(0.785)	0.027	0.137	(0.558)	0.013	0.158	(0.700)	0.021
Utilities	122	**0.266**	(2.127)	0.129	**0.226**	(2.349)	0.095	**0.191**	(2.538)	0.094
Communication	122	0.022	(0.709)	0.030	**0.031**	(2.024)	0.090	**0.024**	(1.843)	0.107
Personal Services	122	-0.002	(-0.042)	0.000	0.050	(0.939)	0.007	0.012	(0.278)	0.001
Business Services	119	-0.023	(-0.476)	0.002	-0.008	(-0.117)	0.000	-0.011	(-0.231)	0.001
Computers	122	**0.076**	(2.626)	0.057	**0.122**	(2.490)	0.128	**0.101**	(3.328)	0.113
Computer Software	122	0.090	(0.909)	0.024	**0.148**	(3.145)	0.104	**0.172**	(4.449)	0.173
Electronic Equipment	122	**0.192**	(2.585)	0.090	**0.165**	(3.027)	0.119	**0.175**	(3.994)	0.159
Measuring and Control Equipment	121	**0.138**	(2.044)	0.049	**0.186**	(2.614)	0.091	**0.151**	(2.288)	0.071
Business Supplies	122	**0.171**	(2.116)	0.118	**0.109**	(1.772)	0.088	0.086	(1.547)	0.073
Shipping Containers	122	**0.122**	(2.494)	0.103	**0.104**	(2.433)	0.048	**0.086**	(2.093)	0.066
Transportation	122	**0.182**	(3.296)	0.214	**0.163**	(3.805)	0.220	**0.136**	(3.266)	0.184
Wholesale	122	**0.108**	(3.339)	0.143	**0.137**	(3.775)	0.164	**0.110**	(2.263)	0.152
Retail	122	-0.050	(-1.294)	0.025	-0.020	(-0.855)	0.003	0.018	(1.154)	0.005
Restaurants, Hotels, Motels	122	0.033	(1.188)	0.007	0.018	(0.263)	0.002	0.035	(0.506)	0.007
Banking	122	**0.132**	(1.917)	0.038	0.075	(1.321)	0.050	0.019	(0.321)	0.006
Insurance	120	0.029	(0.549)	0.020	0.074	(1.506)	0.080	0.050	(1.342)	0.042
Real Estate	117	-0.135	(-0.605)	0.023	0.045	(0.556)	0.006	0.039	(0.455)	0.004
Trading	122	0.056	(1.250)	0.024	0.038	(1.205)	0.017	0.025	(1.164)	0.017
Other	0	-	-	-	-	-	-	-	-	-

earnings, I also find a positive and statistically significant relationship between the ISM PMI and future earnings revisions. Simply, in all cases in which realized earnings exhibit a significant relationship with lagged values of the ISM PMI, analysts fail to fully recognize this, in turn contributing to a significant relationship between lagged values of the ISM PMI and subsequent earnings revisions.

Also evident in Table 6.9 is substantial variation across sectors in the predictability of future earnings revisions with the ISM PMI. Regressions R^2s for aggregate sector earnings revisions deflated by lagged book value range from 0.001 (Telecommunication Services) to 0.248 (Materials). Similar differences are evident for equally-weighted and median per share revision measures. To increase the granularity of results I repeat regressions of annual earnings revisions on lagged observations of the ISM PMI (on a rolling quarterly basis) for revision measures aggregated by the Fama-French 49 industries.[180] Results are provided in Table 6.10. Substantial variation in estimated slope coefficients and regression R^2s across industries is clearly evident.[181]

Evidence of systematic sector- and industry-driven variation in the efficiency of analysts' forecasts with respect to the ISM PMI consequently implies sector- and industry-driven variation in the predictability of earnings revisions. This in turn motivates investigation of the relationship between predicted industry revisions and future industry returns. I explore this notion in the following section.

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[180] Effectively regressions are performed for 48 industries given I have no observations for the "Other" industry.

[181] In addition, the standard deviation of estimated slope coefficients across the Fama-French 49 industries is larger than the standard deviation of estimated slope coefficients across the 10 GICS sectors, highlighting the increased granularity of the Fama-French results.

6.7 *Earnings revision predictability and returns*

PRECEDING SECTIONS PROVIDE evidence for the inefficiency of analysts' earnings forecasts with respect to the ISM PMI. That inefficiency is robust to a range of conditioning variables, but I present evidence of substantial variation in the efficiency of aggregated analysts' forecasts across sectors and industries. Given many researchers have published evidence of significant relationships between earnings revisions and stock returns,[182] I investigate the relationship between predicted earnings revisions (predicted on the basis of estimated inefficiency) and returns.

In Table 6.11 I provide summary results for regressions of aggregate market stock returns on three measures of aggregate market earnings revisions (actual revisions rather than predicted revisions). For ΔEE^r and ΔEB^r, returns are value-weighted. For $\Delta ebeq^r$, returns are equally-weighted.[183] Returns are calculated for rolling 3, 6, 9 and 12 month periods. The 3 month returns, measured from the start of the earnings revision period to the end of the first quarter, are regressed on the full four quarter revision. This approach is also applied to 6 and 9 month returns. The 12 month return regressions therefore exactly overlap the four quarter earnings revision periods.

For the two value-weighted series the estimated coefficient on earnings revisions is significant out to the nine month returns regression. None of the estimated coefficients on equally-weighted revisions are significant. Hence, at the aggregate market level there is no evident utility in employing the predictability of equally-

[182] Examples include Imhoff and Lobo (1984), Cornell and Landsman (1989), Liu and Thomas (2000), Capstaff, Paudyal and Rees (2001), Clement and Tse (2003), Gleason and Lee (2003), Barth and Hutton (2004), Beaver, Cornell, Landsman and Stubben (2008) and Da and Warachka (2009).

[183] Returns include both capital appreciation and dividends, and are aggregated across the same companies included in each quarter of the earnings revision time series. Return data is sourced from CRSP.

Table 6.11 Univariate regressions of aggregate returns on aggregate earnings revisions, 1979–2009

Measures of aggregate market returns (value- or equally-weighted) are regressed on 4 quarter earnings revisions. Return horizons are calculated from the start of the 4 quarter revision period. The 3 month return horizon therefore represents returns over the first quarter of the 4 quarter revision period, while the 12 month return horizon completely overlaps the revision period. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}_t^{\mathrm{r}} + \varepsilon_t$$

R_t represents aggregate market returns (value-weighted for ΔEE^r and ΔEB^r, and equally-weighted $\Delta ebeq^r$) and $\Delta \mathrm{E}_t^{\mathrm{r}}$ represents the measure of aggregate 4 quarter earnings revisions. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

Return horizon (months)	ΔEE^r	ΔEB^r	$\Delta ebeq^r$
3	**0.266**	**1.615**	1.132
	(2.309)	(2.690)	(1.244)
	0.079	0.089	0.019
6	**0.456**	**2.866**	1.429
	(1.938)	(2.113)	(0.778)
	0.106	0.127	0.014
9	**0.570**	**3.616**	1.326
	(1.838)	(2.069)	(0.666)
	0.101	0.124	0.007
12	0.609	3.908	0.665
	(1.050)	(1.251)	(0.182)
	0.083	0.104	0.001

weighted earnings revisions to predict returns, given the lack of evidence of a significant relationship between equally-weighted returns and actual revisions. There is evidence of a significant relationship between value-weighted returns and value-weighted aggregated earnings revisions, but not for the full four quarter revision period. As the return horizon increases, the range of new information impacting returns similarly increases, resulting in larger standard errors for estimated slope coefficients and reduced statistical significance. However, for the two value-weighted series the respective magnitudes of the estimated slope coefficients increase monotonically as the return horizon lengthens.[184]

Combining evidence from prior sections on the predictability of four quarter ahead earnings revisions with evidence of a significant relationship between actual earnings revisions and returns (albeit over horizons shorter than the full revision period) motivates investigation of the prediction of aggregate returns with predicted earnings revisions. In particular, given evidence of substantial variation in the predictability of revisions at the industry level presented in Table 6.10, this suggests an industry-based investment strategy employing predicted industry revisions to derive a long-short portfolio driven by relative predicted revisions.

In Table 6.12 I present results from time series regressions of Fama-French industry three month returns on annual industry realized earnings revisions. As per Table 6.11 the start of the three month return horizon matches the start of the 12 month revision period. All statistically-significant slope coefficients are, as should be expected, positive. Approximately two-thirds of the value-weighted industry results have statistically significant slope coefficients. Stronger 12 month earnings revisions are therefore associated with positive three month returns.

[184] A positive relationship between analysts' earnings revisions and stock returns has similarly been reported by a number of researchers (although in my research the result is for value-weighted aggregated market earnings revisions). Examples include Imhoff and Lobo (1984), Cornell and Landsman (1989), Liu and Thomas (2000), Clement and Tse (2003), Gleason and Lee (2003) and Beaver, Cornell, Landsman and Stubben (2008).

Table 6.12 Univariate regressions of Fama-French industry returns on industry earnings revisions, 1979–2009

Measures of industry returns (value- or equally-weighted) are regressed on 4 quarter industry earnings revisions. Return horizons are calculated from the start of the 4 quarter revision period. The 3 month return horizon therefore represents returns over the first quarter of the 4 quarter revision period. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and R^2 for regressions of the following form:

$$R_t^i = \alpha + \beta \Delta E_t^{ri} + \varepsilon_t$$

R_t^i represents aggregate industry returns (value-weighted for ΔEB^r, and equally-weighted $\Delta ebeq^r$) and ΔE_t^{ri} represents the measure of aggregate 4 quarter earnings revisions for industry i. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

Industry	ΔEB^r			$\Delta ebeq^r$		
	$\hat{\beta}$	t	R^2	$\hat{\beta}$	t	R^2
Agriculture	**0.636**	(3.250)	0.095	0.207	(0.581)	0.012
Food Products	-0.073	(-0.119)	0.000	-0.970	(-1.617)	0.032
Candy & Soda	-0.480	(-1.327)	0.007	-0.307	(-1.363)	0.013
Beer & Liquor	0.087	(0.457)	0.001	**0.458**	(1.793)	0.020
Tobacco Products	**0.893**	(3.047)	0.054	**0.381**	(1.932)	0.016
Recreation	0.368	(1.039)	0.014	0.086	(0.352)	0.001
Entertainment	**1.512**	(2.788)	0.078	0.075	(0.247)	0.000
Printing and Publishing	**1.422**	(1.962)	0.077	1.419	(1.148)	0.066
Consumer Goods	0.263	(1.500)	0.008	**1.207**	(2.211)	0.044
Apparel	**1.823**	(4.431)	0.083	0.280	(0.760)	0.005
Healthcare	**1.386**	(3.541)	0.067	**0.611**	(1.724)	0.014
Medical Equipment	0.448	(0.521)	0.004	0.273	(0.413)	0.001
Pharmaceutical Products	0.615	(1.147)	0.010	-0.529	(-1.103)	0.007
Chemicals	0.503	(1.161)	0.024	**0.826**	(1.776)	0.036
Rubber and Plastic Products	**0.858**	(2.118)	0.027	**0.895**	(2.258)	0.040
Textiles	**2.112**	(3.890)	0.100	**2.140**	(3.070)	0.083
Construction Materials	**0.986**	(2.985)	0.058	0.588	(1.225)	0.015
Construction	**0.945**	(4.076)	0.088	**1.127**	(2.697)	0.054
Steel Works etc	**0.911**	(3.169)	0.130	**1.178**	(4.861)	0.186
Fabricated Products	-0.019	(-0.100)	0.000	0.278	(0.851)	0.006
Machinery	**0.966**	(2.384)	0.091	**1.247**	(2.788)	0.091
Electrical Equipment	0.896	(0.831)	0.011	**1.259**	(2.075)	0.044
Automobiles and Trucks	**1.012**	(2.539)	0.050	-0.566	(-1.455)	0.013
Aircraft	**0.720**	(1.900)	0.054	**1.476**	(2.490)	0.088
Shipbuilding, Railroad Equipment	**1.670**	(3.142)	0.105	0.174	(0.523)	0.002
Defense	**0.637**	(2.394)	0.041	0.248	(1.182)	0.008
Precious Metals	**0.569**	(2.099)	0.040	**0.580**	(2.040)	0.026
Non-Metallic and Ind Met Mining	**0.561**	(2.799)	0.093	**0.581**	(2.719)	0.050
Coal	**0.667**	(5.334)	0.142	**0.874**	(2.352)	0.130
Petroleum and Natural Gas	**0.992**	(3.081)	0.138	**0.696**	(1.671)	0.077
Utilities	**0.714**	(4.245)	0.139	**1.348**	(4.027)	0.186
Communication	**2.936**	(2.535)	0.081	0.528	(0.322)	0.002
Personal Services	**0.653**	(2.198)	0.047	-0.356	(-1.441)	0.012
Business Services	**0.834**	(2.512)	0.040	0.304	(0.775)	0.005
Computers	0.665	(1.124)	0.010	-0.540	(-1.087)	0.006
Computer Software	0.713	(1.415)	0.037	-0.019	(-0.036)	0.000
Electronic Equipment	**1.606**	(4.599)	0.181	**0.943**	(2.053)	0.025
Measuring and Control Equipment	**0.962**	(2.883)	0.062	0.508	(1.575)	0.016
Business Supplies	**0.537**	(1.989)	0.024	**0.761**	(2.724)	0.025
Shipping Containers	0.766	(1.544)	0.035	0.379	(1.175)	0.011

Table continues overleaf

Table 6.12 Univariate regressions of Fama-French industry returns on industry earnings revisions, 1979–2009

Table continued from previous page

Industry	ΔEB^r			$\Delta ebeq^r$		
	$\hat{\beta}$	t	R^2	$\hat{\beta}$	t	R^2
Transportation	**0.952**	(2.448)	0.050	**0.752**	(1.936)	0.020
Wholesale	0.302	(0.532)	0.003	0.438	(0.648)	0.006
Retail	**1.201**	(1.705)	0.039	0.615	(0.755)	0.006
Restaurants, Hotels, Motels	0.328	(1.115)	0.006	0.094	(0.199)	0.000
Banking	0.682	(1.587)	0.050	**1.341**	(2.148)	0.059
Insurance	**2.496**	(2.577)	0.091	**0.854**	(2.175)	0.021
Real Estate	**1.575**	(2.333)	0.198	**0.926**	(1.684)	0.033
Trading	**1.533**	(6.382)	0.134	**1.282**	(2.355)	0.052
Other	-	-	-	-	-	-

However, there is also considerable variation in the strength of the relationship between revisions and returns across industries: both in terms of estimated slope coefficients and regression R^2s. For the value-weighted results, estimated slope coefficients range from an insignificant value of -0.480 to a significant value of 2.936. R^2s range from 0.000 to 0.198. It is this variation in the relationship between industry returns and revisions, in combination with evidence of revision predictability, that signals the potential for significant returns from an industry-based investment strategy.

To evaluate the relationship between predicted earnings revisions and returns I firstly regress aggregated Fama-French industry earnings revisions (deflated by lagged book value) on lagged values of the PMI. A separate time-series regression is run for each industry.[185] Industries are then divided into deciles each quarter on the basis of a ranking of fitted values of year-ahead earnings revisions. Three month returns in the quarter following the start of the forecast revision period are then calculated for each decile portfolio (the matching of return and revision periods is identical to that employed for the three month results in Table 6.11).

Panel A in Table 6.13 provides simple averages of quarterly returns for each decile portfolio, followed by value-weighted average returns. Equally- and value-weighted risk adjusted returns are provided in Panel B.

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[185] Given predicted revisions are obtained from an ex post regression on the full datatset, I investigate time variation in the relationship between revisions and lagged explanatory variables. I perform Chow tests for structural change in estimated coefficients on a bifurcated time series of aggregate market earnings revisions deflated by lagged book value. Chow test statistics are insignificant at the 5% level for regressions of market revisions deflated by lagged book value on (1) lagged revisions, market realized earnings changes, ISM PMI and the default spread; (2) the lagged ISM PMI and default spread; and, (3) the lagged ISM PMI alone. In contrast, regime-dependent regressions in sub-section 6.6.3 provide evidence of significant differences in estimated coefficients conditioned on the NBER dating of expansions and contractions (although contraction phases represent less than 13% of the time series evaluated). To mitigate the risk of over-fitting, I do not generate predicted industry revisions conditioned on economic regimes for prediction of industry returns.

Table 6.13 Univariate regressions of Fama-French industry returns on predicted industry earnings revisions, 1979–2009

Industry earnings revisions are regressed on the lagged ISM PMI. Regressions are of the following form:

$$\Delta \mathrm{E}_t^{ri} = \alpha + \beta_{\mathrm{S}} \mathrm{S}_{t-4} + \varepsilon_t$$

$\Delta \mathrm{E}_t^{ri}$ refers to aggregate industry 4 quarter earnings revisions deflated by lagged book value and S_{t-4} represents the most recent month-end value of the ISM PMI prior to the date at which analysts' earnings forecasts are aggregated. Fitted values for industry revisions are then sorted into deciles based on the magnitude of the predicted revisions, and subsequent average decile returns are calculated. This process is repeated quarterly and average returns over each industry time series are reported below (Panel A). Return horizons are calculated from the start of the fitted 4 quarter revision period. The 3 month return horizon therefore represents returns over the first quarter of the 4 quarter revision period. In addition, decile equally-weighted and value-weighted excess returns are regressed on the Fama-French 3 factor model as per the following regression:

$$\mathrm{R}_t^i - \mathrm{R}_t^f = \alpha_i + \beta_{Rm}\left(\mathrm{R}_t^m - \mathrm{R}_t^f\right) + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_t$$

Estimated risk-adjusted returns, α_i, are provided in Panel B. t ratios are in parentheses. Results in bold are statistically significant at the 10% level.

A. Average returns	Deciles										
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High - Low
Equally-weighted	**2.333**	**3.156**	**3.144**	**2.918**	**2.961**	**3.083**	**2.989**	**3.223**	**3.654**	**2.987**	0.654
	(2.201)	(3.499)	(3.486)	(3.411)	(3.293)	(3.305)	(4.317)	(3.717)	(4.909)	(3.640)	(0.854)
Value-weighted	**1.969**	**2.922**	**3.234**	**3.001**	**2.962**	**2.742**	**3.056**	**3.504**	**3.543**	**2.948**	0.979
	(1.675)	(2.557)	(2.949)	(2.511)	(2.891)	(3.108)	(3.987)	(4.106)	(4.476)	(3.709)	(1.231)
B. Risk-adjusted returns											
Equally-weighted	-0.937	-0.007	-0.128	-0.221	-0.205	-0.313	-0.105	0.009	1.014	-0.012	0.925
	(-1.398)	(-0.021)	(-0.362)	(-0.547)	(-0.587)	(-0.734)	(-0.253)	(0.024)	(2.335)	(-0.025)	(1.242)
Value-weighted	**-1.334**	0.292	0.001	0.326	0.117	-0.564	-0.047	0.364	1.106	0.205	**1.539**
	(-1.885)	(0.614)	(0.002)	(0.570)	(0.254)	(-1.299)	(-0.107)	(0.759)	(2.043)	(0.496)	(2.008)

Risk adjusted returns for industries are estimated as per Fama and French (1997), being the intercept, α_i, in a regression of excess returns (three month returns less the risk free rate, $\mathrm{R}_t^i - \mathrm{R}_t^f$) on market excess returns, small minus big (*SMB*) portfolio returns and high minus low (*HML*) portfolio returns.[186] Regressions are therefore of the following form:

$$\mathrm{R}_t^i - \mathrm{R}_t^f = \alpha_i + \beta_{Rm}\left(\mathrm{R}_t^m - \mathrm{R}_t^f\right) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \varepsilon_t \tag{6.8}$$

All decile portfolio average returns are statistically significant. However, the differences between decile 10 (high predicted revisions) returns and decile 1 (low predicted revisions) returns are not. Only in the case of risk-adjusted value-weighted returns is the difference significant, with a negative and statistically significant value-weighted return for decile 1 and positive but insignificant value-weighted return for decile 10. Hence, while there is evidence of predicted earnings revisions exhibiting a significant relationship with three month future returns, I do not obtain conclusive evidence that the model is able to explain systematic variation in future industry returns.

The model employed to derive predicted earnings revisions for Table 6.13 employs the ISM PMI as the sole explanatory variable for future earnings revisions. However, in prior sections I also provide evidence of relationships between earnings revisions and lagged values of default spreads and, in certain circumstances, lagged values of revisions and changes in realized earnings. I therefore estimate a variation of equation 6.6, regressing industry earnings revisions on lagged values of industry revisions, aggregate market revisions,

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[186] *HML* and *SMB* returns are as per the Fama and French (1993) three factor model. *HML* returns are the differences between returns on the top and bottom 30% of NYSE, Amex and Nasdaq stocks ranked on book-to-market. *SMB* returns are the differences between returns on stocks below the median level of market equity and those above the median level of market equity. Return data is sourced from Ken French's web data library, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

industry realized earnings changes, aggregate market realized earnings changes, the ISM PMI and the default spread:

$$\begin{aligned}\Delta \mathrm{E}_t^{ri} = \alpha + \beta_{\Delta \mathrm{E}^{\mathrm{r}i}} \Delta \mathrm{E}_{t-5}^{\mathrm{r}i} + \beta_{\Delta \mathrm{E}^{\mathrm{a}i}} \Delta \mathrm{E}_{t-5}^{\mathrm{a}i} + \beta_{\Delta \mathrm{E}^{\mathrm{r}}} \Delta \mathrm{E}_{t-5}^{\mathrm{rm}} + \beta_{\Delta \mathrm{E}^{\mathrm{a}}} \Delta \mathrm{E}_{t-5}^{\mathrm{am}} \\ + \boldsymbol{\beta}_{\mathrm{S}} \mathbf{S}_{t-4} + \varepsilon_t\end{aligned} \tag{6.9}$$

$\Delta \mathrm{E}_t^{ri}$ refers to the aggregate industry four quarter earnings revisions deflated by lagged book value, $\Delta \mathrm{E}_{t-5}^{\mathrm{r}i}$ is this same variable lagged five quarters, $\Delta \mathrm{E}_{t-5}^{\mathrm{rm}}$ is aggregate market earnings revisions lagged five quarters, and $\Delta \mathrm{E}_{t-5}^{\mathrm{a}i}$ and $\Delta \mathrm{E}_{t-5}^{\mathrm{am}}$ refer to five quarter lags of aggregate industry and market four quarter changes in realized earnings (deflated by book value), respectively. $\mathbf{S}_{t-4}$ represents a vector of the most recent month-end value of the economic state variables prior to the date at which analysts' earnings forecasts are aggregated. As for Table 6.13, industries are then divided into deciles each quarter on the basis of a ranking of fitted values of year-ahead earnings revisions and three month future returns are then calculated for each decile portfolio. Results are presented in Table 6.14.

Only decile 1 (low predicted revisions) has a statistically insignificant equally-weighted average return, while decile 10 (high predicted revisions) has not only a statistically significant average return, but also the highest return across all deciles. The difference between decile 10 and decile 1 returns is also statistically significant. The same is true of value-weighted average returns. In Panel B of Table 6.14 I present risk-adjusted returns, on an equally-weighted basis and a value-weighted basis. Decile 1 risk-adjusted returns are negative and statistically significant for both value and equally-weighted results. Decile 10 risk-adjusted returns are positive and statistically significant for equally-weighted results, but not for value-weighted risk-adjusted returns. Nonetheless, the difference between decile 10 and decile 1 is positive and statistically significant in both instances.

Table 6.14 Univariate regressions of Fama-French industry returns on predicted industry earnings revisions (full model), 1979–2009

Industry earnings revisions are regressed on lagged industry earnings revisions, lagged industry realized earnings changes, lagged market earnings revisions, lagged market realized earnings changes, lagged ISM PMI and lagged credit spreads. Regressions are of the following form:

$$\Delta \mathrm{E}_t^{ri} = \alpha + \beta_{\Delta \mathrm{E}^{ri}} \Delta \mathrm{E}_{t-5}^{ri} + \beta_{\Delta \mathrm{E}^{ai}} \Delta \mathrm{E}_{t-5}^{ai} + \beta_{\Delta \mathrm{E}^{\mathrm{rm}}} \Delta \mathrm{E}_{t-5}^{\mathrm{rm}} + \beta_{\Delta \mathrm{E}^{\mathrm{am}}} \Delta \mathrm{E}_{t-5}^{\mathrm{am}} + \boldsymbol{\beta}_S \mathbf{S}_{t-4} + \varepsilon_t$$

$\Delta \mathrm{E}_t^{ri}$ refers to aggregate industry 4 quarter earnings revisions deflated by lagged book value, $\Delta \mathrm{E}_{t-5}^{ri}$ is this same variable lagged 5 quarters, $\Delta \mathrm{E}_{t-5}^{\mathrm{rm}}$ is aggregate market earnings revisions lagged 5 quarters, and $\Delta \mathrm{E}_{t-5}^{ai}$ and $\Delta \mathrm{E}_{t-5}^{\mathrm{am}}$ refer to 5 quarter lags of aggregate industry and market 4 quarter changes in realized earnings (deflated by book value), respectively. $\mathbf{S}_{t-4}$ represents a vector of the most recent month-end values of the economic state variables prior to the date at which analysts' earnings forecasts are aggregated. Fitted values for industry revisions are then sorted into deciles based on the magnitude of the predicted revisions and subsequent average decile returns are calculated. This process is repeated quarterly and average returns over each industry time series are reported below (Panel A). Return horizons are calculated from the start of the fitted 4 quarter revision period. The 3 month return horizon therefore represents returns over the first quarter of the 4 quarter revision period. In addition, decile equally-weighted and value-weighted excess returns are regressed on the Fama-French 3 factor model as per the following regression:

$$\mathrm{R}_t^i - \mathrm{R}_t^f = \alpha_i + \beta_{Rm}\left(\mathrm{R}_t^m - \mathrm{R}_t^f\right) + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_t$$

Estimated risk-adjusted returns, α_i, are provided in Panel B. t ratios are in parentheses. Results in bold are statistically significant at the 10% level.

A. Average returns											
	Deciles 1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High - Low
Equally-weighted	1.366	**2.230**	**3.298**	**2.640**	**2.823**	**2.948**	**2.956**	**3.394**	**3.666**	**4.011**	**2.645**
	(1.153)	(2.458)	(3.880)	(2.745)	(2.952)	(3.434)	(3.475)	(3.918)	(4.447)	(5.062)	(2.568)
Value-weighted	1.367	**2.283**	**3.394**	**2.480**	**2.724**	**2.456**	**2.708**	**4.377**	**3.650**	**3.700**	**2.333**
	(0.992)	(3.074)	(3.643)	(2.559)	(2.479)	(2.910)	(2.916)	(4.399)	(4.509)	(4.904)	(1.824)
B. Risk-adjusted returns											
Equally-weighted	**-1.700**	**-0.795**	0.067	-0.577	-0.266	0.070	-0.021	0.351	**0.864**	**1.161**	**2.861**
	(-2.626)	(-2.186)	(0.171)	(-1.393)	(-0.690)	(0.176)	(-0.060)	(0.629)	(1.962)	(1.907)	(3.469)
Value-weighted	**-1.707**	-0.105	0.200	-0.682	-0.127	-0.272	-0.057	**1.466**	0.827	0.868	**2.575**
	(-1.989)	(-0.247)	(0.440)	(-1.400)	(-0.240)	(-0.726)	(-0.134)	(2.379)	(1.613)	(1.564)	(2.249)

Therefore, with the more comprehensive model for future industry earnings revisions, predictable earnings revisions can explain significant variation in future industry returns.

6.8 Concluding remarks

RESULTS FROM REGRESSIONS of aggregate market earnings revisions on lagged economic state variables provide evidence of analyst forecast inefficiency, in particular with regard to the ISM PMI. I find evidence of analyst underreaction to past values of the ISM PMI. This underreaction is robust to a range of conditioning factors including size, book-to-market ratios and analyst coverage. However, I find evidence of significant variation in the strength of the relationship between aggregated earnings revisions and lagged values of the ISM PMI across sectors and industries. Employing industry variation in this relationship, in combination with industry variation in the relationship between earnings revisions and returns, I find evidence of significant predictability of systematic variation in industry returns.

Evidence of systematic underreaction by analysts in aggregate to the ISM PMI is surprising in light of the considerable attention this economic factor receives from market practitioners and the media. My results suggest that analysts do revise earnings in response to changes in the ISM PMI, and this reaction is justified by evidence presented of a statistically significant relationship between aggregated realized earnings growth and lagged values of the ISM PMI. However, evidence of systematic underreaction to the ISM PMI suggests further investigation of predictable errors in aggregated analysts' earnings forecasts is warranted, along with the implications of those errors for the predictability of aggregated stock returns.

Appendix 6A Timely analyst forecasts

I/B/E/S CONSENSUS FORECASTS are calculated monthly from eligible individual analysts' forecasts. The calculation date, known as the I/B/E/S statistical period, is the Thursday before the third Friday of the month. I/B/E/S removes what are believed to be stale forecasts from the consensus measure, but many eligible forecasts can still date from some months prior to the statistical period date. Consequently, there may be large differences in the information set available to different analysts at the respective points in time each forecast was submitted.

As noted in Section 5.4, O'Brien (1988a) and Brown (1991) report evidence of improved forecast accuracy with more recent analyst forecasts. Hess and Kreutzmann (2009) respond to this problem by investigating forecasts at the individual analyst level. My response is to perform robustness tests on the eligibility period for analysts' forecasts. I generate aggregate earnings revision variables from analysts' forecasts restricted to the period between the I/B/E/S statistical period date and the calendar month end (termed here "month-end" forecasts) representing an eligibility period of typically less than two weeks. I can therefore be sure that analysts were in possession of the economic state variables investigated, given the macroeconomic data will have been released roughly three to four weeks prior to the date at which analysts submitted their forecasts. These results can then be compared with results from regressions employing all eligible analyst forecasts prior to the statistical period date. Note that this requires the use of the I/B/E/S detail dataset, which, with data requirements for analysis, restricts the sample period to March 1984–December 2009.

Results for regressions of month-end forecast revisions on lagged revisions, lagged realized earnings changes, the ISM PMI and credit spreads are presented in Table

6A.1. These are compared with results for all eligible forecasts up to the statistical period date, with the time series similarly restricted to 1984–2009.

In both sets of regressions the estimated coefficient on the ISM PMI is positive and statistically significant. Therefore, analysts' earnings forecasts appear to be inefficient with respect to the ISM PMI even when ISM PMI data is a number of weeks old. In addition, the estimated coefficients on the ISM PMI for the month-end forecasts are all larger than those reported for the full analyst sample. Hence, there is no evidence of any improvement in forecast efficiency with respect to the ISM PMI when evaluating efficiency with month-end forecasts. Consequently, results presented in Section 6.5 are robust to the eligibility period for analysts' forecasts. Therefore, to maximize the time period that can be evaluated, all other analysis in Chapter 6 employs the full analyst sample set.

Table 6A.1 Comparison of month-end analysts' earnings forecasts with all analysts' earnings forecasts, 1984–2009

Measures of aggregate market 4 quarter earnings revisions are regressed on economic state variables lagged to ensure the economic data in question was available to analysts prior to the submission of earnings forecasts at the start of the 4 quarter revision period, and lagged earnings revisions and lagged realized earnings. On the left-hand side of the table only forecasts published between the I/B/E/S statistical period and the calendar month-end are employed. On the right-hand side of the table all eligible analysts' forecasts submitted prior to the I/B/E/S statistical period are employed. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2 for regressions of the following form:

$$\Delta \mathrm{E}_t^{\mathrm{r}} = \alpha + \beta_{\Delta \mathrm{E}^{\mathrm{r}}} \Delta \mathrm{E}_{t-5}^{\mathrm{r}} + \beta_{\Delta \mathrm{E}^{\mathrm{a}}} \Delta \mathrm{E}_{t-5}^{\mathrm{a}} + \boldsymbol{\beta}_{\mathrm{S}} \mathbf{S}_{t-4} + \varepsilon_t$$

$\Delta \mathrm{E}_t^{\mathrm{r}}$ represents the measure of aggregate 4 quarter earnings revisions and $\mathbf{S}_{t-4}$ represents a vector of the most recent month-end value of the economic state variable prior to the date at which analysts' earnings forecasts are aggregated. $\Delta \mathrm{E}_{t-5}^{\mathrm{r}}$ represents earnings revisions lagged 5 quarters. $\Delta \mathrm{E}_{t-5}^{\mathrm{a}}$ represents realized earnings changes lagged 5 quarters. The lagged realized earnings and earnings revisions measures are consistent with the construction of the dependent variable in terms of numerator (earnings or earnings per share) and deflator. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Month-end analysts' forecasts					All analysts' forecasts				
Dependent variable	$\Delta \mathrm{E}_{t-5}^{\mathrm{r}}$	$\Delta \mathrm{E}_{t-5}^{\mathrm{a}}$	ISM PMI	Default spread	Adj. R^2	$\Delta \mathrm{E}_{t-5}^{\mathrm{r}}$	$\Delta \mathrm{E}_{t-5}^{\mathrm{a}}$	ISM PMI	Default spread	Adj. R^2
$\Delta \mathrm{EE}^{\mathrm{r}}$	-0.117	0.171	**1.175**	-5.336	0.310	-0.244	0.184	**0.657**	**-6.036**	0.400
	(-0.582)	(1.151)	(5.415)	(-1.531)		(-0.769)	(1.473)	(3.303)	(-2.409)	
$\Delta \mathrm{EB}^{\mathrm{r}}$	-0.119	0.212	**0.208**	-0.668	0.265	-0.237	0.217	**0.119**	-0.719	0.304
	(-0.517)	(0.951)	(4.754)	(-0.809)		(-0.602)	(1.031)	(3.407)	(-1.608)	
$\Delta \mathrm{ebeq}^{\mathrm{r}}$	**-0.187**	**0.173**	**0.223**	**1.782**	0.258	0.142	0.078	**0.100**	-0.264	0.236
	(-2.046)	(1.701)	(6.484)	(2.010)		(0.576)	(0.361)	(2.362)	(-0.562)	
$\Delta \mathrm{ebmed}^{\mathrm{r}}$	-0.074	0.147	**0.118**	-0.098	0.152	0.104	0.017	**0.070**	-0.751	0.244
	(-0.342)	(0.462)	(2.772)	(-0.169)		(0.285)	(0.040)	(2.066)	(-1.528)	

7 *Aggregated earnings, revisions and stock returns*

7.1 *Introductory concepts*

CAMPBELL (1991) DECOMPOSES stock returns into expected returns, shocks to expected returns (discount rate effects) and shocks to cash flows (cash flow effects). Within this framework Kothari, Lewellen and Warner (2006) employ aggregated realized earnings in tests that generate evidence of a strong discount rate effect in aggregated returns. Further, the magnitude of the discount rate effect in their sample is sufficient to result in *negative* correlation between aggregate returns and contemporaneous aggregate earnings growth.

This finding is important for two reasons in particular. It contrasts with evidence of *positive* correlation between returns and contemporaneous earnings growth at the individual stock level[187] and it runs contra to the implications of a range of theoretical models.[188]

However, to evaluate the cash flow and discount rate effects in returns within Campbell's framework, a good proxy for unexpected earnings is required. Kothari et al. (2006) principally employ changes in realized earnings as a proxy for unexpected earnings. In some tests they also include proxies for unexpected earnings based on time series models of changes in realized earnings.[189] They do not evaluate any proxy for unexpected earnings based on the expectations of surveyed market participants. Kothari et al. explicitly recognize this potential weakness in their analysis, commenting "In some tests, we would ideally like to have an estimate of the market's earnings surprise" (p. 549).[190] Their statement represents a key motivating force for this chapter.

I believe the measures of aggregated earnings revisions outlined in Chapters 3 and 4, and employed in empirical investigations in Chapter 6, represent an alternative proxy for aggregated unexpected earnings that meets Kothari et al.'s (2006) desire for a measure of changes in market expectations. In addition, focusing on returns around earnings announcements, Brown, Hagerman, Griffin and Zmijewski (1987a) conclude that "unexpected earnings that are based on financial analysts' earnings forecasts, in general, explain abnormal returns better than other proxies"

[187] Kothari et al. (2006) provide evidence of positive correlation between stock returns and contemporaneous earnings growth in cross-sectional regressions. Similarly, the literature on earnings response coefficients generally supports this result. Examples include Ball and Brown (1968), Beaver, Clarke and Wright (1979) and Teets and Wasley (1996).

[188] Examples include Merton (1973), Lucas (1978), Breeden (1979), Campbell and Cochrane (1999) and Chan and Kogan (2002). These are discussed in Chapter 2.

[189] Specifically, they evaluate the forecast error from an autoregressive model of realized earnings and the forecast error from an autoregressive model that includes lagged returns as an additional explanatory variable for future realized earnings changes.

[190] Similarly, Shivakumar (2010), in reference to analysis focusing solely on realized earnings announcements, comments that "A more powerful approach to investigate the information content of aggregate earnings would be one that considered all types of earnings disclosures, including management forecasts and analysts' forecasts" (p. 337). In this chapter I consider the latter.

(p. 160).[191] In tandem with the measures of aggregated realized earnings also outlined in Chapters 3 and 4 (which are closely related to Kothari et al.'s measures of aggregated realized earnings), the different proxies for unexpected earnings may be contrasted and compared. Hence, this analysis represents a robustness test on Kothari et al.'s results, employing a proxy for unexpected earnings more closely aligned with their research aims.

In addition, this analysis adds to the literature investigating the relationship between analysts' earnings revisions and stock returns.[192] I estimate the relationship between earnings revisions and returns (both at individual stock and aggregate market levels) and estimate the relative cash flow and discount rate effects in the impact of aggregate *earnings revisions* on returns. This contrasts, for example, with Kothari et al.'s (2006) analysis of cash flow and discount rate effects in aggregated changes in *realized earnings*. I am not aware of previous research employing the same or similar methodology for aggregated analysts' earnings revisions.[193]

In cross-sectional analysis of the relationship between earnings surprise and returns my results are consistent with those of Kothari et al. (2006). I find evidence of a positive and statistically significant relationship between 12 month earnings revisions and contemporaneous returns (and between 12 month changes in realized earnings and contemporaneous returns).

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[191] Brown, Hagerman, Griffin and Zmijewski (1987a) investigate five proxies for unexpected earnings: one based on a random walk model, three based on time series models and one based on analysts' forecasts from *The Value Line Investment Survey*.

[192] Examples include Cornell and Landsman (1989), Liu and Thomas (2000), Clement and Tse (2003), Gleason and Lee (2003), Beaver, Cornell, Landsman and Stubben (2008) and Da and Warachka (2009).

[193] Chen and Zhao (2008) employ value-weighted aggregated analysts' forecasts to estimate cash flow and discount rate effects, but do so in the context of a discounted valuation model.

However, in time series regressions, in contrast with the results of Kothari et al. (2006), I do not find evidence of a negative (let alone statistically significant) relationship between aggregate earnings surprise and contemporaneous returns. Nor do I find evidence of a significant negative relationship between these variables for a range of sub-portfolios (size quintiles, book-to-market quintiles and sectors). Employing the full length of the available forecast dataset (1979–2009), I find evidence of a positive (albeit insignificant) relationship between aggregated changes in realized earnings and aggregated returns, and between aggregated earnings revisions and contemporaneous returns. Consequently, my results conflict with Kothari et al.'s conclusions.

Robustness tests on sample sub-periods suggest the differing results are partially a consequence of the use of different time periods (Kothari et al. (2006) focus on 1970–2000, while my core dataset runs from 1979 through to 2009). In robustness tests, exactly replicating Kothari et al.'s described methodology and dataset for quarterly and non-overlapping annual data, I provide evidence of the dependence of their results upon the time period evaluated. This serves to highlight instability through time in the relationships identified by Kothari et al.

Further, they state their results provide "new evidence that discount-rate shocks explain a significant fraction of aggregate stock returns"(p. 538). Applying their approach for estimation of discount rate and cash flow effects in the impact of aggregate earnings surprise on returns (measuring surprise both in terms of changes in realized earnings and earnings revisions), I find no evidence of a statistically significant discount rate effect. I do find evidence of a positive and significant cash flow effect.

Overall, my research suggests that evidence for the conclusions of Kothari et al. (2006), with respect to the magnitude of discount rate effects in the impact of aggregate earnings surprise on returns, is weaker than implied by their results. My results are not inconsistent with a discount rate effect in aggregate returns. For example, a positive but insignificant relationship between aggregate returns and contemporaneous aggregate earnings revisions could be the result of a positive and significant cash flow effect combined with a significant negative impact from a discount rate effect. However, I find no evidence of a discount rate effect that is large enough to cause a negative relationship between aggregate earnings surprise and contemporaneous aggregate returns. Nor am I able to identify a significant discount rate effect in return decomposition analysis. Consequently, I find no evidence to support the contention that while cash flow effects dominate stock-level returns, discount rate effects dominate market returns.

The theoretical background and empirical evidence relevant to this research are discussed in Section 2.5. Variable construction and summary statistics are discussed in Chapters 3 and 4. A brief recap of issues is provided in Section 7.2, followed by presentation of core results (focusing on the regression of individual stock and aggregate returns on proxies for stock and aggregate earnings surprise). Robustness tests are outlined in Section 7.3. In Section 7.4 I employ procedures outlined by Kothari et al. (2006) to estimate the relative magnitude of cash flow and discount rate effects in the impact of proxies for aggregate earnings surprise on aggregate returns. Concluding remarks are provided in Section 7.5.

7.2 Aggregated earnings, revisions and returns

THE KEY FEATURE of Kothari et al.'s (2006) research is the difference in the relationship between changes in realized earnings and contemporaneous returns at the stock level versus the aggregate market level. At the stock level they find evidence that the relationship is statistically significant and *positive*. At the aggregate market level they find evidence that the relationship is statistically significant and *negative*. These results are not necessarily inconsistent. For example, Kothari et al. suggest individual stock returns may be driven more by firm-specific cash flow effects, while the diversification effect of aggregation causes market-wide discount rate effects to dominate at the market level. Patatoukas and Yan (2009) provide a theoretical framework in which the impact of earnings surprise for individual stocks on macroeconomic growth expectations is small, and consequently has little impact on the discount rate. However, the impact of aggregate earnings surprise may be large, increasing the size of the discount rate effect relative to the cash flow effect at the aggregate level compared to the individual stock level.

Kothari et al.'s (2006) findings have provided motivation for a range of subsequent studies that seek to clarify and explain discount and cash flow effects in aggregate earnings surprise.[194] I return to Kothari et al.'s core results, incorporate a new proxy for earnings surprise, and evaluate the robustness of their results including comparisons with the findings of more recent studies.

7.2.1 Earnings revisions and returns

THE MEASURES OF aggregated earnings revisions employed in Chapter 6, for evaluation of the informational efficiency of analysts' forecasts, may be employed as alternative (and unique) proxies for aggregate earnings surprise. As discussed in Section 7.1, I believe these measures are also closely aligned with Kothari et al.'s (2006) stated desire for "an estimate of the market's earnings surprise" (p. 549), and the analytical framework provided by Campbell's (1991) earnings decomposition (which requires a good proxy for unexpected earnings).

[194] Examples include Chen and Zhao (2008), Ball, Sadka and Sadka (2009), Hirshleifer, Hou and Teoh (2009), Sadka and Sadka (2009) and Cready and Gurun (2010).

Briefly recapping variable construction outlined in Chapter 3, aggregated earnings revisions are derived from time-weighted combinations of realized earnings and I/B/E/S FY1 and FY2 earnings per share estimates. Each quarter a proxy measure of forecast 12 month forward earnings is generated by time-weighting the forecasts, with weights determined by the calendar quarter and a company's balance date. Similarly, at the end of each 12 month period, a time-weighted measure of 12 month trailing earnings expectations is generated from realized earnings announced to that point and FY1 forecast earnings.[195] The difference between forecast 12 month forward earnings and period-end 12 month trailing earnings expectations is a measure of annual earnings revisions (and represents a proxy for annual earnings surprise). Aggregated and deflated as per the measures of realized earnings changes (and calculated at the individual stock level on per share data for cross-sectional regressions), I obtain a range of proxies for market earnings surprise based on surveyed expectations.

Beginning with the application of Kothari et al.'s (2006) regression analysis to aggregated earnings revision variables, I regress aggregated annual stock returns on lagged measures of aggregated annual earnings revisions. Regressions are of the following form:

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{r}}_{t-l} + \varepsilon_t \qquad (7.1)$$

$\Delta \mathrm{E}^{\mathrm{r}}_{t-l}$ represents a measure of aggregated annual forecast earnings revisions with lags, l, of zero to four quarters. R_t represents aggregated annual stock returns (value-weighted, equally-weighted or median returns matched to the aggregation method employed for earnings revisions). In aggregate regressions Kothari et al. (2006) measure market returns as the CRSP value-weighted index. To ensure maximum consistency between returns and explanatory variables I calculate value-

[195] Period-end earnings still represent expectations given the final quarter for the annual period will not have been announced.

weighted, equally-weighted and median return series from stocks included in the aggregated earnings measures.[196] Hence, the stocks included in aggregate returns are matched with the stocks included in measures of aggregate earnings revisions (this also applies to analysis of aggregate changes in realized earnings and all sub-group analysis, including size quintiles, price-to-book quintiles and sectors).

A further critical difference between the dataset employed by Kothari et al. (2006) and that employed here is the time period investigated. Kothari et al. evaluate earnings and returns data from 1970 through to 2000. Given limitations on availability of earnings revision data, my dataset runs from the first quarter of 1979 through to the fourth quarter of 2009. I demonstrate in this chapter the difference in timeframes has important implications for research conclusions.[197]

Table 7.1 provides estimated slope coefficients, t statistics and adjusted R^2s for regressions of returns on a range of lags of annual forecast earnings revisions (for rolling quarters). Results in Panel A are obtained from regressions of individual stock 12 month returns on annual revisions in earnings per share (deflated by lagged book value per share), Δeb^r, for December years. Time series averages of the annual cross-sectional regressions are then calculated, mimicking the Fama and MacBeth (1973) regressions performed by Kothari et al. (2006). Results in Panel B are obtained from regressions of aggregated returns on lagged values of aggregated revisions, over rolling quarters. ΔEE^r represents aggregated annual earnings revisions deflated by lagged forecast earnings, ΔEB^r is the same measure of earnings revisions deflated by lagged aggregate book value, $\Delta ebeq^r$ is an equally-weighted sum of annual earnings per share revisions deflated by lagged book value

[196] Stock returns include distributions and are sourced from CRSP.

[197] For additional discussion of the similarities and differences between Kothari et al.'s dataset and variable construction, and that employed here, refer to Chapters 3 and 4.

Table 7.1 Returns regressed on forecast revisions, 1979–2009

Stock returns are regressed on lagged annual earnings forecast revisions. Panel A provides results for time series averages of cross-sectional regression results performed on individual stocks for December year annual data. Panel B provides results for time series regressions of quarterly aggregated annual returns on aggregated annual earnings revisions. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios and adjusted R^2 for regressions of the following form:

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{r}}_{t-l} + \varepsilon_t$$

For Panel B, R_t represents aggregate market returns (value-weighted for ΔEE^r and ΔEB^r, equally-weighted for $\Delta ebeq^r$ and median returns for $\Delta ebmed^r$). Lags, l, of 0 to 4 quarters are evaluated. $\Delta \mathrm{E}^{\mathrm{r}}_t$ represents the measure of aggregated 4 quarter forecast revisions. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios for the aggregate time series regressions. Results in bold are statistically significant at the 10% level.

	Lag	Univariate regressions			Multivariate regressions		
		Estimated slope coef.	t-statistic	Adj. R^2	Estimated slope coef.	t-statistic	Adj. R^2
A. Cross-sectional regressions							
Δeb^r	0	**1.530**	8.237	0.084	**2.564**	10.837	0.132
	1	**0.769**	5.126	0.026	**-0.903**	-4.871	
	2	0.144	1.029	0.011	**-0.766**	-3.768	
	3	-0.008	-0.056	0.013	0.159	0.794	
	4	-0.095	-0.644	0.016	0.075	0.413	
B. Aggregate time series regressions							
ΔEE^r	0	0.609	1.050	0.076	**1.684**	2.630	0.096
	1	0.379	0.742	0.024	**-1.079**	-2.607	
	2	0.264	0.504	0.005	0.218	0.434	
	3	0.173	0.370	-0.003	**-0.823**	-1.698	
	4	0.151	0.359	-0.005	0.622	1.106	
ΔEB^r	0	3.908	1.251	0.096	**9.245**	2.974	0.117
	1	2.426	0.821	0.032	**-5.049**	-2.362	
	2	1.687	0.541	0.009	0.532	0.199	
	3	1.151	0.400	-0.001	**-4.245**	-1.795	
	4	1.042	0.395	-0.003	3.533	1.146	
$\Delta ebeq^r$	0	0.665	0.182	-0.007	**10.650**	1.835	0.011
	1	-1.084	-0.370	-0.005	**-14.135**	-3.603	
	2	-0.935	-0.296	-0.006	2.092	0.495	
	3	-0.421	-0.127	-0.008	1.340	0.283	
	4	-0.389	-0.107	-0.008	0.913	0.195	
$\Delta ebmed^r$	0	-1.730	-0.351	0.000	6.875	1.248	0.021
	1	-2.856	-0.742	0.014	**-9.103**	-2.296	
	2	-2.593	-0.647	0.009	-3.157	-0.690	
	3	-1.417	-0.398	-0.004	-1.644	-0.301	
	4	-0.239	-0.064	-0.008	6.531	1.306	

per share and $\Delta ebmed^r$ represents median values of the per share data used to calculate $\Delta ebeq^r$. Value-weighted returns are employed in regressions on ΔEE^r and ΔEB^r. Equally-weighted and median annual returns are employed in regressions on $\Delta ebeq^r$ and $\Delta ebmed^r$, respectively.

In cross-sectional regressions, the time series average of the estimated slope coefficient on Δeb^r is positive and statistically significant at a lag of 0. This result is consistent with the common findings of other researchers regarding the relationship between earnings revisions and stock returns.[198]

In univariate regressions the estimated slope coefficients for aggregate revisions with a lag of 0 (Panel B) are also positive (but insignificant) for ΔEE^r, ΔEB^r and $\Delta ebeq^r$. Only for $\Delta ebmed^r$ is the estimated coefficient negative (but insignificant). The estimated coefficients on the aggregate earnings revision measures in multivariate regressions are all positive for a lag of 0, and statistically significant for three of the four aggregate variables presented (but changing coefficient signs for other lags highlights the presence of multicollinearity).

Arguably the most important element of Kothari et al.'s (2006) findings is a negative relationship between market returns and contemporaneous aggregated changes in earnings, because it starkly contrasts with evidence of a positive relationship at the individual stock level. The results in Table 7.1, for an alternative earnings surprise proxy, contradict this key component of their findings. However, given the nine year shift in the time periods investigated (from 1970–2000 for Kothari et al. to 1979–2009 for my research), it is possible research conclusions may differ as a result of time variation in observed relationships.

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[198] Examples include Cornell and Landsman (1989), Clement and Tse (2003) and Beaver, Cornell, Landsman and Stubben (2008).

Kothari et al. (2006) repeat regressions of market returns on measures of aggregated earnings changes for three sub-periods (1970–1979, 1980–1989 and 1990–2000). They do not provide a table of findings, but comment that results are similar, albeit with fewer significant slope coefficients. Further, they employ earnings data for the S&P 500 from 1936 to 2000 as a robustness test on their results. For the full 64 years of quarterly seasonally-differenced earnings data (quarter earnings less earnings for the same quarter in the previous year) they obtain a negative (but insignificant) slope coefficient on two measures of aggregated earnings changes. However, for two measures of earnings surprise (derived from prediction errors from an autoregressive model) the estimated slope coefficients are positive. In addition, for the 1936–1969 sub-period, estimated coefficients on three out of the four proxies for earnings surprise evaluated are positive, while the fourth is negative but insignificant. Estimated slope coefficients reported by Kothari et al. tend to be more negative (and exhibit greater statistical significance) when lagged by one or two quarters. The authors suggest that this may be due to slower (and/or less frequent) release of earnings information in earlier years. That is possible. But importantly it means that their finding of negative correlation between market returns and contemporaneous earnings changes is largely a consequence of a significant relationship in their main sample period, 1970–2000, and not in earlier years.[199]

In Table 7.2 I repeat regressions of aggregate returns on a rolling quarterly measure of annual earnings revisions (in this instance deflated by lagged earnings forecasts) for three sub-periods: 1979–1989, 1990–1999 and 2000–2009. I obtain a negative (but insignificant) slope coefficient for 1979–1989, and positive estimated coefficients for 1990–1999 and 2000–2009 (and the latter coefficient is statistically

[199] This would also help explain Sadka and Sadka's (2009) evidence for a negative relationship between market returns and contemporaneous earnings growth – their sample period runs from 1965 through to 2000.

Table 7.2 Returns regressed on forecast revisions within sub-periods, 1979–2009

Time series regressions of quarterly aggregated annual returns on lagged aggregated annual earnings revisions are performed for sub-periods. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios and adjusted R^2 for regressions of the following form:

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{r}}_{t-l} + \varepsilon_t$$

R_t represents value-weighted stock returns. Lags, l, of 0 to 4 quarters are evaluated. $\Delta\mathrm{E}^{\mathrm{r}}_t$ represents aggregated earnings revisions deflated by lagged aggregated forecast earnings. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Lag	Univariate regressions			Multivariate regressions		
		Estimated slope coef.	t-statistic	Adj. R^2	Estimated slope coef.	t-statistic	Adj. R^2
A. March 1979 – December 1989							
$\Delta\mathrm{EE}^{\mathrm{r}}$	0	-0.408	-0.690	0.010	0.196	0.188	-0.016
	1	-0.481	-0.748	0.023	-0.520	-0.377	
	2	-0.503	-0.775	0.027	-0.115	-0.134	
	3	-0.391	-0.539	0.006	-1.324	-0.948	
	4	-0.132	-0.152	-0.023	1.409	0.741	
B. March 1990 – December 1999							
$\Delta\mathrm{EE}^{\mathrm{r}}$	0	0.862	1.188	0.117	0.108	0.148	0.112
	1	0.948	1.553	0.146	-0.170	-0.380	
	2	**1.082**	2.085	0.198	**1.089**	1.742	
	3	**0.955**	2.580	0.152	0.422	0.857	
	4	**0.725**	2.053	0.081	-0.401	-0.602	
C. March 2000 – December 2009							
$\Delta\mathrm{EE}^{\mathrm{r}}$	0	**1.057**	2.051	0.411	**3.075**	6.857	0.587
	1	0.717	0.072	0.168	**-2.774**	-3.224	
	2	0.636	0.344	0.097	0.436	0.506	
	3	0.554	0.715	0.048	0.125	0.146	
	4	0.474	0.730	0.019	0.355	0.685	

significant). Hence, there is evidence of time-variation in the relationship between aggregate returns and contemporaneous revisions, but correlation between the two is positive measured over the whole sample period.

Consequently, employing an alternative proxy for aggregate earnings surprise – annual earnings revisions – I do not find evidence consistent with Kothari et al.'s (2006) results for aggregated changes in realized earnings. I find evidence of a positive (but insignificant) relationship between annual earnings revisions and contemporaneous aggregate returns for 1979–2009.[200] Sub-period analysis highlights variation through time in the relationship between aggregate revisions and returns, suggesting the possibility that Kothari et al.'s results may be period-dependent. In the following sub-section I revisit Kothari et al.'s analysis for aggregated changes in realized earnings and further investigate time variation in observed relationships.

7.2.2 Realized earnings and returns

TABLE 7.3 REPLICATES regression results for Table 7.1, employing annual changes in realized earnings measures in place of earnings revisions. Regressions are of the following form:

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[200] It is possible these results are impacted by analyst forecast bias. Evidence of positive bias in analysts' forecasts is provided by Abarbanell (1991), Brown, Foster and Noreen (1985), Lim (2001) and Stickel (1990). In Chapter 4 I illustrate the presence of forecast bias in aggregated analysts' forecasts. Over the time period evaluated, I find aggregate forecast annual earnings growth at the start of a 12 month period is on average approximately nine percentage points higher than final realized growth for the same 12 month period. If market participants are aware of persistent bias in analysts' forecasts then returns should anticipate the necessary analyst revisions to correct bias as a financial year progresses. However, without a predictive model of time-varying forecast bias (a concept beyond the scope of this research) I am unable to quantify the impact of time-varying bias (if any) on estimated slope coefficients in Table 7.1. Instead, the impact of average bias will be reflected in estimated intercepts for regressions of aggregate returns on contemporaneous aggregate earnings revisions. Indications of returns anticipating revisions are provided in the preceding chapter, where I discuss evidence of a significant relationship between annual aggregate earnings revisions and shorter term returns (in particular, 3 and 6 month returns). However, the estimated slope coefficients in these regressions are positive and are therefore not consistent with Kothari et al.'s conclusions of a negative relationship between aggregate earnings surprise and contemporaneous returns.

Table 7.3 Returns regressed on changes in realized earnings, 1979–2009

Stock returns are regressed on lagged 4 quarter changes in realized earnings. Panel A provides results for time series averages of cross-sectional regression results performed on individual stocks for December year annual data. Panel B provides results for time series regressions of quarterly aggregated annual returns on aggregated annual changes in earnings. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios and adjusted R^2 for regressions of the following form:

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{a}}_{t-l} + \varepsilon_t$$

For Panel B, R_t represents aggregate market returns (value-weighted for ΔEE^a and ΔEB^a, equally-weighted for $\Delta ebeq^a$ and median returns for $\Delta ebmed^a$). Lags, l, of 0 to 4 quarters are evaluated, with lag 1 representing returns 1 quarter after the end of the earnings change period (thus representing post-announcement returns). $\Delta \mathrm{E}^{\mathrm{a}}_t$ represents the measure of aggregated 4 quarter earnings changes. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios for the aggregate time series regressions. Results in bold are statistically significant at the 10% level.

	Lag	Univariate regressions			Multivariate regressions		
		Estimated slope coef.	t-statistic	Adj. R^2	Estimated slope coef.	t-statistic	Adj. R^2
A. Cross-sectional regressions							
Δeb^a	0	**1.257**	7.192	0.135	**1.297**	7.019	0.169
	1	**0.980**	5.877	0.076	**0.370**	2.463	
	2	**0.546**	3.797	0.031	**-0.404**	-2.513	
	3	**0.235**	1.877	0.014	-0.054	-0.453	
	4	0.022	0.191	0.014	**0.327**	2.509	
B. Aggregate time series regressions							
ΔEE^a	0	0.211	0.923	0.055	**0.366**	1.958	0.129
	1	0.197	0.156	0.047	**-0.380**	-3.338	
	2	0.260	1.594	0.076	0.059	0.321	
	3	0.316	1.539	0.102	**0.257**	1.813	
	4	0.315	1.639	0.090	0.176	1.182	
ΔEB^a	0	2.008	1.207	0.084	**3.586**	2.263	0.143
	1	1.865	1.315	0.071	**-3.198**	-3.342	
	2	2.185	1.604	0.091	0.144	0.099	
	3	2.496	1.455	0.107	**2.099**	1.956	
	4	2.374	1.487	0.086	1.309	1.009	
$\Delta ebeq^a$	0	2.806	1.389	0.075	**7.636**	3.691	0.129
	1	1.623	0.936	0.020	**-3.955**	-2.006	
	2	1.300	0.726	0.008	**-4.985**	-2.511	
	3	1.501	0.710	0.010	3.355	1.452	
	4	1.394	0.609	0.006	2.876	1.200	
$\Delta ebmed^a$	0	2.669	0.522	0.022	**14.066**	2.479	0.132
	1	0.810	0.215	-0.006	**-11.638**	-2.222	
	2	0.395	0.102	-0.008	-3.741	-0.667	
	3	1.119	0.278	-0.005	-0.649	-0.120	
	4	2.591	0.650	0.008	**9.327**	1.965	

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{a}}_{t-l} + \varepsilon_t \tag{7.2}$$

$\Delta \mathrm{E}^{\mathrm{a}}_{t-l}$ represents a measure of annual changes in realized earnings with lags, l, of 0–4 quarters. R_t represents annual stock returns (value-weighted, equally-weighted or median returns matched to the aggregation method employed for realized earnings). Kothari et al. (2006) measure annual returns at lag 0 for the period ending four months after the end of the calendar year. This is to capture returns after earnings have been announced.[201] As discussed in Chapter 3, I ensure that all stocks included in a given period report earnings within one quarter after the firm's balance date. Therefore regression results in Table 7.3 for a lag of one quarter incorporate post-announcement returns for the last quarterly balance date.

Kothari et al. (2006) present results for regressions based on equation 7.2 for quarterly data (seasonally-differenced quarterly realized earnings) and annual data (non-overlapping annual earnings changes for firms with December financial year ends). For comparability with forecast data, and to maximize the length of the time period evaluated, I employ annual changes in realized earnings derived from rolling four quarter sums of quarterly earnings. I am therefore able to investigate in more detail the annual results of Kothari et al., which arguably provide stronger support for their conclusions than the quarterly results,[202] while not being restricted by the implications for available degrees of freedom resulting from the use of non-overlapping annual data.[203] As in prior chapters, Newey-West standard errors are employed to account for autocorrelation resulting from overlapping data.

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[201] However, they acknowledge their sample will likely include stocks which fail to report earnings until much later.

[202] In their annual regressions Kothari et al. (2006) report statistically significant slope coefficients for four measures of aggregated changes in realized earnings and four measures of earnings surprise, at a two-sided 10% level. In their quarterly regressions Kothari et al. report fewer statistically significant slope coefficients.

[203] In robustness tests not reported here I restrict my sample to stocks with December fiscal year ends and run regressions of aggregated returns on annual changes in realized earnings on a rolling quarterly basis. All research conclusions are unchanged. This should

The cross-sectional results presented in Panel A are consistent with the earnings response literature and with Kothari et al. (2006). The estimated coefficient on Δeb^{a} at a lag of 0 is positive and statistically significant in both univariate and multivariate regressions. However, the results in Panel B of Table 7.3 differ markedly from those reported by Kothari et al., who find negative and statistically significant coefficients on four measures of aggregated changes in realized earnings at a lag of 0 for annual regressions (and negative estimated coefficients on changes in realized earnings for quarterly regressions).[204] In contrast, the estimated coefficients in Table 7.3 for univariate regressions on aggregated changes in earnings are all positive, regardless of lag. They are also all insignificant. Negative coefficients only appear in multivariate regressions, beginning at a lag of one quarter, but sign changes from univariate results highlight the presence of multicollinearity.

In Table 7.4 I provide summary results for aggregated changes in realized earnings (deflated by lagged forecast earnings) over the three sub-periods investigated in Table 7.2. In univariate regressions with no lag I obtain a statistically significant negative slope coefficient for the earliest sub-period, with positive coefficients for the latter two sub-periods (and statistically significant for 2000–2009). Hence, as for results from regressions employing earnings revisions as a proxy for earnings surprise, sub-period analysis suggests time variation in observed relationships.

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not be surprising given the majority of stocks included in the full sample have December fiscal year ends (approximately 80%).

[204] These results are also inconsistent with Ball, Sadka and Sadka (2009). They employ principal components analysis to provide evidence of negative correlation between earnings factors and contemporaneous returns. Hirshleifer, Hou and Teoh (2009) report evidence suggesting that the negative relationship observed by Kothari et al. is a consequence of a negative relationship between changes in accruals and contemporaneous returns. However, direct comparison between Kothari et al. and Hirshleifer et al. is complicated by the former's use of operating income after depreciation as a proxy for earnings. When Hirshleifer et al. strip accruals out of their earnings measure they find a positive relationship between this cash flow proxy and contemporaneous aggregate returns. For further details on these and other researchers' efforts to explain Kothari et al.'s results see Section 2.5.

Table 7.4 Returns regressed on changes in realized earnings within sub-periods, 1979–2000

Time series regressions of quarterly aggregated annual returns on lagged aggregated annual earnings growth are performed for sub-periods. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios and adjusted R^2 for regressions of the following form:

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{a}}_{t-l} + \varepsilon_t$$

R_t represents value-weighted stock returns. Lags, l, of 0 to 4 quarters are evaluated, with lag 1 representing returns 1 quarter after the end of the earnings change period (thus representing post-announcement returns). $\Delta \mathrm{E}^{\mathrm{a}}_t$ represents aggregated earnings growth. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Lag	Univariate regressions			Multivariate regressions		
		Estimated slope coef.	t-statistic	Adj. R^2	Estimated slope coef.	t-statistic	Adj. R^2
A. March 1979 – December 1989							
$\Delta \mathrm{EE}^{\mathrm{a}}$	0	**-0.671**	-3.160	0.257	-0.325	-1.350	0.268
	1	**-0.597**	-2.565	0.193	**-0.809**	-4.086	
	2	-0.313	-1.030	0.034	0.390	1.257	
	3	-0.027	-0.080	-0.025	0.114	0.393	
	4	0.203	0.624	-0.002	0.111	0.375	
B. March 1990 – December 1999							
$\Delta \mathrm{EE}^{\mathrm{a}}$	0	0.025	0.106	-0.026	-0.296	-1.251	0.183
	1	0.238	1.116	0.039	0.041	0.225	
	2	**0.427**	2.417	0.184	**0.450**	1.740	
	3	**0.443**	2.833	0.200	0.111	0.447	
	4	**0.356**	2.013	0.119	0.035	0.301	
C. March 2000 – December 2009							
$\Delta \mathrm{EE}^{\mathrm{a}}$	0	**0.374**	2.713	0.418	**0.571**	9.607	0.592
	1	0.299	0.074	0.252	**-0.322**	-3.087	
	2	0.327	0.019	0.257	-0.211	-0.926	
	3	0.369	0.147	0.273	**0.396**	1.718	
	4	0.342	0.776	0.195	**0.224**	3.883	

While similar, Kothari et al.'s (2006) variable construction is not identical to that employed here. For example, they employ seasonally-differenced realized earnings compared with my use of annual changes in annual earnings (over rolling quarters). Differences between their results and mine could also be a consequence of variation in sample sets, their use of market returns rather than the aggregated returns of stocks included in earnings variables, issues with my use of overlapping data, and a range of other potential issues. I therefore construct a new dataset precisely matching the eligibility requirements specified by Kothari et al.[205] I also follow their variable construction methodology, creating a quarterly time series of seasonally-differenced earnings and an annual time series of annual changes in earnings. These changes are aggregated across stocks and deflated by lagged aggregated earnings, lagged aggregated book value or lagged aggregated market capitalization. I then regress quarterly returns on lagged values of the seasonally-differenced earnings and regress annual returns on lagged values of the annual aggregated changes in earnings (for December year-end companies only in the case of annual regressions). These regressions mimic those specified by Kothari et al., with a lag of 1 in the quarterly regressions referring to returns one quarter after the end of the earnings period (matching the quarter in which earnings are normally announced). A lag of 0 in the annual regressions refers to changes in realized returns matched to the return in the year ending April, after the December balance date.

Summary results from these regressions are provided in Table 7.5 for three measures of aggregated seasonally-differenced earnings (quarterly regressions in Panel A) and three measures of aggregated annual December year-end changes in

[205] All NYSE, Amex and Nasdaq stocks with required quarterly data are included. Earnings are before extraordinary items and discontinued operations. Firms must have either March, June, September or December financial year-ends, stock prices in excess of $1 and be within the middle 99% of observations of ΔEP^a each quarter.

Table 7.5 Returns regressed on changes in realized earnings within sub-periods, for all qualifying CRSP/Compustat stocks, 1970–2009

Time series regressions of aggregated returns on lagged aggregated changes in earnings are performed for the full sample period and sub-periods. The sample set matches that described by Kothari, Lewellen and Warner (2006). Quarterly returns are regressed on seasonally-differenced quarterly earnings in Panel A and annual returns are regressed on December year annual changes in annual earnings in Panel B (returns at lag 0 in Panel B are for the year ending April, after the December balance date). Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios and adjusted R^2 for regressions of the following form:

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{a}}_{t-l} + \varepsilon_t$$

R_t represents value-weighted market returns. Lags, l, represent quarters in Panel A and years in Panel B. $\Delta \mathrm{E}^{\mathrm{a}}_t$ represents the measure of aggregated changes in earnings (aggregated seasonally-differenced earnings deflated by lagged earnings, lagged book value or lagged market capitalization for quarterly regressions and aggregated annual changes in earnings for December year-end companies in the case of annual regressions). Results in bold are statistically significant at the 10% level.

	Lag	ΔEE^a			ΔEB^a			ΔEP^a		
		$\hat{\beta}$	t	Adj. R^2	$\hat{\beta}$	t	Adj. R^2	$\hat{\beta}$	t	Adj. R^2
A. Quarterly regressions										
1970 – 2000	0	**-0.103**	-2.058	0.026	**-3.195**	-1.934	0.022	**-5.444**	-2.163	0.029
	1	**-0.126**	-2.537	0.042	**-3.891**	-2.379	0.036	**-5.849**	-2.337	0.035
	2	0.010	0.198	-0.008	0.547	0.329	-0.007	0.093	0.037	-0.008
	3	-0.050	-0.984	0.000	-1.303	-0.784	-0.003	-1.688	-0.665	-0.005
	4	**-0.086**	-1.726	0.016	-2.588	-1.568	0.012	-2.700	-1.069	0.001
1979 – 2009	0	**0.027**	1.790	0.018	**1.788**	2.579	0.044	**2.456**	1.692	0.015
	1	0.011	0.651	-0.005	0.804	1.010	0.000	0.655	0.364	-0.007
	2	-0.002	-0.110	-0.008	-0.043	-0.053	-0.008	-0.260	-0.145	-0.008
	3	-0.002	-0.105	-0.008	0.036	0.045	-0.008	-0.169	-0.094	-0.008
	4	0.012	0.701	-0.004	0.267	0.321	-0.007	0.838	0.449	-0.007
1970 – 2009	0	0.022	1.377	0.006	**1.379**	1.911	0.016	1.502	1.022	0.000
Full sample	1	0.005	0.263	-0.006	0.319	0.391	-0.005	-0.596	-0.335	-0.006
	2	-0.003	-0.172	-0.006	-0.145	-0.178	-0.006	-0.565	-0.318	-0.006
	3	-0.006	-0.327	-0.006	-0.221	-0.269	-0.006	-0.816	-0.455	-0.005
	4	0.004	0.229	-0.006	-0.284	-0.335	-0.006	-0.746	-0.404	-0.005
B. Annual regressions										
1970 – 2000	0	**-0.521**	-2.758	0.180	**-4.206**	-2.553	0.155	**-5.568**	-2.377	0.134
	1	0.115	0.541	-0.024	1.397	0.763	-0.014	2.635	1.051	0.003
	2	0.248	1.169	0.012	2.195	1.196	0.014	2.263	0.898	-0.007
1979 – 2009	0	**0.226**	1.972	0.088	**2.330**	2.147	0.107	3.575	1.499	0.040
	1	-0.003	-0.022	-0.034	-0.085	-0.073	-0.034	1.016	0.413	-0.028
	2	-0.031	-0.225	-0.033	-0.957	-0.673	-0.019	-0.173	-0.062	-0.034
1970 – 2009	0	0.170	1.564	0.036	1.725	1.678	0.044	1.741	0.825	-0.008
Full sample	1	-0.017	-0.154	-0.026	-0.203	-0.190	-0.025	0.630	0.294	-0.024
	2	-0.005	-0.041	-0.026	-0.588	-0.456	-0.021	0.390	0.161	-0.026

earnings (annual regressions in Panel B). In addition, regressions are run for three periods; 1970–2000 (matching Kothari et al.'s (2006) focus period), 1979–2009 (matching the period for which I have both aggregated realized and forecast variables), and the full dataset, 1970–2009.

For the period from 1970 through to 2000, in both quarterly and annual regressions, all estimated slope coefficients at a lag of 0 are negative and statistically significant. This is Kothari et al.'s (2006) result.[206] However, all estimated slope coefficients at lags of 0 for the period from 1979–2009 are positive (and five of the six presented are also statistically significant). For the full 40 year sample period all estimated slope coefficients at a lag of 0 are positive (with one significant).

These results demonstrate, replicating the methodology employed by Kothari et al. (2006) precisely as described in their paper, that results are sensitive to the time period being analyzed. The significant negative relationship identified by Kothari et al. appears to be largely a product of inverse correlation between aggregate returns and contemporaneous aggregate changes in earnings in the 1970s and 1980s. Further, Kothari et al.'s analysis of S&P data for the 34 years prior to 1970, combined with my analysis of more recent data, suggests there was a positive relationship (although largely insignificant) between aggregated returns and contemporaneous changes in earnings for the majority of the period from 1936 through to 2009. These results suggest that the negative correlation between aggregate returns and contemporaneous earnings changes, so central to Kothari et

[206] Estimated coefficients and R^2s in Table 7.3 are also very similar to those reported for equivalent regressions by Kothari et al. For example, they report an estimated coefficient on their measure of ΔEB^a of -2.35 at a lag of 0 and -3.39 at a lag of one quarter, compared with equivalent estimates in Table 7.3 of -3.20 and -3.89, respectively. Regression R^2s for these examples are identical to those reported by Kothari et al. to two decimal places. The similarity between results is even stronger for price-deflated measures.

al.'s conclusions, is a product of the time period investigated (in particular, the first 20 years of their principal dataset).

These results therefore lead to the same conclusions as those reported in Section 7.2.1. I do not find evidence of a significant negative relationship between aggregated returns and contemporaneous aggregated earnings surprise (measured either as changes in realized earnings or surveyed earnings revisions). Hence, I do not find evidence of a significant discount rate effect in aggregated earnings changes; i.e. a discount rate effect sufficient to result in negative correlation between earnings changes (or revisions) and contemporaneous returns.

However, these results do not preclude the existence of a discount rate effect in aggregate returns. Positive estimated slope coefficients in cross-sectional regressions for a lag of 0 in both Table 7.1 and Table 7.3, but insignificant coefficients in aggregate time series regressions (for a lag of 0), imply the existence of a discount rate effect. But this effect is not large enough to generate significant negative coefficients in these tests. In Section 7.5 I employ two stage regressions that attempt to estimate the relative significance of cash flow and discount rate effects within the overall return response estimated in this section. Before doing so, the following section provides a range of robustness tests on results in an attempt to identify variation in the relationship between aggregated changes in realized earnings (or forecast revisions) and contemporaneous returns for a range of sub-portfolios.

7.3 Robustness tests

7.3.1 Timely forecasts

IN THE PREVIOUS two chapters I have highlighted potential problems with I/B/E/S forecasts that have been included in the monthly summary procedures, but which may have been submitted to I/B/E/S some months prior to the aggregation date. While I/B/E/S endeavours to remove stale forecasts, there will undoubtedly be forecasts included in the aggregation process which do not represent the true expectations of analysts at that point in time. To evaluate the impact of this issue on conclusions, I generate the same measures of earnings revisions, but with eligible forecasts from analysts restricted to those that have been submitted to I/B/E/S between what I/B/E/S term the statistical period, and the end of the respective month. The statistical period ends on the Thursday before the third Friday of the month. By restricting the sample to forecasts submitted to I/B/E/S between this date and the end of the month I ensure that only the most timely forecasts are included in the aggregation process (I term these month-end forecasts). However, as noted in prior chapters, a limitation of this requirement is that sufficient individual analyst data is available only back to the first quarter of 1984.

The aggregate time series regressions reported in Table 7.1 are repeated for earnings revisions derived from month-end forecasts, and summary results are presented in Table 7.6. For lags of 0 to 2 quarters the estimated slope coefficients in the univariate regressions are positive for all revision measures presented. While they are statistically insignificant, the *t* statistics on estimated coefficients are almost all higher than their respective values reported for the full sample set in

Table 7.6 Returns regressed on forecast revisions – month-end forecasts, 1984–2009

Time series regressions of quarterly aggregated annual returns on lagged aggregated annual earnings revisions are performed for month-end analysts' forecasts. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios and adjusted R^2 for regressions of the following form:

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{r}}_{t-l} + \varepsilon_t$$

R_t represents aggregate market returns (value-weighted for ΔEE and ΔEB, equally-weighted Δebeq and median returns for Δebmed). Lags, l, of 0 to 4 quarters are evaluated. $\Delta \mathrm{E}^{\mathrm{r}}_t$ represents the measure of aggregated 4 quarter forecast revisions. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios for the aggregate time series regressions. Results in bold are statistically significant at the 10% level.

	Lag	Univariate regressions			Multivariate regressions		
		Estimated slope coef.	t-statistic	Adj. R^2	Estimated slope coef.	t-statistic	Adj. R^2
ΔEE	0	0.426	1.355	0.083	0.364	1.275	0.070
	1	0.397	1.415	0.069	**0.240**	1.688	
	2	0.315	1.228	0.037	-0.015	-0.109	
	3	0.257	1.157	0.019	-0.049	-0.276	
	4	0.195	0.803	0.006	-0.113	-0.442	
ΔEB	0	2.691	1.564	0.109	2.512	1.647	0.094
	1	2.380	1.444	0.081	**1.318**	2.205	
	2	1.801	1.211	0.039	-0.818	-1.022	
	3	1.630	1.103	0.026	-0.243	-0.219	
	4	1.336	0.872	0.013	-0.035	-0.025	
Δebeq	0	1.102	0.621	0.001	1.917	1.182	-0.012
	1	0.496	0.375	-0.008	0.054	0.058	
	2	0.348	0.287	-0.009	0.598	0.412	
	3	-0.267	-0.202	-0.010	-0.541	-0.417	
	4	-0.676	-0.543	-0.007	-1.223	-0.858	
Δebmed	0	1.573	0.686	0.006	3.535	1.351	0.010
	1	0.609	0.401	-0.008	-1.694	-1.220	
	2	0.771	0.580	-0.006	-2.278	-1.171	
	3	1.680	1.199	0.005	1.450	0.987	
	4	2.053	1.490	0.013	2.341	1.523	

Table 7.1.[207] Hence, the results for the month-end forecast dataset do not support the notion that prior results are a consequence of distortions caused by the inclusion of stale forecasts in measures of aggregate earnings revisions.

7.3.2 Alternative proxies for earnings surprise

I HAVE REPEATED cross-sectional regressions in Table 7.1 for changes in earnings per share deflated by lagged price, and equivalent aggregate measures of revisions deflated by lagged market capitalization, rather than lagged book value. I find conclusions are unchanged. For example, in cross-sectional regressions the price deflated versions of changes in realized earnings per share and earnings per share revisions are positively and significantly related to contemporaneous stock returns. In addition, aggregate changes in realized earnings and earnings revisions deflated by market capitalization are positively correlated with contemporaneous market returns (but mostly insignificant).

7.3.3 Period end in cross-sectional regressions

CROSS-SECTIONAL RESULTS reported in Tables 7.1 and 7.3 represent time series averages of estimated slope coefficients for December year annual data. To investigate whether results are sensitive to the choice of period end I repeat these regressions for realized earnings changes and forecast revisions for the four quarters ending March, June and September. Summary results are provided in the appendix to this chapter in Tables 7A.1 (for realized earnings per share changes) and 7A.2 (for earnings per share revisions). Results are consistent across all variations on the period end. In all cases, estimated slope coefficients in univariate

[207] Higher *t* ratios are partially the result of the shortening of the time-period investigated, with the removal of the four earliest years from the full sample (the sub-period analysis provided evidence of a negative relationship between aggregate revisions and returns for the first 10 years of the data).

regressions are positive and statistically significant with a lag of 0 and also positive and significant for a lag of 1 quarter.

7.3.4 Size portfolios

SHIVAKUMAR (2010) MAKES the following observation regarding analysis of the relationship between aggregate earnings and returns:

> Another issue in studies focusing on market reactions to aggregate earnings news is the almost exclusive focus on returns to the value-weighted or equally weighted market portfolio. Although these market portfolios reflect information on aggregate cash flows as well as on aggregate discount rates, they would be insufficient for a full understanding of discount rate news, as this is potentially driven by multiple risk factors. Researchers could gainfully relate aggregate earnings to other risk factor proxies. (p. 338)

Reflecting Shivakumar's concern, in this and the following two sub-sections I repeat prior analysis for a range of sub-portfolios determined by size, book-to-market ratios and industry membership.

Kothari et al. (2006) report evidence of positive correlation between returns and realized earnings changes for both large and small stocks (defined by market capitalization tercile) at the individual stock level. At the aggregate level they report negative and significant coefficients on earnings changes for large stocks at a lag of 0, but positive and insignificant estimated coefficients on small stocks. Estimated coefficients on aggregated small stock earnings changes are negative at a lag of one quarter.

I perform regressions of aggregate returns on lagged aggregated earnings revisions for portfolios determined by size quintile. Results for aggregated earnings revisions deflated by lagged book value are reported in Table 7.7. As a further robustness test, results for equally-weighted earnings per share revisions deflated by lagged book value per share are provided in Table 7A.3 in the appendix to this chapter. Across all quintiles the estimated slope coefficients on ΔEB^r are positive at a lag of

Table 7.7 Returns regressed on forecast revisions by size quintiles for ΔEB^r, 1979–2009

Time series regressions of quarterly aggregated annual returns on lagged aggregated annual earnings revisions (deflated by lagged aggregated book value) are performed for size quintiles. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios and adjusted R^2 for regressions of the following form:

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}^r_{t-l} + \varepsilon_t$$

R_t represents value-weighted stock returns. Lags, l, of 0 to 4 quarters are evaluated. $\Delta \mathrm{E}^r_t$ represents aggregated earnings revisions deflated by lagged aggregated book value. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Lag	Univariate regressions			Multivariate regressions		
		Estimated slope coef.	t-statistic	Adj. R^2	Estimated slope coef.	t-statistic	Adj. R^2
Q1 (largest)	0	3.946	1.414	0.115	**7.647**	3.044	0.124
	1	2.600	0.891	0.045	**-3.236**	-1.954	
	2	1.876	0.650	0.017	0.346	0.184	
	3	1.310	0.522	0.003	-2.675	-1.619	
	4	1.029	0.422	-0.002	1.692	0.606	
Q2	0	2.361	0.971	0.024	6.654	1.591	0.042
	1	0.877	0.466	-0.004	-2.842	-1.055	
	2	0.202	0.086	-0.008	-4.296	-1.339	
	3	0.443	0.170	-0.007	0.056	0.024	
	4	0.971	0.332	-0.004	3.197	1.293	
Q3	0	2.392	0.766	0.020	**8.901**	3.005	0.080
	1	0.195	0.071	-0.008	**-6.419**	-3.404	
	2	-0.579	-0.190	-0.007	-0.637	-0.346	
	3	-0.745	-0.302	-0.006	**-4.884**	-2.138	
	4	0.284	0.108	-0.008	**5.284**	1.888	
Q4	0	2.219	0.849	0.012	**6.794**	2.083	0.029
	1	0.088	0.035	-0.008	**-4.658**	-2.331	
	2	0.102	0.042	-0.008	-2.208	-0.905	
	3	0.220	0.104	-0.008	-0.703	-0.370	
	4	1.137	0.547	-0.004	2.757	1.195	
Q5 (smallest)	0	2.206	0.742	0.007	**8.896**	2.914	0.065
	1	-0.850	-0.325	-0.006	**-6.274**	-2.646	
	2	-1.269	-0.512	-0.004	**-4.807**	-2.137	
	3	-0.023	-0.011	-0.008	-0.226	-0.118	
	4	1.358	0.559	-0.004	**4.502**	1.783	

Table 7.8 Returns regressed on forecast revisions by book-to-market quintiles for ΔEB^r, 1979–2009

Time series regressions of quarterly aggregated annual returns on lagged aggregated annual earnings revisions (deflated by lagged aggregated book value) are performed for price-to-book quintiles. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios and adjusted R^2 for regressions of the following form:

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}^{r}_{t-l} + \varepsilon_t$$

R_t represents value-weighted stock returns. Lags, l, of 0 to 4 quarters are evaluated. $\Delta \mathrm{E}^{r}_{t}$ represents aggregated earnings revisions deflated by lagged aggregated book value. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Lag	Univariate regressions			Multivariate regressions		
		Estimated slope coef.	t-statistic	Adj. R^2	Estimated slope coef.	t-statistic	Adj. R^2
Q1 (lowest)	0	2.817	1.653	0.038	**4.657**	3.113	0.061
	1	0.040	0.023	-0.008	**-1.483**	-1.748	
	2	-1.256	-0.579	0.000	-1.155	-1.203	
	3	-2.261	-0.721	0.014	-1.905	-1.057	
	4	-1.634	-0.521	0.003	-0.209	-0.095	
Q2	0	2.189	0.975	0.039	**4.047**	2.073	0.030
	1	0.780	0.394	-0.002	-1.707	-1.592	
	2	0.232	0.117	-0.008	-1.351	-1.354	
	3	0.445	0.203	-0.007	-0.497	-0.357	
	4	0.581	0.317	-0.006	1.422	0.794	
Q3	0	**3.887**	1.917	0.141	**4.288**	2.179	0.107
	1	3.022	1.505	0.082	0.657	0.525	
	2	2.000	0.906	0.030	-1.201	-0.955	
	3	1.456	0.619	0.011	0.412	0.373	
	4	0.746	0.415	-0.004	-0.993	-0.495	
Q4	0	4.519	1.622	0.137	**5.246**	2.766	0.109
	1	3.219	1.007	0.065	-0.265	-0.165	
	2	2.988	0.888	0.047	0.309	0.171	
	3	2.238	1.119	0.022	-0.774	-0.777	
	4	1.589	0.875	0.006	-0.399	-0.215	
Q5 (highest)	0	4.003	1.477	0.133	**7.875**	3.087	0.152
	1	2.562	1.231	0.048	**-3.966**	-1.846	
	2	1.502	0.990	0.010	1.058	0.571	
	3	0.433	0.303	-0.007	-3.244	-1.498	
	4	0.208	0.132	-0.008	1.999	0.652	

0 in Table 7.7. Contrasting with Kothari et al.'s (2006) results, the estimated slope coefficients at a lag of 0 for the largest stocks are higher (more positive) than those obtained for the smallest stocks. However, the reverse is true for equally weighted revisions. Nonetheless, estimated slope coefficients for a lag of 0 are negative for just two of the quintiles in Table 7A.3, and are insignificant across all quintiles. Consequently, employing earnings revisions as a measure of earnings surprise I find no evidence of a significant negative relationship between aggregate returns and contemporaneous aggregate revisions within any size quintile.

7.3.5 Book-to-market portfolios

I REGRESS RETURNS on time series of earnings revisions for portfolios determined by book-to-market quintiles. Results for ΔEB^r across quintile portfolios are provided in Table 7.8, with results for $\Delta ebeq^r$ included in Table 7A.4 in the appendix. Like results presented for size quintiles, all estimated coefficients on ΔEB^r are positive at a lag of 0. Also like results presented for size quintiles, estimated slope coefficients for a lag of 0 are negative for just two of the quintiles in Table 7A.4, and all are insignificant. Consequently, I find no evidence of a significant negative relationship between aggregate returns and contemporaneous aggregate revisions within any book-to-market quintile.

7.3.6 Sector portfolios

AS A FINAL check on the sign and significance of the relationship between aggregate revisions and returns, in Table 7.9 I provide results of regressions of annual GICS level I sector returns on contemporaneous sector earnings revisions (for both ΔEB^r and $\Delta ebeq^r$). Patatoukas and Yan (2009) note that one implication of their theoretical model is that the discount effect should be larger for more cyclical stocks. This is because earnings surprise for cyclical stocks is likely to be correlated

Table 7.9 Univariate regressions of sector returns on sector earnings revisions, 1979–2009

Time series regressions of quarterly aggregated returns on the contemporaneous aggregated annual earnings revisions are performed sectors. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2 for regressions of the following form:

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}_t^{\mathrm{r}} + \varepsilon_t$$

R_t represents either value-weighted or equally-weighted stock returns. $\Delta \mathrm{E}_t^{\mathrm{r}}$ represents either aggregated earnings revisions deflated by lagged book value ($\Delta \mathrm{EB}^{\mathrm{r}}$) or equally-weighted earnings per share revisions deflated by lagged book value per share ($\Delta \mathrm{ebeq}^{\mathrm{r}}$) for GICS level I sectors. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Telecom. Services	Utilities
$\Delta \mathrm{EB}^{\mathrm{r}}$	**2.146**	0.820	2.243	1.224	1.067	3.116	**5.518**	**3.705**	1.442	**9.561**
	(3.266)	(1.154)	(0.633)	(0.511)	(0.935)	(1.232)	(4.185)	(3.359)	(1.307)	(2.609)
	0.184	0.019	0.031	0.011	0.010	0.026	0.289	0.119	0.031	0.146
$\Delta \mathrm{ebeq}^{\mathrm{r}}$	**4.240**	0.809	0.699	-0.770	0.046	0.605	4.819	-0.061	0.844	3.220
	(4.587)	(0.775)	(0.248)	(-0.177)	(0.031)	(0.171)	(1.551)	(-0.020)	(0.946)	(0.718)
	0.238	0.009	0.002	0.001	0.000	0.001	0.085	0.000	0.009	0.017

with market earnings surprise.[208] If relative cyclicality is defined by the relative strength of the relationship between value-weighted realized earnings and contemporaneous macroeconomic growth (e.g. industrial production growth), then the Materials, Industrials, Consumer Discretionary and Information Technology sectors are the most cyclical, while the Consumer Staples, Health Care, Telecommunication Services and Utilities sectors are the least cyclical (these regressions are discussed in Chapter 5). However, the results presented in Table 7.9 are not consistent with a distinct relationship between relative cyclicality and the strength of the discount rate effect. Estimated slope coefficients on ΔEB^r are positive across all sectors, and statistically significant for four (Energy, Financials, Information Technology and Utilities). Estimated slope coefficients on $\Delta ebeq^r$ are positive for seven of the ten sectors, and significant for just one (Energy). Therefore, consistent with the preceding tests, I do not find evidence of a significant negative relationship between aggregate returns and contemporaneous aggregate revisions for any of the portfolios analyzed.

Overall, these robustness tests highlight considerable consistency across regressions. Contrary to Kothari et al.'s (2006) results I find no evidence of a significant negative relationship between aggregate returns and contemporaneous aggregate changes in earnings. Nor do I find evidence of a significant negative relationship between aggregate returns and contemporaneous aggregate earnings revisions. Nonetheless, as already noted, this does not preclude the existence of a discount rate effect in returns in response to earnings surprise. But it does imply that any discount rate effect is not of sufficient magnitude over the period investigated to drive the negative correlation reported by Kothari et al. In the following section I use the two stage regression approach employed by Kothari et

[208] Like Kothari et al. (2006), Patatoukas and Yan's (2009) analysis is limited to earnings surprise proxies derived from changes in realized earnings.

al. to estimate the relative magnitudes of cash flow and discount rate effects within the overall response of aggregate returns to aggregate earnings surprise.

7.4 Cash flow and discount rate effects

7.4.1 Campbell's (1991) return decomposition

RECAPPING DISCUSSION IN Chapter 2 on the decomposition of returns, Campbell's (1991) framework may be expressed by equation 7.3:

$$h_t = \mathrm{E}_{t-1}(h_t) + \eta_{d,t} - \eta_{h,t} \tag{7.3}$$

h_t represents the log real return on a stock for the period from the end of t-1 to the end of t, $\mathrm{E}_{t-1}(h_t)$ denotes the expected value at the end of t-1 for h_t, $\eta_{d,t}$ denotes the impact on returns of the change from t-1 to t in expected future dividends and $\eta_{h,t}$ represents the impact on returns of the change in expected future returns. That is, returns are determined by expected returns, changes in expected dividends and changes in expected returns. In addition, the relationship between unexpected earnings and each of the three components of returns may be expressed as follows:

$$\mathrm{cov}(\Delta e_t, h_t) = \mathrm{cov}(\Delta e_t, \mathrm{E}_{t-1}(h_t)) + \mathrm{cov}(\Delta e_t, \eta_{d,t}) - \mathrm{cov}(\Delta e_t, \eta_{h,t}) \tag{7.4}$$

Δe_t in this context represents earnings surprise for the period from t-1 to t. It is presumed that the covariance between earnings surprise and the change in expected future dividends is positive ($\mathrm{cov}(\Delta e_t, \eta_{d,t}) > 0$). In addition, Kothari et al. (2006) note that expected returns at time t-1 for period t and earnings surprise for that period should be uncorrelated if a good proxy is employed for Δe_t ($\mathrm{cov}(\Delta e_t, \mathrm{E}_{t-1}(h_t)) = 0$). Therefore, they conclude that their evidence of a significant negative relationship between Δe_t and h_t at the aggregate market level implies a significant positive relationship between earnings surprise and changes in expected returns ($\text{cov}(\Delta e_t, \eta_{h,t}) > 0$). That is, a positive relationship between earnings surprise and shocks to discount rates.[209]

However, my results in the preceding sections of this chapter call in to question the existence of a significant negative relationship between aggregate earnings surprise and returns. In almost all variations on this relationship evaluated I find a positive, but statistically insignificant, relationship between aggregate earnings surprise and returns. If the cash flow effect of earnings surprise on returns is positive and significant ($\text{cov}(\Delta e_t, \eta_{d,t}) > 0$) then the discount rate effect of earnings surprise on returns may be negative, but not sufficiently large to generate the negative overall relationship between aggregate earnings surprise and returns observed by Kothari et al. (2006). However, it is not clear from the analysis of prior sections whether the discount rate effect is statistically significant. In this section I employ the two stage regression methodology applied by Kothari et al. to estimate the individual and relative significance of cash flow and discount rate effects of aggregate earnings surprise on returns.

The primary aim of this analysis is to provide further clarification regarding the sign and magnitude of the relationship between earnings surprise and shocks to expected returns (the discount rate effect in equation 7.4, $\text{cov}(\Delta e_t, \eta_{d,t})$). Unfortunately, despite the utility of Campbell's decomposition framework, the disentangling of cash flow and discount rate effects in security returns is notoriously difficult, requiring good proxies for the respective effects.[210]

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[209] In the presence of investor rationality, expected returns equal discount rates (the difference has been eliminated by trading activity).

[210] Further complicating matters, Ball, Sadka and Sadka (2009) find evidence suggesting that the cash flow effect and discount rate effects may be highly correlated, meaning it may not be possible to distinguish between the two. Similarly, Hecht and Vuolteenaho (2006) report evidence of commonly employed proxies for cash flow effects *or* discount rate effects exhibiting correlation with cash flow *and* discount rate effects, obfuscating the relative significance of each separate effect. Chen and Zhao (2009) also raise concerns regarding

Macroeconomic proxies for discount rates previously employed by researchers include changes in short term interest rates, changes in the term structure of interest rates and changes in the default spread for discount rate effects. GNP and industrial production growth have been employed as macroeconomic proxies for cash flow effects.[211] However, to illustrate the difficulties involved, taking changes in short term interest rates as an example, rising short rates may be positively correlated with rising expected returns but may also be correlated with expected increases in macroeconomic growth which in turn may have future cash flow implications. In addition, Campbell's (1991) framework relates earnings surprise to shocks to discount rates, not realized changes in discount rates. Nonetheless, in the interests of consistency I apply the same process employed by Kothari et al.

Kothari et al.'s (2006) two stage regression methodology is designed to first estimate the relationship between earnings surprise and discount rate proxies. Regressions are of the general form of equation 7.5:

$$\Delta \mathrm{E}_t = \alpha + \boldsymbol{\beta}_{\mathrm{M}} \mathbf{M}_t + \varepsilon_t \tag{7.5}$$

In the context of this analysis, $\Delta \mathrm{E}_t$ represents a measure of aggregated annual changes in realized earnings or a measure of aggregated annual earnings revisions, and $\mathbf{M}_t$ represents a vector of discount rate proxies.

Regression results can be employed to estimate the component of earnings surprise explained by changes in discount rates (Fitted $\Delta \mathrm{E}_t$), and residual variation in

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attempts to estimate discount rate effects by regressing returns on a discount rate proxy, and implied cash flow effects from the residual.

[211] Chen, Roll and Ross (1986) present evidence of positive correlation between industrial production growth and stock returns, and positive correlation between measures of both term and credit spreads and stock returns. Fama (1990) employs measures of the default spread and term spread as discount rate proxies and growth in industrial production as a cash flow proxy. Schwert (1990) employs default spreads and term spreads as discount rate proxies and industrial production growth as a cash flow proxy. Industrial production growth, short term interest rates, the term structure of interest rates and credit spreads are also employed by Chen (1991) as indicators of current and future economic activity (including GNP growth), and Chen relates these to expected returns. Simlarly, Hecht and Vuolteenaho (2006) employ default spreads and term spreads as expected return proxies.

earnings surprise (Residual ΔE_t), that is unrelated to changes in discount rates (assuming the use of good proxies for changes in discount rates). Aggregate returns are then regressed on the fitted and residual components of earnings surprise to estimate the magnitude of discount rate effects in earnings surprise for returns.

Regressions are consequently of the following form:

$$R_t = \alpha + \beta_1(\text{Fitted } \Delta E_t) + \beta_2(\text{Residual } \Delta E_t) + \varepsilon_t \quad (7.6)$$

R_t represents aggregate market returns (value-weighted, equally-weighted or median returns depending on the weighting scheme employed to generate the aggregate earnings surprise variable). The same approach may be applied to cash flow effect proxies. Results from the application of this methodology to aggregate changes in earnings and aggregate earnings revisions are discussed in the following three sub-sections.

7.4.2 Discount rate effects

I EMPLOY THREE proxies for discount rates that are very similar to those employed by Kothari et al. (2006): annual changes in 3 month US Treasury bill yields (ΔBill), annual changes in the difference between 10 year US Treasury bond yields and 3 month bill yields (ΔTerm), and annual changes in the difference between the yield on Moody's Baa-rated commercial bonds and the yield on Moody's Aaa-rated commercial bonds (ΔDefault).[212] For Stage I regressions, I regress measures of aggregated changes in realized earnings and aggregated earnings revisions on these three discount rate proxies. Estimated slope coefficients, *t* statistics and adjusted R^2s are presented in Table 7.10.

[212] The definitions of ΔBill, ΔTerm and ΔDefault are selected on the basis of consistency with bill yields, term structure and default spreads employed in prior chapters. Kothari et al. (2006) use 1 year Treasury bill yields rather than 3 month yields in the calculation of ΔBill and as one component of ΔTerm. In unreported tests I find conclusions are unchanged when I employ their specifications for ΔBill and ΔTerm. ΔDefault is identical to Kothari et al.'s ΔCredit.

Table 7.10 Changes in realized earnings (and earnings revisions) regressed on discount rate proxies, then returns regressed on fitted and residual values, 1979–2009

A 2 stage regression procedure is performed, with Stage I consisting of the time series regression of a quarterly measure of aggregated annual changes in realized earnings (or aggregated annual earnings revisions) on a set of discount rate proxies. Regressions are of the following form:

$$\Delta \mathrm{E}_t = \alpha + \boldsymbol{\beta}_{\mathrm{M}} \mathbf{M}_t + \varepsilon_t$$

$\Delta \mathrm{E}_t$ represents the measure of aggregated annual changes in realized earnings (Panel A) or the measure of aggregated annual earnings revisions (Panel B), and $\mathbf{M}_t$ represents a vector of discount rate proxies. In Stage II aggregated returns are regressed on predicted and residual values obtained from the Stage I regression:

$$\mathrm{R}_t = \alpha + \beta_1(\text{Fitted } \Delta\mathrm{E}_t) + \beta_2(\text{Residual } \Delta\mathrm{E}_t) + \varepsilon_t$$

R_t represents value-weighted, equally-weighted or median stock returns. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Stage I				Stage II		
	ΔBill	ΔTerm	ΔDefault	Adj. R^2	Fitted	Residual	Adj. R^2
A. Aggregated changes in realized earnings							
ΔEE^a	**5.275**	-0.769	**-11.348**	0.385	0.349	0.118	0.066
	(4.922)	(-0.678)	(-2.483)		(1.364)	(0.476)	
ΔEB^a	**0.748**	-0.095	-1.162	0.436	2.273	1.793	0.077
	(5.350)	(-0.644)	(-1.648)		(1.229)	(1.022)	
$\Delta ebeq^a$	**0.627**	0.019	**-1.516**	0.397	3.385	2.401	0.070
	(4.691)	(0.148)	(-2.266)		(1.293)	(1.324)	
$\Delta ebmed^a$	**0.322**	-0.044	-0.387	0.381	2.335	2.888	0.014
	(4.877)	(-0.779)	(-1.056)		(0.491)	(0.832)	
B. Aggregated earnings revisions							
ΔEE^r	**2.776**	-0.461	1.832	0.508	0.198	**1.056**	0.110
	(8.246)	(-1.003)	(0.911)		(0.352)	(3.155)	
ΔEB^r	**0.477**	-0.092	0.157	0.510	1.679	**6.343**	0.126
	(8.413)	(-1.169)	(0.499)		(0.552)	(4.026)	
$\Delta ebeq^r$	**0.348**	-0.056	**0.444**	0.361	-2.801	2.759	0.005
	(4.260)	(-0.538)	(2.144)		(-0.490)	(0.444)	
$\Delta ebmed^r$	**0.321**	0.008	**0.413**	0.443	-4.938	0.964	0.016
	(4.404)	(0.084)	(3.123)		(-0.794)	(0.141)	

Firstly, across Panel A (aggregated changes in realized earnings) and Panel B (aggregated earnings revisions) the estimated slope coefficients on ΔBill are the only ones that are consistently of the right sign (in terms of consistency with Kothari et al.'s (2006) conclusion of pro-cyclicality in discount rates) and statistically significant.[213] That is, a positive coefficient on ΔBill reflects a positive relationship between earnings surprise and this proxy for discount rates, and consequently a negative impact from the discount rate effect in aggregate earnings surprise on returns. For regressions employing aggregated changes in realized earnings as the dependent variables, the signs on estimated coefficients for ΔTerm and ΔDefault are negative. Thus rising values of these factors are associated with lower values for aggregated earnings changes. Hence, they enter equation 7.4 with the wrong sign to be consistent with the role of proxy for discount rates.[214] However, for regressions employing measures of aggregated forecast revisions as independent variables, the estimated coefficients on ΔDefault are positive (and in two instances significant). Therefore, for this alternative measure of earnings surprise, the signs on estimated coefficients for ΔDefault are consistent with this factor acting as a proxy for changes in discount rates.

Secondly, results for Stage II regressions on the right-hand side of Table 7.10 are markedly different from those reported by Kothari et al. (2006). While for both quarterly and annual datasets they report negative and statistically significant coefficients on fitted earnings surprise, I find no significant coefficients on fitted earnings surprise and six of the eight estimates provided are positive. Further, all of the estimated coefficients on residual earnings surprise are positive. Most notably, the estimated coefficients on residual surprise for the two value-weighted

[213] A result which is consistent with the findings of Kothari et al. (2006) and Patatoukas and Yan (2009).

[214] Repeating regressions presented in Panel A of Table 7.10 for aggregate returns shifted forward one quarter (thus reflecting returns incorporating announced earnings for the full 12 month period) has no material impact on conclusions.

earnings revision variables are also statistically significant. Therefore, I do not find evidence of a significant discount rate effect in any of the measures of earnings surprise evaluated. But if the discount rate proxies employed are indeed good proxies then positive and, in select instances, significant estimates for residual earnings surprise represent evidence of a cash flow effect in earnings surprise.

To evaluate whether correlation between the proxies for discount rate changes could be the cause of incorrect signs on ΔTerm and ΔDefault in many of the regressions presented, I regress measures of earnings surprise on each discount change proxy separately. Aggregate returns are then regressed on fitted and residual earnings surprise from each of these regressions. Results for aggregated revisions are presented in Table 7.11.[215] The same process is also applied to aggregated changes in earnings as a further robustness test, and these results are presented in Table 7A.5 in the appendix to this chapter.

Conclusions are not materially changed. Estimated coefficients on ΔBill in Table 7.11 (Panel A) remain positive and significant. Estimated coefficients on ΔTerm (Panel B) are negative, but are now also significant. In Stage II regressions I find only positive estimated coefficients on fitted revisions (and slope coefficients are significant in Panel B). Further, the estimated coefficients on residual revisions in Panel A are positive and significant for ΔEE^r and ΔEB^r. Nowhere is there evidence of a negative and significant coefficient on fitted revisions. Results are similar for fitted and residual earnings surprise when surprise is defined by aggregated

[215] Results for aggregated revisions on ΔDefault are not included in Table 7.10 given estimated coefficients in univariate regressions on ΔDefault (not reported here) were insignificant for all dependent variables evaluated, in turn rendering Stage II regression results meaningless.

Table 7.11 Earnings revisions regressed on single discount rate proxies, then returns regressed on fitted and residual values, 1979–2009

A 2 stage regression procedure is performed, with Stage I consisting of the time series regression of a measure of aggregated annual revisions to earnings on a single discount rate proxy (ΔBill in Panel A and ΔTerm in Panel B). Regressions are of the following form:

$$\Delta \mathrm{E}_t^{\mathrm{r}} = \alpha + \beta_{\mathrm{M}} \mathrm{M}_t + \varepsilon_t$$

$\Delta \mathrm{E}_t^{\mathrm{r}}$ represents the measure of aggregated earnings revisions and M_t represents the discount rate proxy. In Stage II aggregated returns are regressed on predicted and residual values obtained from the Stage I regression:

$$\mathrm{R}_t = \alpha + \beta_1(\text{Fitted } \Delta \mathrm{E}_t^{\mathrm{r}}) + \beta_2(\text{Residual } \Delta \mathrm{E}_t^{\mathrm{r}}) + \varepsilon_t$$

R_t represents value-weighted or equally-weighted stock returns. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios and adjusted R^2. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Stage I		Stage II		
	Slope	Adj. R^2	Fitted	Residual	Adj. R^2
A. Revisions regressed on ΔBill					
$\Delta \mathrm{EE}^{\mathrm{r}}$	**2.902**	0.505	0.284	**0.946**	0.093
	(7.623)		(0.507)	(3.172)	
$\Delta \mathrm{EB}^{\mathrm{r}}$	**0.509**	0.511	1.622	**6.339**	0.127
	(7.368)		(0.522)	(4.402)	
$\Delta \mathrm{ebeq}^{\mathrm{r}}$	**0.356**	0.346	0.512	0.748	-0.015
	(4.657)		(0.082)	(0.144)	
B. Revisions regressed on ΔTerm					
$\Delta \mathrm{EE}^{\mathrm{r}}$	**-2.636**	0.200	**1.430**	0.396	0.108
	(-3.372)		(2.965)	(0.623)	
$\Delta \mathrm{EB}^{\mathrm{r}}$	**-0.476**	0.215	**7.920**	2.765	0.121
	(-3.471)		(2.991)	(0.778)	
$\Delta \mathrm{ebeq}^{\mathrm{r}}$	**-0.314**	0.128	**9.291**	-0.679	0.018
	(-2.418)		(2.035)	(-0.164)	

changes in annual realized earnings (Table 7A.5). All estimated coefficients for both fitted and residual series are positive.[216]

Finding no evidence of a significant discount rate effect of the correct sign across any of the measures of aggregate earnings surprise evaluated, I change focus to cash flow effects. These are evaluated in the following sub-section.

7.4.3 Cash flow effects

KOTHARI ET AL. (2006) only perform the two stage regression analysis for discount rate proxies. In this section I extend their analysis to cash flow proxies. Following Fama (1990) and Schwert (1990), amongst others, I employ growth in industrial production as a proxy for changes in expected future cash flows. Measures of aggregated annual earnings surprise are regressed on contemporaneous annual growth in US industrial production. As per the two stage process for estimating discount rate effects, the estimated coefficients from these regressions are employed to generate fitted and residual series for aggregate earnings surprise (the component of earnings surprise explained by the expected future cash flow proxy and the orthogonal residual). Specifically, I am seeking evidence of a positive and significant cash flow effect, initial evidence for which is present in positive and significant coefficients on select measures of residual earnings revisions in the evaluation of discount rate effects. Summary results are provided in Table 7.12 for four measures of aggregated changes in realized earnings (Panel A) and four measures of aggregated earnings revisions (Panel B).

[216] Kothari et al. (2006) include a lagged dependent variable in Stage I regressions "to soak up residual autocorrelation remaining after controlling for interest rates" (p. 562). I repeat all regressions presented in Table 7.10 with the addition of a four-quarter lagged dependent variable in each respective Stage I regression. Results are presented in Table 7A.6 in the appendix to this chapter. The lagged dependent variables are only significant when aggregated earnings revisions are employed as the proxy for earnings surprise. All conclusions remain unchanged.

Table 7.12 Changes in realized earnings (and earnings revisions) regressed on industrial production growth, then returns regressed on fitted and residual values, 1979–2009

A 2 stage regression procedure is performed, with Stage I consisting of the time series regression of a quarterly measure of aggregated annual changes in realized earnings (or aggregated annual earnings revisions) on industrial production growth. Regressions are of the following form:

$$\Delta \mathrm{E}_t = \alpha + \boldsymbol{\beta}_{\mathrm{M}}\mathbf{M}_t + \varepsilon_t$$

$\Delta \mathrm{E}_t$ represents the measure of aggregated annual changes in realized earnings (Panel A) or the measure of aggregated annual earnings revisions (Panel B), and $\mathbf{M}_t$ represents annual industrial production growth. In Stage II aggregated returns are regressed on predicted and residual values obtained from the Stage I regression:

$$\mathrm{R}_t = \alpha + \beta_1(\text{Fitted } \Delta \mathrm{E}_t) + \beta_2(\text{Residual } \Delta \mathrm{E}_t) + \varepsilon_t$$

R_t represents value-weighted, equally-weighted or median stock returns. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Stage I		Stage II		
	IP growth	Adj. R^2	Fitted	Residual	Adj. R^2
A. Aggregated changes in realized earnings					
ΔEE[a]	**2.990**	0.330	0.523	0.053	0.119
	(2.649)		(1.655)	(0.308)	
ΔEB[a]	**0.390**	0.354	4.008	0.887	0.128
	(2.569)		(1.635)	(0.725)	
Δebeq[a]	**0.391**	0.444	3.089	2.576	0.068
	(3.155)		(1.311)	(1.161)	
Δebmed[a]	**0.213**	0.528	4.579	0.501	0.031
	(3.845)		(0.878)	(0.113)	
B. Aggregated earnings revisions					
ΔEE[r]	**0.966**	0.216	**1.618**	0.321	0.134
	(1.796)		(1.712)	(0.791)	
ΔEB[r]	**0.179**	0.244	**8.756**	2.288	0.143
	(1.932)		(1.738)	(1.020)	
Δebeq[r]	0.071	0.047	17.136	-0.284	0.029
	(1.400)		(0.993)	(-0.090)	
Δebmed[r]	**0.074**	0.092	13.113	-3.364	0.059
	(2.122)		(0.959)	(-0.941)	

The estimated coefficients on industrial production growth are positive for all variables analyzed, and in only one instance fail specified criteria for statistical significance. Therefore, the estimated relationships between industrial production growth and these measures of aggregate earnings surprise are consistent with industrial production acting as a proxy for expected future cash flows (positive coefficients). In addition, the estimated coefficients on fitted earnings surprise are all positive. They are also significant for the two value-weighted aggregate revision regressions, and only narrowly miss set criteria for significance for the two value-weighted realized earnings regressions. Equally-weighted and median measures will be more heavily influenced by smaller companies. Results for value-weighted aggregate measures of earnings surprise are consistent with both industrial production growth as a proxy for aggregate expected future cash flows and consistent with a significant cash flow effect in the impact of aggregate earnings revisions on aggregate returns.

Chen and Zhao (2008) also report evidence of a significant cash flow effect in aggregate returns. They attribute the difference between their results and those of Kothari et al. (2006) to their use of I/B/E/S forecast data rather than realized earnings, and different empirical methodology (analysts' forecasts are employed in a discounted valuation model to derive proxies for cash flow and discount rate news). My results suggest that even with the same methodology, findings that conflict with those of Kothari et al. may be generated.

As a further test of cash flow effects in aggregate returns I include two additional explanatory variables in Stage I regressions: 12 month log changes in the Institute of Supply Management's Purchasing Managers' Index (ΔISM) and 12 month log changes in the University of Michigan's Consumer Sentiment Index (ΔCons. Sent.). Regression results are provided in Table 7.13. Estimated coefficients on changes in

Table 7.13 Changes in realized earnings (and earnings revisions) regressed on growth proxies, then returns regressed on fitted and residual values, 1979–2009

A 2 stage regression procedure is performed, with Stage I consisting of the time series regression of a quarterly measure of aggregated annual changes in realized earnings (or aggregated annual earnings revisions) on a set of growth proxies. Regressions are of the following form:

$$\Delta \mathrm{E}_t = \alpha + \boldsymbol{\beta}_{\mathrm{M}}\mathbf{M}_t + \varepsilon_t$$

$\Delta \mathrm{E}_t$ represents the measure of aggregated annual changes in realized earnings (Panel A) or the measure of aggregated annual earnings revisions (Panel B), and $\mathbf{M}_t$ represents a vector of growth proxies. In Stage II aggregated returns are regressed on predicted and residual values obtained from the Stage I regression:

$$\mathrm{R}_t = \alpha + \beta_1(\text{Fitted } \Delta\mathrm{E}_t) + \beta_2(\text{Residual } \Delta\mathrm{E}_t) + \varepsilon_t$$

R_t represents value-weighted, equally-weighted or median stock returns. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Stage I				Stage II		
	IP growth	ΔISM	ΔCons. Sent.	Adj. R^2	Fitted	Residual	Adj. R^2
A. Aggregated changes in realized earnings							
ΔEE^a	**3.169**	**-0.302**	0.220	0.361	0.416	0.087	0.085
	(2.474)	(-1.990)	(1.156)		(1.263)	(0.432)	
ΔEB^a	**0.416**	**-0.046**	0.035	0.406	3.028	1.268	0.093
	(2.821)	(-2.455)	(1.578)		(1.300)	(0.870)	
$\Delta ebeq^a$	**0.415**	**-0.026**	0.010	0.464	1.574	**3.931**	0.082
	(4.020)	(-1.881)	(0.505)		(0.651)	(1.991)	
$\Delta ebmed^a$	**0.240**	**-0.022**	-0.001	0.625	0.545	6.345	0.047
	(4.589)	(-4.604)	(-0.069)		(0.114)	(1.435)	
B. Aggregated earnings revisions							
ΔEE^r	**1.169**	**-0.179**	0.020	0.333	0.486	0.676	0.070
	(3.390)	(-3.650)	(0.260)		(0.447)	(1.585)	
ΔEB^r	**0.211**	**-0.029**	0.004	0.345	3.299	**4.251**	0.090
	(3.477)	(-3.392)	(0.304)		(0.549)	(1.863)	
$\Delta ebeq^r$	**0.106**	**-0.023**	-0.009	0.176	-13.342	4.072	0.121
	(2.952)	(-2.727)	(-0.706)		(-1.496)	(1.340)	
$\Delta ebmed^r$	**0.108**	**-0.020**	-0.010	0.276	-9.295	1.415	0.058
	(3.936)	(-3.223)	(-1.058)		(-0.959)	(0.386)	

consumer sentiment are positive in five out of the eight sets of regression results presented. However, all estimated slope coefficients on ΔISM are negative (and significant). Therefore, although there may be positive cash flow effects within the overall relationship between aggregate earnings surprise and ΔISM, they are swamped by other negative effects. In the previous chapter I noted there is evidence of the ISM PMI index providing leading signals for US monetary policy. It may be that ΔISM therefore is of more utility as a proxy for discount rate effects than for cash flow effects. However, in regressions replicating the analysis in Table 7.10 with the addition of ΔISM as an explanatory factor in Stage I regressions (not shown here), I still find no evidence of a negative and statistically significant discount rate effect (conversely, *t* statistics on residual earnings surprise increase in these tests).

7.4.4 Discount proxy levels and returns

A FINAL POSSIBILITY considered by Kothari et al. (2006) is that their evidence for a negative relationship between aggregate earnings surprise and contemporaneous returns is a consequence not of changes in expected returns (discount rates) but a negative relationship between earnings surprise and the level of expected returns. In the context of Campbell's (1991) return decomposition (equations 7.3 and 7.4), it is possible that $\mathrm{cov}(\Delta e_t, \mathrm{E}_{t-1}(h_t)) < 0$. While they do not believe this to be the case,[217] they re-run their two stage analysis for discount rate proxies, including lagged values of the levels of each of the three discount rate proxies as additional explanatory variables in Stage I regressions. They report that estimated coefficients on these additional variables are insignificant in all regressions. In Table 7.14 I report results from performing this analysis for both

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[217] Kothari et al. (2006) note for $\mathrm{d}E_t$ (their equivalent of Δe_t in equations 7.3 and 7.4) that "if $\mathrm{d}E_t$ is a good proxy for unexpected earnings, it must be uncorrelated with anything known prior to t, including r_t" (p. 566), where r_t refers to returns, and "the explanatory power [of $\mathrm{d}E_t$] seems too large to be driven by the ex ante level of discount rates" (p. 566).

aggregated changes in realized earnings (Panel A) and aggregated revisions (Panel B). While I do find statistically significant coefficients on some of the additional Stage I factors, I find no evidence of a significant negative relationship between aggregate returns and any of the fitted earnings surprise series. Consequently, across all core decomposition analysis and all robustness tests I do not find a single example of a significant discount rate effect in the impact of evaluated measures of aggregate earnings surprise on aggregate returns.

7.5 Concluding remarks

KOTHARI ET AL.'S (2006) finding of a significant negative relationship between aggregate returns and contemporaneous earnings growth has provided the motivation for a number of researchers to attempt to explain the difference between stock level and aggregate market results.

However, employing an alternative proxy for market earnings surprise based on aggregated analysts' revisions, I find no evidence of a significant negative relationship between aggregate earnings surprise and contemporaneous returns. In addition, results presented in this chapter suggest Kothari et al.'s (2006) findings may be partially a consequence of a significant negative relationship between aggregate returns and contemporaneous changes in earnings in the earlier years of their dataset, and not a more persistent longer term phenomenon.

Subject to the limitations of the two stage regression approach to estimating relative cash flow and discount rate effects, I find no evidence of a significant discount effect in the impact of aggregate earnings surprise on market returns. However, I do find evidence supporting the presence of a significant positive cash flow effect.

Table 7.14 Changes in realized earnings (and earnings revisions) regressed on changes and lagged levels of discount rate proxies, then returns regressed on fitted and residual values, 1979–2009

A 2 stage regression procedure is performed, with Stage I consisting of the time series regression of a measure of aggregated annual changes in realized earnings (or aggregated annual earnings revisions) on a set of discount rate proxies, including 4 quarter lagged levels of discount rate proxies. Regressions are of the following form:

$$\Delta \mathrm{E}_t = \alpha + \boldsymbol{\beta}_{\mathrm{M}} \mathbf{M}_t + \varepsilon_t$$

$\Delta \mathrm{E}_t$ represents the measure of aggregated annual changes in realized earnings (Panel A) or the measure of aggregated annual earnings revisions (Panel B), and $\mathbf{M}_t$ represents a vector of discount rate proxies. In Stage II aggregated returns are regressed on predicted and residual values obtained from the Stage I regression:

$$\mathrm{R}_t = \alpha + \beta_1(\text{Fitted } \Delta \mathrm{E}_t) + \beta_2(\text{Residual } \Delta \mathrm{E}_t) + \varepsilon_t$$

R_t represents value-weighted, equally-weighted or median stock returns. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Stage I							Stage II		
	ΔBill	ΔTerm	ΔDefault	Bill	Term	Default	Adj. R^2	Fitted	Resid.	Adj. R^2
A. Aggregated changes in realized earnings										
ΔEE^a	**5.768**	1.349	-13.052	0.871	**3.440**	-8.587	0.396	0.344	0.108	0.066
	(4.509)	(0.785)	(-1.346)	(0.487)	(1.676)	(-0.865)		(1.235)	(0.458)	
ΔEB^a	**0.773**	0.107	-1.641	0.170	0.365	-1.406	0.456	2.665	1.360	0.084
	(4.576)	(0.501)	(-1.478)	(0.849)	(1.403)	(-1.243)		(1.252)	(0.837)	
$\Delta ebeq^a$	**0.629**	0.264	**-2.128**	0.073	0.315	-1.692	0.447	2.972	2.651	0.067
	(4.171)	(1.338)	(-1.968)	(0.348)	(1.240)	(-1.325)		(1.088)	(1.545)	
$\Delta ebmed^a$	**0.316**	0.097	**-0.899**	0.117	**0.228**	**-1.276**	0.494	3.477	1.763	0.016
	(4.533)	(0.939)	(-2.465)	(1.327)	(1.968)	(-2.397)		(0.605)	(0.529)	
B. Aggregated earnings revisions										
ΔEE^r	**2.285**	-0.856	-1.990	0.270	-0.775	**-5.887**	0.568	0.417	**0.872**	0.077
	(4.828)	(-1.156)	(-0.809)	(0.424)	(-1.068)	(-1.819)		(0.594)	(2.661)	
ΔEB^r	**0.409**	-0.131	-0.432	0.055	-0.078	**-0.968**	0.555	2.830	**5.303**	0.097
	(5.078)	(-1.064)	(-0.953)	(0.511)	(-0.579)	(-1.759)		(0.711)	(3.258)	
$\Delta ebeq^r$	**0.317**	-0.056	0.355	-0.093	-0.103	-0.085	0.384	-3.658	3.623	0.020
	(2.934)	(-0.347)	(0.843)	(-0.783)	(-0.517)	(-0.144)		(-0.634)	(0.619)	
$\Delta ebmed^r$	**0.262**	-0.028	0.104	-0.063	-0.152	-0.405	0.518	-5.917	2.947	0.046
	(3.630)	(-0.246)	(0.499)	(-0.983)	(-1.335)	(-1.278)		(-0.950)	(0.489)	

Importantly, these results are not simply a product of the addition of post-2000 data to Kothari et al.'s (2006) analysis. In robustness tests on the period extending from 1936 through to 1969 they do not find evidence of a negative and statistically significant contemporaneous relationship between aggregate earnings surprise and aggregate returns. My robustness tests on the period from 1979 through to 2009 similarly are not consistent with a significant negative relationship between these variables. Consequently, it is the negative relationship between aggregate earnings surprise and contemporaneous returns in the 1970's that is key to Kothari et al.'s results.[218]

While these results do not preclude the existence of a discount effect in aggregate returns, they do suggest the effect is smaller than implied by Kothari et al.'s (2006) research. Results also do not support the contention that discount rate effects in aggregate market returns are larger than cash flow effects, nor the contention that discount rate effects dominate aggregate returns while cash flow effects dominate stock-level returns.

[218] An inverse relationship between aggregate earnings surprise and contemporaneous returns in the 1970's may be a consequence of high unexpected inflation during this decade. High unexpected inflation could result in positive surprise in nominal earnings, but may also result in unexpectedly high positive discount rate shocks. However, a full examination of explanations of time variation in the relative magnitude of cash flow and discount rate effects in the relationship between aggregate earnings surprise and returns is beyond the scope of this study.

Appendix 7A Additional robustness tests

Table 7A.1 Cross-sectional regressions of returns on changes in realized earnings for Δeb^a, 1979–2009

Time series averages of cross-sectional regressions performed on individual stocks are presented for March, June, September and December year annual data. Results provided are estimated slope coefficients, $\hat{\beta}$ and t ratios for regressions of the following form:

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{a}}_{t-l} + \varepsilon_t$$

Lags, l, of 0 to 4 quarters are evaluated, with lag 0 representing returns 1 quarter after the end of the earnings change period (thus representing post-announcement returns). $\Delta \mathrm{E}^{\mathrm{a}}_t$ represents annual changes in realized earnings per share deflated by lagged book value per share. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios for the aggregate time series regressions. Results in bold are statistically significant at the 10% level.

	Lag	Univariate regressions		Multivariate regressions	
		Estimated slope coef.	t-statistic	Estimated slope coef.	t-statistic
March years	0	**0.810**	7.349	**1.089**	6.565
	1	**0.435**	4.379	0.014	0.112
	2	0.106	1.298	**-0.437**	-2.494
	3	-0.098	-1.184	**-0.171**	-1.724
	4	**-0.191**	-2.154	**0.352**	2.402
June years	0	**0.896**	6.648	**2.076**	5.511
	1	**0.515**	6.140	**-1.184**	-4.060
	2	**0.160**	1.899	0.059	0.435
	3	-0.094	-0.706	**-0.506**	-2.125
	4	-0.168	-1.346	**0.609**	3.475
September years	0	**0.900**	6.112	**1.636**	6.254
	1	**0.543**	3.873	-0.220	-1.322
	2	**0.274**	2.202	**-0.723**	-5.005
	3	0.084	0.637	-0.072	-0.684
	4	-0.019	-0.120	**0.523**	3.838
December years	0	**0.980**	5.877	**1.660**	6.527
	1	**0.546**	3.797	**-2.095**	-2.095
	2	**0.235**	1.877	**-0.223**	-2.227
	3	0.022	0.191	**-0.327**	-3.022
	4	-0.074	-0.634	**0.451**	4.112

Table 7A.2 Cross-sectional regressions of returns on earnings revisions for Δeb^r, 1979–2009

Time series averages of cross-sectional regressions performed on individual stocks are presented for March, June, September and December year annual data. Results provided are estimated slope coefficients, $\hat{\beta}$ and t ratios for regressions of the following form:

$$R_t = \alpha + \beta \Delta E^r_{t-l} + \varepsilon_t$$

Lags, l, of 0 to 4 quarters are evaluated, with lag 0 representing returns 1 quarter after the end of the earnings change period (thus representing post-announcement returns). ΔE^r_t represents annual forecast revisions for earnings per share deflated by lagged book value per share. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios for the aggregate time series regressions. Results in bold are statistically significant at the 10% level.

	Lag	Univariate regressions		Multivariate regressions	
		Estimated slope coef.	t-statistic	Estimated slope coef.	t-statistic
March years	0	**1.215**	6.891	**1.227**	4.777
	1	**0.839**	6.102	**0.718**	3.713
	2	0.247	1.662	**-0.692**	-3.883
	3	-0.132	-0.923	**-0.625**	-3.291
	4	-0.107	-0.754	0.253	1.572
June years	0	**1.164**	7.416	**1.339**	6.154
	1	**0.738**	6.774	-0.247	-1.171
	2	**0.493**	4.104	**0.476**	2.168
	3	0.092	0.625	**-0.428**	-3.034
	4	-0.121	-0.677	-0.084	-0.414
September years	0	**1.275**	8.920	**2.406**	7.943
	1	**0.510**	3.434	**-1.388**	-4.388
	2	0.228	1.495	0.012	0.053
	3	0.141	0.926	-0.036	-0.161
	4	0.025	0.160	0.299	1.690
December years	0	**1.530**	8.237	**2.564**	10.837
	1	**0.769**	5.126	**-0.903**	-4.871
	2	0.144	1.029	**-0.766**	-3.768
	3	-0.008	-0.056	0.159	0.794
	4	-0.095	-0.644	0.075	0.413

Table 7A.3 Returns regressed on forecast revisions by size quintiles for Δebeq^r, 1979–2009

Time series regressions of quarterly equally-weighted annual returns on the lagged sum of equally-weighted earnings per share revisions (deflated by lagged book value per share) are performed for size quintiles. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios and adjusted R^2 for regressions of the following form:

$$\mathrm{R}_t = \alpha + \beta \Delta \mathrm{E}^{\mathrm{r}}_{t-l} + \varepsilon_t$$

R_t represents equally-weighted stock returns. Lags, l, of 0 to 4 quarters are evaluated. $\Delta \mathrm{E}^{\mathrm{r}}_t$ represents equally-weighted earnings per share revisions deflated by lagged book value per share. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Lag	Univariate regressions			Multivariate regressions		
		Estimated slope coef.	t-statistic	Adj. R^2	Estimated slope coef.	t-statistic	Adj. R^2
Q1 (largest)	0	0.804	0.415	-0.003	0.402	0.104	-0.031
	1	0.814	0.555	-0.003	-0.267	-0.152	
	2	0.985	0.616	-0.001	-0.769	-0.403	
	3	1.271	0.706	0.004	2.192	1.040	
	4	1.073	0.503	0.000	-0.312	-0.130	
Q2	0	-0.165	-0.080	-0.008	1.580	0.468	-0.025
	1	-0.645	-0.357	-0.006	**-3.482**	-1.750	
	2	-0.184	-0.075	-0.008	0.943	0.423	
	3	0.214	0.069	-0.008	-0.926	-0.591	
	4	0.600	0.165	-0.007	1.984	0.819	
Q3	0	-0.463	-0.211	-0.007	1.961	0.791	-0.026
	1	-1.260	-0.578	0.000	**-3.531**	-1.926	
	2	-1.053	-0.468	-0.003	-0.226	-0.101	
	3	-0.701	-0.280	-0.006	0.682	0.327	
	4	-0.562	-0.200	-0.007	0.187	0.060	
Q4	0	0.487	0.212	-0.007	2.755	0.841	-0.030
	1	-0.390	-0.188	-0.008	**-4.281**	-1.915	
	2	0.221	0.101	-0.008	1.259	0.554	
	3	0.353	0.161	-0.008	0.657	0.280	
	4	0.224	0.091	-0.008	-0.030	-0.010	
Q5 (smallest)	0	2.494	0.594	0.006	**9.308**	2.024	
	1	-0.563	-0.161	-0.008	**-8.709**	-3.050	
	2	-0.352	-0.118	-0.008	-1.683	-0.692	
	3	0.905	0.332	-0.007	-0.136	-0.058	
	4	2.104	0.754	0.000	3.987	1.165	

Table 7A.4 Returns regressed on forecast revisions by book-to-market quintiles for Δebeq^r, 1979–2009

Time series regressions of quarterly equally-weighted annual returns on the lagged sum of equally-weighted earnings per share revisions (deflated by lagged book value per share) are performed for price-to-book quintiles. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios and adjusted R^2 for regressions of the following form:

$$\mathrm{R}_t = \alpha + \beta\Delta\mathrm{E}^{\mathrm{r}}_{t-l} + \varepsilon_t$$

R_t represents equally-weighted stock returns. Lags, l, of 0 to 4 quarters are evaluated. $\Delta\mathrm{E}^{\mathrm{r}}_t$ represents equally-weighted earnings per share revisions deflated by lagged book value per share. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Lag	Univariate regressions			Multivariate regressions		
		Estimated slope coef.	t-statistic	Adj. R^2	Estimated slope coef.	t-statistic	Adj. R^2
Q1 (lowest)	0	-1.019	-0.547	0.000	-1.903	-0.961	0.002
	1	-0.705	-0.379	-0.005	-1.700	-1.018	
	2	0.140	0.062	-0.008	0.721	0.402	
	3	0.908	0.381	-0.002	2.056	1.486	
	4	0.899	0.345	-0.003	0.498	0.199	
Q2	0	-0.682	-0.258	-0.006	0.576	0.206	-0.014
	1	-1.002	-0.364	-0.003	**-4.326**	-2.447	
	2	-0.037	-0.014	-0.008	1.925	1.050	
	3	0.387	0.163	-0.008	0.109	0.044	
	4	0.619	0.246	-0.006	1.302	0.564	
Q3	0	2.004	0.966	0.014	3.213	1.340	-0.007
	1	1.150	0.598	-0.001	0.463	0.260	
	2	0.133	0.065	-0.008	-1.787	-0.784	
	3	-0.363	-0.159	-0.008	-1.106	-0.675	
	4	-0.578	-0.228	-0.007	0.406	0.162	
Q4	0	1.005	0.351	-0.005	5.189	1.163	-0.004
	1	-0.662	-0.313	-0.007	**-6.790**	-3.291	
	2	0.399	0.176	-0.008	1.654	0.626	
	3	0.512	0.223	-0.008	-0.338	-0.136	
	4	0.885	0.370	-0.006	1.831	0.628	
Q5 (highest)	0	1.692	0.376	0.001	**11.724**	2.656	0.094
	1	-1.327	-0.438	-0.003	**-7.873**	-2.238	
	2	-2.651	-1.104	0.010	-3.318	-1.167	
	3	-2.931	-1.348	0.012	-4.899	-1.009	
	4	-1.661	-0.532	-0.002	5.073	1.249	

Table 7A.5 Changes in realized earnings regressed on single discount rate proxies, then returns regressed on fitted and residual values, 1979–2009

A 2 stage regression procedure is performed, with Stage I consisting of the time series regression of quarterly aggregated changes in annual earnings on a single discount rate proxy (ΔBill in Panel A, ΔTerm in Panel B and ΔDefault in Panel C). Regressions are of the following form:

$$\Delta \mathrm{E}_t^{\mathrm{a}} = \alpha + \beta_{\mathrm{M}} \mathrm{M}_t + \varepsilon_t$$

$\Delta \mathrm{E}_t^{\mathrm{a}}$ represents the measure of aggregated changes in annual earnings and M_t represents the discount rate proxy. In Stage II aggregated returns are regressed on predicted and residual values obtained from the Stage I regression:

$$\mathrm{R}_t = \alpha + \beta_1(\text{Fitted } \Delta \mathrm{E}_t^{\mathrm{a}}) + \beta_2(\text{Residual } \Delta \mathrm{E}_t^{\mathrm{a}}) + \varepsilon_t$$

R_t represents value-weighted stock returns. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Stage I		Stage II		
	Slope	Adj. R^2	Fitted	Residual	Adj. R^2
A. Changes in realized earnings regressed on ΔBill					
ΔEE^a	**5.967**	0.332	0.138	0.247	0.052
	(3.948)		(0.522)	(1.009)	
ΔEB^a	**0.826**	0.403	1.000	2.703	0.092
	(4.148)		(0.586)	(1.643)	
B. Changes in realized earnings regressed on ΔTerm					
ΔEE^a	**-5.881**	0.155	**0.641**	0.128	0.099
	(-2.704)		(2.866)	(0.452)	
ΔEB^a	**-0.790**	0.177	**4.771**	1.387	0.116
	(-2.563)		(2.990)	(0.669)	
C. Changes in realized earnings regressed on ΔDefault					
ΔEE^a	**-15.578**	0.102	**1.061**	0.106	0.177
	(-1.856)		(3.375)	(0.677)	
ΔEB^a	-1.752	0.080	**9.433**	1.296	0.198
	(-1.384)		(3.409)	(1.215)	

Table 7A.6 Changes in realized earnings (and earnings revisions) regressed on changes in discount rate proxies and lagged dependent variables, then returns regressed on fitted and residual values, 1979–2009

A 2 stage regression procedure is performed, with Stage I consisting of the time series regression of a measure of aggregated annual changes in realized earnings (or aggregated annual earnings revisions) on a set of discount rate proxies and a four quarter lagged dependent variable. Regressions are of the following form:

$$\Delta \mathrm{E}_t = \alpha + \boldsymbol{\beta}_{\mathrm{M}}\mathbf{M}_t + \Delta \mathrm{E}_{t-4} + \varepsilon_t$$

$\Delta \mathrm{E}_t$ represents the measure of aggregated annual changes in realized earnings (Panel A) or the measure of aggregated annual earnings revisions (Panel B), and $\mathbf{M}_t$ represents a vector of discount rate proxies. In Stage II aggregated returns are regressed on predicted and residual values obtained from the Stage I regression:

$$\mathrm{R}_t = \alpha + \beta_1(\text{Fitted } \Delta \mathrm{E}_t) + \beta_2(\text{Residual } \Delta \mathrm{E}_t) + \varepsilon_t$$

R_t represents value-weighted, equally-weighted or median stock returns. Results provided are estimated slope coefficients, $\hat{\beta}$, t ratios (in parentheses) and adjusted R^2. Newey-West standard errors with automatic bandwidth selection are employed to calculate t ratios. Results in bold are statistically significant at the 10% level.

	Stage I					Stage II		
	ΔBill	ΔTerm	ΔDefault	$\Delta \mathrm{E}_{t-4}$	Adj. R^2	Fitted	Residual	Adj. R^2
A. Aggregated changes in realized earnings								
ΔEE^a	**5.249**	-0.780	**-11.416**	0.018	0.369	0.358	0.112	0.065
	(4.480)	(-0.559)	**(-1.709)**	(0.063)		(1.367)	(0.447)	
ΔEB^a	**0.726**	-0.090	-1.237	0.067	0.419	2.567	1.556	0.078
	(4.617)	(-0.528)	(-1.509)	(0.248)		(1.300)	(0.849)	
$\Delta ebeq^a$	**0.577**	0.068	**-1.784**	0.157	0.392	4.161	1.875	0.080
	(4.089)	(0.319)	**(-2.357)**	(0.503)		(1.554)	(1.033)	
$\Delta ebmed^a$	**0.287**	-0.017	**-0.576**	0.199	0.366	4.291	1.648	0.018
	(4.121)	(-0.251)	**(-1.822)**	(0.967)		(0.783)	(0.423)	
B. Aggregated earnings revisions								
ΔEE^r	**2.074**	**-0.619**	-1.463	**0.399**	0.555	0.511	**0.793**	0.070
	(6.341)	(-1.799)	(-0.781)	(3.854)		(0.829)	(1.895)	
ΔEB^r	**0.361**	**-0.119**	-0.374	**0.372**	0.546	3.451	**4.830**	0.091
	(6.433)	(-1.845)	(-1.356)	(3.237)		(0.971)	(2.342)	
$\Delta ebeq^r$	**0.270**	-0.047	-0.001	0.340	0.391	0.243	0.567	-0.017
	(3.214)	(-0.386)	(-0.004)	(1.573)		(0.052)	(0.090)	
$\Delta ebmed^r$	**0.283**	0.021	0.084	**0.329**	0.473	-2.543	-1.892	-0.004
	(3.964)	(0.201)	(0.357)	(1.769)		(-0.411)	(-0.257)	

8 Conclusions

8.1 Overview

IN THIS THESIS I develop aggregate market measures of changes in realized earnings, analysts' forecasts of changes in earnings and analysts' earnings revisions for US stocks, focusing on the period extending from 1979 through to 2009. These variables are employed in three principal examinations of the information in aggregated analysts' forecasts and characteristics of those forecasts. Firstly, I evaluate the information in aggregated analysts' forecasts for future macroeconomic activity. Secondly, I evaluate the informational efficiency of aggregated forecasts with respect to past economic state variables, and consequent implications for the predictability of revisions and returns. Thirdly, I revisit the analysis of Kothari, Lewellen and Warner (2006), investigating the relationship between measures of aggregate earnings surprise and market returns.

This research adds to the finance and accounting literature by (1) being the first time series examination of the relationship between aggregated US analysts' earnings forecasts and future indicators of economic activity; (2) being the first evaluation of US analyst efficiency, with respect to a wide range of economic variables, at the aggregate market level; and, (3) being the first study to apply Kothari et al.'s analysis of aggregated realized earnings to the arguably superior measure of aggregate market earnings surprise, aggregated analysts' revisions.

The following three sections provide summaries and conclusions for each empirical chapter.

8.2 The macroeconomic information in aggregated analysts' forecasts

IN CHAPTER 5 I acknowledge the observation by Shivakumar (2010) that "Prior studies note that aggregate earnings news is probably related to market returns because it provides information about the macroeconomy, but little is known about the macroeconomic content of such earnings" (p. 338). By aggregating analysts' earnings revisions, and investigating the information in those earnings for measures of future macroeconomic activity, I seek to elucidate the macroeconomic content of earnings forecasts.

Prior research has found evidence of a strong positive relationship between firm earnings and contemporaneous measures of macroeconomic activity. In addition, prior research has found evidence of positive and statistically significant information in analysts' earnings forecasts for future realized earnings. Combined, these findings motivate my principal hypothesis that there is statistically significant information in aggregated analysts' earnings forecasts for future macroeconomic activity. I find evidence in favour of both of the underlying drivers of the principal hypothesis at the aggregate market level. I also find evidence of statistically significant information in aggregated analysts' earnings forecasts for future macroeconomic activity. In particular, information in aggregated forecasts for future industrial production growth up to six quarters ahead.

I also present evidence of three forms of systematic variation in the magnitude of information in aggregated forecasts. Firstly, I find less information in the forecasts of firms which engage in substantial earnings smoothing relative to firms which engage in little smoothing. Smoothing reduces earnings volatility. If smoothing reduces the magnitude of the relationship between earnings and macroeconomic activity, it is reasonable to expect (assuming analysts incorporate expected smoothing into forecasts) that smoothing will reduce the magnitude of information in forecasts for future macroeconomic activity. I find evidence in support of this hypothesis. Secondly, I provide evidence of a relationship between the magnitude of information in aggregated forecasts for future industrial production and firm size. Small firm forecasts explain more of variation in future industrial production growth than large firm forecasts. This appears to be partially a result of size-based variation in smoothing, but not entirely. Further investigation of the relationship between firm size and the predictive power of aggregated forecasts for future industrial production growth is required to determine causes of this effect.

The third hypothesized form of systematic variation in the magnitude of information in aggregated forecasts is based on relative earnings cyclicality. If stocks' realized earnings display variation in their relationship with contemporaneous macroeconomic activity, it is reasonable to expect that their forecasts will similarly display variation in their information content for future macroeconomic activity. That is, variation in their information content that is related to the historic cyclicality of their realized earnings. I find evidence in favour of this hypothesis.

Combining these results (more information for future industrial production growth in the earnings forecasts of low smoothers and small firms, and more information in the earnings forecasts of highly cyclical firms), I find that the aggregated forecasts of small cyclical firms contain statistically significant *marginal* information for future industrial production growth even in combination with a range of additional economic state variables.

In Chapter 5 I also compare the *implicit* information for future industrial production growth in aggregated analysts' forecasts with the *explicit* forecasts for industrial production growth made by economists. I find evidence in favour of superior information in aggregated analysts' forecasts.

8.3 The informational efficiency of aggregated analysts' forecasts

WHILE RESULTS PRESENTED in Chapter 5 provide evidence of statistically significant information in aggregated forecast changes in earnings for future industrial production growth, they do not preclude inefficient incorporation of past economic state variables in the forecasting process. In Chapter 6 I investigate the efficiency of aggregated analysts' forecasts with respect to a range of macroeconomic variables by regressing aggregated revisions on lagged values of industrial production growth, consumer sentiment, inflation, the term structure of interest rates, default spreads and a selection of additional factors.

I focus in particular on the efficiency of analysts' forecasts with respect to the Institute of Supply Management's Purchasing Managers' Index for Manufacturers (ISM PMI). This measure of business sentiment has received relatively little attention in the accounting and finance literature despite evidence discussed in

Chapter 6 of its importance as a lead indicator of economic activity and the considerable attention it receives from practitioners. I find evidence that aggregate realized earnings changes are significantly related to lagged levels of the ISM PMI (positive correlation) and analysts' forecasts are significantly related to lagged levels of the ISM PMI (also positive correlation). However, I find evidence that analysts underreact to the ISM PMI. Regressing measures of aggregated annual earnings revisions on lagged values of the ISM PMI alone (values of the ISM PMI available to analysts prior to the quarterly aggregation dates), I obtain regression R^2s ranging from approximately 0.21 to 0.31, depending on the aggregation process. I obtain adjusted R^2s as high as 0.53 in equivalent multivariate regressions including factors such as lagged revisions and lagged realized earnings changes as additional independent variables. Therefore, I find evidence of substantial predictive power in simple regressions for aggregated year-ahead earnings revisions.

Significant underreaction is evident across portfolios formed on the basis of firm size, book-to-market ratios and both size and analyst coverage combined. In regressions conditioned on the economic regime, I find evidence of underreaction to the ISM PMI as principally a feature of economic expansions.

Evidence is presented of variation in the relationship between aggregated earnings revisions and lagged values of the ISM PMI across GICS sectors and Fama-French industries. This variation is employed to derive long-short industry portfolios each quarter on the basis of relative predicted earnings revisions (long high predicted revisions, decile 10 industries, and short low predicted revisions, decile 1 industries). The difference between decile 10 and decile 1 three month returns in the period after portfolio formation is positive and statistically significant on both an equally-weighted and value-weighted basis. Portfolio risk-adjusted returns from the Fama-French three factor model are also positive and statistically significant. Therefore, I obtain evidence of significant predictability of aggregated earnings revisions, which in turn is employed to explain significant systematic variation in future industry returns.

8.4 Aggregated revisions and returns

KOTHARI, LEWELLEN AND Warner (2006) estimate cash flow and discount rate effects in aggregated realized earnings. They find evidence of a significant negative relationship between changes in aggregate realized earnings and contemporaneous market returns. Within Campbell's (1991) return decomposition framework, Kothari et al. cite their results as evidence of a significant discount rate effect in the response of market returns to aggregate earnings surprise. Further, the discount effect is larger than the cash flow effect of earnings surprise on contemporaneous returns. Their results provide evidence of a cash flow effect dominating the impact of earnings surprise on returns at the individual stock level, but a discount rate effect dominating at the aggregate market level. However, they acknowledge a desire for an alternative proxy for earnings surprise, as opposed to their use of changes in realized earnings or, in some of their tests, simple time series models of surprise derived from realized earnings and lagged returns.

In empirical tests closely aligned with those of Kothari et al. (2006), I employ aggregated analysts' earnings revisions as a proxy for earnings surprise. I therefore investigate the robustness of their findings to a proxy for earnings surprise consistent with their research aims. Like Kothari et al.'s results for realized earnings, I find evidence of a positive and statistically significant relationship between earnings revisions and contemporaneous returns for individual firms. However, unlike Kothari et al., at the aggregate market level I find evidence of a positive relationship (albeit insignificant) between aggregate revisions and contemporaneous aggregate returns. I obtain the same result for aggregate changes in realized earnings. Methodological differences between Kothari et al. and my research are slight. The key difference is their focus period for analysis runs from 1970 through to 2000, while (given restrictions on available data for analysts' forecasts) my focus sample period runs from 1979 through to 2009. To evaluate the impact of this difference I exactly replicate Kothari et al.'s analysis as described in their paper. I find evidence strongly suggestive of time variation in the relationship between aggregate changes in realized earnings and contemporaneous market returns. While they find evidence of a significant negative relationship from 1970 to 2000 (confirmed in my robustness tests), for the period from 1979 to 2009 the relationship is positive and significant. For the full period from 1970 through to 2009 I provide evidence of a positive, albeit insignificant, relationship.

Combining these results with evidence presented by Kothari et al. of a positive relationship between quarterly returns and contemporaneous seasonally-differenced S&P 500 earnings from 1936 through to 1969, the evidence overall suggests that the relationship between this proxy for aggregate earnings surprise and contemporaneous returns is on average positive, not negative. Employing aggregate earnings revisions as an alternative (and in this context arguably superior) proxy for earnings surprise, I similarly find evidence of a positive relationship between aggregate earnings surprise and contemporaneous returns. My results do not support the contention of a discount effect at the aggregate level that is larger than the cash flow effect.

8.5. *Final conclusions*

SHIVAKUMAR (2007) MAKES the following pertinent observation:

> Aggregate corporate earnings, aggregate stock market returns and the macroeconomy are highly interrelated; each of these variables affects the others, while at the same time being affected by the others. It is important to discern these relationships in order to improve our understanding of capital markets and economies. The finance and economics literatures have made some progress in relating stock market returns to macroeconomic activities, but little research exists on the link between aggregate corporate earnings and either stock market returns or macroeconomic activities. (p. 65)

This view of the literature regarding aggregate realized earnings can equally be applied to aggregate forecast earnings, and represents an important source of motivation for my research. In this thesis I employ a range of empirical tests to provide further insights on the interrelationships between realized earnings, forecast earnings, macroeconomic variables and returns, focusing on analysis at the aggregate market level. Evidence is presented of the utility of aggregated analysts' earnings forecasts for the prediction of macroeconomic activity. Evidence is also presented of the predictability of aggregated analysts' revisions as a consequence of systematic errors in the forecasting process (with implications for explaining systematic variation in future industry returns). In addition, aggregate earnings revisions are employed in tests providing evidence against the contention by recent analyses of a discount effect in the impact of aggregate earnings surprise on contemporaneous market returns that is larger than the cash flow effect.

Future research directions suggested by my analysis include evaluation of the information in aggregated analysts' forecasts for a range of other macroeconomic factors (examples include inflation and interest rates), further evaluation of relationships between predictable analyst errors (revisions) and systematic variation in returns (for example, employing quarterly analyst forecast revisions), and more detailed investigation of time variation in the relationship between proxies for aggregated earnings surprise and contemporaneous market returns. In addition, there is considerable potential for further analysis of cross-sectional variation in the information in aggregated analysts' forecasts for future macroeconomic activity. Notably, in Chapter 5 I identified size-related variation in the informativeness of aggregated forecasts that was not fully explained by size-based variation in income smoothing nor (given the use of aggregated forecasts) the relative information environments for small and large firms. This size effect in the informativeness of aggregated forecasts for future industrial production growth remains a puzzle.

Despite the voluminous body of literature evaluating the how, why and what of equity analysts' output, this thesis illustrates there remains much to be investigated.

References

Abarbanell, J. S. (1991). Do analysts' earnings forecasts incorporate information in prior stock price changes? *Journal of Accounting and Economics, 14*(2), 147–165.

Abarbanell, J. S., & Bernard, V. L. (1992). Tests of Analysts' Overreaction/Underreaction to Earnings Information as an Explanation for Anomalous Stock Price Behavior. *The Journal of Finance, 47*(3), 1181–1207.

Abarbanell, J. S., & Lehavy, R. (2000). *Differences in Commercial Database Reported Earnings: Implications for Inferences Concerning Analyst Forecast Rationality, the Association between Prices and Earnings, and Firm Reporting Discretion*. Working Paper.

Abdolmohammadi, M., Simnett, R., Thibodeau, J. C., & Wright, A. M. (2006). Sell-Side Analysts' Reports and the Current External Reporting Model. *Accounting Horizons, 20*(4), 375–389.

Acker, D., & Duck, N. (2009). *On the Reliability of IBES Earnings Announcement Dates and Forecasts*. Working Paper. University of Bristol.

Ackert, L. F., & Hunter, W. C. (1995). Rational Expectations and Security Analysts' Earnings Forecasts. *Financial Review, 30*(3), 427–443.

Affleck-Graves, J., Davis, L. R., & Mendenhall, R. R. (1990). Forecasts of earnings per share: Possible sources of analyst superiority and bias. *Contemporary Accounting Research, 6*(2), 501–517.

Aiolfi, M., Rodriguez, M., & Timmermann, A. (2010). Understanding Analysts' Earnings Expectations: Biases, Nonlinearities, and Predictability. *Journal of Financial Econometrics, 8*(3), 305–334.

Anilowski, C., Feng, M., & Skinner, D. J. (2007). Does earnings guidance affect market returns? The nature and information content of aggregate earnings guidance. *Journal of Accounting and Economics, 44*(1–2), 36–63.

Baghestani, H., & Kianian, A. M. (1993). On the rationality of US macroeconomic forecasts: evidence from a panel of professional forecasters. *Applied Economics, 25*(7), 869–878.

Ball, R., & Brown, P. (1967). Some Preliminary Findings on the Association between the Earnings of a Firm, Its Industry, and the Economy. *Journal of Accounting Research, 5*, 55–77.

Ball, R., & Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research, 6*(2), 159–178.

Ball, R., Sadka, G., & Sadka, R. (2009). Aggregate Earnings and Asset Prices. *Journal of Accounting Research, 47*(5), 1097–1133.

Ball, R., & Watts, R. (1972). Some Time Series Properties of Accounting Income. *The Journal of Finance, 27*(3), 663–681.

Barth, M. E., & Hutton, A. P. (2004). Analyst Earnings Forecast Revisions and the Pricing of Accruals. *Review of Accounting Studies, 9*(1), 59–96.

Basu, S., Markov, S., & Shivakumar, L. (2010). Inflation, Earnings Forecasts, and Post-Earnings Announcement Drift. *Review of Accounting Studies, 15*(2), 403–440.

Beaver, W., Cornell, B., Landsman, W. R., & Stubben, S. R. (2008). The Impact of Analysts' Forecast Errors and Forecast Revisions on Stock Prices. *Journal of Business Finance & Accounting, 35*(5, 6), 709–740.

Beaver, W. H., Clarke, R., & Wright, W. F. (1979). The Association between Unsystematic Security Returns and the Magnitude of Earnings Forecast Errors. *Journal of Accounting Research, 17*(2), 316–340.

Beidleman, C. R. (1973). Income Smoothing: The Role of Management. *The Accounting Review, 48*(4), 653–667.

Berkman, H., & Truong, C. (2009). Event Day 0? After-Hours Earnings Announcements. *Journal of Accounting Research, 47*(1), 71–103.

Bernstein, W. J., & Arnott, R. D. (2003). Earnings Growth: The Two Percent Dilution. *Financial Analysts Journal, 59*(5), 47–55.

Bhattacharya, U., Daouk, H., & Welker, M. (2003). The World Price of Earnings Opacity. *The Accounting Review, 78*(3), 641–678.

Bhushan, R. (1989). Firm characteristics and analyst following. *Journal of Accounting and Economics, 11*(2-3), 255–274.

Biddle, G. C., & Ricks, W. E. (1988). Analyst Forecast Errors and Stock Price Behavior Near the Earnings Announcement Dates of LIFO Adopters. *Journal of Accounting Research, 26*(2), 169–194.

Botosan, C. A., & Plumlee, M. A. (2005). Assessing Alternative Proxies for the Expected Risk Premium. *Accounting Review, 80*(1), 21–53.

Breeden, D. T. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics, 7*(3), 265–296.

Brennan, M. J., & Hughes, P. J. (1991). Stock Prices and the Supply of Information. *The Journal of Finance, 46*(5), 1665–1691.

Bretz, R. J. (1990). Behind the Economic Indicators of the NAPM Report on Business. *Business Economics, 25*(3), 42–48.

Brown, L. D. (1991). Forecast selection when all forecasts are not equally recent. *International Journal of Forecasting, 7*(3), 349–356.

Brown, L. D. (1993). Earnings forecasting research: its implications for capital markets research. *International Journal of Forecasting, 9*(3), 295–320.

Brown, L. D., Hagerman, R. L., Griffin, P. A., & Zmijewski, M. E. (1987a). An evaluation of alternative proxies for the market's assessment of unexpected earnings. *Journal of Accounting and Economics, 9*(2), 159–193.

Brown, L. D., Hagerman, R. L., Griffin, P. A., & Zmijewski, M. E. (1987b). Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings. *Journal of Accounting and Economics, 9*(1), 61–87.

Brown, L. D., Richardson, G. D., & Schwager, S. J. (1987). An Information Interpretation of Financial Analyst Superiority in Forecasting Earnings. *Journal of Accounting Research, 25*(1), 49–67.

Brown, L. D., & Rozeff, M. S. (1978). The Superiority of Analyst Forecasts as Measures of Expectations: Evidence from Earnings. *The Journal of Finance, 33*(1), 1–16.

Brown, P., & Ball, R. (1967). Some Preliminary Findings on the Association between the Earnings of a Firm, Its Industry, and the Economy. *Journal of Accounting Research, 5*, 55–77.

Brown, P., Foster, G., & Noreen, E. (1985). *Security Analyst Multi-Year Earnings Forecasts and the Capital Market*. Sarasota, Florida: American Accounting Association.

Burgstahler, D. C., & Eames, M. J. (2003). Earnings Management to Avoid Losses and Earnings Decreases: Are Analysts Fooled? *Contemporary Accounting Research, 20*(2), 253–294.

Butler, K. C., & Lang, L. H. P. (1991). The Forecast Accuracy of Individual Analysts: Evidence of Systematic Optimism and Pessimism. *Journal of Accounting Research, 29*(1), 150–156.

Cahan, S. F., Liu, G., & Sun, J. (2008). Investor Protection, Income Smoothing, and Earnings Informativeness. *Journal of International Accounting Research, 7*(1), 1–24.

Calegari, M., & Fargher, N. L. (1997). Evidence that Prices Do Not Fully Reflect the Implications of Current Earnings for Future Earnings: An Experimental Markets Approach. *Contemporary Accounting Research, 14*(3), 397–433.

Campbell, J. Y. (1991). A Variance Decomposition for Stock Returns. *The Economic Journal, 101*(405), 157–179.

Campbell, J. Y., & Cochrane, J. H. (1999). By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior. *The Journal of Political Economy, 107*(2), 205–251.

Campbell, J. Y., & Vuolteenaho, T. (2004). Inflation Illusion and Stock Prices. *The American Economic Review, 94*(2), 19–23.

Capstaff, J., Paudyal, K., & Rees, W. (2001). *Revisions of Earnings Forecasts and Security Returns: Evidence from Three Countries*. Working Paper.

Cenesizoglu, T. (2008). *Size, Book-to-Market Ratio and Macroeconomic News*. Working Paper. HEC Montreal.

Chan, K., & Hameed, A. (2006). Stock price synchronicity and analyst coverage in emerging markets. *Journal of Financial Economics, 80*(1), 115–147.

Chan, Y. L., & Kogan, L. (2002). Catching up with the Joneses: Heterogeneous Preferences and the Dynamics of Asset Prices. *The Journal of Political Economy, 110*(6), 1255–1285.

Chen, L., & Zhao, X. (2008). *What Drives Stock Price Movement?* Working Paper.

Chen, L., & Zhao, X. (2009). Return Decomposition. *Review of Financial Studies, 22*(12), 5213–5249.

Chen, N.-F. (1991). Financial Investment Opportunities and the Macroeconomy. *The Journal of Finance, 46*(2), 529–554.

Chen, N.-F., Roll, R., & Ross, S. A. (1986). Economic Forces and the Stock Market. *The Journal of Business, 59*(3), 383–403.

Chen, Q., & Jiang, W. (2006). Analysts' Weighting of Private and Public Information. *The Review of Financial Studies, 19*(1), 319–355.

Cheng, Q. (2005). The Role of Analysts' Forecasts in Accounting-Based Valuation: A Critical Evaluation. *Review of Accounting Studies, 10*(1), 5–31.

Chordia, T., & Shivakumar, L. (2005). Inflation Illusion and Post-Earnings-Announcement Drift. *Journal of Accounting Research, 43*(4), 521–556.

Chugh, L. C., & Meador, J. W. (1984). The Stock Valuation Process: The Analysts' View. *Financial Analysts Journal, 40*(6), 41–48.

Clarke, J., & Subramanian, A. (2006). Dynamic forecasting behavior by analysts: Theory and evidence. *Journal of Financial Economics, 80*(1), 81–113.

Claus, J., & Thomas, J. (2001). Equity Premia as Low as Three Percent? Evidence from Analysts' Earnings Forecasts for Domestic and International Stock Markets. *The Journal of Finance, 56*(5), 1629–1666.

Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics, 27*(3), 285–303.

Clement, M. B., Hales, J., & Xue, Y. (2011). Understanding Analysts' use of Stock Returns and other Analysts' Revisions When Forecasting Earnings. *Journal of Accounting and Economics, 51*(3), 279–299.

Clement, M. B., & Tse, S. (2005). Financial Analyst Characteristics and Herding Behavior in Forecasting. *The Journal of Finance, 60*(1), 307–341.

Clement, M. B., & Tse, S. Y. (2003). Do Investors Respond to Analysts' Forecast Revisions as If Forecast Accuracy Is All That Matters? *The Accounting Review, 78*(1), 227–249.

Cochrane, J. H. (2008). Financial Markets and the Real Economy. In M. Rajnish (Ed.), *Handbook of the Equity Risk Premium* (pp. 237–325). San Diego: Elsevier.

Cohen, L., & Lou, D. (2010). *Complicated Firms*. Paper presented at the American Finance Association 2011 Meetings, University of Chicago, Booth School of Business.

Cornell, B., & Landsman, W. R. (1989). Security Price Response to Quarterly Earnings Announcements and Analysts' Forecast Revisions. *The Accounting Review, 64*(4), 680–692.

Cotter, J., Tuna, I., & Wysocki, P. D. (2006). Expectations Management and Beatable Targets: How Do Analysts React to Explicit Earnings Guidance? *Contemporary Accounting Research, 23*(3), 593–624.

Cragg, J. G., & Malkiel, B. G. (1968). The Consensus and Accuracy of Some Predictions of the Growth of Corporate Earnings. *The Journal of Finance, 23*(1), 67–84.

Cready, W. M., & Gurun, U. G. (2010). Aggregate Market Reaction to Earnings Announcements. *Journal of Accounting Research, 48*(2), 289–334.

Crichfield, T., Dyckman, T., & Lakonishok, J. (1978). An Evaluation of Security Analysts' Forecasts. *The Accounting Review, 53*(3), 651–668.

Da, Z., & Warachka, M. C. (2009). Cashflow risk, systematic earnings revisions, and the cross-section of stock returns. *Journal of Financial Economics, 94*(3), 448–468.

Das, S., Levine, C. B., & Sivaramakrishnan, K. (1998). Earnings Predictability and Bias in Analysts' Earnings Forecasts. *The Accounting Review, 73*(2), 277–294.

De Zwart, G., & Van Dijk, D. (2008). *The Inefficient Use of Macroeconomic Information in Analysts' Earnings Forecasts in Emerging Markets*. Working Paper. RSM Erasmus University / Erasmus School of Economics. Rotterdam.

Dechow, P., Ge, W., & Schrand, C. (2010). Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics, 50*(2-3), 344–401.

Dugar, A., & Nathan, S. (1995). The Effect of Investment Banking Relationships on Financial Analysts' Earnings Forecasts and Investment Recommendations. *Contemporary Accounting Research, 12*(1), 131–160.

Elton, E. J., & Gruber, M. J. (1972). Earnings Estimates and the Accuracy of Expectational Data. *Management Science, 18*(8), B409–B424.

Elton, E. J., Gruber, M. J., & Gultekin, M. N. (1984). Professional Expectations: Accuracy and Diagnosis of Errors. *The Journal of Financial and Quantitative Analysis, 19*(4), 351–363.

Fama, E. F. (1990). Stock Returns, Expected Returns, and Real Activity. *The Journal of Finance, 45*(4), 1089–1108.

Fama, E. F., & Babiak, H. (1968). Dividend Policy: An Empirical Analysis. *Journal of the American Statistical Association, 63*(324), 1132–1161.

Fama, E. F., & French, K. R. (1988). Dividend yields and expected stock returns. *Journal of Financial Economics, 22*(1), 3–25.

Fama, E. F., & French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics, 25*(1), 23–49.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance, 47*(2), 427–465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3–56.

Fama, E. F., & French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics, 43*(2), 153–193.

Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *The Journal of Political Economy, 81*(3), 607–636.

Feng, M., & McVay, S. (2010). Analysts' Incentives to Overweight Management Guidance When Revising Their Short-Term Earnings Forecasts. *The Accounting Review, 85*(5), 1617–1646.

Fildes, R., & Lam, K. (1990). *Efficient use of information by financial analysts in the formation of short term earnings forecasts*. Working paper. Manchester Business School.

Foster, G. (1986). *Financial Statement Analysis* (2nd ed.). Englewood Cliffs, New Jersey: Prentice-Hall.

Francis, J., & Philbrick, D. (1993). Analysts' Decisions As Products of a Multi-Task Environment. *Journal of Accounting Research, 31*(2), 216–230.

Frankel, R., & Lee, C. M. C. (1998). Accounting valuation, market expectation, and cross-sectional stock returns. *Journal of Accounting and Economics, 25*(3), 283–319.

Fried, D., & Givoly, D. (1982). Financial analysts' forecasts of earnings : A better surrogate for market expectations. *Journal of Accounting and Economics, 4*(2), 85–107.

Friesen, G., & Weller, P. A. (2006). Quantifying cognitive biases in analyst earnings forecasts. *Journal of Financial Markets, 9*(4), 333–365.

Gavious, I. (2009). An Empirical Analysis of Analyst Reaction to the Extent and Direction of Earnings Management. *International Research Journal of Finance and Economics, 27*, 145–167.

Gebhardt, W. R., Lee, C. M. C., & Swaminathan, B. (2001). Toward an Implied Cost of Capital. *Journal of Accounting Research, 39*(1), 135–176.

Gleason, C. A., & Lee, C. M. C. (2003). Analyst Forecast Revisions and Market Price Discovery. *The Accounting Review, 78*(1), 193–225.

Glushkov, D. (2009). *Overview of IBES on WRDS: Research and Data Issues*: Wharton, University of Pennsylvania.

Gomme, P., & Greenwood, J. (1995). On the cyclical allocation of risk. *Journal of Economic Dynamics and Control, 19*(1–2), 91–124.

Gonedes, N. J. (1973). Properties of Accounting Numbers: Models and Tests. *Journal of Accounting Research, 11*(2), 212–237.

Graham, J. R. (1999). Herding among Investment Newsletters: Theory and Evidence. *The Journal of Finance, 54*(1), 237–268.

Guttman, I. (2010). The Timing of Analysts' Earnings Forecasts. *The Accounting Review, 85*(2), 513–545.

Harris, E. S. (1991). Tracking the Economy with the Purchasing Managers' Index. *Federal Reserve Bank of New York Quarterly Review, 16*(3), 61–69.

Hecht, P., & Vuolteenaho, T. (2006). Explaining Returns with Cash-Flow Proxies. *The Review of Financial Studies, 19*(1), 159–194.

Hess, D., & Kreutzmann, D. (2009). *Earnings Expectations and Macroeconomic Conditions*. Working Paper. University of Cologne.

Higgins, H. N. (2002). *Analyst Earnings Forecasts For Recession Periods*. Working Paper. Worcester Polytechnic Institute.

Hirshleifer, D., Hou, K., & Teoh, S. H. (2009). Accruals, cash flows, and aggregate stock returns. *Journal of Financial Economics, 91*(3), 389–406.

Hirst, D. E., Hopkins, P. E., & Wahlen, J. M. (2004). Fair Values, Income Measurement, and Bank Analysts' Risk and Valuation Judgments. *The Accounting Review, 79*(2), 453–472.

Hong, H., & Kubik, J. D. (2003). Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts. *The Journal of Finance, 58*(1), 313–351.

Hong, H., Kubik, J. D., & Solomon, A. (2000). Security Analysts' Career Concerns and Herding of Earnings Forecasts. *The RAND Journal of Economics, 31*(1), 121–144.

Howe, J. S., Unlu, E., & Yan, X. (2009). The Predictive Content of Aggregate Analyst Recommendations. *Journal of Accounting Research, 47*(3), 799–821.

Hughes, J., Liu, J., & Su, W. (2008). On the relation between predictable market returns and predictable analyst forecast errors. *Review of Accounting Studies, 13*(2), 266–291.

Hunter, W. C., & Ackert, L. F. (1993). Business cycles and analysts' forecasts: Further evidence of rationality. *Economic Review–Federal Reserve Bank of Atlanta, 78*(6), 13–22.

Imhoff, E. A., Jr., & Lobo, G. J. (1984). Information Content of Analysts' Composite Forecast Revisions. *Journal of Accounting Research, 22*(2), 541–554.

Imhoff, E. A., Jr., & Pare, P. V. (1982). Analysis and Comparison of Earnings Forecast Agents. *Journal of Accounting Research, 20*(2), 429–439.

Irvine, P. J. (2004). Analysts' Forecasts and Brokerage-Firm Trading. *The Accounting Review, 79*(1), 125–149.

Jung, B., Shane, P. B., & Yang, Y. (2009). *Do Financial Analysts' Long-Term Growth Forecasts Reflect Effective Effort Towards Informative Stock Recommendations?* Working Paper.

Kang, Q., Liu, Q., & Qi, R. (2010). Predicting Stock Market Returns with Aggregate Discretionary Accruals. *Journal of Accounting Research, 48*(4), 815–858.

Kauffman, R. G. (1999). Indicator Qualities of the NAPM Report on Business. *Journal of Supply Chain Management, 35*(2), 29–36.

Klein, P. A., & Moore, G. H. (1988). N.A.P.M. Business Survey Data: Their Value as Leading Indicators. *Journal of Purchasing and Materials Management, Winter*, 32–40.

Koenig, E. F. (2002). Using the Purchasing Managers' Index to Assess the Economy's Strength and the Likely Direction of Monetary Policy. *Federal Reserve Bank of Dallas Economic & Financial Policy Review, 1*(6), 1–14.

Koller, T., Goedhart, M., & Wessels, D. (2005). *Valuation: Measuring and Managing the Value of Companies* (4th ed.). Hoboken, N.J.: John Wiley & Sons, Inc.

Kothari, S. P., Lewellen, J., & Warner, J. B. (2006). Stock returns, aggregate earnings surprises, and behavioral finance. *Journal of Financial Economics, 79*(3), 537–568.

Kothari, S. P., & Shanken, J. (1992). Stock return variation and expected dividends: A time-series and cross-sectional analysis. *Journal of Financial Economics, 31*(2), 177–210.

Kross, W., Ro, B., & Schroeder, D. (1990). Earnings Expectations: The Analysts' Information Advantage. *The Accounting Review, 65*(2), 461–476.

Lambert, D., Matolcsy, Z., & Wyatt, A. (2009). *How do Analysts Forecast Earnings?* Working Paper.

Lang, M. H., Lins, K. V., & Miller, D. P. (2003). ADRs, Analysts, and Accuracy: Does Cross Listing in the United States Improve a Firm's Information Environment and Increase Market Value? *Journal of Accounting Research, 41*(2), 317–345.

Lang, M. H., & Lundholm, R. J. (1996). Corporate Disclosure Policy and Analyst Behavior. *The Accounting Review, 71*(4), 467–492.

Lettau, M., & Ludvigson, S. C. (2005). Expected returns and expected dividend growth. *Journal of Financial Economics, 76*(3), 583–626.

Leuz, C., Nanda, D., & Wysocki, P. D. (2003). Earnings management and investor protection: an international comparison. *Journal of Financial Economics, 69*(3), 505–527.

Lev, B. (1980). On the Use of Index Models in Analytical Reviews by Auditors. *Journal of Accounting Research, 18*(2), 524–550.

Libby, R., Tan, H.-T., & Hunton, J. E. (2006). Does the Form of Management's Earnings Guidance Affect Analysts' Earnings Forecasts? *The Accounting Review, 81*(1), 207–225.

Lim, T. (2001). Rationality and Analysts' Forecast Bias. *The Journal of Finance, 56*(1), 369–385.

Lindsey, M. D., & Pavur, R. J. (2005). As the PMI Turns: A Tool for Supply Chain Managers. *Journal of Supply Chain Management, 41*(1), 30–39.

Lintner, J. (1956). Distribution of Incomes of Corporations Among Dividends, Retained Earnings, and Taxes. *The American Economic Review, 46*(2), 97–113.

Little, I. M. D. (1962). Higgledy Piggledy Growth. *Bulletin of the Oxford Institute of Economics and Statistics, 24*(4), 387–412.

Liu, C.-C., & Ryan, S. G. (2006). Income Smoothing over the Business Cycle: Changes in Banks' Coordinated Management of Provisions for Loan Losses and Loan Charge-Offs from the Pre-1990 Bust to the 1990s Boom. *The Accounting Review, 81*(2), 421–441.

Liu, J., & Thomas, J. (2000). Stock Returns and Accounting Earnings. *Journal of Accounting Research, 38*(1), 71–101.

Liu, X. (2005). *Analysts' Response to Earnings Management*. Working Paper. University of Texas.

Livnat, J., & Mendenhall, R. R. (2006). Comparing the Post-Earnings Announcement Drift for Surprises Calculated from Analyst and Time Series Forecasts. *Journal of Accounting Research, 44*(1), 177–205.

Ljungqvist, A., Malloy, C., & Marston, F. (2009). Rewriting History. *Journal of Finance, 64*(4), 1935–1960.

Löffler, G. (1998). Biases in analyst forecasts: cognitive, strategic or second-best? *International Journal of Forecasting, 14*(2), 261–275.

Longstaff, F. A., & Piazzesi, M. (2004). Corporate earnings and the equity premium. *Journal of Financial Economics, 74*(3), 401–421.

Lucas, R. E. (1977). Understanding Business Cycles. In K. Brunner & A. H. Meltzer (Eds.), *Stabilization of the Domestic and International Economy*. Amsterdam: North-Holland Publishing Company.

Lucas, R. E. (1978). Asset Prices in an Exchange Economy. *Econometrica, 46*(6), 1429–1445.

Lundholm, R. J., & Sloan, R. G. (2007). *Equity valuation and analysis with eVal* (2nd ed.). Boston, Mass.: McGraw-Hill/Irwin.

Lys, T., & Sohn, S. (1990). The association between revisions of financial analysts' earnings forecasts and security-price changes. *Journal of Accounting and Economics, 13*(4), 341–363.

Magee, R. P. (1974). Industry-Wide Commonalities in Earnings. *Journal of Accounting Research, 12*(2), 270–287.

Maines, L. A., & Hand, J. R. M. (1996). Individuals' Perceptions and Misperceptions of Time Series Properties of Quarterly Earnings. *The Accounting Review, 71*(3), 317–336.

Markov, S., & Tamayo, A. (2006). Predictability in Financial Analyst Forecast Errors: Learnings or Irrationality? *Journal of Accounting Research, 44*(4), 725–761.

McNees, S. K. (1992). How large are economic forecast errors? *New England Economic Review*, 25–42.

Merton, R. C. (1973). An Intertemporal Capital Asset Pricing Model. *Econometrica, 41*(5), 867–887.

Mikhail, M. B., Walther, B. R., & Willis, R. H. (1999). Does Forecast Accuracy Matter to Security Analysts? *The Accounting Review, 74*(2), 185–200.

Modigliani, F., & Cohn, R. A. (1979). Inflation, Rational Valuation and the Market. *Financial Analysts Journal, 35*(2), 24–44.

Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics, 58*(1-2), 215–260.

Moses, O. D. (1987). Income Smoothing and Incentives: Empirical Tests Using Accounting Changes. *The Accounting Review, 62*(2), 358–377.

Muth, J. F. (1961). Rational Expectations and the Theory of Price Movements. *Econometrica, 29*(3), 315–335.

Narayanan, V. K., & Fahey, L. (Eds.). (2001). *Macroenvironmental Analysis: Understanding the Environment Outside the Industry* (2nd ed.). New York: John Wiley & Sons, Inc.

Nelson, M. W., Elliott, J. A., & Tarpley, R. L. (2002). Evidence from Auditors about Managers' and Auditors' Earnings Management Decisions. *The Accounting Review, 77*(Supplement 2002), 175–202.

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica, 55*(3), 703–708.

Newey, W. K., & West, K. D. (1994). Automatic Lag Selection in Covariance Matrix Estimation. *The Review of Economic Studies, 61*(4), 631–653.

O'Brien, P. C. (1988a). Analysts' forecasts as earnings expectations. *Journal of Accounting and Economics, 10*(1), 53–83.

O'Brien, P. C. (1988b). Analysts' forecasts as earnings expectations. *Journal of Accounting and Economics, 10*(1), 53–83.

O'Brien, P. C. (1994). *Corporate Earnings Forecasts and the Macroeconomy*. Working Paper. University of Waterloo.

Palepu, K. G., Healy, P. M., & Bernard, V. L. (2004). *Business analysis & valuation using financial statements: text & cases* (3rd ed.). Mason, Ohio: Thomson/South-Western.

Patatoukas, P. N., & Yan, H. (2009). *The Impact of Earnings Surprises on Stock Returns: Theory and Evidence*. Working Paper. Yale International Center for Finance.

Payne, J. L., & Thomas, W. B. (2003). The Implications of Using Stock-Split Adjusted I/B/E/S Data in Empirical Research. *The Accounting Review, 78*(4), 1049–1067.

Penman, S. H. (2001). *Financial Statement Analysis and Security Valuation*. Boston, Mass.: McGraw-Hill/Irwin.

Piotroski, J. D., & Roulstone, D. T. (2004). The Influence of Analysts, Institutional Investors, and Insiders on the Incorporation of Market, Industry, and Firm-Specific Information into Stock Prices. *Accounting Review, 79*(4), 1119–1151.

Previts, G. J., Bricker, R. J., Robinson, T. R., & Young, S. J. (1994). A Content Analysis of Sell-Side Financial Analyst Company Reports. *Accounting Horizons, 8*(2), 55–70.

R Development Core Team. (2010). R: A Language and Environment for Statistical Computing: R Foundation for Statistical Computing.

Ramnath, S., Rock, S., & Shane, P. (2008). The Financial Analyst Forecasting Literature: A Taxonomy with Suggestions for Further Research. *International Journal of Forecasting, 24*(1), 34–75.

Reilly, F. K. (1979). *Investment Analysis and Portfolio Management* (1st ed.). Hinsdale, Illinois: The Dryden Press.

Reilly, F. K., & Brown, K. C. (2006). *Investment Analysis and Portfolio Management* (8th ed.). Mason, Ohio: Thomson/South-Western.

Rogers, R. K., & Grant, J. (1997). Content analysis of information cited in reports of sell-side financial analysts. *Journal of Financial Statement Analysis, 3*(1), 17–30.

Sadka, G., & Sadka, R. (2009). Predictability and the earnings-returns relation. *Journal of Financial Economics, 94*(1), 87–106.

Schipper, K. (1991). Analysts' Forecasts. *Accounting Horizons,* pp. 105–121.

Schwert, G. W. (1990). Stock Returns and Real Activity: A Century of Evidence. *The Journal of Finance, 45*(4), 1237–1257.

Shivakumar, L. (2007). Aggregate earnings, stock market returns and macroeconomic activity: A discussion of 'does earnings guidance affect market returns? The nature and information content of aggregate earnings guidance'. *Journal of Accounting and Economics, 44*(1–2), 64–73.

Shivakumar, L. (2010). Discussion of Aggregate Market Reaction to Earnings Announcements. *Journal of Accounting Research, 48*(2), 335–342.

Simpson, A. (2010). Analysts' Use of Nonfinancial Information Disclosures. *Contemporary Accounting Research, 27*(1), 249–288.

Stark, T. (2010). *Realistic Evaluation of Real-Time Forecasts in the Survey of Professional Forecasters*: Federal Reserve Bank of Philadelphia

Stickel, S. E. (1990). Predicting Individual Analyst Earnings Forecasts. *Journal of Accounting Research, 28*(2), 409–417.

Stickel, S. E. (1993). Accuracy improvements from a consensus of updated individual analyst earnings forecasts. *International Journal of Forecasting, 9*(3), 345–353.

Stone, F. (1977). Information requirements of security analysts. In R. Abdel-khalik & T. Keller (Eds.), *Information Requirements of Security Analysts*: Duke University Press, Durham, NC.

Teets, W. R., & Wasley, C. E. (1996). Estimating earnings response coefficients: Pooled versus firm-specific models. *Journal of Accounting and Economics, 21*(3), 279–295.

Thomson Financial. (2004). *Thomson I/B/E/S Global Aggregates–User Guide.*

Thomson Financial. (2008). *Estimates Glossary: A Guide to Understanding the Terms and Conventions of the First Call and I/B/E/S Estimates Database.*

Tucker, J. W., & Zarowin, P. A. (2006). Does Income Smoothing Improve Earnings Informativeness? *Accounting Review, 81*(1), 251–270.

Vassalou, M. (2003). News related to future GDP growth as a risk factor in equity returns. *Journal of Financial Economics, 68*(1), 47–73.

Vuolteenaho, T. (2002). What Drives Firm-Level Stock Returns? *The Journal of Finance, 57*(1), 233–264.

Yeung, P. E. (2009). Uncertainty and Expectation Revisions after Earnings Announcements. *Contemporary Accounting Research, 26*(1), 273–301.

Zhang, X. F. (2006). Information Uncertainty and Analyst Forecast Behavior. *Contemporary Accounting Research, 23*(2), 565–590.

Zhang, Y. (2008). Analyst responsiveness and the post-earnings-announcement drift. *Journal of Accounting and Economics, 46*(1), 201–215.