FINANCIAL ANALYSTS' UNDERREACTION AND

REPUTATION-BUILDING INCENTIVES

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ABSTRACT

This thesis examines the role of reputation in financial analysts' underreaction in earnings forecasts. Prior research suggests that the reputation effect mitigates short-term economic incentives that lead to overly optimistic forecasts, and hence, increases forecast accuracy (i.e., an aspect of high quality forecasts). In contrast, I hypothesise that certain factors affecting analyst reputation lead to analysts' underreaction. Specifically, when faced with uncertainty, analysts employ underreaction as a mechanism to improve consistency between their forecast revisions and subsequent news (i.e., another aspect of high quality forecasts), so as to protect themselves from incurring a higher reputation cost of inaccuracy for inconsistent versus consistent consecutive forecast revisions and forecast errors (i.e., asymmetric reputation cost).

 In my first research question, I examine the asymmetric reputation cost theory that predicts underreaction increasing with uncertainty and asymmetric reputation cost. I contextualise my study in business cycles where both factors change. I predict and find that uncertainty is greater during recessions than expansions whereas asymmetric reputation cost is greater during expansions than recessions (i.e., reputation concerns are greater during expansions). Further, I find that analysts' underreaction is greater during expansions than recessions. The implication is that the asymmetric reputation cost, rather than the uncertainty, drives analysts' underreaction. In my second research question, I investigate the differential underreaction to good news versus bad news in relation to short-term economic incentives and the reputation-building incentives simultaneously. If analysts put more emphasis on short-term gains, they will underreact more to bad news than good news, particularly during recessions where the short-term economic incentives are heightened. On the contrary, if analysts are more concerned with their reputations, they will underreact less (more) to bad

news than good news during recessions (expansions), because bad (good) news is more likely to follow in bad (good) times and, accordingly, they can incorporate the current bad (good) news with greater confidence. My findings are consistent with the reputation-building incentive theory, but inconsistent with the short-term incentive theory. Robustness tests and further research considering industry/firm specific information provide consistent results. Overall, the thesis suggests that analysts underreact to information due to their reputation concerns.

For my family

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CHAPTER 1

INTRODUCTION

1.1   Research objective

This thesis examines the role of reputation in the bias in financial analysts' earnings forecasts. I focus on a form of bias known as underreaction, whereby analysts react with restraint to information about future earnings. I hypothesise that certain factors affecting analyst reputation lead analysts to underreact to news about future earnings.

1.2   The link between reputation and underreaction

Analysts have incentives to build reputation due to long-term economic benefits. It is well known that analyst reputation depends on forecast accuracy (e.g., Stickel, 1992; Hong and Kubik, 2003; Jackson, 2005; Fang and Yasuda, 2009). However, prior literature suggests accuracy is not all that matters. Reputation also relates to forecast frequency, forecast timeliness, and the consistency in previous forecast errors (e.g., Stickel, 1992; Clement and Tse, 2003; Hilary and Hsu, 2012). Investors show a stronger response to analysts when their forecasts are timelier and their prior forecast errors are more consistent, even if those forecasts are less accurate. In this thesis, I focus on a particular feature of analysts' forecasts – consistency in the direction of forecast revisions and subsequent information – and I examine how this feature affects reputation of analysts.

Prior literature (e.g., Raedy, Shane, and Yang, 2006) posits that for a given level of forecast inaccuracy, analysts suffer larger reputation costs when new information leads them to revise forecasts in a direction opposite to their previous revisions, compared to the situation when new information is in a same direction as their previous revisions (referred to as asymmetric reputation cost). This theory is based on the idea that investors buying stocks prefer good news that is followed by more good news, pushing stock price upwards while

investors selling stocks prefer bad news that is followed by more bad news, driving stock price down further. That is, they prefer the consistency in the direction of current news and future news. When new information contradicts analysts' revisions that investors have already acted on, investors stand to lose and, accordingly, impose a larger reputation penalty on the analysts. The asymmetric reputation penalty can arise even if investors do not act on an analyst's revisions. When new information is in the same direction as the prior forecast revision, investors are likely to view the new information as confirming the analyst's prior opinion. In contrast, new information in the opposite direction is likely to cause doubt about the quality of the analyst's forecast.

By reacting in a restrained manner to information about future earnings (i.e., underreacting), analysts can rationally create a greater likelihood that subsequent information will cause them to revise their forecasts in the same (rather than the opposite) direction as their most recent forecast revision. As a result, analysts minimise their reputation costs. This theory predicts that underreaction increases with the risk of subsequent disconfirming information (i.e., uncertainty) and the disproportionate cost associated with revision reversal (i.e., asymmetric reputation cost).

In short, when faced with uncertainty about future earnings, analysts employ underreaction as a mechanism to protect themselves from having to reverse their opinion and incur larger reputation costs.

1.3   Specific research questions

To examine the role of reputation in analysts' underreaction, I investigate whether underreaction increases with uncertainty and asymmetric reputation cost as the reputation cost theory predicts. I set my study in the context of business cycles. This is motivated by a lack of evidence on the association between the business cycle and underreaction, even

though prior research indicates that macroeconomic conditions are a fundamental factor affecting both earnings and earnings forecasts.[1]

Another motivation to include the business cycle is that it provides an interesting setting where uncertainty and asymmetric reputation cost are expected to move in opposite directions. During recessionary periods, firms are more reluctant and slower to disclose information (e.g., Lang and Lundholm, 1993; Hong, Lim, and Stein, 2000; Lim, 2001; Brown, 2001b; Chordia and Shivakumar, 2002; Klein and Marquardt, 2006) and the quality of macroeconomic forecasts is relatively poor (Higgins, 2002a; 2002b). Both result in a less rich information environment. Also, firms are more likely to report losses and to include transitory items in earnings in recessions (e.g., Johnson, 1999; Klein and Marquardt, 2006; Jenkins, Kane, and Velury, 2009), resulting in less persistent and predictable earnings. Accordingly, I predict that uncertainty about future earnings is greater during recessions than during expansions.

On the contrary, I expect that asymmetric reputation cost is lower during recessions than during expansions. Investors' decisions in evaluating analysts hinge on investors' own value functions – they experience more pain with a loss than they feel happy with an equal-sized gain (e.g., Kahneman and Tversky, 1979; Shefrin and Statman, 1985; Kahneman and Tversky, 1992; Olsen, 1997; Ding, Charoenwong, and Seetoh, 2004; Abdellaoui, Bleichrodt, and Paraschiv, 2007). During bad times, an investor experiences relatively less displeasure from the same amount of losses when most other investors lose money. On the other hand, during good times when other investors enjoy gains, he suffers even more deprivation from losses. Hence, when an analyst's forecast sends a signal that is different from the implication

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[1] Studies that document an association between macroeconomic conditions and earnings forecasts include Reilly (1979), Chugh and Meador (1984), Rogers and Grant (1997), Gitman and Joehnk (1999), Penman (2001), and Lundholm and Sloan (2007). Studies that document an association between macroeconomic conditions and earnings include Lucas (1977), Gomme and Greenwood (1995), Johnson (1999), Chordia and Shivakumar (2002), Bernstein and Arnott (2003), Jin (2005), Klein and Marquardt (2006).

of subsequent news, the investor imposes a larger penalty on that analyst during good times than bad times.

Therefore, my first research question is whether underreaction in analysts' earnings forecasts depends on the business cycle. Evidence on this question sheds lights on how reputation affects underreaction. The tests also allow me to examine whether uncertainty or asymmetric reputation cost plays a dominant role in determining underreaction. I predict that uncertainty is higher in recessions and asymmetric reputation cost is higher in expansions. Therefore, if underreaction is more (less) during recessions than during expansions, then uncertainty (reputation cost) matters more than reputation cost (uncertainty).

In my second research question, I consider the potential difference in analysts' underreaction to good news versus bad news. The reputation theory predicts that analysts will underreact in order to reserve their opinion about firms' prospect. In the context of the business cycle, it is generally expected that good (bad) news is more likely to happen during good (bad) times.[2] During expansionary periods, if analysts anticipate that good news is more likely to follow good news and good news is more likely to follow bad news (i.e., bad news is more likely to be reversed), analysts will need to underreact more to bad news than to good news in order to protect themselves from reversing their forecast revisions. On the other hand, during recessionary periods, bad news is more likely to follow bad news and bad news is more likely to follow good news (i.e., good news is more likely to be reversed). Therefore, analysts will need to underreact more to good news than bad news in recessions.

Meanwhile, there is another school of thought that focuses on analysts' short-term economic incentives. This literature also has implications for the differential underreaction to good versus bad news. Prior studies suggest that analysts publish optimistically biased forecasts due to conflicts of interest. That is, analysts have short-term economic incentives to

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[2] This assumption is supported by the observed correlation between business cycles and investor confidence measures shown in Appendix 3-A.

intentionally issue overly optimistic forecasts to please management for better access to private information, to generate more trade commissions, and to secure job promotions (e.g., Francis and Philbrick, 1993; Hong and Kubik, 2003; Jackson, 2005). When analysts react to bad news in a more restrained manner (i.e., underreact more to bad news than to good news), their earnings forecasts are optimistic on balance. Accordingly, studies suggest that analysts tend to underreact more to bad news than to good news due to these short-term economic incentives (e.g., Easterwood and Nutt, 1999; Hugon and Muslu, 2010).

In the setting of the business cycle, I conjecture that a weakened economy may enhance analysts' short-term economic incentives. When the economy worsens, greater uncertainty and less predictable earnings increase the demand for, and the benefits of obtaining, private information (e.g., Das, Levine, and Sivaramakrishnan, 1998; Lim, 2001). Since management is a vital source of private information, the incentive for analysts to maintain good management relations is greater during recessionary periods. In addition, a weakened economy is generally associated with greater stock volatility, greater stock market illiquidity, and less investor participation (e.g., Hamilton and Lin, 1996; Naes, Skjeltorp, and Odegaard, 2011), all of which increases the pressure to generate trades. Lastly, analysts are more worried about keeping their jobs due to the deteriorated labour market in economic downturns. Given the greater level of the incentives to maintain management relations, to generate trades, and to enhance job security during recessions, analysts will behave more opportunistically to gain these benefits according to the theory based on these incentives. Consequently, the excessive underreaction to bad news versus good news will be greater during recessions than expansions.

Hence, my second question is whether and how the differential underreaction to good news versus bad news depends on the business cycle. The above discussions indicate that the two types of incentives conflict with each other and lead to different predictions. Specifically,

the theory on reputation-building incentives predicts that analysts will underreact more to good news than bad news in recessions, but underreact more to bad news than good news in expansions; whereas, according to the short-term economic incentives, analysts will underreact more to bad news than good news, and this greater underreaction to bad news will be more pronounced during recessions than expansions. Results regarding the second question will shed light on the type of incentives analysts are more concerned with when they react to new information.

1.4   Summary of findings

Using a sample of quarterly earnings forecasts of US firms between 1984 and 2009, I examine analysts' underreaction to information in prior earnings announcements and underreaction to other earnings-related information reflected in stock returns. I find analysts underreact to both types of earnings information, consistent with prior studies. With respect to the first research question, the results suggest that underreaction to both types of information is more pronounced during expansions than recessions. I also find that uncertainty is greater during recessions than expansions, and that asymmetric reputation cost is greater during expansions than recessions, consistent with my arguments. These findings indicate that uncertainty is not the only factor that determines underreaction. Given the positive impact of uncertainty on underreaction, analysts would have underreacted to information in a more pronounced manner during recessions to avoid the heightened uncertainty. The finding shows otherwise, clearly demonstrating that the asymmetric reputation cost effect, rather than the uncertainty effect, dominates.

With reference to the second question, the findings suggest that the differential underreaction depends on the business cycle. While I do not directly test for cyclical variations in short-term economic incentives, a preliminary analysis from my initial sample

provides evidence suggesting that analysts have greater career-concern incentives when the economy is worse. I find that forecast optimism bias is greater on average during recessions than expansions. This is consistent with the link between optimism and the short-term economic incentives suggested in the prior literature, and consistent with my conjecture of greater short-term economic incentives during recessions. However, I do not find results suggesting that analysts excessively underreact to bad news in recessions as predicted by the short-term incentive argument. In fact, additional analysis shows that analysts underreact more to bad news than to good news in prior earnings announcements during expansions only, but not recessions. Furthermore, analysts show more underreaction to good news than to bad news reflected in stock returns during recessions but not expansions. Both findings are consistent with the reputation theory but inconsistent with the short-term incentive theory.

Given that all the evidence from my study (Chapters 2 through 5) supports the reputation cost theory, I further examine the theory in Chapter 6 by investigating the interaction effect of the business cycle (time variation) and certain industry- and firm-specific attributes (cross-sectional variation) on analysts' underreaction. Specifically, I examine how earnings cyclicality, earnings quality, and analyst following, affect the impact of the business cycle on analysts' underreaction.

First, I predict and find that the business cycle impacts underreaction only for cyclical industries but not for non-cyclical industries. Second, I predict that firms with lower quality earnings have a higher level of uncertainty. Given a certain level of the asymmetric reputation cost, analysts' underreaction will be more pronounced for firms with lower quality earnings due to the higher uncertainty for these firms. Also, for firms with higher quality earnings, analysts are more confident in predicting these earnings, and hence, any increase in asymmetric reputation cost (e.g., from a recession to an expansion) will have less marginal effect on analysts' underreaction. While the results are not prevalently significant, there is

some evidence consistent with my predictions. Third, I examine the assumption underlying the asymmetric reputation cost theory, i.e., market frictions prevent market prices from immediately undoing underreaction in analysts' forecasts. If there are no frictions, then market prices will include all information immediately and investors will not benefit from analysts' underreaction. Accordingly, I predict that (1) analysts' underreaction would be greater for firms that are more severely affected by market frictions and (2) the impact of market frictions on underreaction is greater when the asymmetric reputation cost is higher. The results show strong evidence that supports both predictions.

Overall, the findings in my main study and further research provide consistent evidence suggesting that analysts underreact to information due to their reputation concerns, and the asymmetric reputation cost of inaccuracy for inconsistent versus consistent consecutive forecasts revisions and forecast errors drives analysts' underreaction.

1.5   Contributions

This thesis makes several contributions to the literature on financial analysts and macroeconomics. First, the thesis answers the call from several review studies (e.g., Ramnath, Rock, and Shane, 2008a; 2008b; Bradshaw, 2011) to examine analysts' incentives in relation to forecast inefficiency. Most existing literature focuses on analysts' short-term economic incentives and optimism bias. By investigating reputation-building incentives and underreaction, the thesis is among the first to provide empirical evidence suggesting that analysts underreact to information to maximise the likelihood of creating consistent news, and hence, to minimise reputation costs. Furthermore, I add to the literature by proposing a new dimension of forecast quality that investors value: the consistency between the implications of analysts' forecasts and subsequent news. Moreover, I develop an indirect

measure for the asymmetric reputation cost that has not been empirically tested in prior studies.

Second, the thesis contributes to the analyst literature by finding that uncertainty is not the only factor that affects analysts' underreaction. The existing literature effectively documents that underreaction increases with uncertainty. However, I find evidence suggesting that in the business cycle context, while uncertainty increases in recessions, underreaction increases in expansions (and so does asymmetric reputation cost). This implies that asymmetric reputation cost, rather than uncertainty, has a dominant effect on underreaction.

Third, the thesis provides evidence on cyclical changes in analyst inefficiency and cyclical changes in analyst incentives, contributing to both analyst and macroeconomics literature. The evidence highlights the importance of including macroeconomic variables that have been frequently absent in analysts' forecast research. Most prior studies focus on cross-sectional analysis. Their results reflect the static, or the time-average level of, analysts' underreaction. As underreaction varies over time, the omission of such time variation, combined with different sample periods used in different studies, may potentially contribute to mixed evidence in various studies.

Fourth, the thesis extends the literature on analyst incentives by examining multiple incentives simultaneously. I employ a setting (i.e., the business cycle) where the coexisting but conflicting reputation-building and short-term economic incentives change in opposite directions. Hence, examining how analysts change their behaviour improves our understanding about which type of incentives matters more to analysts. The thesis finds evidence suggesting that, on the aggregate level, analysts emphasise long-term reputations more than short-term economic gains when reacting to new information. The conflicts of interest documented in the optimism research do not seem to be a compelling issue here.

Fifth, the thesis contributes to the literature by examining the interaction effect between the time variation (in the form of the business cycle) and the cross-sectional variation (in the form of industry- or firm-specific information) on underreaction. Prior studies focus on analysts' efficiency with respect to either firm-specific factors or macroeconomic factors, or both in rare cases. The interaction between analysts' responses to aggregate conditions and to firm-specific factors has received little attention in the literature. The thesis provides evidence for the interaction effect, and hence shows the importance for researchers to consider both cross-period and cross-sectional variations in their study designs.

Finally, the thesis has implications for regulators. Recent scandals involving analysts and investment banks spread the belief that analyst research is severely affected by the conflicts of interest. Consequently, a series of regulatory and enforcement actions have taken place in the US to address these conflicts of interest. However, prior studies find that the regulatory changes have not achieved the intended aims (e.g., Mayew, 2006; Libby, Hunton, Tan, and Seybert, 2008) and have created some adverse effects (e.g., Kadan, Madureira, Wang, and Zach, 2009). This thesis demonstrates that analysts care about their reputations. Thus, a successful way to minimise conflicts of interest may be to create regulations that makes variables affecting analyst reputation more transparent to investors, allowing them to make better judgements of the quality of each individual analyst's research, e.g., make analysts' historical forecasting records readily available to all investors (especially individual investors).[3]

1.6 Thesis structure

The remainder of this thesis is organised as follows. Chapter 2 provides background information on analysts and reviews literature on inefficiency in analysts' forecasts,

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[3] In the Global Research Analyst Settlement, the US regulators require firms to make certain information public for purposes of enabling the market to generate objective rankings of analysts.

incentive-based explanations for the inefficiency, and the impact of the business cycle on earnings forecasts. Chapter 3 develops hypotheses on cyclical variations in analysts' underreaction based on the links between underreaction and analysts' incentives. Chapter 4 discusses research methodology including variable measurements and empirical estimation models. Chapter 5 presents data and results. This includes a preliminary analysis based on the initial sample, final sample selection, summary of key variables, and results from the estimation models and additional robustness tests. Chapter 6 extends the main study and further investigates whether the association between underreaction and the business cycle depends on earnings cyclicality, earnings quality, and analyst following, respectively. Finally, Chapter 7 summarises and concludes the thesis.

CHAPTER 2

BACKGROUND AND RELATED STUDIES

In this chapter, I review theoretical arguments and empirical evidence related to analyst efficiency and business cycles. Specifically, I focus on four streams of the literature. First, I provide background on sell-side analysts, including analysts' activities and their reporting environment. This background highlights the important role that analysts have in capital markets and explains why academic researchers are so interested in examining analysts. Simply speaking, analysts help ensure efficient pricing and resource allocation in capital markets. For the purposes of my thesis, I focus on earnings forecasts made by sell-side analysts.

Second, I discuss the research on analyst efficiency. A pervasive finding of decades of research on analysts is that their decisions are not fully efficient. I highlight two empirical regularities with respect to analyst inefficiency in earnings forecasts: optimism and underreaction. My discussion regarding optimism builds on two recent review studies, i.e., Ramnath et al. (2008a) and Bradshaw (2011). They share common views that (1) the tendency for optimism appears to be diminishing over time and (2) inferences about optimism bias depend on multiple factors. In contrast, recent studies find consistent evidence that analysts underreact to a range of information prior to the publishing their earnings forecasts. These findings motivate my focus on underreaction.

Third, I present incentive-based explanations for inefficiency of earnings forecasts in two broad categories: short-term economic incentives and long-term reputation building incentives. I start with a discussion of the various incentives that allegedly cause conflicts of interest in analyst report, and explain how these incentives affect analyst efficiency, particularly in terms of optimism and excessive underreaction to bad news versus good news.

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Then I discuss a series of regulatory changes in the US that were enacted to address the conflicts of interest in analyst research. Next I discuss analysts' reputation building incentives and their effects on earnings forecast quality. While the primary focus in the literature is on reputation and forecast accuracy, I highlight a few studies that examine the reputation effect on other aspects of forecast efficiency/quality. Specifically, Raedy et al.'s (2006) "asymmetric reputation cost" theory and Hugon and Muslu's (2010) "market demand for conservative analysts" theory are discussed in detail because they related directly to underreaction.

Fourth, I review the research investigating the impact of business cycles on earnings forecasts. I begin with an introduction of the business cycle concept. Evidence on the association between earnings pro-cyclicality and the business cycles follows. This line of research supports the recommendation made by popular textbooks to incorporate the business cycles in forecasting earnings. While empirical studies suggest that analysts are able to incorporate macroeconomic information in earnings forecasts with some degree of efficiency, the effect of business cycles on analysts' underreaction in earnings forecasts remains unresolved.

2.1   The role of financial analysts and earnings forecasts in capital markets

Financial analysts are prominent information intermediaries in capital markets. They receive, analyse, and process financial information. Generally, there are two types of financial analysts. Buy-side analysts work for fund management firms or institutional investors. They make stock recommendations about which stocks their employer should buy, sell, and hold. Sell-side analysts, on the other hand, work for brokerage firms and provide reports about firms they follow to the brokerage firm's clients, including both individual

investors and buy-side analysts employed by institutional investors. Consistent with the bulk

of prior research, I focus on sell-side analysts (hereafter analysts).

Bradshaw (2011) presents a summary of analysts' activities in information gathering,

analysis, and communication processes. First, analysts gather information from various

sources, e.g., earnings and other information from public records and filings by a firm, such

as proxy statements and quarterly and annual reports; reports containing industry and macro-

economic outlooks; public conference calls where a firm's management disclose financial

results and answer analysts' questions about the firm's past performance and future prospects;

and other management communications such as small group or one-on-one meetings with

senior members of management teams.[4] Second, analysts use their expertise to analyse firms'

strategies, accounting policies, and future prospects for sales and earnings growth. Finally,

analysts prepare reports and provide earnings forecasts, target price forecasts (valuation), and

specific stock recommendations (buy-sell-hold).

Analysts convey these outputs to market participants via formal or informal channels.

Formal channels involve formal reports, broker notes, or formal presentations; informal

channels include brokerage client communication, press interviews, industry meetings, etc.

Eventually, investors may use these outputs from analysts as inputs for their own trading

decisions. To the extent that analysts provide incremental information or improve the

distribution of existing information, analysts can increase the efficiency of stock prices and

improve resource allocation in capital markets.

Ramnath et al. (2008a) provide a comprehensive diagram depicting the analyst

reporting environment as shown in Figure 1. In addition to the above description of analysts'

information gathering, analysis, and communication processes, this diagram also shows that

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[4] However, in many markets, this latter type of information gathering became difficult and potentially illegal due to regulations imposed after the corporate scandals of the early 2000s. One example is Regulation Fair Disclosure in the US.

regulatory and institutional factors and analysts' incentives have an impact on analysts'

decisions and research outputs (some of these topics are discussed in section 2.3).

Analysts' Reporting Environment
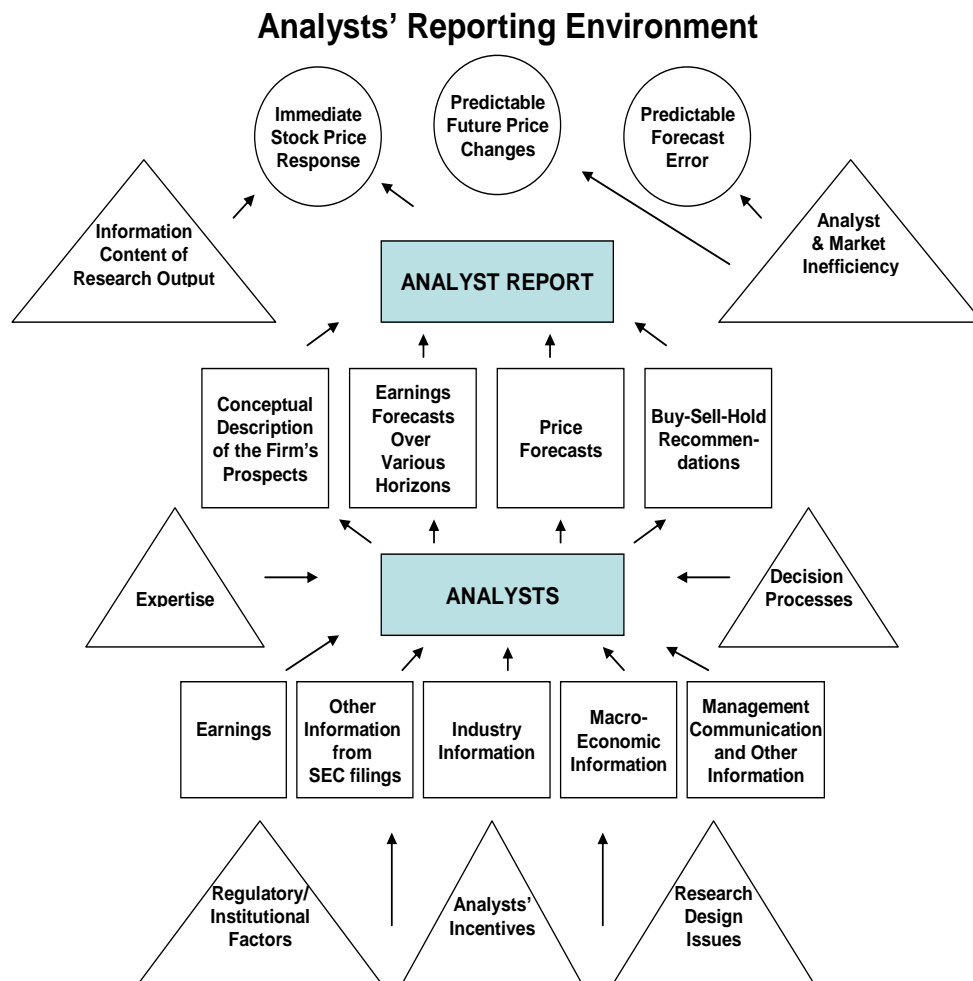
Figure 1   Analysts' reporting environment

(Source: Ramnath et al., 2008a, Fig 3.1, p. 320)

Efficiency or inefficiency of the information outputs communicated from analysts to

the markets, at least partly, can be assessed *ex post*, e.g., forecast accuracy and the

profitability of the analyst's recommendations. If analysts' forecasting processes and capital

markets are efficient, then analysts' forecasts and market prices will immediately reflect all

information. On the other hand, if analysts and capital markets are inefficient, we would be

able to observe predictable analyst forecast errors and/or stock price changes in association with prior information. More discussion of analyst efficiency is provided in section 2.2.

Data providers such as I/B/E/S, Value Line, First Call, and Zacks maintain databases of analysts' forecasts and recommendations which facilitates large sample studies. Not surprisingly, a voluminous quantity of research on analysts has been published over the past few decades. For example, Brown, Foster, and Noreen (1985) cite over 200 papers and Brown (1993) cites 171 papers in reviewing research on earnings forecasts. Ramnath et al. (2008a) review around 250 analysts-related studies published in top 11 journals between 1993 and 2006. Additionally, as of early 2012, there were over 200 papers listed on SSRN (Social Science Research Network database) written after 2009.

Bradshaw (2011, p. 9) summarises the reasons for the widespread interest in analysts:

On one hand, analysts are one of the preeminent market information intermediaries, distributing forecasts and results of their analysis to institutional and individual investors. Thus, examining properties of the analysts' forecasts and analysis helps us understand the nature of the information that seems to be impounded in stock prices. Another perspective is that analysts are a good proxy for beliefs held by investors in general, so examining properties of analyst data provides insight into how investors in general utilize and process accounting information like financial statements, footnotes, and other financial disclosures. Finally, having elevated analysts to the status of an interesting set of economics agents for detailed study, it is intrinsically interesting to study what analysts do and how they utilize financial accounting information. This final reason explains most of the current work on analysts.

While analysts undertake multiple tasks, generating earnings forecasts is among the most important tasks. First, earnings forecasts reflect the market's expectation of a firm's

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future performance. Evidence from numerous studies on forecast accuracy and association between market prices and earnings forecasts suggests that these forecasts are a superior proxy for market expectations compared to alternatives like time-series models (Fried and Givoly, 1982; Brown, Griffin, Hagerman, and Zmijewski, 1987). Further, investors and buy-side analysts care about whether a firm will be able to meet its earnings forecast. Moreover, earnings forecasts are important inputs to price forecasting decisions (Bandyopadhyay, Brown, and Richardson, 1995; Bradshaw, 2002) and stock recommendation decisions (Bradshaw, 2004; Loh and Mian, 2006). Therefore, the quality of earnings forecasts can affect the quality of price forecasts and stock recommendations. For instance, Bandyopadhyay et al. (1995) find that changes in one-year ahead (two-year ahead) Value Line earnings forecasts can explain about 30% (60%) of the variation in their target price forecasts. Similarly, Loh and Mian (2006) find that more accurate forecasts lead to more profitable stock recommendations. Although stock recommendations might be the ultimate judgement analysts make on a stock, earning forecasts are a finer signal of analysts' views on the stock they follow when compared to the buy, sell, or hold recommendations which are categorical (Nocera, 1997).

Overall, as information intermediaries, analysts play an important role in the capital markets. Among analysts' activities, forecasting earnings has significant implications. As a result, I focus on earnings forecasts in this thesis.

2.2   Inefficiency in earnings forecasts

Market efficiency assumes that stock prices reflect all known information and instantly change to reflect new information. In a similar sense, efficiency in analysts' earnings forecasts refers to the notion that analysts incorporate all available information in their forecasts, including market-wide information and firm-specific information. Researchers

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generally test forecast efficiency by estimating regressions of forecast errors (output) on a range of variables reflecting information (inputs) available to analyst prior to their forecasts. Ackert and Hunter (1995) summarise that full efficiency in analysts' forecasts requires "(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".

Numerous studies have examined a wide array of information inputs, such as past earnings, past market prices, past forecast revisions, and more recently, financial statement information. In spite of the sophistication ascribed to analysts' ability to interpret accounting information for investors, a large body of research demonstrates some degree of inefficiency in analysts' earnings forecasts (see Schipper, 1991; Brown, 1993; Ramnath et al., 2008a). Generally, research documents two distinct phenomena with respect to analyst inefficiency: optimism bias and underreaction. Optimism bias refers to forecasts that systematically exceed reported earnings, whereas underreaction refers to a positive correlation between current-period forecast errors (defined as reported earnings minus forecasted earnings) and information about future earnings available prior to the forecast date.

A typical regression model to test analyst inefficiency is as follows:

$$Forecast\ error = \alpha + \beta * \text{prior news variables} + \varepsilon_t \tag{2.1}$$

where the forecast error is defined as reported earnings minus forecasted earnings.

Researchers generally interpret α as evidence for analyst bias, and β on prior news variables as evidence for misreaction (Abarbanell and Lehavy, 2003). When earnings forecasts are fully efficient, both α and β will be zero, implying analysts are unbiased and efficiently incorporate prior news about future earnings. A negative (positive) α implies optimism bias (pessimism bias) and a positive (negative) β implies analyst underreaction (overreaction) to prior news. Equation (2.1) clearly demonstrates that underreaction and

optimism bias are two distinct phenomena. The direction of forecast errors due to underreaction depends on prior news. That is, in the wake of good news (bad news), underreaction results in positive (negative) forecast errors. On the contrary, optimism bias always results in negative forecast errors.

2.2.1 Optimism bias

Analyst forecast research (Biddle and Ricks, 1988; Stickel, 1990; Abarbanell, 1991, among many others) provides support for forecast optimism bias (see Brown, 1993, for a detailed review). These studies infer optimism bias largely from the statistical properties of earnings forecasts, e.g., negative mean or median forecast errors (i.e., a negative α in Equation 2.1), or positive intercepts from regressions of forecasts on reported earnings. Essentially, these properties result from the tendency that forecasts are higher than reported earnings.

Recent reviews, however, cast doubt on the optimism bias in analyst earnings forecasts. Ramnath et al. (2008a, p. 374) review a broad range of recent research and observe that the evidence supporting overall optimism is "contextually confined and sample-period specific". Similarly, Bradshaw (2011, p. 17) points out that the generalisation of analysts being routinely optimistic is "not on average descriptive". Particularly, they discuss several factors that affect studies' ability to draw conclusions about forecast bias.

The first factor is the sample period. Evidence from recent periods does not consistently support optimism (Ramnath et al., 2008a). In fact, forecasts appear to move from optimism to pessimism over time. For example, Brown (2001b) notes that median forecast errors have moved from negative to zero to positive over the 1984-1999 period, indicating a shift from optimism bias to no bias to pessimism bias. Likewise, Chan, Karceski, and Lakonishok (2007) find that both mean and median latest forecast error using I/B/E/S data

undergoes an upward shift over the 1984-2004 period. Particularly, the proportion of nonnegative forecast errors (meaning that actual earnings exceed forecasts) climbs over time from 49% in the late 1980s to 76% in 1999-2000.

The second factor is the mean or median forecast errors that studies use. Ramnath et al. (2008a) observe that mean forecast errors tend to be negative while median not (e.g., Richardson, Teoh, and Wysocki, 2004). This phenomenon can be explained (or at least in part) by skewness in the distribution of earnings. Both earnings and forecast errors are negatively skewed with the median greater than the mean.

The third factor is the forecast horizon (staleness of the forecast). Analysts tend to issue optimistic forecasts at early stages and revise them downwards gradually before the earnings announcement, which is described as a walk-down pattern by Richardson et al. (2004). Ramnath et al. (2008a) discuss that the longer the forecast horizon, the more optimistic the forecast (e.g., Richardson et al., 2004; Raedy et al., 2006; Louis, Lys, and Sun, 2008). Bradshaw (2011) comments that at least for short-term forecasts, it is not descriptive to generalise that analysts' forecasts are optimistic.

Actual data is the fourth factor. Different data sources lead to different conclusions. For example, Ramnath, Rock, and Shane (2005) find optimism bias using Value line data, but no bias using I/B/E/S data over the 1993-1997 period. The reason is most likely to be the correspondence between forecast earnings and actual earnings. According to I/B/E/S, their archived actual earnings figures are adjusted to match the earnings definition being forecasted by the majority of analysts. If analysts forecast earnings excluding non-recurring items or abnormal accruals, then I/B/E/S excludes these items from bottom line earnings as the actual. Ramnath et al. (2008a) comment that using matched actual earnings appears to reject optimism bias. In a similar vein, Bradshaw (2011) states that the non-correspondence between the actual and forecast earnings would have mechanically caused upward bias. He

also notes that researchers identify the year of 1992 as a marked shift in the correspondence of actual and forecasted earnings. The greater degree of non-correspondence may contribute to the persistent optimism found in pre-1992 studies, which relates to the sample period factor discussed above.

The fifth factor is statistical tests. As Ramnath et al. (2008a) discuss, different inferences of forecast bias result from different data adjustments (truncating or partitioning distribution) and different statistical methods (parametric or non-parametric). This is due to the presence of the two asymmetries that Abarbanell and Lehavy (2003) find in forecast error distributions. The tail asymmetry is greater extreme negative forecast errors in number and magnitude than extreme positive forecast errors (the left tail is bigger than the right tail). The middle asymmetry is a higher incidence of small positive relative to small negative (more errors are slightly positive than slightly negative).

The final factor is selection bias. Analysts exhibit selection bias in which they are reluctant to issue negative opinions. Hence, they selectively report only favourable opinions. What appears to be optimism could "simply reflect the fact that we do not get to observe analysts' pessimistic views" (Bradshaw, 2011, p. 18). Bradshaw also conjectures an increasing tendency for analysts to publish negative opinions due to the recent implementation of analyst regulations (e.g., NASD 2711 and NYSE 472 requiring analysts provide benchmark distributions of the brokerage's recommendations and target prices).[5] To the extent that the regulations address selection bias, this may explain why optimism has declined in recent years.

To conclude, as much as optimism is documented in numerous studies, inferences about forecast bias are dependent on the factors discuss above. Analysts appear to be less optimistic over time.

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[5] See subsection 2.3.1.3 for more discussions on recent analyst regulations and related effects.

2.2.2   Analysts' underreaction

Early on, accounting researchers discovered that investors underreact in capital markets. Ball and Brown (1968) identify the post-earnings-announcement drift, i.e., stock returns continue to drift in the direction of earnings surprises for several months after the earnings are announced. Bernard and Thomas (1990) and Ball and Bartov (1996) confirm the robustness of Ball and Brown's findings using more recent data. They interpret their findings as evidence of investors' underreaction to earnings information. Later studies also document underreaction in analyst forecasts and that analysts' underreaction can partly explain investors' underreaction (Abarbanell and Bernard, 1992).

Analysts underreact if they issue a new earnings forecast or revise an outstanding forecast that insufficiently adjusts for publicly available information at the forecast release date. Analysts' underreaction results in a positive correlation between current-period forecast errors (defined as reported earnings minus forecasted earnings) and information about future earnings available prior to the forecast date, that is, a positive β in Equation (2.1) discussed above.

Analysts are found to underreact to various types of information about earnings: prior period earnings change (Abarbanell and Bernard, 1992), prior forecast errors (e.g., Mendenhall, 1991; Abarbanell and Bernard, 1992; Raedy et al., 2006), and prior stock returns (Lys and Sohn, 1990; Abarbanell, 1991; Ali, Klein, and Rosenfeld, 1992; Raedy et al., 2006; Clement, Hales, and Xue, 2011), and prior forecast revisions (Elliott, Philbrick, and Weidman, 1995; Clement et al., 2011).

In sum, while analysts' underreaction continues to be documented in recent studies, the literature has raised concerns about the existence or significance of optimism in recent

years. This provides motivation for the thesis to investigate analysts' inefficiency with a primary focus on analysts' underreaction.

2.3 Analysts' incentives

Recent literature has shifted focus from merely reporting statistical properties of earnings forecasts to seeking explanations for the forecast inefficiency in terms of analysts' psychology or economic incentives (Ramnath et al., 2008b). Psychology-based explanations state that analysts are inefficient when processing information and making decisions for cognitive psychology reasons. Analysts are attached to companies they follow so much so that they lose objectivity and become optimistic. Alternatively, analysts appear unaware or incapable of fully understanding and accounting for certain features embedded in the underlying earnings when they issue new forecasts. With respect to underreaction, psychology-based studies suggest that analysts do not fully understand or incorporate in their forecasts the difference between the prior year's permanent and transitory earnings components (Ali et al., 1992), conservative accounting numbers (Louis et al., 2008; Pae and Thornton, 2010), and high accruals that are associated with negative future earnings reductions (Bradshaw, Richardson, and Sloan, 2001). Because cognitive judgement errors are reduced with experience, analysts underreact to prior earnings information less as their experience following a firm increases (Mikhail, Walther, and Willis, 2003).

Meanwhile, another stream of studies attempts to provide incentive-based explanations for optimism and underreaction. In his review of four decades of research on analysts, Bradshaw (2011) encourages researchers to focus on analyst activities within the context of what their incentives are. He comments:

> *As research studies have begun to consider activities beyond basic earnings*
>
> *forecasting, it has become necessary (and interesting) to examine analysts' incentives*

> *and investigate what role they might play in the empirical regularities developed over the past several decades of research (e.g., optimism). (p. 16)*

Hence, in this section, I focus on the literature that provides incentive-based explanations. Specifically, I broadly categorise and discuss two types of analysts' incentives. The first category includes certain economic incentives that allegedly adversely affect analyst efficiency. Analysts are incentivised to behave opportunistically in order to gain economic benefits. Because such opportunism cannot sustain in a long run, I refer to these incentives as short-term economic incentives. The second category focuses on analysts' incentives to build and maintain long-term reputations. Because reputations are associated with long-term economic benefits, I refer to these incentives as long-term reputation building incentives. Essentially, both types of incentives have an economic basis and can be viewed as economic incentives.

2.3.1   Short-term economic incentives

Studies within this category argue that the inefficiency in earnings forecasts is due to certain economic incentives analysts have, rather than their inability to fully understand and/or fully incorporate certain aspects of information in earnings forecasts. I discuss various incentives that cause conflicts of interest in analyst research, and the effects of these incentives on optimism and underreaction, respectively. Finally, I discuss the recent regulatory changes aimed at addressing these conflicts of interest, and the effects of the recent regulations.

2.3.1.1 Short-term economic incentives and optimism

Incentive-based studies argue that analysts appear to be optimistic due to analysts' economic incentives that cause conflicts of interest in analyst research. Evidence from these

studies suggests that analysts are rational but strategically bias their earnings forecasts upward, or selectively follow firms for which they have favourable views, due to several economic incentives: (1) cultivating management relations to access more information, (2) facilitating investment banking business, and (3) stimulating trading commissions.

Cultivating management relations to access more information

Francis and Philbrick (1993) predict that analysts report optimistic forecasts to cultivate good relations with management. Management is a vital source for analysts to gather information on a firm. Naturally analysts would wish to maintain good relations with management by trying not to publish negative views about the firm if possible. To test the prediction, they use Value Line data between 1987 and 1989. Value Line is not a brokerage or an underwriter. In other words, Value Line analysts are only responsible for forecasting earnings and do not make stock recommendations or rank firms by price performance timeliness.[6] Any bias in Value Line analysts' forecasts cannot be due to analysts' desire to affect timeliness ranks or due to incentives to promote security transactions. Francis and Philbrick (1993) find earnings forecasts are more optimistic for "sell" and "hold" stocks than for "buy" stocks that other analysts recommend. The results support their hypothesis that analysts display a tendency towards unjustified optimism to maintain management relations when recommendations are negative. They conclude that in a multi-task environment, analysts' forecasting decisions are influenced by interactions among tasks.

Following Francis and Philbrick (1993), Das et al. (1998) further argue analysts' incentives to curry favour with management are greater when the benefits of obtaining private information are greater (i.e., earnings are unpredictable). Using Value Line 1989-1993 data, Das et al. (1998) find that analysts make relatively optimistic forecasts when

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[6] The Value Line timeliness rank measures probable relative price performance of the approximately 1,700 stocks during the next 6 to 12 months on a scale from 1 (highest) to 5 (lowest).

earnings are least predictable, consistent with the argument that analysts believe that by issuing optimistic forecasts, they obtain better information from managers.

Drawing on the management relation argument, Lim (2001) argues that unbiased forecasts are not the most accurate forecast from the perspective of minimising mean square error. Analysts may trade-off optimism against pessimism in the hope of having better access to information and, consequently, improving forecast accuracy. Lim (2001) predicts and finds that optimism is greater when demand for private information is higher, i.e., when firm size is smaller, analyst following is fewer, and target-specific uncertainty is higher.

Finally, Ke and Yu (2006) provide evidence on benefits that result from pleasing management through biased earnings forecasts. Based on both I/B/E/S quarterly and annual forecasts from 1983 to 2000, they find analysts who issue earnings forecasts that are initially optimistic, followed by pessimistic earnings forecasts, have more accurate earnings forecasts and are less likely to be fired by their employers. The effect of such biased earnings forecasts on forecast accuracy and firing is stronger when analysts cover firms with heavy insider selling and hard-to-predict earnings. These results are consistent with the hypothesis that analysts use biased earnings forecasts to curry management favour in order to obtain better access to management's private information. They also show that their findings hold for analysts employed by both investment banks and pure brokerage firms (i.e., those without investment banking businesses). Thus, their results cannot be solely driven by the alleged investment banking incentive which is discussed next.

Facilitating investment banking business

When companies need access to the capital markets, they inevitably require professional assistance from investment banks. It is alleged that investment banks reward their sell-side analysts for providing favourable opinions about the firms that those banks underwrite and try to underwrite. Consequently, analysts are incentivised to publish overly

optimistic views due to the potentially lucrative underwriting fees. Researchers have extensively examined this allegation, and many find that affiliated analysts tend to be more optimistic in terms of forecasts and recommendations.

Lin and McNichols (1998) examine the impact of underwriting-business-related incentives on earnings forecasts and stock recommendations. Using I/B/E/S data of firms making seasoned equity offerings between 1985 and 1994, they find that affiliated analysts who work for underwriters or co-underwriters issue relatively optimistic long-term earnings growth and stock recommendations. Similarly, Dechow, Hutton, and Sloan (2000) employ I/B/E/S data from 1981 to 1990 and find analysts' long-term growth forecasts are optimistic around equity offerings but affiliated analysts are more optimistic than unaffiliated analysts.

Michaely and Womack (1999) focus on IPO firms in First Call for the years 1990 and 1991, and find that lead underwriter analysts publish 50% more buy recommendations for IPO firms than do unaffiliated analysts of the remaining brokerage firms. Based on a small sample from CIRR and Investext between 1983 and 1988, Dugar and Nathan (1995) document similar findings of more optimistic recommendations issued by affiliated analysts. Further, they find that earnings forecasts of various horizons are relatively optimistic when issued by affiliated analysts than unaffiliated analysts.

Stimulating trading commissions

Brokerage firms receive income through handling investors' trades. Thus, trading volume is a common measure of performance for brokerage firms to reward their research analysts (Cowen, Groysberg, and Healy, 2006; Beyer and Guttman, 2011). Cowen et al. (2006) argue that investors can act on a positive view at relatively low cost by buying the stock, whereas investors can only act on a negative view when they already own the stock or when they are willing to incur the additional costs of short selling. In addition, institutional investors typically demand analysts to provide them with new purchase ideas, because most

of them (except hedge fund trading) are prohibited from shorting stocks. Accordingly, analysts wish to optimistically bias their opinion to generate purchases.

Hayes (1998) models an analyst's information production decision in the presence of incentives to generate trade. He argues that trade-generation incentives can affect analysts' decisions of initial coverage and forecast accuracy. Irvine (2004) uses Canadian data in 1994 and finds that optimistic stock recommendations generate greater trading commissions. In terms of earnings forecasts, he finds that forecasts departing from the consensus increase trade, but biased forecasts do not. Irvine (2004) interprets his findings to imply that analysts appear to have more incentives to optimistically bias recommendations than earnings forecasts.

Jackson (2005) uses more extensive data between 1992 and 2002 in Australian firms. He examines broker market share in association with optimism of analysts' one-year-ahead earnings forecasts relative to other analysts, relative optimism of two-year-ahead forecasts, and optimism reflected in the actual recommendation, while controlling for investment-banking relationships, broker size, and analyst reputation. When he includes all three types of optimism in the regression, recommendation optimism dominates the forecast optimism. He interprets the results to mean that analysts are more likely to convey optimism via softer messages, because they may get away with excessive optimism more easily as recommendations typically are not time-horizon specific. Further, conducting individual regressions, Jackson finds that broker market share in the current year is positively related with one-year-ahead forecast optimism, two-year-ahead forecast optimism, and recommendation optimism, respectively. These findings are consistent with the hypothesis that optimistic analysts generate more trading volumes for brokerage firms, and that earnings forecast optimism is an important channel on its own. Additionally, he finds reputable analysts generate more trading volumes as well. Because forecast accuracy generates higher

reputation, Jackson suggests that analysts face a tension between making unbiased forecasts to develop reputation and forecasting optimistically to generate trading commissions. He develops an analytical model and demonstrates that forecast optimism can exist in equilibrium.

Beyer and Guttman (2011) extend Jackson's (2005) work and further develop a theoretical model of an analyst's forecasting strategy in a setting where the analyst's payoff depends on (1) the trading volume of investors who receive his forecast and (2) his forecast error. The model is built on an assumption that analysts trade-off costs from forecast errors against incentives to generate trading volume. In the model, the analyst's bias is increasing in his private signal. If the signal is unfavourable (favourable) sufficiently enough to cause informed investors to sell (buy) shares, he biases the forecast downward (upward). Also, the upward biases are more frequent than downward biases. Their model shows optimistic forecasts on average, consistent with above mentioned empirical findings.

While the aforementioned studies investigate the effect of one single incentive at a time, an interesting study by Cowen et al. (2006) investigates different types of security firms to compare the impact of multiple incentives on optimism. They partition their investment bank observations from the period 1996-2002 into two groups. One group funds research through investment banking businesses and trading activities, whereas the other group only has trading fees as a primary source of income. The results show that analysts who work at the firms with no investment banking businesses make more optimistic forecasts and recommendations than others. This evidence suggests that the trading incentive is stronger than the investment banking incentive in driving optimism bias.

Related to the above-mentioned incentives, Hong and Kubik (2003) investigate earnings forecasts and analyst implicit incentives (i.e., career concerns) by examining movements of roughly 12,000 analysts across 600 brokerage houses between the years of

1983 and 2000. They consider an analyst at a higher-status brokerage house to have a better job with higher compensation and prestige. They find that analysts' career success is a function of forecasting ability. Extremely accurate (inaccurate) analysts are more likely to experience a move up (down) the brokerage house hierarchy. After controlling for accuracy, they document that relative optimism in forecasts is positively associated with promotions. Further analyses show that promotions depend relatively more on optimism and less on accuracy in two situations: (1) for investment bank analysts in particular and (2) during the stock market mania in the late 1990s. Hong and Kubik (2003) offer a plausible interpretation of these findings. While analysts are evaluated on their earnings forecasting and stock valuing ability, they are also rewarded for optimistically biased forecasts by their brokerage firms which wish to promote stocks so that will generate underwriting business and garner trading commissions.

2.3.1.2 Short-term economic incentives and underreaction

While much research on optimism bias adopts the incentive view, research on underreaction is based largely on psychology. However, there are few studies that attempt to attribute underreaction to economic incentives.

Trueman (1990) developed a theoretical model that assumes analysts have various forecasting abilities and are rewarded for their forecasting reputation. Investors assume analysts only issue forecasts in a Bayesian manner when justified by their private information. Trueman (1990) hypothesises that analysts with weak forecast ability are incentivised to convince investors that they have skills to develop timely private information. When they do not have such private information, they must underreact to the public information so as not to reveal the lack of private information. This theory needs empirical examination. Also, it does not seem to explain why underreaction in late earnings forecasts still exists.

Abarbanell (1991) attempts to explain the observed omission of price change information from analysts' earnings forecasts, i.e., underreaction to stock returns. He questions the explanation of analysts being inefficient in processing public information, because it seems not reasonable that analysts would fail to recognise their tendency to underweight information over long periods. Instead, he posits that "the private information is more easily inferred by investors if it is not combined with other signals whose information content is open to individual interpretation" (p. 164). Hence, analysts have incentives to provide a new forecast only when they have obtained new private information independently of price changes. Ramnath et al. (2008a), however, find this explanation less convincing because prior studies document that useful and accurate forecasts matter to analysts who, in turn, wish to include all available information in their forecasts.

While these two theories do not appear to fall in the range of the short-term economic incentives discussed in the previous subsection, the incentives described by Trueman (1990) and Abarbanell (1991) are obviously driven by analysts' opportunism. By trying to either conceal the lack of private information or making forecasts look more convincing, analysts are not being more efficient and these behaviours cannot render long-term economic benefits to analysts. Moreover, investors, particularly institutional investors, can distinguish between different levels of analyst forecast quality (more discussions follow later).

Apparently, the phenomenon of underreaction cannot be directly linked to the short-term economic incentives because empirical evidence from the literature suggests that analysts underreact to both good and bad news. Underreaction to good news results in a pessimistic forecast, and hence, it does not fit into the optimism picture. However, several studies take a deeper look at underreaction and examine underreaction to bad news versus good news separately. They document that analysts' underreaction to prior bad news exceeds underreaction to good news (e.g., Easterwood and Nutt, 1999; Pae and Thornton, 2010).

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Since any excessive underreaction to bad news leads to an optimistic outcome on balance, researchers attribute the asymmetric underreaction to the short-term economic incentives.

Francis and Philbrick (1993) find that Value Line analysts show significantly greater optimism for firms with less favourable stock recommendations that other analysts have reported because analysts wish to appease management. This pattern of asymmetric optimism is similar to the underreaction to bad news documented in Mendenhall (1991) and Abarbanell and Bernard (1992) that leads to optimistic forecasts in the wake of bad news. The authors further suggest that the management-relation cultivating incentive could explain underreaction to bad news. Easterwood and Nutt (1999) find evidence indicating that analysts underreact to negative information, but overreact to positive information.[7] They attribute these systematically optimistic reactions to aforementioned short-term economic incentives.

Building on the notion that analysts asymmetrically underreact to prior news due to these incentives, Hugon and Muslu (2010) further hypothesise that market would demand for analysts who do not underreact to prior news asymmetrically. They use the asymmetric underreaction to bad news versus good news as a proxy for the relative degree of conservatism of analysts as opposed to aggressive/optimistic analysts. Analysts who respond stronger to bad news versus good news (i.e., underreact less to bad news) than other peers are deemed more conservative. Hugon and Muslu (2010) find that analysts who underreact relatively more to bad news are less accurate, and have less market response.

2.3.1.3 Recent regulatory changes and effects

The idea that analysts' economic incentives adversely affect analyst efficiency is not only of academic interest, but also of market participants' interest. In the midst of the US

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[7] It is worth noting that evidence on excessive underreaction is mixed. Contradictory to Easterwood and Nutt (1999), several studies find evidence suggesting a general underreaction to both good news and bad news. In particular, Raedy et al. (2006) do not find incremental underreaction for bad news observations. In fact, some of their results suggest a lesser degree of underreaction in the bad news group.

stock market bubble of the late 1990s, brokerage houses allegedly "threw whatever concern they had for objectivity in their research out the window … as the job description for being an analyst became more tied to promoting stocks than ever" (Hong and Kubik, 2003, p. 316). The subsequent stock market crash and several scandals involving analysts and banks during the 2000-2001 period triggered tremendous concerns about analysts' conflicts of interest and analysts' optimistically biased research that was misleading to investors. Several analysts and banks were charged with violating the public trust by publishing biased research.[8] For example, Jack Grubman faced multi-million-dollar fines and lifetime bans from the securities industry, and ten of the largest investment banks agreed to pay $1.4 billion in fines through the Global Research Analyst Settlement. A series of regulatory and enforcement actions have taken place in the US to address certain conflicts of interest that affected analysts' research, hence, promoting the integrity of and investor confidence in analysts and their research.

The US Securities and Exchange Commission (SEC) promulgated Regulation Fair Disclosure (Reg FD hereafter) in 2000 that prohibits firms' selective disclosure. Before the Reg FD rule, most companies did not allow small investors to attend conference calls between management and analysts. The rule mandates that all public firms must disclose material information to all investors at the same time. The purpose is to increase the transparency in firms' communications with investors, which to some extent may weaken analysts' favour currying incentive.

Additionally, the NYSE and NASD enforced new rules regarding research analysts issued in 2002 (NYSE 472 and NASD 2711 rules). The main purpose of the new rules is to sever the ties between investment banking and research departments. Among other measures, the rules limited the relationships and communications between investment banking and research personnel, prohibited analyst compensation that is based on specific investment

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[8] See http://www.sec.gov/news/speech/factsheet.htm and
http://www.ag.ny.gov/media_center/2002/dec/dec20b_02.html.

banking transactions, and banned subject companies from reviewing research reports before publication (except for checking factual accuracy). The new rules also established stringent disclosure requirements for research reports. These requirements were aimed at providing better information to interpret research outputs in a proper and meaningful manner, and to identify potential conflicts of interest. For example, along with the research report, analysts have to disclose whether they received compensation based on investment banking revenue, whether they hold a position as an officer or a director in the subject company, or whether the subject company is a client of the firm. Also, the research report must explain the meaning of its rating system and disclose the percentage recommendations in the "buy," "hold," and "sell" categories.

Further along the same lines, the Regulation Analyst Certification by the SEC in 2003 requires research analysts to certify that the views expressed in the report accurately reflect their personal views and disclose whether or not they received compensation in connection with their specific recommendations or views.

The Global Research Analyst Settlement in 2003 between regulators (the SEC, the NYSE, the NASD, and the New York Attorney General) and ten US investment banks required regulatory measures aimed at severing the ties between investment banks and research departments, similar to – and in some cases more stringent than – the NYSE's and NASD's new rules. The Global Settlement required a physical separation of investment banking and research divisions at brokerage firms, and that the research department's budget and research analyst' compensation and evaluation be determined without regard to investment banking revenues.

Following the regulations, a number of studies examined the effects of the regulations on analysts' conflicts of interest. Some evidence shows that the regulatory changes do achieve their intended objectives. Gintschel and Markov (2004), among others**,** document the

efficacy of Reg FD. They find that the average price impact associated with the dissemination of analysts' information is significantly lower by 28% from the pre-regulation level, and that the difference in price impact between optimistic analysts and non-optimistic analysts in the post-Reg FD period is 50% lower compared to its pre-regulation level. These findings are consistent with Reg FD curtailing the flow of information from managers to analysts and levelling the financial analysts' playing field, implying a reduction in firms' selective disclosures to analysts. Given optimism is partly driven by analysts' incentives to curry management favour to access better information, the evidence of reduced differential price impact between optimistic versus non-optimistic analysts after Reg FD appears to be consistent with the notion that the regulation addressed the favour-currying incentive.

Kadan et al. (2009) study the impact on analysts' recommendations of the regulatory changes after Reg FD, that is, Global Analyst Research Settlement and related regulations aimed at mitigating the interdependence between research and investment banking. Kadan et al. (2009) obtain stock recommendations from I/B/E/S and compare them in the post-Reg period (September 2002-December 2004) to the pre-Reg period (November 2000-August 2002). They find that optimistic recommendations have become less frequent and more informative, whereas neutral and pessimistic recommendations have become more frequent and less informative. This is consistent with Barber et al. (2006) that find a more balanced recommendation mix in the post-Reg period. Further, the likelihood of issuing optimistic recommendations no longer depends on affiliation with the covered firm. These findings provide evidence supporting the regulations' efficacy.

Meanwhile, studies also find evidence suggesting otherwise. With respect to Reg FD, while it may prohibit selected disclosure (e.g., via small group meeting between management and analysts), it is arguable that analysts are still concerned about maintaining good relations with management even in a post-Reg FD environment. Good management relations allow the

analyst to participate during earnings conference calls by asking questions which can facilitate the generation of new and valuable private information. In an experimental study employing 81 experienced sell-side analysts, Libby et al. (2008) examine the management relation incentive and the optimistic or pessimistic pattern in analysts' forecasts. Their results suggest that analysts exhibit optimism early in the quarter but pessimism late in the quarter, and this forecasting pattern is helpful for analysts to build good management relations (future favoured conference call participation). They conclude that recent regulatory changes may have lessened but have not eliminated the management relation incentive.

Using archived post-Reg FD conference call transcripts, Mayew (2006) documents that the probability of an analyst asking a question during an earnings conference call is increasing in the favourableness of the analyst's outstanding stock recommendation. Downgrades are associated with decreases in access to management during the conference call relative to other recommendation change activity. While he finds that analyst prestige moderates these effects, the finding confirms the notion that managers discriminate among analysts by allowing more management access to more favourable analysts. Evidence from these two studies suggests that analysts are still concerned about maintaining good relations with management even in a post-Reg FD environment. Similarly, Kadan et al. (2009) document that affiliated analysts are still reluctant to issue pessimistic recommendations after the Global Settlement.

In addition to not achieving the intended aims, the regulations are likely to create unintended but adverse effects. Following the regulations, many brokerage houses have migrated from the traditional five-tier rating system (strong buy, buy, hold, sell, strong sell) to a three-tier system (buy, hold, sell). A number of studies find that the overall informativeness of recommendations has declined (e.g., Kadan et al., 2009).

Moreover, conflicts of interest are unlikely to disappear after these regulations. Analysts' incentives may simply move away from the addressed conflicts (such as favour currying or investment-banking business generating) towards other aspects, e.g., trade commission generating (e.g., Jackson, 2005) or internal career concerns because brokerage houses apparently reward optimistic analysts who promote stocks (e.g., Hong and Kubik, 2003), which ultimately generate a similar effect.

2.3.2 Long-term reputation building incentives

Game theory states that in the presence of repeated interaction between agents, agents have incentives to build and preserve reputation and not to behave opportunistically as they would in a single-shot game (Kreps and Wilson, 1982). The accounting and finance literature has applied this concept and demonstrated that the reputation effect can mitigate agency problems in various contexts: between managers and shareholders (Fama, 1980), in debt markets (Diamond, 1989; 1991), in underwriting businesses (Carter and Manaster, 1990; Carter, Dark, and Singh, 1998; Fang, 2005).

In the context of financial analysts, the game theory would predict that analysts, because they repeatedly interact with clients, have incentives to cultivate a good reputation by publishing forecasts and recommendations that effectively serve the needs of those clients. As analysts' reputation increases (decreases), the market tends to reward (penalise) the analysts with promotions (demotions) in their careers. Analysts who are influential among institutional investors can generate hefty trading commissions for their brokerages. Results from CEOs' surveys also show that the reputation of a brokerage house's analyst covering the industry is an important determinant in choosing an underwriter for their initial public offerings and seasoned equity offerings.

Buy-side fund manager surveys provide rankings that correlate directly with analyst reputation, such as the Institutional Investor's survey in US. Sell-side security analysts who are ranked the top three in each industry are called "All-American" and are compensated by their firms and the market for this honour. Two of the most important criteria for a high ranking are the analyst's expertise in making earnings forecasts and picking stocks. Another example is the East Coles survey in Australia. As such, investors have the power to impose implicit reputation costs on analysts on the basis of the quality of their earnings forecasts, stock recommendation, and research via investment decisions and responses to surveys ranking the analysts.

2.3.2.1 Reputation and forecast accuracy

Empirical research has used these survey rankings as a proxy for reputation and examined the reputation effect in analysts' forecasts. Stickel (1992) finds that top ranked analysts provide forecasts with more accuracy than other analysts, suggesting a positive relation between analyst reputation and performance. His finding is confirmed by Jackson (2005) and Fang and Yasuda (2009), among others. In particular, Jackson (2005) adds further evidence that more accurate analysts acquire higher future (end-of-period) reputations. This implies that the market updates analyst reputation in a consistent way. Leone and Wu (2007), in a recent working paper, investigate analyst rankings beyond the positive relation between ranking and analyst performance. They document that the performance by ranked analysts is due to their superior ability, and that this superior ability appears to stem from an innate talent rather than greater experience. This evidence supports rankings as an effective and meaningful proxy for high quality and reputable analysts. Further, reputable analysts have a greater ability to affect price (e.g., Stickel, 1992; Jackson, 2005; Hilary and Hsu, 2012),

suggesting investors can discern the quality forecasts and differentiate analysts by their reputation.

Several studies also established empirical links between analysts' reputations (forecast accuracy) and long-term economic benefits, such as promotions, favourable job separations, and future broker trading volume. Earlier studies provide evidence on forecast accuracy and career concerns. Mikhail et al. (1999) find an analyst is more likely to turn over if his forecast accuracy is lower than his peers after controlling for firm- and time-period effects, forecast horizon, and industry forecasting experience. Hong, Kubik, and Solomon (2000) confirm this finding. They also find that forecast accuracy is directly related to the likelihood of promotion, particularly for analysts with less experience.

While these two studies imply a positive reputation effect on analysts' career given the reputation/forecast accuracy link, Hong and Kubik (2003) directly test this effect using a reputation proxy. They argue that, in practice, brokerage houses wish to hire analysts who have a reputation for forecasting expertise among the buy-side investors. Therefore, more accurate and reputable analysts shall be rewarded with higher compensation. They use two indirect proxies for better jobs: the status of brokerage house that the analyst works at and the importance of stocks (large market capitalization or large analyst following) that the analyst is assigned to cover. Hong and Kubik (2003) find that analysts who are extremely accurate (inaccurate) relative to other analysts are more likely to experience a move up (down) the brokerage house hierarchy. The results for important stock coverage are similar.

Jackson (2005) examines whether analysts with better reputations generate significantly higher future trading volume for the brokerage house they work for. Using Australian data, he measures analyst reputation by constructing two variables: a percentile ranking of the analyst relative to other analysts covering the stock and a dummy variable of the analyst being ranked in the top three. The analyses are done separately for all stocks and

large top 100 stocks, while controlled for the size of the broker and investment-banking relationships. The findings show that analyst reputation in the previous year has a significantly positively impact on broker market share in the following year, both in a statistic and economic sense.

The links between analyst reputation, forecast accuracy, and the long-term economic benefits documented from empirical studies demonstrate that analysts have economic incentives to enhance their reputation by improving the accuracy of their forecasts. Jackson (2005) argues that reputation is an effective mechanism against opportunistic behaviour by analysts. He suggests that a successful way to address conflicts of interest might be policies that make analysts' reputation more transparent and increase the implicit penalty for opportunistic behaviour, hence increasing analysts' concerns for their reputation. For example, the requirement in the Global Research Analyst Settlement makes previous analyst forecasting track records more transparent. This enables investors (particularly individual investors) to evaluate the performance of analysts and form objective rankings about them.

Fang and Yasuda (2009) add more direct evidence that reputation is a disciplinary mechanism in analysts' research. They argue that if reputation is a mere indicator of analyst ability or skill without any disciplinary effect on conflicts of interest, then any change in incentives for short-term opportunism will affect all analysts (reputable or non-reputable) equally. In other words, the differential in research quality between reputable and non-reputable analysts will remain unchanged over time regardless of whether short-term economic incentives vary. However, if non-reputable analysts have less to lose from a damaged reputation than reputable analysts, non-reputable analysts will act more opportunistically when short-term gains rise. Therefore, a dynamic setting where the severity of conflicts of interest varies over time can help answer whether reputation mitigates these conflicts.

Focusing on one particular incentive of underwriting-related compensation, Fang and Yasuda (2009) use market-wide underwriting volume in the equity new issues market (including both Initial Public Offerings and Secondary Equity Offerings) as a proxy for the severity of conflicts of interest. The reputation-as-discipline hypothesis is that superiority of reputable analysts' forecasts over non-reputable analysts' is greater during peak years of the new issues market.

Using forecast accuracy and unbiasedness as measures of research quality, Fang and Yasuda (2009) find that reputable analysts (with an All-American designation) are more accurate. In terms of unbiasedness, they find that reputable analysts become less positively biased relative to other analysts in peak years for the tech sector. For the non-tech sector, the level of reputable analysts' bias does not change relative to other analysts. The findings support the hypothesis that reputation has a disciplinary role in mitigating conflicts of interest. They conduct separate analysis on research quality in association with the reputation effect at the personal level and the bank level, and find that personal reputation works as an effective device against conflicts of interest, while bank reputation alone does not. The last finding contradicts Cowen et al. (2006). They find that optimism was lower for bulge underwriter firm analysts than others. Cowen et al. (2006) suggest that firm reputation reduces research optimism. However, Cowen et al. (2006) do not control for reputation at the analyst level. Reputable firms can attract and hire more reputable analysts more easily. Therefore, the observed negative association between optimism and firm reputation may be driven by an omitted variable, i.e., personal reputation.

In short, the literature has demonstrated that analysts have incentives to build a long-term personal reputation. In order to achieve it, they aim to provide high quality earnings forecasts. Evidence from studies discussed so far all relates to one single feature of quality forecasts, i.e., forecast accuracy.

2.3.2.2 Reputation and other forecast properties

A few studies add to the literature by presenting evidence on the effect of reputation on other dimensions of quality forecasts, such as timeliness, frequency, and consistency in previous forecast errors. Stickel (1992) finds that reputable analysts provide forecasts with more frequency and larger market price impacts (particularly for large upward forecast revisions) than other analysts. Schipper (1991) comments that "to the extent having the forecast sooner (even at the cost of less accuracy) implies greater investing profits to consumers of analysts' earnings forecasts, the loss function implied by pleasing customers will create a preference for timeliness" (p. 113). Clement and Tse (2003) later find evidence suggesting that stock return responses are greater for timely (early) forecasts than for later forecasts, even though timely forecasts are generally less accurate than later forecasts. Hilary and Hsu (2012) investigate consistency in forecast errors (i.e., errors are always negative or always positive) and find that analysts who deliver consistent forecast errors tend to be more reputable and are less likely to be demoted. They also find these analysts have greater ability to affect prices. Importantly, this effect of forecast error consistency on price changes is larger than that of forecast accuracy, particularly when institutional investors' presence is higher. They argue that Bayesian investors can unravel a systematic bias. Therefore, forecasts by analysts who display more consistent forecast errors are more informative.

Raedy et al. (2006) develop a theoretical model in which analysts' reputations suffer more (less) when subsequent news contradicts (confirms) analysts' views about a firm's future, for a given level of forecast inaccuracy. In the situation where subsequent news contradicts their views, analysts have to reverse their perceptions about the firm's prospects in their next reports. Frequent reversal of opinions affects the analyst's credibility both in public and within their brokerage firms. In addition, investors who buy or sell stocks based

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on forecast revisions stand to lose when later news contradicts the revisions. For example, when investors buy (sell) a stock following an upward (downward) revision, and later earnings announcement turns out to be lower (higher) than the latest forecast, they lose money. Consequently, analysts suffer more reputation costs than just being inaccurate. On the contrary, when subsequent news confirms analysts' views, analysts are proven to be in the right direction and investors who follow their revised forecasts are winners. Their reputation is affected by forecast inaccuracy, but not as negatively as in the first situation.

Given such an asymmetric loss function, Raedy et al. (2006) posit that analysts' underreact to information about earnings (e.g., restrain their forecast revisions) so as to create a greater probability that subsequent information will lead to forecast revisions (or a revision in investor expectations) in the same direction as their previous forecast revisions, rather than the opposite direction. This way, analysts minimise their reputation costs. Appendix 2-A provides a graphic depiction of their theory.

They further point out that when capital market frictions prevent stock prices from immediately unravelling analysts' underreaction in their forecasts, underreaction benefits investors who buy (sell) stocks following analysts' upward (downward) revisions. Otherwise, analysts would not face the asymmetric reputation loss imposed by the markets. Both theory and empirical evidence confirm that markets cannot unravel analysts' underreaction immediately (see Raedy et al. 2006). As a result, investors may prefer analysts' underreaction.

Raedy et al.'s (2006) theoretical model implies that underreaction increases with (1) the incremental reputation costs associated with revision reversal and (2) the uncertainty of subsequent disconfirming information about earnings. In the empirical part of their study, they employ quarterly data from 1984 through 1999 for US firms where each firm-quarter is required to have I/B/E/S one- and two-quarter ahead forecasts available within 20 calendar days after the initial quarter's earnings announcement and 40 days before the one-quarter-

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ahead earnings announcement. They find analysts underreact to both earnings surprise and earnings-related information that is reflected in stock returns. Most importantly, they find such underreaction is significantly greater in two-quarter-horizon forecasts than in one-quarter-horizon forecasts. Because forecast horizon is a proxy for uncertainty, the findings suggest underreaction increases with uncertainty, supporting their theory.

Raedy et al.'s (2006) theory adds to the reputation-building incentive literature by linking reputation to another dimension of quality earnings forecasts. As discussed above, investors care about whether the signals contained in earnings forecasts are consistent with the direction of future news. When analysts fail to do so, their reputation is adversely affected. Due to the asymmetric reputation loss function when faced with uncertainty, analysts prefer to underreact to available information to minimise their reputation loss. In this regard, to develop or maintain reputation, analysts' goal is to publish forecasts that convey a correct signal. The correctness means not only the historical norm of being accurate, but also being consistent with the implication of subsequent information. This theory is similar in the spirit of Hilary and Hsu (2012). Rather than looking at reputation and consistency in previous forecast error pattern like Hilary and Hsu (2012), the asymmetric reputation theory links reputation to the consistency between the direction of forecast revisions and that of subsequent news implications. As such, analysts' underreaction is a rational behaviour driven by the reputation-building incentive.

Also related to underreaction, Hugon and Muslu (2010) investigate conservatism in analysts' forecasts (i.e., less underreaction to bad news versus good news relatively to others). They argue that conservative analysts are not driven by short-term economic incentives (discussed in section 2.3.1) and, consequently, are more efficient and are in greater demand. They find that conservative analysts yield more accurate and persistent earnings forecasts, work for larger brokerage houses, and are more likely to be *Institutional Investor* All-

Americans. In addition, they find a stronger market response to forecast revisions of conservative analysts. Thus, they infer that the market generates demand for conservative analysts. In fact, this market demand is in line with analysts' reputation generation incentives.

Hugon and Muslu (2010) include persistent earnings forecasts as an efficient forecast dimension. They define persistence as a stronger association of forecast revisions with longer-term earnings revisions. They regress the two-year-ahead revisions on one-year-ahead revisions, an analyst conservatism measure, the interaction term between the prior two variables, and a set of control variables. Their results show that the interaction term is positive and significant, suggesting that more conservative analysts provide more persistent forecasts. While they do not directly test the link between reputation and persistence, the associations between analyst conservatism, reputation, and persistence establish an empirical link between reputation and persistence.

Interestingly, the persistence measure defined by Hugon and Muslu (2010) captures part of the concept of consistency between forecast revisions and future news as suggested in the asymmetric reputation theory. The positive association means that the direction of current forecast revison (the one-year-ahead revisions) is consistent with the direction of subsequent earnings news (the two-year-ahead forecast errors). As such, the findings in Hugon and Muslu (2010) provide evidence indicating that forecasts that are consistent with future news are informative and demanded by the markets.

Overall, this section reviews incentive-based studies in the earnings forecasts literature. Evidence from a number of studies demonstrates that analysts' inefficiency is driven by a range of short-term economic incentives. While recent regulatory changes targeting analysts' conflicts of interest appear to have some effects, many studies find that the short-term economic incentives, particularly trading commissions and management relations, do not disappear after the regulations. Meanwhile, several studies find that reputation is a

disciplinary mechanism that mitigates short-term economic incentives and increases the quality of earnings forecasts. Studies have suggested that reputation is positively associated with forecast accuracy, frequency, consistency in the pattern of forecast errors, and the relatively smaller underreaction to bad news versus good news.

Thus, analysts appear to face conflicting incentives: on one hand, they can generate short-term gains by issuing optimistic forecasts; on the other hand, they want to build a reputation by providing high quality forecasts. Given the evidence that optimism is diminishing along with methodological concerns about the optimism research, my thesis focuses on economic incentive-based explanations for analysts' underreaction. In particular, I examine underreaction in relation to analysts' economic incentives in the context of changing macroeconomic conditions.

2.4   Business cycles and earnings/earnings forecasts

In the macroeconomics literature, business cycles (also referred as economic cycles or economic fluctuations) are described as the periodic but irregular expansions and contractions in economic activity around a growth trend. They are normally measured by the growth rate in gross domestic products (GDP) and other macroeconomic variables such as the inflation rate and the unemployment rate. Research finds similarities in business cycles both over time and across countries (Krainer, 2003). Macroeconomic theories seek to explain why business cycles exist and to identify the appropriate macroeconomic policies that would correct the problems caused by business cycles. Figure 2 illustrates a typical business cycle.
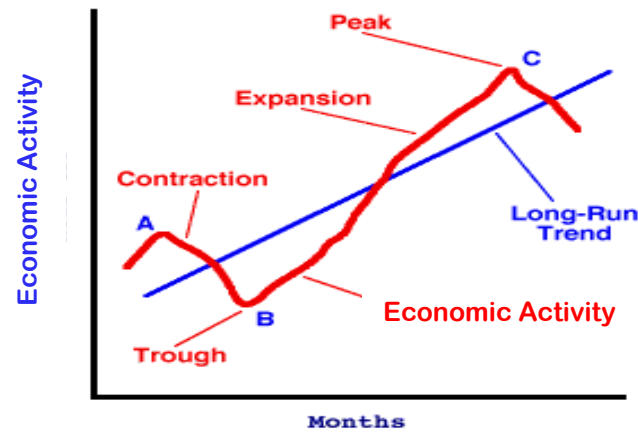
Figure 2   A typical business cycle

(Source:http://www.amosweb.com/cgi-bin/awb_nav.pl?s=wpd&c=dsp&k=business+cycles)

Expansions are periods from the trough to the peak, in which economic activity tends to increase. Recessions (or contractions) are periods from the peak to the trough, in which economic activity declines. In the US, business cycles are officially labelled by the National Bureau of Economic Research (NBER) which classifies business cycles into expansions and recessions. Specifically, the NBER identifies a recession as a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, and industrial production. Table 2-1 lists the official business cycles for the US economy since 1950.

In this thesis, I investigate whether analysts' underreaction in earnings forecasts depends on business cycles. Underlying the question are two key elements. The first element is that there is an association between reported earnings and business cycles. The second element is that analysts understand this association and incorporate it in earnings forecasts. As a macroeconomic condition affects a firm's fundamentals, the literature has examined earnings and earnings forecasts in association with business cycles. The following two subsections discuss the related literature in terms of these two underlying elements.

Table 2-1 The NBER official business cycles for the US economy

BUSINESS CYCLE REFERENCE DATES		DURATION IN MONTHS			
Peak	Trough	Contraction	Expansion	Cycle	
Quarterly dates		*Peak*	*Previous trough*	*Trough from*	*Peak from*
are in parentheses		*to*	*to*	*Previous*	*Previous*
		Trough	*this peak*	*Trough*	*Peak*
July 1953(II)	May 1954 (II)	10	45	55	56
August 1957(III)	April 1958 (II)	8	39	47	49
April 1960(II)	February 1961 (I)	10	24	34	32
December 1969(IV)	November 1970 (IV)	11	106	117	116
November 1973(IV)	March 1975 (I)	16	36	52	47
January 1980(I)	July 1980 (III)	6	58	64	74
July 1981(III)	November 1982 (IV)	16	12	28	18
July 1990(III)	March 1991(I)	8	92	100	108
March 2001(I)	November 2001 (IV)	8	120	128	128
December 2007 (IV)	June 2009 (II)	18	73	91	81

The National Bureau of Economic Research (NBER) classifies business cycles in US into expansions and contractions (or recessions) based on economic activity measured in total input, income, and employment. Expansions are periods from the trough to the peak, in which economic activity tends to increase. Contractions are periods from the peak to the trough, in which economic activity decreases.

2.4.1 Business cycles and earnings

Business cycle theory posits a positive relationship between firm earnings and cycles. Lucas (1977) discusses key features of business cycles, and one of the features is "business profits show high conformity and much greater amplitude than other series" (p. 9). Gomme and Greenwood (1995) develop a general equilibrium real business cycle model that provides a theoretical framework for pro-cyclicality of corporate profits.

Empirical evidence across the economics, accounting, and finance literatures widely shows an agreement that earnings are pro-cyclical. Chordia and Shivakumar (2002) find that earnings vary monotonically with the business cycle as measured by nominal GDP growth and inflation. Similarly, Bernstein and Arnott (2003) report a close long-term relationship between GDP and corporate profits in the US. Corporate profits have remained around 8 to

12% of GDP since 1929 except the Great Depression. Jin (2005) documents that sales growth, changes in profit margin, income before extraordinary items, net income, and total asset growth are positively associated with real GDP growth. Interestingly, he notes that the association is more pronounced during recessions than expansions. Taking an aggregate approach, Kothari, Lewellen and Warner (2006) find a strong positive association between changes in aggregate earnings and contemporaneous economic activity (including annual growth in GDP, industrial production and aggregate consumption). Focusing on the negative earnings in US, Klein and Marquardt (2006) document that accounting losses are mainly determined by business cycle factors such as recession, annual percentage change in GDP, and change in total industrial production. Finally, using non-US data, Gomme and Greenwood (1995) and De Zwart and Van Dijk (2008) document pro-cyclicality of earnings in seven OECD countries and 29 emerging markets, respectively.

In addition to the pro-cyclicality of earnings, a small body of accounting research also evaluates other documented features of earnings in association with business cycles. Johnson (1999) reports that earnings are more persistent and earnings response coefficients (ERC) are larger in expansions when growth rates are high than in recessions when growth rates are low. Khurana, Martin, Pereira, and Raman (2006) find that firms exhibit less earnings conservatism during expansionary periods. Earnings conservatism refers to the tendency that firms recognise losses in a timelier fashion than gains. They argue that the penalty for reporting bad news is greater when the economy is good. Consequently, firms face greater incentives to delay recording bad news in their earnings at such times. Similarly, Jenkins et al. (2009) report greater earnings conservatism during recessions. However, they argue that firms report more conservatively to avoid increased litigation risk and regulatory scrutiny in recessions. Jenkins et al. (2009) also find that earnings are more value relevant during

economic recessions. They explain that investors place greater weight on firms' current earnings in predicting future earnings in recessions where uncertainty is greater.

Overall, evidence suggests that earnings are pro-cyclical, and that certain characteristics of earnings (such as persistence, responsiveness to stock price, conservatism, and value relevance) vary with business cycles.

2.4.2   Business cycles and earnings forecasts

Given the empirical evidence on the impact of the business cycle on firm earnings, logically macroeconomic factors shall be an input for earnings forecasts and security valuations. In fact, a number of accounting and finance textbooks identify an analysis of the business cycle among the first steps in the forecasting and valuation process, e.g., Reilly (1979), Gitman and Joehnk (1999), Narayanan and Fahey (2001), Penman (2001), Soffer and Soffer (2003), Palepu, Healy, and Bernard (2004), Koller, Goedhart, and Wessels (2005), and Lundholm and Sloan (2007). These textbooks stress the importance of understanding earnings cyclicality and the necessity of using macroeconomic factors in security analysis. They recommend an understanding of relevant relations, sensitivities, and effects of macroeconomic changes, rather than predicting explicit macroeconomic variables per se.

In practice, analysts are known to factor economic outlook in their growth and earnings forecasts, albeit with some degree of variation in approaches across institutions. Elton, Gruber, and Gultekin (1984) observe that analysts either use a top-down or bottom-up approach. The top-down approach means analysts "start with forecasts for the economy as a whole, then prepare industry studies, and finally prepare forecasts for individual firms"; The bottom-up approach means analysts "start with the forecasts for individual firms and only after such forecasts are prepared, check with the economists' forecasts for macroeconomic consistency" (p. 355). Further evidence provided by analyst survey data (Chugh and Meador,

1984) and content analysis of analysts' reports (Previts, Bricker, Robinson, and Young, 1994; Rogers and Grant, 1997; Abdolmohammadi, Simnett, Thibodeau, and Wright, 2006) reinforces the understanding of macroeconomics as an important element of forecasting process in analysts' practice.

In spite of the role of the business cycle as an input to the earnings forecasting process, little research has investigated the relationship between business cycles and earnings forecasts. Brown (1993) evaluates the earnings forecast literature and comments that "the macroeconomic and industry factors asserted by analysts to be important cues to their decisions have been ignored" (p. 313). Almost two decades after his comment, the research on business cycles and earnings forecasts has not advanced much.

Chopra (1998) explores earnings forecasts for S&P 500 index firms from 1985 to 1997. He observes that the rolling 12-month-ahead earnings growth forecasts are too optimistic and within a too narrow range compared with actual growth. Further, he documents an inverse relation between earnings growth forecast errors and 12-month-lagged actual economic growth (IP).[9] The magnitude of growth forecast errors is greatest when IP growth is at a peak or trough. He offers an intuitive, but alternative explanation, for the seemingly improved earnings forecasts since 1993, i.e., while analysts maintain their optimism, earnings grow strongly during the long economic expansions and happen to match the usual analyst optimism. He suggests that analysts may focus too much on firm-specific issues but not enough on the overall macroeconomic environment.

Two academic studies examine forecast efficiency with respect to explicit macroeconomic variables. In contrast to Chopra's observation, their results are unable to reject the hypothesis of analyst rationality regarding macroeconomic activity. Hunter and Ackert (1993) include various macroeconomic variables as regressors in a regression of

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[9] Chopra (1998) finds that earnings growth lags IP growth by 12 months on average, and their correlation is 77%.

forecast errors from I/B/E/S quarterly data 1984-1990. They find insignificant coefficients on changes in the consumer price index, unemployment rate, and oil prices, although the change in gross national product is significant. Basu, Markov, and Shivakumar (2010) document that forecast errors for their portfolio based on relative inflation exposure can be predicted by expected inflation measures, but not industrial production. While the results appear to be mixed, there is evidence that analysts efficiently incorporate macroeconomic factors in earnings forecasts.

Specific to the two phenomena in earnings forecast inefficiency, evidence on the impact of business cycles is even more limited, particularly in terms of underreaction to earnings news. Prior studies have investigated time series changes in forecasts errors, e.g., Brown (2001b) suggests that analysts appear to be less optimistic over time. However, the business cycle factor is largely ignored with two exceptions.

Higgins (2002a) identifies the fourth quarter in 1990 as a recession period in the US and examines the attributes of analyst earnings forecasts in comparison with non-recession fourth quarters from 1984 to 1994. As a recession is difficult to predict by economic forecasters, Higgins (2002a) argues financial analysts face more task difficulty in recessions. She finds that earnings forecasts are more inaccurate, more optimistically biased, and more dispersed in the recession period than in other non-recession periods. During the recession period, the earnings forecasts of cyclical firms are more inaccurate and more optimistically biased than are those of other firms.

Higgins (2002b) examines analysts' earnings forecasts of Japanese firms during the 1989-1998 period, one of the country's worst and potentially longest recessions in the post-war era, using earnings forecasts of US firms as a benchmark. The findings suggest that forecast errors of Japanese firms have increased during the period, while those of US firms have decreased. The less accurate forecasts in Japan are mainly explained by three factors, all

of which are pertinent to the economic downturn. The foremost factor is the increasing frequency of losses reported by firms, which is consistent with more recent findings that more firms report losses during recessions (Klein and Marquardt, 2006) and that loss firms are difficult to forecast (Hwang, Jan, and Basu, 1996). The second factor is declining GDP growth. During prolonged economic downturns, governments and organisations tend to issue optimistic economic forecasts. Therefore, the optimistic expectations for GDP growth results in optimistically biased earnings forecasts, causing increased forecast errors. Another factor is the increased earnings volatility. This is also consistent with previous findings that firms' earnings are less persistent during recessions than expansions (Johnson, 1999), and that firms with high earnings volatility are inherently more difficult to forecast than those with less volatile earnings (Kross, Ro, and Schroeder, 1990).

Higgins (2002a, 2002b) focuses on optimism and the business cycle from cognitive perspectives, that is, a recession is more difficult to forecast. Hence, it is associated with greater optimism and dispersion. This appears to contradict the implication of analysts' efficiency in regard to macroeconomic factors inferred from Hunter and Ackert (1993) and Basu et al. (2010). Analysts' ability to understand macroeconomic factors and the observed cyclical variation in forecast optimism beg further explanations that go beyond cognitive or psychological reasons. In addition, the two 2002 studies conducted by Higgins only examine one economic recession due to the limited data period. More research is needed to further investigate a longer time period that spans several business cycles.

This section evaluates the importance of incorporating macroeconomic factors in earnings forecasts both in theory and in practice. However, little research has investigated the relationship between business cycles and earnings forecasts. Particularly, to my knowledge, no study has examined underreaction in relation to business cycles. Different from Higgins (2002a, 2002b), my thesis examines analysts' underreaction in relation to business cycles

from an incentive perspective using data from a longer time period. Unlike Hunter and Ackert (1993) and Basu et al. (2010), I focus on the effect of business cycles on the underreaction to earnings news (earnings surprise and stock returns), rather than forecast efficiency explicitly related to macroeconomic variables.

2.5   Summary

This chapter surveys the related literature in the areas of inefficiency in earnings forecasts, incentive-based explanations for such inefficiency, and earnings forecasts in relation to business cycles. Prior studies document optimism and underreaction with regard to inefficiency in earnings forecasts, albeit optimism in recent years appears to be less significant. While early studies offered psychological or cognitive explanations for forecast inefficiency, recent literature is more interested in incentives-based explanations. A large stream of the literature demonstrates that analysts' economic incentives cause conflicts of interest, resulting in forecasts that reflect optimism bias and excessive underreaction to bad versus good news. While recent regulatory changes aim to curtail some of the conflicts of interest, evidence shows incentives relating to trade commission and management relations still exist in the post-regulation period.

Another stream of literature adopts reputation theory, positing that analysts are incentivised to develop good reputations in the long term. Studies find evidence suggesting that reputation is a disciplining mechanism that can mitigate short-term economic incentives and increase the quality of earnings forecasts in terms of forecast accuracy, frequency, consistency of forecast errors, and analysts' conservatism. Due to coexisting but different types of incentives, analysts face a conflict between providing high quality forecasts to build their reputation and misleading investors via optimistic forecasts to generate short-term gains. Thus, with respect to analysts' underreaction in particular, the literature suggests links

between underreaction and multiple incentives: reputation incentives and underreaction in general with short-term economic incentives leading to excessive underreaction to bad news versus good news.

Last, given the substantial amount of evidence on the impact of macroeconomic conditions on firms' earnings, surprisingly little research examines earnings forecasts in association with business cycles, particularly the impact of business cycles on underreaction to earnings news.

Overall, the survey of extant literature reveals limited understanding with regard to:

(1) incentive-based explanations for analysts' underreaction, and

(2) the impact of business cycles on underreaction to earnings news.

My thesis extends the literature by examining the link between analysts' underreaction and economic incentives in the context of business cycles. Specifically, I focus on the reputation effect and examine reputation-building incentives in relation to underreaction. Further, I examine reputation-building incentives in relation to differential underreaction while considering the implications of short-term economic incentives simultaneously. Thus, my thesis will enhance our understanding on whether analysts' reputation concerns drive underreaction and whether analysts trade-off the coexisting but conflicting reputation-building and short-term economic incentives in different economic conditions.

Appendix 2-A

The following figure illustrates Raedy et al.'s (2006) asymmetric reputation cost theory from an intuitive perspective, i.e., why underreaction rather than overreaction is more likely to create consistency between forecast revisions and subsequent news (i.e., earnings announcement).
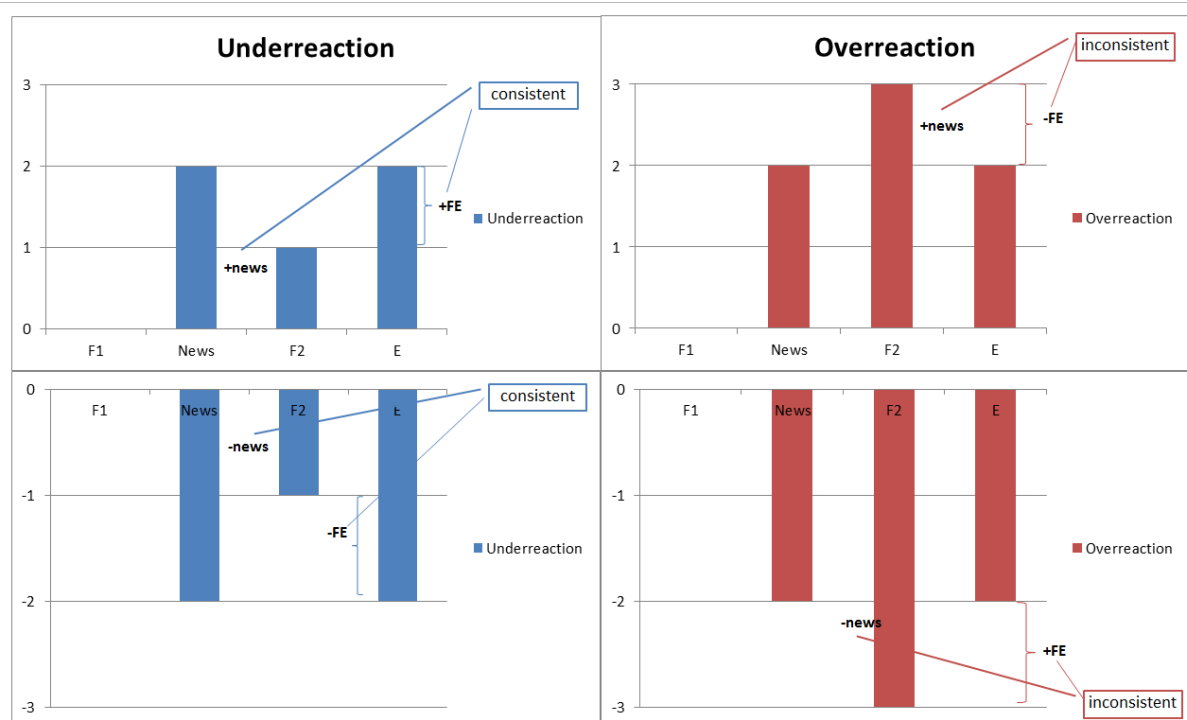
Figure 3   Underreaction/overreaction and consistency in analysts' forecasts

Figure 3 includes four situations depending on whether news is good or bad and whether an analyst underreacts or overreacts to the news. The upper panels assume a good news situation while the lower panels assume a bad news situation. The two panels on the left-hand side depict underreaction and the right-hand side panels depict overreaction. Assume an analyst predicts that a firm's upcoming earnings is $0 in his first forecast (F1). Also assume good news happens after F1, resulting in a $2 increase in the firm's actual earnings. In the top left panel, the analyst underreacts to the news and revises his forecast upwards only by $1. Later when earnings is announced to be $2, the forecast error (or the

revision in investor expectations) is positive ($2-$1), consistent with the positive prior news

reflected in the forecast revision. In contrast, the top right panel depicts that the analyst

overreacts to the news by revising the forecast upwards to $3. This causes a negative forecast

error ($2-$3), and hence, inconsistency between the later news and the analyst's most recent

revision. Similarly, in the lower two panels for a bad news situation, underreaction (the left

panel) creates consistency between the forecast revision and later earnings announcement

whereas overreaction (the right panel) fails to do so.

CHAPTER 3

HYPOTHESES DEVELOPMENT

This chapter develops hypotheses on cyclical variations in underreaction based on the links between analysts' underreaction and economic incentives discussed in Chapter 2. The logic in developing the hypotheses is that if certain incentives vary with business cycles, then due to the incentive-underreaction links, analysts' underreaction will accordingly vary with the business cycles. Thus, the hypotheses are dual tests for (1) analysts' incentives vary cyclically and (2) underreaction is driven by analysts' incentives.

Specifically, section 3.1 focuses on the reputation-building incentive solely, hypothesising an association between business cycles and analysts' underreaction in general. The hypothesised association relies on the reputation effect literature and the asymmetric reputation cost theory, in particular. I start with predictions about cyclical variations in the factors that lead to underreaction, i.e., uncertainty and asymmetric reputation cost. Regarding the uncertainty hypothesis, I argue that during bad times, firms are reluctant and slower to disclose information, earnings are more likely to include large transitory items, and macroeconomic forecasts are of poorer quality. All these factors lead to greater uncertainty in recessions. Regarding the asymmetric reputation cost hypothesis, I draw on investor loss aversion theory and argue that expansionary periods are associated with greater investor loss aversion, and hence, a more severe reputation penalty when the signal implied by analysts' forecasts is subsequently proven incorrect. This leads to greater asymmetric reputation cost during expansions. Finally, taking into account the predicted cyclical changes in uncertainty and asymmetric reputation cost (of which the directions are opposite), I hypothesise an unsigned relationship between business cycles and underreaction in general.

Section 3.2 distinguishes good news and bad news when estimating underreaction to earnings and earnings-related news. Based on the reputation theory, I predict that analysts will need to underreact more to good news than bad news in recessions, in order to protect themselves from reversing their forecast revisions, because good news is more likely to be reversed in bad times. I also consider the implications of short-term economic incentives as suggested in the prior literature. If short-term economic incentives are the main driving force, then one would expect that analysts will underreact more to bad news than good news in recessions when short-term economic incentives are stronger. Clearly, the conflicting incentives create a tension in predicting the direction of the cyclical variation in differential underreaction. As a result, I hypothesise an unsigned association between business cycles and analysts' asymmetric underreaction to bad versus good news.

3.1 Underreaction in general

As previously noted, underreaction in general is related only to reputation-building incentives. The literature does not offer any theory on short-term economic incentives to explain underreaction in general. Thus, this section hypothesises the potential cyclical changes in underreaction in general, focusing on reputation-building incentives.

Subsection 2.3.2 reviews a large body of research that demonstrates a positive reputation effect on analysts' forecast quality. Reputation is associated with long-term economic benefits including job security, promotions, favourable job separations, and future broker trading volume (Mikhail et al., 1999; Hong et al., 2000; Hong and Kubik, 2003; Jackson, 2005). Hence, analysts are incentivised to improve the quality of their earnings forecasts due to the reputation effect. As the literature commonly uses forecast accuracy as a forecast performance indicator, the vast majority of existing studies on reputation-building incentives focus on accuracy. These studies provide evidence suggesting that reputable

analysts produce more accurate forecasts than non-reputable analysts. Examples include Stickel (1992), Hong and Kubik (2003), Jackson (2005), Leone and Wu (2007), and Fang and Yasuda (2009).

While accuracy is certainly important and a major contributor to forecast quality, it represents only one dimension of quality and the usefulness of earnings forecasts. A few studies investigate other dimensions of forecast quality. They document that reputation is positively associated with forecast frequency (Stickel, 1992), analyst conservatism (Hugon and Muslu, 2010), consistency in previous forecast errors (Hilary and Hsu, 2012), and larger market price impacts (in all the three studies).

While some of these quality features might be correlated with each other, forecasts that contain different dimensions of quality obviously provide investors with different aspects of information. For example, Hilary and Hsu (2012) find that consistency in forecast errors has a positive effect on market price changes, and that this effect is even larger than that of accuracy when the proportion of institutional investors is higher. This implies that, for investors, other features of forecast quality are as important as, or more important than, accuracy. Therefore, I examine the link between reputation and a different dimension of analyst quality.

Following reputation effect theory and Raedy et al.'s (2006) asymmetric reputation cost theory (see subsection 2.3.2 for detailed discussions), I focus on the consistency between analysts' view about the firm's future (e.g., the direction of forecast revisions) and subsequent news implications (e.g., earnings announcement). I argue that with the arrival of new information, analysts prefer not to fully incorporate it in forecasts, but underreact to new information while maintaining a certain range of accuracy. This way, they can create a higher probability of having the same direction between the signal implied in their forecasts and subsequent news, hence protecting them from incurring a larger amount of implicit reputation

cost imposed by investors. Hugon and Muslu (2010) find evidence suggesting that the persistence between one- and two-year-ahead analysts' revisions, an empirical example of consistency between analysts' view and subsequent news, is demanded by the markets.

The asymmetric reputation cost theory predicts that underreaction increases with uncertainty and asymmetric reputation cost. To gauge the impact of business cycles on underreaction, it is necessary to first evaluate how business cycles impact the two determining factors of underreaction. Hence, the following subsections hypothesise cyclical variations in uncertainty and asymmetric reputation cost, respectively.

3.1.1 Uncertainty and business cycles

The level of information uncertainty is likely to be different across business cycles due to several reasons. First, different states of the economy are associated with different disclosure behaviour, resulting in different levels of information richness. As discussed in subsection 2.4.1, prior research finds empirical evidence suggesting that earnings are pro-cyclical (Chordia and Shivakumar, 2002) and that accounting losses are dominantly determined by recessions (Klein and Marquardt, 2006). Firms are more likely to have bad news in bad times. Brown (2001b) finds that managers in loss firms are reluctant to forewarn analysts of impending bad news. In a similar vein, Lang and Lundholm (1993) find that analyst ratings of corporate disclosures are lower for poor-performing companies than for well-performing companies. Hong et al. (2000) and Lim (2001) further confirm that when companies are sitting on bad news, managers tend to be less forthcoming. Therefore, firms are more reluctant and slower to disclose information at the aggregate level in recessionary periods, resulting in greater information uncertainty.

Furthermore, firms show different reporting behaviour in different economic conditions. Prior research demonstrates that earnings are less persistent and earnings response

coefficients are smaller in recessions (Johnson, 1999), and that earnings are more conservative in recessions (Jenkins et al., 2009). Analysts are faced with more uncertainty when firms may include more transitory items or recognise bad news faster in recessions. In short, the increased level of earnings losses, volatility, and conservatism are expected to increase the level of uncertainty about earnings during recessions. This expectation is consistent with evidence from prior studies, albeit indirectly, that loss firms and high earnings volatility firms are more difficult to forecast (Kross et al., 1990; Hwang et al., 1996).

Moreover, the poor quality of macroeconomic forecasts for recessions creates greater uncertainty about earnings. The macroeconomic outlook is one of key inputs to analysts' forecast models. The reliability of economic forecasts contributes to information certainty about firms' future sales and earnings. However, the economic forecast literature has revealed that economists in US and world-wide generally are unable to predict recessions in advance, often underestimate the extent of recessions until late in the course of the recession, and are unable to distinguish between slow/negative growth and rapid growth (see Higgins 2002a for more details). Reasons include the lack of reliable real-time data and predictive models, and the lack of incentives for forecasting recessions. This predictive failure in recessions makes forecasting earnings more difficult. This is consistent with Chopra's (1998) and Higgins' (2002a) findings of more inaccurate earnings growth forecasts and earnings forecast during recessions. During recessionary periods, economic indicators have started to show unfavourable signs. Given the poor quality of the macroeconomic forecasts for recessions in history, financial analysts are more uncertain about economic growth rates, which they use to project sales and earnings, than in an expansion. Thus, uncertainty about future sales and earnings is expected to be greater in recessions than in expansions.

The above three arguments unanimously suggest uncertainty to be greater in recessions than expansions. Consistent with this expectation, Higgins' (2002a) finds that

forecast dispersion (a well-used proxy for information uncertainty) is greater in one recessionary period than other non-recessionary periods. Accordingly, my first hypothesis is (all hypotheses are stated in the alternative form):

H1a: Uncertainty about future earnings is greater during recessions than during expansions.

The asymmetric reputation cost theory posits that analysts' underreaction increases with uncertainty and asymmetric reputation cost. While asymmetric reputation cost is a relatively new concept in the literature, the effect of uncertainty on analyst underreaction has been examined empirically. Zhang (2006) presents evidence that greater information uncertainty predicts greater analyst underreaction, i.e., more positive (negative) forecast errors and subsequent forecast revisions following good (bad) news. Raedy et al. (2006) find underreaction increases with uncertainty measured by the length of forecast horizon. Clement et al. (2011) view analyst underreaction as a cautious reaction to uncertainty or ambiguity in the precision of a signal: "to the extent that analysts are uncertain about how informative a stock return or analyst revision is likely to be, we expect them to temper their use of these signals, consistent with psychological research on conservatism and ambiguity aversion" (p. 282). While they take a psychological perspective to explain underreaction, their view nonetheless supports the positive effect of uncertainty on underreaction. Given the existing theory and empirical evidence on the uncertainty-underreaction link, a reasonable prediction as an extension of H1a would be that analyst underreaction is greater in recessions than expansions *ceteris paribus*. Next, I study the other factor that leads to underreaction, i.e., asymmetric reputation cost.

3.1.2   Asymmetric reputation cost and business cycles

As discussed in subsection 2.3.2, investors have the power to impose implicit reputation costs on analysts via investment decisions and responses to surveys ranking the analysts. This is demonstrated by empirical links among forecast quality, analysts' rankings, and market response. Prior studies find that investors' value function determines their investment decisions and, consequently, influences their investment performance. Clearly, investors' decisions in evaluating analysts hinge on investors' own value function, as much as analysts' forecast quality. In the following paragraphs, I briefly discuss loss aversion (a widely accepted value function theory in the economics and finance literature) and its linkage to asymmetric reputation cost theory. Drawing on Hwang and Satchell (2010) who find that loss aversion changes depending on market conditions, I develop a hypothesis on the association between asymmetric reputation cost and business cycles.

Kahneman and Tversky's (1979; 1992) prospect theory is widely accepted in the literature to describe investors' value function. According to prospect theory, individuals are concerned with the changes in wealth (in terms of gains or losses) rather than with its final state. Moreover, individuals are more sensitive to losses than to gains – an individual feels more painful with a loss than he feels happy with an equal-sized gain. Specifically, an individual's value function is concave with respect to gains and convex with respect to losses, and the value function has a much steeper slope for losses than gains. This phenomenon is referred to "loss aversion".

Empirical research has examined prospect theory in the equity markets. Evidence has accumulated that investors (including professional investment managers) have an asymmetric risk attitude towards gains and losses when making investment decisions and that they are more concerned with losses than gains, confirming loss aversion theory. Examples include Shefrin and Statman (1985), Olsen (1997), and Ding et al. (2004) among others. Abdellaoui

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et al. (2007) further find the existence of loss aversion both at the aggregate and at the individual level.

Investors' loss aversion has implications for asymmetric reputation cost. Loss aversion and asymmetric reputation cost are linked due to the fact that investors use analysts' forecasts to make investment decisions. Numerous studies have documented that forecasts have information content (see Ramath et al., 2008a, for details). A recent example, Beaver, Cornell, Landsman, and Stubben (2008), find forecast errors, and quarter- and year-ahead earnings forecast revisions have significant effects on stock prices, indicating that each conveys information content. In particular, quarter-ahead forecast revisions are relatively more important in affecting stock prices. This, among many others, provides evidence that investors do act on analysts' forecasts. I have discussed in subsection 2.3.2 that investors who buy or sell stocks based on forecast revisions stand to lose when later news contradicts analysts' opinion about the firm's prospect (e.g., forecast revisions), and this is a major reason why asymmetric reputation cost arises. When investors are more afraid to incur a loss, they would experience a greater amount of displeasure for the same amount of loss. Consequently, investors would impose higher implicit reputation costs on the analyst (e.g., via ranking systems) if subsequent information creates a reversal of expectations about the firm. To this effect, one can reasonably expect that greater investors' loss aversion leads to greater asymmetric reputation cost imposed on analysts.

Hwang and Satchell (2010) find evidence suggesting greater loss aversion in good times than bad times. They examine the robustness and appropriateness of loss aversion utility functions in financial markets. Specifically, they use a typical asset allocation problem for investors with loss aversion utility to determine the appropriate ranges of loss aversion parameters, including two curvature parameters explaining the sensitivity of utility to losses and gains, and a coefficient of loss aversion measuring the relative disutility of losses against

gains. They find that US investors are more loss averse than Kahneman and Tversky (1992)

suggest and because the curvature on losses is larger than that of gains, investors are more

sensitive to the changes in losses than to the equivalent changes in gains. Importantly, in their

analytical part, they find that the loss aversion coefficient is larger during boom periods (or

bull markets) than during recessions (bear markets), indicating that loss aversion changes

depending on market conditions. Their empirical results, based on US and UK data, support

their analytical results. In particular, they propose a loss aversion coefficient of 3.25 for the

US investors, which should be increased and reduced by 1.5 during bull and bear markets,

respectively. These calculated numbers demonstrate the significance of the effect of market

conditions on loss aversion.

Hwang and Satchell (2010) offer an intuition about their finding: during boom periods

when other investors enjoy gains, an investor suffers relatively more deprivation from losses;

during recessions, on the other hand, he experiences relatively less displeasure from the same

amount of losses when most other investors lose money. Alternatively speaking, relative

performance matters to investors' value function. In a similar vein, Conrad, Cornell, and

Landsman (2002) demonstrate that investor reaction to earnings disappointments is more

adverse during good times.[10] Cohen and Zarowin (2007) take a similar view in the context of

earnings management and find greater earnings management in expansions because of

managers' stronger incentive to avoid poor earnings performance in good times.

Conrad et al. (2002) and Cohen and Zarowin (2007) indicate that investors impose a

greater penalty on firms with bad news in good times than bad times. This research looks at a

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[10] Conrad et al.(2002) use regime-switching models to explain why the aggregate market can respond more
strongly to bad news than good news in good times due to the uncertainty about the state of the economy. When
investors are highly confident the market is in a good state, further good news has little impact on investor
beliefs. However, bad news causes market prices to fall because (1) bad news causes investors to infer a lower
probability that the market is in the good state, and (2) as uncertainty in the state of the economy increases, risk-
averse investors require a higher expected rate of return to hold stocks. When investors believe that the economy
is in a bad state and good news arrives, the inferred probability that the market is in a good state increases; thus,
the positive impact on prices is offset by the rising discount rate generated by increased investor uncertainty.

different perspective that investors impose a larger penalty on analysts when they believe that

the analysts are responsible for their losses during good times than bad times (i.e., when the

signal contained in analysts' forecasts is different from what subsequent news implies).

In short, this subsection has argued that (1) greater loss aversion results in greater

asymmetric reputation cost, and (2) loss aversion is greater during expansions than recessions.

Thus, I hypothesise:

H1b: *Analysts' asymmetric reputation cost is greater during expansions than during*

     recessions.

There are a few issues worth discussing. First, the notion of greater loss aversion

during expansions appears to be inconsistent with the house-money effect, a phenomenon of

increased risk seeking in the presence of a prior gain. Thaler and Johnson (1990) propose that

decision makers' risk-taking is affected by prior gains and losses. They conduct real money

experiments and find that when faced with sequential gambles, people are more willing to

take risk if they made money on prior gambles than if they lost. They interpret these findings

as revealing that losses are less painful to people if they occur after prior gains, and more

painful if they follow prior losses. Barberis, Huang, and Santos (2001) incorporate this in the

capital market asset pricing framework. These authors argue that investors' loss aversion

depends on their prior investment performance. Particularly, investors become less loss

averse after a prior gain because the prior gain will cushion any subsequent loss, making it

more bearable. Conversely, they become more loss averse after a prior loss because they are

more sensitive to additional setbacks after being burned by the initial loss. In the business

cycle context, Barberis et al.'s (2001) framework would mean that investors are more afraid

to making more loss when they have already suffered losses during recessions. That is, loss

aversion might have been greater in recession. However, Hwang and Satchell (2010) address

this issue in their paper:

> *[O]ur main results should still hold for the dynamic loss aversion function*
>
> *proposed by Barberis et al. (2001). Allowing loss aversion to depend on past gains*
>
> *and losses should not change our main results that loss aversion increases during bull*
>
> *markets. Intuitively, the regret and house money effects from past losses and gains*
>
> *differ from the relative effects that investors feel by comparing others' performance.*
>
> *(p. 2437)*

More importantly, the house-money effect per se is still debatable. Zhang and

Semmler (2009) point out that the Barberis et al. (2001) theory does not consider the so

called break-even effect, whereby even if they have some losses in the previous period,

people may also become (more) risk-seeking in the current period in the hope of getting a

chance to break even. Therefore, the effect of losses in the current period on decisions in the

next period may not be as clear as that of gains. That is, previous losses in stocks may induce

risk seeking. Zhang and Semmler's (2009) empirical results from US data support their

finding that previous losses do not always induce risk-aversion possibly due to the break-

even effect.

Another issue is the measurement for good and bad times. The above-mentioned

studies do not universally use business cycles to measure good and bad times. However,

business cycle data are widely used as measures for either business or market conditions.

Researchers have documented substantial linkages between an economy's performance and

financial market performance. For example, King and Rebelo (2000) and Ahmad (2005)

document a strongly pro-cyclical stock price index.[11] Particularly for the US economy, one of

the major empirical facts is the positive correlation between the stock price index and real

economy activity over the course of many business cycles. Hwang and Satchell (2010) use

the regime switching model (see p. 2431 in their paper for details) and identify bull and bear

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[11] Ahmad (2005) notes that S&P 500 stock price index is much more volatile than real GDP.

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markets within their sample period from 1989 to 2008. Bear markets include 1990, 1998, 2000-2003, and 2007-2008, concurrent with the NBER recessionary periods. Conrad et al. (2002) use relative P/E ratios to measure the level of sentiment in the markets. McLean and Zhao (2011) document a significant and positive correlation between investor sentiment and business cycle variables. Thus, it is meaningful for this study to use business cycles as a proxy for good and bad times.

To summarise, this section argues that different economic conditions create dynamic changes in the two factors leading to underreaction. Specifically, the level of uncertainty is predicted to be greater in recessions whereas asymmetric reputation cost is expected to be greater in expansions. As uncertainty and asymmetric reputation cost are expected to move in opposite directions across business cycles, there is a tension in predicting the change in analysts' underreaction in relation to business cycles. The result of this study would provide evidence on whether the reputation effect or the uncertainty effect dominates and ultimately influences analysts' underreaction. Accordingly, the hypothesis about underreaction in general and business cycles is unsigned:

H1c: Analysts' underreaction is different during recessions than during expansions.

3.2   Asymmetric underreaction to bad news versus good news

This section further investigates analysts' underreaction by separating good news and bad news. Drawing on the prior literature, I hypothesise cyclical variations in asymmetric underreaction to bad versus good news. Both types of analysts' incentives have implications for asymmetric underreaction. Hence, I discuss my hypothesis development based on reputation-building incentives in the first subsection and short-term economic incentives in the second subsection.

3.2.1   Reputation-building incentives and asymmetric underreaction

With respect to reputation-building incentives, Hugon and Muslu (2010) argue that analysts who care about their reputation should restrain them from excessively underreacting to bad news, because such behaviour is driven by short-term economic incentives. They find that conservative analysts are more likely to be All-Americans ranked by *Institutional Investor* and engender stronger market responses than aggressive analysts. This evidence is important in the sense that investors, particularly institutional investors, are able to identify more efficient analysts from those who behave opportunistically due to various short-term economic incentives, and consequently, they reward efficient analysts with higher rankings and larger price movements. As such, one would expect analysts driven by reputation-building incentives to show symmetric underreaction to bad and good news. In the business cycle context, this theory does not appear to allow for any cyclical variation in underreaction. On the other hand, Raedy et al. (2006) offer a richer reputation-building incentive theory that allows the symmetry or asymmetry in underreaction to vary with business cycles.

The asymmetric reputation cost theory posits that analysts underreact to prior information to create the possibility of having the same direction between the implications of subsequent information (on a revision in investor expectations) and previous forecasts (forecast revisions). Consider a stable economic environment where there is a fifty-fifty chance of future news being good or bad at the aggregate level. The reputation-building incentive would lead to a symmetric underreaction to good news and bad news. For example, Raedy et al. (2006) find no significant difference in underreaction to good news than to bad news observations.[12] This is consistent with Hugon and Muslu's (2010) view of conservative analysts with symmetric underreaction due to reputation concerns.

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[12] Some evidence from Raedy et al. (2006) suggests there is significantly less underreaction for the bad news observations.

Now take variations in economic conditions into consideration. In good times, investors generally are confident that the economy is in the good state. Accordingly, investors and analysts generally believe that good news is more likely to follow. This is supported by the observed correlation between business cycles and investor confidence measures (see Appendix 3-A). Analysts have incentives to maintain consistency between their views and future news, protecting themselves from reversing their revisions. If they anticipate that, in expansions, good news is more likely to follow good news, and good news is more likely to follow bad news, they need to underreact more to bad news than to good news in expansions. In other words, if a firm currently has good news, analysts would respond more to good news because the likelihood of future good news is high, hence the higher likelihood of being consistent. In contrast, if the firm currently has bad news in good times, analysts will respond less to bad news. That is, analysts would relatively underreact more to bad news in expansions to minimise the likelihood of revision reversals during expansions. In this argument, the asymmetric reputation cost is held constant because we focus on expansions. The differential reaction to good versus bad news is due to the different level of uncertainty about future good versus bad news in expansions.

Likewise, during recessions analysts believe that bad news is more likely to follow generally, so they would underreact more to good news than to bad news to protect themselves from reversing their view about the firm's prospect. In other words, analysts are expected to exhibit excessive underreaction to good versus bad news during recessionary periods.

3.2.2   Short-term economic incentives and asymmetric underreaction

In this subsection, I consider the implications of short-term economic incentives on analysts' differential underreaction. Prior research has established the link between short-

term economic incentives and analyst inefficiency, providing arguments and evidence that analysts publish optimistic forecasts due to the desire to maintain good management relations, to generate more trade commissions, and to secure job promotions (e.g., Francis and Philbrick, 1993; Hong and Kubik, 2003; Jackson, 2005). Rather than optimism bias that many studies have examined, I consider the asymmetric response to the upcoming news as a type of optimistic forecast behaviour, i.e., a greater level of underreaction to bad news versus good news. The excessive underreaction to bad news leads to an optimistic outcome on balance. Hence, such behaviour can be attributed to analysts' short-term economic incentives (Easterwood and Nutt, 1999; Hugon and Muslu, 2010). Hugon and Muslu (2010) provide empirical evidence that aggressive analysts are less reputable and have lower ability to affect price, compared to analysts who underreact to bad news in a less pronounced manner.[13] Their study examines the excessive underreaction relative to that of other analysts whereas I investigate the time-variation of excessive underreaction at the aggregate level.

Given the linkage between excessive underreaction to bad news and short-term economic incentives, the potential cyclical changes in excessive underreaction depend upon how short-term economic incentives change in different business cycles. Accordingly, I discuss in the following paragraphs how a weakened economy affects these incentives, mainly from three perspectives: management relations, trade generation, and job concerns.

First, with respect to the incentive to maintain good management relations, previous research has found that this incentive is greater when benefits of obtaining or demands for private information are higher, e.g., when earnings are more unpredictable (Das et al., 1998) and target-specific uncertainty is higher (Lim, 2001). While these findings are based on the firm level, the same argument can apply to a more general level. As earnings are less

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[13] In their paper, Hugon and Muslu (2010) refer to aggressive analysts as analysts that make weaker revisions in response to bad news versus good news relative to their peers. That is, the excessive underreaction to bad news for aggressive analysts is more pronounced.

predictable and uncertainty about the firm is greater in recessions, one would expect the incentive to maintain management relations to be greater during recessionary periods.

Second, with respect to the trade commission incentive, recessions are generally associated with greater stock volatility and greater stock market illiquidity. Hamilton and Lin (1996), among others, find that economic recessions are the single largest factor contributing to stock market volatility, accounting for over 60% of the variance of stock returns. Naes et al. (2011) document a strong relation between stock market illiquidity (i.e., the costs of trading equities) and recessionary periods. Due to the increased stock volatility and trading costs, investors are more cautious to participate in the equity markets. Naes et al. (2010) find that investor participation (especially in small firms) decreases when the economy worsens. Therefore, analysts are faced with more pressure to generate trades in recessions. The pressure is heightened when the weakened economy reduces the number of firms about which analysts could have favourite views and issue positive recommendations. Consequently, they may have to issue optimistic forecasts that deviate from their true belief about the firm.

Last, with respect to analysts' job concerns, the labour market in the finance industry (among other industries) deteriorates in economic downturns. The weak economy and volatile stock markets reduces the probability that investors would want analysts' opinions and advice in the near future, which triggers job cuts in the financial industry. According to the Bureau of Labor Statistics (Series Id: CES5500000001), the average growth rate of US financial industry employees after 1981 is 1.98% in expansionary years versus -0.67% in recessionary years. Particularly in the most recent recession, the financial industry employment in June 2010 has declined by 7.73% since the last peak in December 2007. Clearly, analysts become more worried about losing their jobs in recessions. The pressure to

generate trades and the pressure to keep their job are not mutually exclusive but complement each other.

In short, analysts have greater incentives to maintain management relations, to generate trading commissions, and to increase their job security during recessions compared to expansions. All of these enhanced economic incentives would lead to a greater level of excessive underreaction to bad versus good news in recessions.

Note that another economic incentive – investment banking businesses – is not included in the above arguments. The reason is that this incentive has little impact on earnings forecasts. While the literature documents that investment banking-related incentives have strong effects on observed optimism in analysts' reports, they are largely reflected in stock recommendations and long-term earnings growth forecasts (e.g., Lin and McNichols, 1998; Michaely and Womack, 1999; Dechow et al., 2000; Irvine, 2004). Even the statistically significant results on recommendations and growth forecasts do not have large economic significance (Bradshaw, 2011).

In terms of earnings forecasts, there are no statistically significant differences in optimism between affiliated and non-affiliated analysts in Lin and McNichols' (1998) study, which Bradshaw (2011) identifies as "one of the most compelling studies to review because of the relatively large sample and well-executed matched sample design". Dugar and Nathan (1995) is perhaps the only study that finds earnings forecasts from affiliated analysts are more optimistic. However, their results are inconsistent with other studies, especially with Jacob, Rock, and Weber (2008) who find affiliated analysts provide superior earnings forecasts due to informational advantages. Ramnath et al. (2008a) comment that Dugar and Nathan's (1995) results are possibly driven by using a smaller and older sample, a smaller set of control variables, and "comparing forecasts from analysts employed by the target's underwriter to all other analysts (as opposed to comparing analysts employed by investment bankers generally

to all others)" (p. 379). In addition to the insignificant effect on earnings forecasts, Cowen et al. (2006) demonstrate that the investment banking incentive is weaker than the trading commission incentive that has been included in the above arguments. As such, I believe that the exclusion of the investment banking incentive in this context is unlikely to have any material impact on my results and inferences.

Overall, the implications of different incentives on asymmetric underreaction in the business cycle context are different, especially during recessions. Specifically, the reputation-building incentive argument predicts that analysts underreact less (more) to bad news than good news in recessions (expansions). On the other hand, the short-term economic incentive argument predicts that analysts generally underreact more to bad news than to good news. When these incentives are enhanced during recessions, the excessive underreaction to bad news is more pronounced. As reputation-building incentives and short-term economic incentives lead to different predictions on the asymmetric underreaction during recessions, the hypothesis on cyclical changes in asymmetric underreaction is unsigned:

H2:   *Analysts' asymmetric underreaction to bad news versus good news is different during recessions than during expansions.*

Appendix 3-A

There are several measures of market confidence, including the Michigan Consumer Sentiment Index, the Conference Board Consumer Confidence Index, and the NFIB Business Optimism Index.[14] In particular, consumer confidence has received some attention in the literature as a measure of investor confidence. Examples include Statman and Fisher (2002), Qiu and Welch (2004), Lemmon and Portniaguina (2006), and Bergman and Roychowdhury (2008). Lemmon and Portniaguina (2006, p. 1501) show that the indexes of consumer expectations from the University of Michigan (one of the Michigan Consumer Confidence Index) and the Conference Board (CBEXP) are good predictors of business cycle peaks and troughs. Advisor Perspectives, a research company, provides charts on correlations between various market confidence measures and the broader economy on its website (the charts can be viewed at http://advisorperspectives.com/dshort/updates/Michigan-Consumer-Sentiment-Index.php). These charts highlight a general pattern that recessions (expansions) are associated with lower (higher) index values of the Michigan Consumer Sentiment Index, the Conference Board Consumer Confidence Index, and the NFIB Business Optimism Index.

In short, the evidence on the correlation between macroeconomic conditions and market confidence supports the notion that investors are optimistic and confident during economic expansions and vice versa. While these index numbers are more volatile, a higher degree of volatility within a certain business cycle would work against this study, i.e., making it harder to find significant results.

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[14] The literature generally uses the University of Michigan index of consumer confidence as a measure of investor optimism/confidence, e.g., Lemmon and Portniaguina (2006). The monthly index is based on a survey of a large number of households on their personal financial situation, their expectations regarding the US economy, and their propensity to consume major household items. The Conference Board Consumer Confidence Index is based on monthly Consumer Confidence surveys, conducted for the Conference Board by Nielsen, a global provider of information and analytics around what consumers buy and watch. The NFIB Business Optimism Index is based on ten indicators from monthly surveys conducted by the National Federation of Independent Business (NFIB).

CHAPTER 4

RESEARCH DESIGN

This chapter presents the research method used in this study to test the hypotheses developed in the previous chapter. The first section describes the forecast time line and defines forecast subperiods between quarterly earnings announcements. Partitioning the quarter into early and late forecast subperiods is important because it allows me to test the hypotheses for periods with different forecast horizons and different amounts of prior information. The second section defines the main variables. The third section presents regression models for each hypothesis.

4.1 Forecast timeline

To evaluate the impact of the business cycle on analysts' underreaction, I focus on one-quarter-ahead earnings forecasts issued between quarterly earnings announcements. I choose one-quarter-ahead forecast for several reasons. First, using quarterly forecasts enables a larger number of observations than using annual forecasts. Second, a quarterly period allows a finer classification of expansions or recessions than an annual period. Last, macroeconomic forecasts are more accurate in a shorter forecast horizon (e.g., one quarter ahead) than a longer horizon (e.g., one year ahead). This alleviates the concern that the results are affected by lower quality with regard to macroeconomic forecasts.

Prior studies document that the pattern of analyst forecasts differs depending on the forecast horizon and that analysts underreact to different types of earnings news. This study examines the research questions by looking at different forecast stages and different types of news. I partition each between announcement period into early and late forecast subperiods as shown in Figure 4.
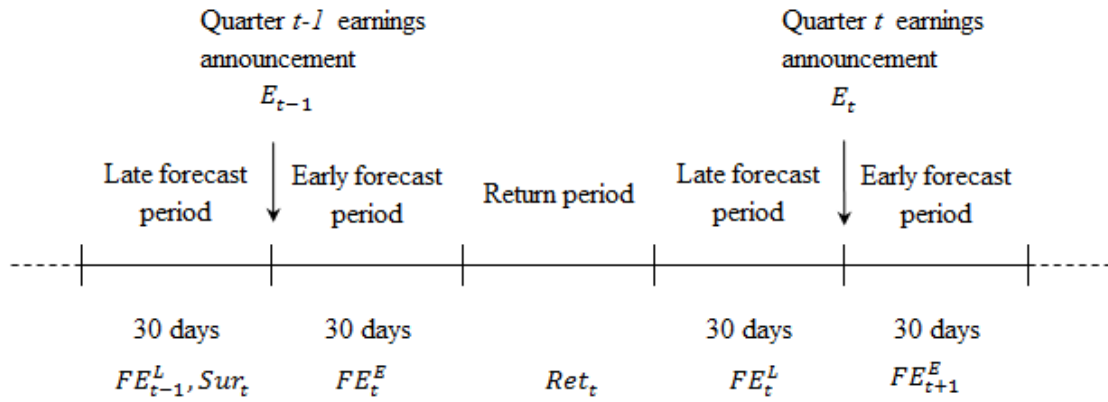
Figure 4 Forecast time line and variables

The early forecast period includes the 30 days immediately following the last quarterly earnings announcement, i.e., the 30-day period after E_{t-1} in Figure 4. The late forecast period includes the 30 days immediately preceding the one-quarter-ahead earnings announcement, i.e., the 30-day period before E_t. As in Raedy et al. (2006), I estimate underreaction to the prior quarterly earnings surprise Sur_t (i.e., prior late forecast error FE_{t-1}^L), using forecasts issued during the early period. I employ forecasts issued during the late period to estimate underreaction to other earnings-related information reflected in returns Ret_t. The rationale is that analysts may put different emphasis on various types of information at different stages.

During the early forecast period, analysts largely respond to the latest earnings announcement, hence the focus is on the underreaction to the prior quarter's earnings surprise. Later, as the end of the forecast period gets closer, analysts will turn their attention to the more concurrent information embedded in returns. Hence, I focus on the underreaction to returns during the late period. As such, all the following tests and analyses are separated for the early and late forecast periods.

4.2   Variable Measurement

This section defines measurement of the main variables employed in the study.

Subsection 4.2.1 introduces basic models for estimating analyst underreaction. The following

subsection defines the control variables in the underreaction estimation models. Subsection

4.2.3 defines measurements for uncertainty, and finally, subsection 4.2.4 defines the business

cycle variables.

4.2.1   Analyst underreaction

Based on the commonly employed model (Equation 2.1) discussed in section 2.2, I

regress forecast errors on prior news to estimate analysts' underreaction. Specifically, I use

Equations (4.1) and (4.2) to measure the degree of underreaction to prior earnings surprises

and prior stock returns, respectively. The firm i subscript is suppressed in all regression

models for briefness.

$$FE_t^E = \alpha + \beta_S Sur_t + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \tag{4.1}$$

$$FE_t^L = \alpha + \beta_R Ret_t + \beta_S Sur_t + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \tag{4.2}$$

where FE_t^E is firm i's early forecast error, i.e., actual quarterly earnings per share minus the

median of all analysts' forecasted earnings issued in the early forecast period for quarter t,

deflated by the stock price at the beginning of quarter t, FE_t^L is the forecast error using

forecasts issued in the late forecast period deflated by the stock price at the beginning of the

quarter, Sur_t is the earnings surprise deflated by the stock price at the beginning of the

quarter (i.e., the late forecast error from the previous quarter, FE_{t-1}^L), Ret_t is the average

daily stock price changes within the period between 31 days after the last quarterly earnings

announcement E_{t-1} and 31 days before one-quarter-ahead earnings announcement E_t. The

reason for using a shortened return accumulation period is that returns may include a postponed market reaction to the prior earnings surprise. For example, many studies have documented the post-earnings-announcement drift. Therefore, the estimate of underreaction to returns may be partly due to underreaction to the prior earnings surprise. Calculating returns from 31 days after E_{t-1} mitigates this issue. I also control for the prior earnings surprise in Equation (4.2) for the same reason. $Controls_k$ denotes control variables that have been found to be correlated with the forecast error in the prior literature. The following subsection 4.2.2 discusses the control variables and their measurement in detail.

As previously noted, I focus on analysts' underreaction to the prior earnings surprise during the early forecast period as modelled in Equation (4.1). When earnings forecasts are fully efficient, both α and β_S will be zero, implying analysts are unbiased and correctly react to prior earnings surprise. A negative α implies optimism bias, i.e., forecasts systematically exceed reported earnings. A positive β_S indicates that earnings forecasts do not move sufficient enough in the direction of the effect of the earnings surprise, representing analysts' underreaction to that surprise. Thus, β_S is the underreaction coefficient that estimates the percentage of the earnings surprise contributing to the forecast error.

In Equation (4.2), I focus on analysts' underreaction to earnings news reflected in stock returns during the late forecast period. I include the prior earnings surprise in the estimate equation to control for the effect of the prior earnings surprise on stock returns. Including earnings surprise also serves the purpose of understanding whether and how analysts' underreaction to earnings surprise differs between the early and late forecast periods. Similar to Equation (4.1), β_S is the underreaction coefficient that estimates the percentage of the earnings surprise contributing to the forecast error, and β_R is the underreaction coefficient that estimates the percentage of the returns contributing to the forecast error.

The literature commonly deflates forecast errors by the beginning period share price to reduce heteroskedasticity. Following this common practice, I use forecast errors scaled by price in the main tests. Cheong and Thomas (2011) find a surprising phenomenon in analyst-followed US firms: forecast errors show little variation with price, and price-deflated forecast errors are, in fact, negatively associated with price. Hence, studies using the price-scaled measure may draw biased inferences if the test variables are also related to price. The authors suggest that researchers include the inverse of price as an additional control variable when using scaled measures, or use the unscaled forecast error measure and include price as an additional variable. Accordingly, this study includes inverse of price in the analyses in robustness tests.[15]

4.2.2 Control variables for analyst forecast errors

To improve the accuracy of the estimate of underreaction, I include the following variables to control for other determinants of analyst forecast errors.

Skewness of the earnings distributions (*MEMD*) is the mean-median difference of I/B/E/S actual earnings per share over the past eight quarters (requiring a minimum of four observations) deflated by the beginning period stock price. Gu and Wu (2003) argue that analysts' optimal forecast is the median rather than the mean earnings. Accordingly, forecast errors may result from a skewed earnings distribution where the mean and median are different. The authors find earnings skewness is significantly positively associated with forecast errors.

Firm size (*LOGSALES*) is the natural log of quarterly sales at the beginning of the quarter. Smaller firms have less public information disclosure. Therefore, analysts are

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[15] The robustness tests that include the inverse of price in the regressions do not show any significantly different results from that of main tests.

incentivised to forecast smaller firms optimistically to curry management communication. Size is expected to be positively related to forecast errors.

Analyst following (*LOGFLLW*) is the natural log of the number of analysts issuing annual forecasts. A greater number of analysts following creates more intense competition among analysts. Consequently, analysts may issue more optimistic forecasts to curry managers' favour. However, analyst following is also correlated with size. Thus, its effect on forecast errors is not clear.

Earnings predictability (*CV*) is the coefficient of variation of earnings per share over the past eight quarters (requiring a minimum of four observations). When firms are less predictable, analysts may have to rely more heavily on management communication, which leads to forecast optimism.

Lead industry-adjusted ROA (*INDROA*) is the firm's realised return on asset, calculated by income before extraordinary items over the 12 months following the forecast quarter divided by the average of quarterly total assets during the 12-month period, minus the median return on assets over the same period of all firms in the same two-digit SIC industry code. McNichols and O'Brien (1997) document that analysts have a selection bias. Francis and Willis (2000) further find that firms with good future prospects are negatively associated with selection bias-induced optimism. Thus, I expect a positive association between *INDROA* and forecast errors.

Loss firm (*LOSS*) is a loss dummy variable that equals 1 if the consensus earnings forecast (an *ex ante* loss measure) is negative and 0 otherwise. Prior studies suggest that firms reporting losses are negatively associated with forecast optimism (Gu and Wu, 2003).

Trading volume (*LOGTV*) is the natural log of the sum of monthly trading volume over the 12-month period before the latest earnings announcement. Hayes (1998) argues that trading commission incentives affect analysts' decisions of initial coverage and forecast

accuracy. Gu and Wu (2003) document a positive relation between trading volume and forecast errors, implying that lower trading volume in the past months enhances analysts' incentives to boost trading volume by forecasting optimistically.

4.2.3   Uncertainty

Barron, Kim, Lim, and Stevens (1998) present a model using analyst earnings forecasts to measure analysts' information environment properties, including uncertainty and information asymmetry. The measure has been well adopted in the literature (see Barron, Stanford, and Yu, 2009). Specifically, the level of uncertainty is determined by the precision of public and idiosyncratic information possessed by analysts. The common error arises from public information and the idiosyncratic error arises from private information. The two types of errors influence forecast dispersion and forecast error in different ways. Therefore, one can measure uncertainty empirically from observable forecast dispersion, error in the mean forecast, and the number of forecasts based on the Barron et al. (1998) model:

$$V_t = \left(1 - \frac{1}{N_t}\right) D_t + SE_t \tag{4.3}$$

where V_t is uncertainty of firm i for period t, N_t is the number of analysts' forecasts, D_t is the dispersion of forecasts, and SE_t is the squared error in the mean forecast, i.e., the squared difference between the actual earnings and the mean forecasted earnings.

Forecast dispersion is also commonly used in the literature as a proxy for information uncertainty (e.g., Zhang, 2006). The more dispersed analysts' opinions about a firm are, the higher the uncertainty about the firm's future earnings. Barron and Stuerke (1998) demonstrate that it is a useful indicator of the uncertainty about the firm. In robustness tests, I use dispersion in analysts' forecasts as an alternative proxy for uncertainty.[16]

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[16] The robustness tests that use forecast dispersion as proxy for uncertainty do not show any significantly different results from the main tests.

4.2.4   Business cycles

I consider three proxies for the business cycle (CY_t). The first proxy is based on the National Bureau of Economic Research (NBER) business cycle data. I define a period as a recession (expansion) period if it falls in a NBER recession (expansion) period for at least half of the period. One concern is that the official recognition of business cycle turning points by NBER usually occurs many months after the event. Such hindsight may be of little relevance for analysts making forecast decisions.

As a result, the second proxy is a real-time business cycle measure based on the Chicago Fed National Activity Index (CFNAI).[17] CFNAI is a weighted average of 85 existing monthly indicators of US economic activity and released on a monthly basis with one month lag. It provides useful information on the current and future course of the US economic activity. Following the conventional practice, I define a period as a contraction period when CFNAI-MA3 is less than -0.7 and an expansion period when the CFNAI-MA3 is greater than -0.7.[18] I construct two dichotomous variables for the first and second proxies (respectively) being 1 for a recessionary period and 0 otherwise.

For the last business cycle proxy, I use the CFNAI-MA3 as a continuous variable. To maintain consistency with the two dichotomous variables when interpreting the results, I multiply CFNAI-MA3 by -1.

4.3   Models

This section presents multivariate regression models for testing the hypotheses developed in Chapter 3, using the variables and forecast periods defined in earlier subsections of this chapter.

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[17] For more details see http://www.chicagofed.org/webpages/publications/cfnai/.
[18] CFNAI-MA3 is constructed to have an average value of zero and a standard deviation of one. Since economic activity tends toward trend growth rate over time, a positive index reading corresponds to growth above trend and a negative index reading corresponds to growth below trend.

4.3.1 Hypothesis 1a: Uncertainty and business cycles

As noted in subsection 3.1.1, I hypothesise that uncertainty about future earnings is greater in recessionary periods than in expansionary periods in H1a. To test this hypothesis, I employ the following regression model:

$$V_t = \alpha_0 + \alpha_1 CY_t + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \qquad (4.4)$$

where the dependent variable V_t is uncertainty derived from Barron et al.'s (1998) model as shown in Equation (4.3), the test variable business cycle CY_t is equal to 1 for a recessionary period and 0 otherwise, $Controls_k$ include a vector of firm-level variables that may affect the degree of uncertainty about the firm, i.e., a bad news indicator *Ds/Dr (*being 1 if earnings surprise or returns is negative and 0 otherwise) and other control variables defined in 4.2.2, and ε_t is the error term.

Because CY_t equals 1 for a recessionary period, the prediction of greater uncertainty in recessionary periods would mean a positive coefficient for CY_t. To statistically test H1a, I employ a *t*-test of the following null and alternative hypothesis:

H^0_{1a}: $\alpha_1 = 0$, H^A_{1a}: $\alpha_1 > 0$

4.3.2 Hypothesis 1b: Asymmetric reputation cost and business cycles

In subsection 3.1.2, Hypothesis 1b states that analysts' asymmetric reputation cost is greater during expansions than during recessions. It is difficult to empirically measure the asymmetric reputation cost. Raedy et al. (2006) provide a model depicting the relations among underreaction, uncertainty, and asymmetric reputation cost. As both underreaction and uncertainty are empirically measureable, the modelled relations enable us to indirectly measure asymmetric reputation cost at different stages of the business cycle.

Raedy et al. (2006) conclude that when a new forecast is optimal, $\beta = r * \frac{a-1}{a+1}$ (see

Raedy et al. for the model development and analysis). β is an underreaction coefficient

analogous to the β_S estimated from Equation (4.1), r is uncertainty relative to the magnitude

of the news, and a is the reputation cost per unit of absolute forecast error when the forecast

revision has a direction opposite to the subsequent forecast error. The reputation cost per unit

of absolute forecast error equals 1 when the revision has the same direction as the subsequent

forecast error. Thus, a is an estimate of relative or asymmetric reputation cost associated with

revision reversal. When we rewrite $\frac{a-1}{a+1}$ as $(1 - \frac{2}{a+1})$, it becomes obvious that $\frac{a-1}{a+1}$ moves

in the same direction as a. Thus, $\frac{a-1}{a+1}$ can act as a proxy for the asymmetric reputation cost. I

use the following model to test H1b:

$$Beta_t = \alpha_0 + \alpha_1 CY_t + \alpha_2 r_t + \alpha_3 (r_t * CY_t) + \varepsilon_t \qquad (4.5)$$

where $Beta_t$ is the quarterly cross-sectional estimate of underreaction to earnings surprise β_S

from Equation (4.1) or underreaction to returns β_R from Equation (4.2), CY_t is the business

cycle indicator equal to 1 for a recessionary period and 0 otherwise, r_t is the Barron et al.

(1998) uncertainty measure V_t relative to the magnitude of the news, i.e., r_t equals V_t deflated

by the absolute value of *Sur* or *Ret*, and ε_t is the error term.

For an expansionary period, the business cycle variable CY_t equals 0. Equation (4.5)

can be shortened to $Beta_t = \alpha_0 + \alpha_2 r_t + \varepsilon_t$. Clearly, α_2 provides a proxy for asymmetric

reputation cost $\frac{a-1}{a+1}$ in expansions. When it is a recessionary period ($CY_t = 1$), Equation (4.5)

can be shown as $Beta_t = \alpha_0 + \alpha_1 + (\alpha_2 + \alpha_3) r_t + \varepsilon_t$. Accordingly, $\alpha_2 + \alpha_3$ provides a

proxy for asymmetric reputation cost ($\frac{a-1}{a+1}$) in recessions. Note that the value of α_2 or

$\alpha_2 + \alpha_3$ is not a direct estimate of the asymmetric reputation cost. Rather, α_3 captures the

change in asymmetric reputation cost across business cycles. H1b hypothesises that the

asymmetric reputation cost is greater during expansions than during recessions, implying

$\alpha_2 > (\alpha_2 + \alpha_3)$. That is, $\alpha_3 < 0$. To statistically test H1b, I employ a *t*-test of the following

null and alternative hypothesis:

H^0_{1b}: $\alpha_3 = 0$, H^A_{1b}: $\alpha_3 < 0$

4.3.3 Hypothesis 1c: Underreaction and business cycles

Hypothesis 1c states that analysts' underreaction is different during recessions than

during expansions. To test H1c, I estimate regressions that allow for a differential

underreaction in expansions and recessions in the overall sample. Specifically, I create an

interaction term between the news variables and the business cycle variable based on

Equations (4.1) and (4.2), respectively.

$$FE_t^E = \alpha_0 + \beta_0 CY_t + \beta_{S1} Sur_t + \beta_{S2}(Sur_t * CY_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \qquad (4.6)$$

$$FE_t^L = \alpha_0 + \beta_0 CY_t + \beta_{R1} Ret_t + \beta_{R2}(Ret_t * CY_t) + \beta_{S1} Sur_t + \beta_{S2}(Sur_t \qquad (4.7)$$

$$* CY_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

where all variables are defined in previous equations.

Equation (4.6) uses analyst forecasts issued within the early forecast period. As

mentioned previously, the focus is on the underreaction to earnings surprise Sur_t. Recall that

the variable CY_t equals 0 (1) for an expansionary (recessionary) period. So Equation (4.6) can

be shown separately as follows:

Expansions: $FE_t^E = \alpha_0 + \beta_{S1} Sur_t + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$

Recessions: $FE_t^E = \alpha_0 + \beta_0 + (\beta_{S1} + \beta_{S2}) Sur_t + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$

The estimate of underreaction to the prior earning surprise is β_{S1} for expansions and $(\beta_{S1} + \beta_{S2})$ for recessions. β_{S2} captures the differential underreaction to the surprise in recessions compared to expansions.

Equation (4.7) employs analyst forecast data issued from the late forecast period and the focus is on the underreaction to earnings news embedded in stock returns Ret_t. Similar to Equation (4.6), the estimate of underreaction to returns is β_{R1} for expansions and $(\beta_{R1} + \beta_{R2})$ for recessions. β_{R2} captures the differential underreaction to returns in recessions compared to expansions. To statistically test H1c, I employ *t*-tests of the following null and alternative hypothesis:

$H^0{}_{1c}$: $\beta_{S2} = 0$, $H^A{}_{1c}$: $\beta_{S2} \neq 0$ for the early forecast period,

$H^0{}_{1c}$: $\beta_{R2} = 0$, $H^A{}_{1c}$: $\beta_{R2} \neq 0$ for the late forecast period.

Furthermore, the sign of the coefficient on the news and business cycle interaction term would reveal which effect matters more to analysts' underreaction. The two driving factors are expected to change differently with the business cycle. Uncertainty is greater during recessions whereas asymmetric reputation cost is greater during expansions. Therefore, if the results show that analysts' underreaction is stronger during recessions than during expansions, i.e., a positive β_{S2} or β_{R2}, it would mean that the uncertainty effect suppresses the asymmetric reputation cost effect on analysts' underreaction. Vice versa, if the findings indicate that analysts' underreaction is stronger during expansions than during recessions, i.e., a negative β_{S2} or β_{R2}, it would mean that the asymmetric reputation cost effect is dominant.

4.3.4   Hypothesis 2: Asymmetric underreaction and business cycles

Hypothesis 2 distinguishes analysts' underreaction to good news and underreaction to bad news. Due to different implications of reputation and short-term economic incentives, analysts' asymmetric underreaction to bad news versus good news is different during

recessions than expansions. In specific, if analysts are driven by reputation-building incentives, then we will expect analysts to underreact less (more) to bad news than good news during recessions (expansions). If analysts are driven by short-term economic incentives, then we will expect analysts to underreact more to bad news than good news, particularly in a more pronounced manner during recessions than expansions (detailed in section 3.2).

Hypothesis 2 involves (1) differential underreaction to good versus bad news and (2) different differential underreaction during expansions versus recessions. Thus, it might be helpful to test asymmetric underreaction first without considering business cycles. The results will reveal whether asymmetric underreaction to good and bad news exists in the sample data. Also, they serve as a benchmark for the complete models for H2. Specifically, I estimate regressions that allow for a differential reaction to bad and good news in the overall sample. For this purpose, I add a bad news indicator and a two-way interaction between the news variable and the bad news indicator based on Equations (4.1) and (4.2).

$$FE_t^E = \alpha_0 + \beta_{S1}DS_t + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * DS_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \qquad (4.8)$$

$$FE_t^L = \alpha_0 + \beta_{R1}DR_t + \beta_{R2}Ret_t + \beta_{R3}(Ret_t \qquad (4.9)$$
$$* DR_t) + \beta_{S1}DS_t + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * DS_t)$$
$$+ \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

where DS_t is a dummy variable being 1 if the earnings surprise is negative and 0 otherwise, DR_t is a dummy variable being 1 if returns is negative and 0 otherwise, and all other variables are defined in previous equations.

The underreaction coefficient is β_{S2} for positive earnings surprises and ($\beta_{S2} + \beta_{S3}$) for negative earnings surprises, and β_{R2} for positive stock returns and ($\beta_{R2} + \beta_{R3}$) for

negative stock returns. The coefficients of interest are β_{S3} and β_{R3}. A significantly positive (negative) β_{S3} or β_{R3} implies that analysts' underreaction to bad news is greater (lower) relative to good news.

To test asymmetric underreaction in relation to the business cycle, I estimate regressions that allow for a differential underreaction to good and bad news differing across business cycle. I add a three-way interaction between news, the bad news indicator, and the business cycle variables on Equation (4.6) and (4.7):

$$FE_t^E = \alpha_0 + \beta_0 CY_t + \beta_{S1} DS_t + \beta_{S2} Sur_t + \beta_{S3}(Sur_t * DS_t) \tag{4.10}$$

$$+ \beta_{S4}(Sur_t * CY_t) + \beta_{S5}(DS_t * CY_t) + \beta_{S6}(Sur_t * DS_t$$

$$* CY_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

$$FE_t^L = \alpha_0 + \beta_0 CY_t + \beta_{R1} DR_t + \beta_{R2} Ret_t + \beta_{R3}(Ret_t * DR_t) \tag{4.11}$$

$$+ \beta_{R4}(Ret_t * CY_t) + \beta_{R5}(DR_t * CY_t) + \beta_{R6}(Ret_t * DR_t$$

$$* CY_t) + \beta_{S1} DS_t + \beta_{S2} Sur_t + \beta_{S3}(Sur_t * DS_t)$$

$$+ \beta_{S4}(Sur_t * CY_t) + \beta_{S5}(DS_t * CY_t) + \beta_{S6}(Sur_t * DS_t * CY_t)$$

$$+ \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

where all variables are defined in previous equations.

Equation (4.10) examines forecasts issued during the early forecast period. Because CY_t and DS_t are dummy variables to distinguish recessions ($CY_t = 1$) versus expansions ($CY_t = 0$), and bad news ($DS_t = 1$) versus good news ($DS_t = 0$), the equation can be shown separately as per the following four scenarios:

Good news during expansions:

$$FE_t^E = \alpha_0 + \beta_{S2} Sur_t + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

Bad news during expansions:

$$FE_t^E = \alpha_0 + \beta_{S1} + (\beta_{S2} + \beta_{S3})Sur_t + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

Good news during recessions:

$$FE_t^E = \alpha_0 + \beta_0 + (\beta_{S2} + \beta_{S4})Sur_t + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

Bad news during recessions:

$$FE_t^E = \alpha_0 + \beta_0 + \beta_{S1} + \beta_{S5} + (\beta_{S2} + \beta_{S3} + \beta_{S4} + \beta_{S6})Sur_t + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

During expansionary periods, the underreaction coefficient is β_{S2} for positive earnings surprises, and $(\beta_{S2} + \beta_{S3})$ for negative earnings surprises. β_{S3} captures the differential underreaction to bad versus good news. A positive (negative) β_{S3} means that analysts' underreaction to bad news is greater (lower) relative to good news during expansions. During recessionary periods, the underreaction coefficient is $(\beta_{S2} + \beta_{S4})$ for positive earnings surprises, and the coefficient is $(\beta_{S2} + \beta_{S3} + \beta_{S4} + \beta_{S6})$ for negative earnings surprises. The coefficient $(\beta_{S3} + \beta_{S6})$ captures the differential underreaction to bad versus good news during recessions. A positive $(\beta_{S3} + \beta_{S6})$ implies that analysts' underreaction to bad news is greater relative to good news during recessions. Finally, β_{S6} captures the difference in the asymmetric underreaction to bad versus good news between recessions and expansions. A positive (negative) β_{S6} means that the excessive underreaction to bad news versus good news is more (less) pronounced during recessions than during expansions.

Hypothesis 2 states that analysts' asymmetric underreaction to bad news versus good news is different during recessions than during expansions. If it is true, then β_{S6} will be significant. With respect to the detailed arguments, if analysts are driven by reputation-building incentives, then we will expect analysts underreact less (more) to bad news than good news during recessions (expansions). That is, we will observe a negative β_{S6}. If analysts are driven by short-term economic incentives, then we will expect analysts' excessive

underreaction to bad news than good news is more pronounced during recessions than expansions. That is, we will observe a positive β_{S6}.

   Likewise, for Equation (4.11) that examines the underreaction to stock returns during the late forecast period, if analysts are driven by reputation-building incentives, then we will observe a negative β_{R6}. If analysts are driven by short-term economic incentives, then we will observe a positive β_{R6}. To statistically test H2, I employ t-tests of the following null and alternative hypothesis:

H^0_2: $\beta_{S6} = 0$, H^A_2: $\beta_{S6} \neq 0$ for the early forecast period,

H^0_2: $\beta_{R6} = 0$, H^A_2: $\beta_{R6} \neq 0$ for the late forecast period.

CHAPTER 5

DATA AND RESULTS

In this chapter, I discuss the sample data and present results from regression analyses. The first section provides a preliminary analysis of analysts and forecast activities in relation to the business cycle based on an initial sample. The second section describes the selection of a final sample and provides summary data for key variables used in the estimation models. The third section reports and discusses regression results. Finally, the last section provides further tests for robustness check.

5.1   Overview of analysts and forecasting activities across business cycles

The initial sample is based on US firms with coverage in the I/B/E/S database. The I/B/E/S database provides summary and individual analyst forecasts of company earnings and other items such as cash flows, price targets, and stock recommendations. Using this database, I select US firms with detailed quarterly earnings forecasts covered during the period from 1984 through 2009. The initial sample includes 1,910,479 firm-analyst-quarter forecast observations, 12,200 firms, 13,327 analysts, and 315 quarters.

I use the initial sample to explore the number of analysts and earnings forecasting activities in relation to the business cycle. In section 3.2, I argue that analysts face heightened short-term economic incentives in recessionary periods due to increased pressures to maintain management relations, to generate trades, and to enhance job security. Thus, I analyse how forecasting activities (e.g., the number of analysts, the number of earnings forecasts, and the number of forecast revisions) vary with the business cycle. Table 5-1 summarises the distribution of the key forecasting activity variables for the initial sample during the 1984-

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2009 period. The summary statistics include mean, standard deviation (STD), the first

quartile (Q1), median, and the third quartile (Q3).

Table 5-1 Descriptive statistics for forecast activity and business cycle variables for
1,910,479 observations in I/B/E/S US file from1984-2009

Variable	Mean	STD	Q1	Median	Q3
Ana/quarter	900	733.15	452	627	1017
Ana%	0.0157	0.1112	-0.0108	0.0000	0.0342
Firm/quarter	961	1221.43	159	256	1651
Firm%	0.0141	0.2067	-0.0143	0.0019	0.0273
Numest	7	9	2	4	8
Numest%	0.2188	0.8967	-0.2500	0.0000	0.3750
Numana	5	5	1	3	6
Numana%	0.1410	0.6577	-0.1250	0.0000	0.2222
Numrev	2	5	0	0	2
Numrev%	0.0129	1.4980	-1.0000	-0.0556	0.0000
Drev	0.31	0.51	0.00	0.00	0.50
Drev%	-0.0444	1.2950	-1.0000	-0.2188	0.0714
NBER_Rec	0.12	0.33	0.00	0.00	0.00
CFNAI_Rec	0.16	0.36	0.00	0.00	0.00
CFNAI_Ind	0.19	0.68	-0.27	-0.01	0.31

This table reports summary statistics of the forecast activities and the business cycle variables for all
　　　1,910,479 firm-quarter observations during the1984-2009 period in the I/B/E/S US file.
Variable definitions:
Ana/quarter is the number of analysts who issue at least one forecast for quarter t.
Ana% is the growth rate of the number of analysts for quarter t compared with quarter t-1.
Firm/quarter is the number of firms that have at least one earnings forecast for quarter t.
Firm% is the growth rate of the number of firms for quarter t compared with quarter t-1.
Numest is the number of earnings forecasts issued for firm i at quarter t.
Numest% is the growth rate of the number of earnings forecasts for firm i at quarter t compared to quarter t-1.
Numana is the number of analysts who follow firm i at quarter t.
Numana% is the growth rate of the number of analysts who follow firm i at quarter t compared to quarter t-1.
Numrev is the number of forecast revisions issued for firm i at quarter t (i.e., *Numest – Numana*).
Numrev% is the growth rate of the number of forecast revisions for firm i at quarter t compared to quarter t-1.
Drev is the number of forecast revisions for firm i at quarter t deflated by the number of analysts following.
Drev% is the growth rate of the number of forecast revisions for firm i at quarter t deflated by analysts
　　　following compared with quarter t-1.
NBER_Rec (business cycle) is a dummy variable being 1 if most of the time in that period falls in a NBER
　　　recession and 0 otherwise.
CFNAI_Rec (business cycle) is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7
　　　and 0 otherwise.
CFNAI_Ind (business cycle) is a continuous variable being CFNAI-MA3 multiplied by -1.

Of all quarters from 1984 through 2009 in the inital sample, 12% (16%) quarters are

identified as NBER (CFNAI) recessions. On average, the sample includes 900 analysts and

961 firms in each quarter. Each firm attracts 5 analysts and 7 earnings forecasts per quarter

on average. This means that 2 out 7 forecasts are forecasts revisions. Each of the analyst-related metrics increases over time except the number of forecast revisions per analyst. For example, the growth in the total number of analysts (*Ana%*) is 1.6%, which is similar to 1.4% for the growth in the number of total firms (*Firm%*). The growth rate for the number of forecasts (*Numest%*) and analysts following each firm (*Numana%*) exceeds growth rate for the number of analysts and firms, meaning that, on average, analysts are covering more firms and generate more forecasts over time. The number of forecast revisions issued for each firm grows at 1.3% quarterly, on average. However, the growth in the number of revisions per firm scaled by the analyst following (*Drev%*) is negative (-4.4%), implying that analysts are updating their forecast less frequently for a particular firm over time.

I examine the association between forecasting activities and the business cycle. Table 5-2 reports the correlation matrix for the key forecasting activity and business cycle variables. The lower diagonal reports Pearson correlations and the upper diagonal reports Spearman correlations. Correlation coefficients in bold are significant at the 5% level at least.

The table shows that the three business cycle variables (*NBER_Rec, CFNAI_Rec, and CFNAI_Ind*) are highly correlated with each other (around 80%). The growth in the number of total analysts per quarter (*Ana%*), the number of total firms (*Firm%*), the number of earnings forecasts per firm quarter (*Numest%*), and analyst following per firm quarter (*Numana%*) are significantly and negatively correlated with economic recession variables (two of the correlations are not significant when the CFNAI index is used). This is consistent with the interpretation that there are fewer analysts and earnings forecasts during recessions than expansions. Interestingly, the growth in the number of forecast revisions per firm (*Numrev%*) and per firm analyst (*Drev%*) are both positively correlated with recessionary periods. This implies that analysts engage in more forecast revisions during recessions than during expansions.

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Table 5-2 Correlation matrix of forecasting activity and business cycle variables

P\S Corr.	NBER _Rec	CFNAI _Rec	CFNAI _Ind	Ana%	Firm%	Numest%	Numana%	Numrev%	Drev%
NBER_Rec		0.566	0.873	-0.176	-0.134	-0.001	-0.002	0.043	0.042
CFNAI_Rec	0.775		0.627	-0.247	-0.110	-0.004	-0.007	0.040	0.040
CFNAI_Ind	0.873	0.791		-0.149	-0.118	0.001	-0.001	0.041	0.040
Ana%	-0.065	-0.101	-0.054		0.587	0.103	0.102	0.038	0.019
Firm%	-0.032	-0.038	0.003	0.776		0.086	0.079	0.023	0.010
Numest%	-0.007	-0.017	-0.001	0.137	0.080		0.825	0.779	0.651
Numana%	-0.014	-0.024	-0.009	0.125	0.073	0.873		0.337	0.168
Numrev%	0.039	0.036	0.041	0.064	0.047	0.707	0.243		0.960
Drev%	0.041	0.040	0.042	0.031	0.027	0.530	0.050	0.921	

This table reports the correlation matrix among the key analysts' forecasting activity and the business cycle variables. The lower diagonal reports the Pearson correlation and the upper diagonal reports Spearman correlation.

Correlation coefficients in bold are significant at the 5% level at least.

Variable definitions:

NBER_Rec (business cycle) is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise.

CFNAI_Rec (business cycle) is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise.

CFNAI_Ind (business cycle) is a continuous variable being CFNAI-MA3 multiplied by -1.

Ana% is the growth rate of the number of analysts for quarter t compared with quarter t-1.

Firm% is the growth rate of the number of firms for quarter t compared with quarter t-1.

Numest% is the growth rate of the number of earnings forecasts for firm i at quarter t compared to quarter t-1.

Numana% is the growth rate of the number of analysts who follow firm i at quarter t compared to quarter t-1.

Numrev% is the growth rate of the number of forecast revisions for firm i at quarter t compared to quarter t-1.

Drev% is the growth rate of the number of forecast revisions for firm i at quarter t deflated by analysts following compared with quarter t-1.

To obtain more statistically rigorous results, I estimate regressions of various forecasting activity variables on the business cycle variables. Specifically, I estimate regressions of (1) the growth in number of analysts while controlling for firm growth, (2) the growth in analyst following for each firm while controlling for analyst and firm number growth, (3) the growth in number of forecasts per firm while controlling for analyst following growth, and (4) the growth in number of forecast revisions while controlling for analyst following growth and the number of forecasts per firm growth. Table 5-3 panels A through D present results from the four regressions, respectively.

Table 5-3 Analysis of forecasting activities in relation to the business cycle

$$DV_t = \alpha_0 + \alpha_1 CY_t + \beta Controls_t + \varepsilon_t$$

Dependent Variable (DV_t)	Independent Variable	NBER_Rec Coefficient (t-statistics)	CFNAI_Rec Coefficient (t-statistics)	CFNAI_Ind Coefficient (t-statistics)
Panel A. *Growth in Number of Analysts*				
Ana%	Intercept	0.0124	0.0134	0.0130
(Growth in No.		(55.03) ***	(70.36) ***	(62.24) ***
Of Analysts)	CY	-0.0144	-0.0183	-0.0123
		(-44.63) ***	(-71.37) ***	(-85.46) ***
	Firm%	0.4166	0.4174	0.4158
	(FirmGrowth)	(27.46) ***	(27.38) ***	(27.44) ***
	Adj R-Sq	60.36%	60.52%	60.74%
Panel B. *Growth in Analyst Following*				
Numana%	Intercept	0.1389	0.1376	0.1396
(Growth in No. of		(92.71) ***	(90.51) ***	(90.51) ***
analyst/firm)	CY	-0.0127	-0.0029	-0.0114
		(-3.54) ***	(-3.83) ***	(-6.75) ***
	Ana%	0.9912	0.9938	0.9822
	(AnalystGrowth)	(19.27) ***	(19.26) ***	(18.99) ***
	Firm%	-0.1856	-0.1860	-0.1827
	(FirmGrowth)	(-8.42) ***	(-8.40) ***	(-8.24) ***
	Adj R-Sq	1.65%	1.65%	1.66%
Panel C. *Growth in Number of Forecasts per Firm*				
Numest%	Intercept	0.0531	0.0522	0.0539
(Growth in No. of		(62.01) ***	(59.82) ***	(65.69) ***
Forecasts/firm)	CY	0.0123	0.0155	0.0041
		(4.65) ***	(6.27) ***	(3.38) ***
	Numana%	1.1891	1.1891	1.1891
	(Analyst/firm Growth)	(250.93) ***	(250.97) ***	(250.85) ***
	Adj R-Sq	76.12%	76.13%	76.12%
Panel D. *Growth in Number of Forecasts Revisions per Firm*				
Numrev%	Intercept	0.2534	0.2510	0.2538
(Growth in No.		(65.6) ***	(66.06) ***	(67.55) ***
Of revisions/firm)	CY	0.0257	0.0376	0.0155
		(3.70) ***	(5.56) ***	(4.95) ***
	Numana%	-2.2881	-2.2876	-2.2877
	(Analyst/firm Growth)	(-79.14) ***	(-79.20) ***	(-79.16) ***
	Numest%	3.7784	3.7778	3.7782
	(Forecast/firm Growth)	(136.22) ***	(136.37) ***	(136.27) ***
	Adj R-Sq	70.07%	70.07%	70.07%

This table reports coefficients and heteroscedasticity-adjusted t statistics (in parentheses) from regressions of forecasting activity variables on the business cycle and control variables.

Panel A reports the regression of the growth in number of analysts on the business cycle variables, controlling for firm number growth. Panel B reports the regression of growth in analyst following for each firm, controlling for analyst and firm number growth. Panel C reports the regression of growth in number of forecasts per firm, controlling for analyst following growth. Panel D reports the regression of growth in number of forecast revisions, controlling for analyst following growth and the number of forecasts per firm growth.

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Variable definitions:

See Table 5-1 for variable definitions.

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Panel A shows that analyst growth (*Ana%)* is significantly related to the business cycle variables (CY_t). The coefficient on *CY* is significant in all regressions with a value of -0.01, meaning that the growth rate of the number of total analysts decrease by 1% when the economy changes from an expansionary period to a recessionary period. The two variables (the business cycle and the firm growth) explain 60% of the variation in analyst growth. In panel B, the coefficient for *CY* is significantly negative, meaning that the growth rate of analyst following for each firm is positively associated with the economic condition. While the low explanatory power implies that there are omitted variables that also determine analyst following, the results are consistent with the earlier analysis that, on average, for each firm analyst following is greater during expansions than during recessions.

In panel C, I consider the growth rate of the number of forecasts for each firm. Table 5-2 reports a negative correlation between this variable and *CY*, meaning that the growth in the number of forecasts for each firm is greater during expansions than recessions. However, when I control for analyst following growth, the coefficient for *CY*, as panel C shows, is significantly positive. Similarly in panel D, when I control for growth in analyst following and growth in the number of forecasts per firm, the coefficient for *CY* is significantly positive for all regressions. This means that analyst revisions are more frequent in recessions than in expansions after taking the growth in analysts following and the number of forecasts into consideration.

Combined, these findings are consistent with the following picture: during recessionary periods, the number of active analysts both in total and on a firm level decreases due to the unfavourable labour market. The number of earnings forecasts decreases because there are fewer analysts following firms and because there are fewer analysts who have a favourable view about the firm. However, analysts appear to revise their forecasts more frequently during recessions than in expansions, perhaps in hopes of stimulating more trading

activity. In brief, these findings support the argument that analyst activity is tied to the economy.

5.2   Sample Data

As noted earlier, I obtain my initial sample from I/B/E/S unadjusted detail files (I/B/E/S.detu_epsus). There are reasons for using these files rather than summary or adjusted files. First, I/B/E/S summary files may contain stale forecasts and the way they are summarised is not suitable for the research design in this study. Using detail files allows me to remove stale forecasts and to summarise multiple forecasts for each firm based on the forecast timeline defined in subsection 4.1. Second, Payne and Thomas (2003) point out that when I/B/E/S adjusts data for stock splits, the rounding procedure results in forecast and actual earnings amounts with only two decimal places. As a result, studies using adjusted files may be prone to inaccurate research conclusions. Accordingly, I extract forecasted earnings and actual earnings (on per share basis) from the I/B/E/S unadjusted files instead of adjusted files, and then use the CRSP cumulative adjustment factor to adjust forecasts and actual earnings for stock splits and dividends on the same basis. Table 5-4 outlines the sample selection procedure.

Table 5-4 Sample selection procedure

Sample derivation	Early forecast group	Late forecast group
Initial sample obtained from I/B/E/S 1984-2009	1,910,479	1,910,479
Less forecasts that are stopped or provided on a different accounting basis	24,431	24,431
	1,886,048	1,886,048
Select forecasts only issued within the required period of time	835,954	415,619
Summarise the consensus forecast on the firm level	216,664	154,416
Less firms with missing data: accounting data from COMPUSTAT, stock price and return data from CRSP, and earnings surprise	165,241	82,975
	51,423	71,441
Less firms that contain values of any continuous variable at the top and bottom 1% of that variable's distribution	10,114	14,261
Final sample	41,309	57,180

Starting with the initial sample of 1,910,479 detailed earnings forecast observations, I

first exclude forecasts that are inactive or used a different accounting basis from the majority

of the forecasts for that firm. Otherwise, these stale forecasts and incomparable forecasts may

produce biased results. This reduces the sample to 1,886,048 earnings forecasts. Of these

forecasts, 835,954 were issued during the early forecast period while 415,619 were issued

during the late forecast period. Stickel (1989) and Raedy et al. (2006) note a similar

asymmetric pattern: greater forecasting activity in the early period than in the late period. I

compute the median forecast for each firm based on individual forecasts issued within the

early or late period. This reduces the sample size to 216,664 firm-quarter observations for the

early forecast group and 154,416 firm-quarter observations for the late group. At this point,

each firm-quarter observation has only a single summary analyst forecast in the early or late

group. After merging with other necessary data collected from COMPUSTAT for

accounting-related variables and CRSP for stock price- and return-related variables, then

removing observations with a missing earnings surprise, the sample size is reduced to 51,423

firm-quarter observations (71,441 firm-quarter observations) for the early (late) group. While

the early group had more observations to begin with, it now is smaller in size than the late

group because it requires forecasts not only from the early forecast period, but also from the

late forecast period with one quarter lag which is needed to calculate the prior earnings

surprise. In contrast, the late group only requires forecasts from the late forecast period.

Following a common practice in the literature to mitigate potential data errors, I trim the

continuous variables at 1 and 99 percentiles of that variable's distribution. The final sample

contains 41,309 firm-quarter observations in the early forecast group and 57,180 firm-quarter

observations in the late forecast group.

Due to the fact that I/B/E/S does not include extraordinary items and some special

items in forecast earnings, I use actual earnings provided by I/B/E/S rather than

COMPUSTAT when calculating forecast errors. This ensures the consistency between

forecasted earnings and actual earning (Philbrick and Ricks, 1991). Using I/B/E/S actual

earnings also addresses concerns raised by Brown and Sivakumar (2003). They emphasise

that the source of actual earnings used in measuring forecast errors is important in making

inferences, and show that I/B/E/S actual earnings perform better than COMPUSTAT

operating earnings in terms of association with stock prices and predicting future earnings.

Table 5-5 summarises the distribution of relevant variables in this study for the 1984-

2009 period. The sample includes 41,309 (57,180) firm-quarter observations covering 4,405

(5,304) firms and 266 (282) quarters in the early (late) forecast period.

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Table 5-5 Descriptive statistics of sample key variables

Panel A. 41,309 firm-quarter observations for the early forecast period from 1984 to 2009

Variable	Mean	STD	Q1	Median	Q3
FE	-0.0006	0.0047	-0.0016	0.0002	0.0014
Sur	0.0005	0.0031	-0.0005	0.0005	0.0016
V	0.0132	0.0358	0.0004	0.0018	0.0087
Disp	0.0039	0.0138	0.0001	0.0004	0.0016
Beta	0.2075	0.3762	0.0051	0.2053	0.4022
NBER_Rec	0.1542	0.3669	0.0000	0.0000	0.0000
CFNAI_Rec	0.1729	0.3782	0.0000	0.0000	0.0000
CFNAI_Ind	0.2584	0.7986	-0.2861	0.0657	0.4315
DS	0.3265	0.4689	0.0000	0.0000	1.0000
MEMD	0.0108	0.0141	0.0032	0.0061	0.0119
LOGSALES	6.0739	1.5381	5.0466	6.1810	7.2826
LOGFLLW	2.6850	0.5234	2.3979	2.7726	3.1355
CV	0.6759	1.2903	0.1863	0.3258	0.6150
INDROA	0.0102	0.0710	-0.0118	0.0056	0.0399
LOSS	0.0598	0.2389	0.0000	0.0000	0.0000
LOGTV	4.5526	1.3674	3.6873	4.6240	5.5948

Panel B. 57,180 firm-quarter observations for the late forecast period from 1984 to 2009

Variable	Mean	STD	Q1	Median	Q3
FE	0.0004	0.0029	-0.0003	0.0003	0.0014
Sur	0.0004	0.0029	-0.0003	0.0003	0.0014
Ret	0.0046	0.0947	-0.0474	0.0088	0.0610
V	0.0041	0.0100	0.0001	0.0006	0.0029
Disp	0.0017	0.0067	0.0000	0.0002	0.0009
Beta	0.1894	0.4429	-0.0084	0.1004	0.2255
NBER_Rec	0.1255	0.3312	0.0000	0.0000	0.0000
CFNAI_Rec	0.1470	0.3541	0.0000	0.0000	0.0000
CFNAI_Ind	0.1642	0.6617	-0.2909	-0.0272	0.3064
DR	0.4563	0.4981	0.0000	0.0000	1.0000
MEMD	0.0101	0.0142	0.0030	0.0057	0.0114
LOGSALES	5.9324	1.5731	4.8104	5.9181	7.0781
LOGFLLW	2.5845	0.6148	2.1972	2.6391	3.0445
CV	0.6702	1.3211	0.1776	0.3164	0.6048
INDROA	0.0136	0.0641	-0.0108	0.0057	0.0400
LOSS	0.0655	0.2473	0.0000	0.0000	0.0000
LOGTV	4.3590	1.4788	3.3286	4.3694	5.3853

Table 5-5 (Continued) Descriptive statistics of sample key variables

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This table reports summary statistics of relevant variables. Early forecast period includes the 30 days immediately following the last quarterly earnings announcement. Late forecast period includes the 30 days immediately preceding the one-quarter-ahead announcement.

Variable definitions:

FE (forecast error) is actual quarterly earnings per share minus the median of all analysts' forecasted earnings issued in the early (or late) forecast period, deflated by the stock price at the beginning of the quarter.

Sur (earnings surprise) is the late forecast error from the previous quarter.

Ret (stock returns) is the average daily stock price changes within the period between 31 days after the last quarterly earnings announcement and 31 days before one-quarter-ahead earnings announcement.

V (uncertainty) is calculated based on the Barron et al. (1998) model using forecast dispersion, error in the mean forecast, and the number of forecasts.

Disp (forecast dispersion) is dispersion in earnings forecasts.

Beta (underreaction coefficient) is the coefficient for earnings surprise or returns in the regression of forecast errors.

NBER_Rec (business cycle) is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise.

CFNAI_Rec (business cycle) is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise.

CFNAI_Ind (business cycle) is a continuous variable being CFNAI-MA3 multiplied by -1.

DS (earnings surprise dummy) is 1 if earnings surprise is negative and 0 otherwise.

DR (returns dummy) is 1 if stock return is negative and 0 otherwise.

MEMD (earnings skewness) is the mean-median difference of I/B/E/S actual earnings per share over the past eight quarters (requiring a minimum of four observations) deflated by the beginning period stock price.

LOGSALES (firm size) is the natural log of quarterly sales at the beginning of the quarter.

LOGFLLW (analyst following) is the natural log of the number of analysts issuing annual forecasts.

CV (earnings predictability) is the coefficient of variation of earnings per share over the past eight quarters (requiring a minimum of four observations).

INDROA (industry-adjusted ROA) is the firm's realised return on asset, calculated by income before extraordinary items over the 12 months following the forecast quarter divided by the average of quarterly total assets during the 12-month period, minus the median return on assets over the same period of all firms by the same two-digit SIC industry code.

LOSS is a dummy variable that equals 1 if the consensus earnings forecast is negative and 0 otherwise.

LOGTV (trading volume) is the natural log of the sum of monthly trading volume over the 12-month period before the latest earnings announcement.

All variables are estimated at the firm-quarter level, except for *Beta* and the business cycle variables that are estimated at the quarter level.

The mean forecast error *(FE)* for the early forecast period is -0.0006, indicating analyst forecast optimism. The economic meaning is that the quarterly forecast earnings on average is higher than the actual earnings by 0.06 cent per dollar of its stock price for the sample firms. However, the median forecast errors for the early forecast period (0.0002) and both mean and median for late period (0.0004 and 0.0003) are all positive, reflecting a slight pessimism bias. These numbers confirm several previous findings: (1) mean and median forecast errors have undergone an upward shift since the mid-1980s that has reduced or eliminated optimism in recent data (Brown, 2001b; Chan et al., 2007), (2) mean errors tend to

be negative while the medians are not (e.g., Richardson et al., 2004), a phenomenon that can be explained, at least partially, by earnings skewness, and (3) analysts tend to issue optimistic forecasts at early stages and revise them downwards gradually before the earnings announcement, which is described as a "walk down". The longer the forecast horizon is, the more optimistic the forecast is (Richardson et al., 2004; Raedy et al., 2006; Louis et al., 2008). Note that the walk down pattern is conceptually different from underreaction. Walk down means an early forecast is always higher than a late forecast whereas underreaction can result in a late forecast higher or lower than an early forecast depending on whether the news occurred in between is good or bad. In addition, Richardson et al. (2004) attribute the walk down to managers' incentives to sell stock after earnings announcements on the firm's behalf (via new equity issuance) or from their personal accounts (insider trades). As such, managers communicate with analysts in a way that guides analysts to make optimistic forecasts at the start of the year and then 'walk down' to beatable targets. Clearly, this earnings-guidance incentive cannot explain analysts' systematic underreaction to news.

As aforementioned, earnings surprise (*Sur*) is the lagged forecast error from the late forecast period. Uncertainty measured by the Barron et al. (1998) model, denoted as *V*, is 0.0132 for the early period, much higher compared to that of the late period (0.0041). Similarly, uncertainty measured by forecast dispersion (*Disp*) is 0.0031 for the early period, higher than 0.0017 for the late period. This confirms that the longer the forecast horizon, the greater the uncertainty about the firm's future earnings. Underreaction estimates *(Beta)* are positive for both period, meaning that analysts underreact to information in both earnings surprise and stock returns. For example, the mean *Beta* for the early period 0.2075 means that the percentage of the earnings surprise contributing to the forecast error is 21% on average.

NBER (CFNAI) recessionary periods account for 16% (18%) of all firm-quarters for the early forecast period. The percentage is similar to the initial sample reported in Table 5-1.

Late forecast data observe a slightly reduced percentage of recessionary quarters. A minority of observations from recessions is expected in the generally expanding US economy. While the imbalance between recessions and expansions could be a potential limitation, the large sample size may mitigate the problem.

With respect to the proportion of bad versus good news, for the prior earnings surprise in the early forecast period, the proportion of bad news *(DS)* is 32.6%. For prior news in stock returns in the late forecast period, the proportion of bad news in stock returns *(DR)* is 45.6%, more balanced than that of earnings surprise. Finally, control variables *MEMD* through *LOGTV* are consistent between the two groups.

Table 5-6 reports further details about the distribution of forecast errors in terms of mean and percentage (in parentheses) by NBER recession/expansion and good news/bad news. For the early forecast period in panel A, the percentage of bad news is slightly greater during recessionary periods (5.3/15.4=34.4%) than during expansionary periods (27.3/84.6=32.3%). For the late forecast period in panel B, the difference is more obvious: bad news accounts for 54% (6.8/12.6) during recessionary periods and 44% (38.8/87.4) during expansionary periods. This means that occurrence of bad news reflected in stock returns is greater when economic conditions are weak. Compared to earnings surprise that reflects previous period forecast errors, returns are contemporaneous with the forecast period, and hence, reflect the macroeconomic conditions of the current period in a more pronounced manner. Forecasts appear to be more optimistic for bad news (-0.0018) than good news observations (-0.00004) during the early period, and be less pessimistic for bad news (0.0003) than good news (0.0005) during the late period. However, early forecasts are more optimistic during recessionary (-0.0011) than expansionary periods (-0.0005) whereas late forecasts are more pessimistic during recessions (0.0005) than during expansions (0.0004).

Table 5-6 Forecast error mean and percentage by the business cycle and news direction

Panel A: Early forecast period 41,309 firm-quarter observations from 1984 to 2009			
FE Mean (percentage)	Good News	Bad News	All
NBER expansion	0.00013 (57.3%)	-0.00167 (27.3%)	-0.00045 (84.6%)
NBER recession	-0.00048 (10.1%)	-0.00232 (5.3%)	-0.00112 (15.4%)
All	-0.00004 (67.4%)	-0.00177 (32.6%)	-0.00055 (100%)
Panel B: Late forecast period 57,180 firm-quarter observations from 1984 to 2009			
FE Mean (percentage)	Good News	Bad News	All
NBER expansion	0.00051 (48.6%)	0.00023 (38.8%)	0.00038 (87.4%)
NBER recession	0.00062 (5.8%)	0.00048 (6.8%)	0.00054 (12.6%)
All	0.00052 (54.4%)	0.00027 (45.6%)	0.00040(100%)

This table presents the distribution of forecast error (denoted by *FE*) in terms of mean and percentage (in parentheses) both by stage of the business cycle (NBER expansion versus recession) and by type of news (good versus bad news).

Panel A reports the results from the early forecast subsample with 41,309 firm-quarter observations from 1984 to 2009. Panel B reports the results from the late forecast subsample with 57,180 firm-quarter observations from 1984 to 2009.

Variable definitions:

FE (forecast error) is actual quarterly earnings per share minus the median of all analysts' forecasted earnings issued in the early (or late) forecast period, deflated by the stock price at the beginning of the quarter.

Table 5-7 shows the correlation matrix of the main variables employed in the regression models for the early forecast period (panel A) and the late forecast period (panel B). Pearson correlations are reported below the diagonal and Spearman correlations are reported above the diagonal. The dependent variable forecast error (*FE*) is significantly (shown in bold) correlated with all test variables and control variables except *CV* (*Disp*) in panel A (B) for the Spearman correlations. Most test and control variables are also correlated with each other, but the correlations do not appear to be high enough to cause problems when these variables are included in the same regression. The variable inflation factor (VIF) analyses I conduct later for each regression also confirm this. Note that correlations among the independent variables in regressions increase the coefficients' standard errors, which reduces the likelihood of finding statistical significance.

Table 5-7 Correlation matrix of main variables

Panel A: Early forecast period 41,309 firm-quarter observations from 1984 to 2009

Variable	FE	Sur	V	Disp	N_Rec	C_Rec	C_Ind	DS	MEMD	LGSALE	LGFLLW	CV	INDROA	LOSS	LOGTV
FE		0.2295	-0.0611	-0.0590	-0.0415	-0.0477	-0.0585	-0.2058	-0.0431	0.0550	0.0470	0.0008	0.1939	-0.0361	0.0809
Sur	0.1985		0.0291	0.0061	0.0036	0.0013	-0.0006	-0.8091	0.0601	0.0095	0.0231	0.0665	0.0437	-0.0187	0.0500
V	-0.3555	-0.0536		0.6281	0.0817	0.0788	0.0865	0.1012	0.3161	0.1082	0.0402	0.2062	-0.1687	0.0844	-0.0357
Disp	-0.0451	-0.0257	0.4986		0.0818	0.0785	0.0843	0.1103	0.3043	0.1743	0.0979	0.1686	-0.1508	0.0904	-0.0100
N_Rec	-0.0536	-0.0127	0.0610	0.0463		0.9262	0.6284	0.0210	0.0736	-0.0096	0.0649	-0.0343	-0.0131	0.0437	0.1836
C_Rec	-0.0574	-0.0138	0.0639	0.0463	0.9262		0.6622	0.0219	0.0753	-0.0070	0.0621	-0.0265	-0.0133	0.0418	0.1678
C_Ind	-0.0620	-0.0170	0.0747	0.0573	0.8301	0.8335		0.0366	0.0788	-0.0125	0.0353	-0.0227	-0.0207	0.0339	0.1346
DS	-0.1801	-0.6398	0.0899	0.0535	0.0210	0.0219	0.0318		0.0917	-0.0580	-0.0766	0.0387	-0.1229	0.0631	-0.0982
MEMD	-0.1417	-0.0261	0.1692	0.1586	0.0689	0.0726	0.0887	0.0757		-0.0323	-0.1373	0.7342	-0.2874	0.2338	-0.0806
LGSALE	0.0926	0.0374	0.0793	0.0659	-0.0055	-0.0028	-0.0126	-0.0614	-0.0336		0.4110	-0.1508	0.0173	-0.1649	0.4981
LGFLLW	0.0707	0.0401	0.0235	0.0202	0.0632	0.0603	0.0548	-0.0756	-0.0959	0.4082		-0.0832	0.0864	-0.0261	0.6084
CV	-0.0405	0.0050	0.0648	0.0609	-0.0279	-0.0242	-0.0279	0.0185	0.4412	-0.1034	-0.0485		-0.2082	0.2643	-0.0136
INDROA	0.2097	0.0660	-0.1107	-0.0516	-0.0281	-0.0273	-0.0277	-0.1077	-0.1885	0.1002	0.0800	-0.1327		-0.2317	0.0620
LOSS	-0.0851	-0.0640	0.0518	0.0714	0.0437	0.0418	0.0401	0.0631	0.2572	-0.1829	-0.0289	0.2473	-0.2803		0.0528
LOGTV	0.0757	0.0511	-0.0194	-0.0045	0.1853	0.1705	0.1868	-0.0955	-0.0414	0.5078	0.6087	-0.0049	0.0533	0.0527	

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Table 5-7 (Continued) Correlation matrix of main variables

Panel B: Late forecast period 57,180 firm-quarter observations from 1984 to 2009

Variable	FE	Sur	Ret	V	Disp	N_Rec	C_Rec	C_Ind	DS	DR	MEMD	LGSALE	LGFLLW	CV	INDROA	LOSS	LOGTV
FE		**0.191**	**0.061**	**0.214**	0.006	**0.043**	**0.043**	**0.020**	**-0.127**	**-0.051**	**0.075**	**0.040**	**0.043**	**0.072**	**0.074**	**-0.019**	**0.058**
Sur	**0.177**		**0.024**	**0.067**	**0.024**	**0.016**	0.014	0.008	**-0.781**	**-0.023**	**0.059**	**0.023**	**0.034**	**0.067**	**0.052**	**-0.028**	**0.045**
Ret	**0.052**	**0.018**		0.010	**-0.013**	**-0.066**	**-0.071**	**-0.054**	**-0.010**	**-0.863**	0.000	**0.013**	0.000	**-0.011**	**0.073**	**-0.039**	-0.008
V	**-0.014**	-0.010	**0.013**		**0.698**	**0.082**	**0.068**	**0.083**	**0.109**	**-0.011**	**0.262**	**0.130**	**0.034**	**0.160**	**-0.114**	**0.084**	-0.007
Disp	**-0.033**	**-0.016**	0.009	**0.648**		**0.068**	**0.056**	**0.071**	**0.111**	0.007	**0.250**	**0.123**	**0.076**	**0.147**	**-0.133**	**0.093**	-0.005
N_Rec	**0.028**	0.007	**-0.075**	**0.058**	**0.035**		**0.934**	**0.609**	0.005	**0.059**	**0.032**	0.008	**0.076**	**-0.046**	**0.014**	**0.038**	**0.205**
C_Rec	**0.029**	0.007	**-0.081**	**0.050**	**0.030**	**0.934**		**0.636**	-0.001	**0.065**	**0.033**	**0.013**	**0.075**	**-0.040**	**0.014**	**0.041**	**0.205**
C_Ind	**0.023**	0.007	**-0.021**	**0.077**	**0.050**	**0.802**	**0.805**		**0.021**	**0.043**	**0.052**	**0.013**	**0.060**	**-0.027**	0.001	**0.041**	**0.171**
DS	**-0.124**	**-0.613**	-0.005	**0.077**	**0.059**	0.005	-0.001	0.014		0.010	**0.085**	**-0.049**	**-0.077**	**0.036**	**-0.105**	**0.060**	**-0.094**
DR	**-0.047**	**-0.022**	**-0.762**	-0.009	-0.006	**0.059**	**0.065**	**0.021**	0.010		0.003	**-0.030**	0.002	**0.023**	**-0.059**	**0.039**	0.008
MEMD	**0.026**	0.005	-0.009	**0.143**	**0.141**	**0.034**	**0.036**	**0.056**	**0.067**	0.009		**-0.039**	**-0.144**	**0.750**	**-0.273**	**0.243**	**-0.102**
LGSALE	**0.050**	**0.028**	**0.020**	**0.096**	**0.048**	**0.011**	**0.015**	**0.014**	**-0.050**	**-0.030**	**-0.035**		**0.441**	**-0.152**	**0.019**	**-0.157**	**0.557**
LGFLLW	**0.050**	**0.039**	0.001	**0.018**	0.007	**0.074**	**0.073**	**0.082**	**-0.075**	0.002	**-0.109**	**0.439**		**-0.088**	**0.109**	**-0.042**	**0.641**
CV	**0.030**	**0.018**	-0.005	**0.053**	**0.048**	**-0.032**	**-0.030**	**-0.028**	**0.018**	0.009	**0.466**	**-0.112**	**-0.059**		**-0.199**	**0.285**	**-0.040**
INDROA	**0.089**	**0.057**	**0.078**	**-0.064**	**-0.069**	0.002	0.003	-0.004	**-0.097**	**-0.057**	**-0.184**	**0.069**	**0.105**	**-0.127**		**-0.227**	**0.087**
LOSS	**-0.045**	**-0.047**	**-0.046**	**0.067**	**0.097**	**0.038**	**0.041**	**0.042**	**0.060**	**0.039**	**0.264**	**-0.169**	**-0.043**	**0.264**	**-0.246**		0.008
LOGTV	**0.050**	**0.040**	-0.010	0.001	**-0.011**	**0.205**	**0.205**	**0.222**	**-0.092**	0.007	**-0.063**	**0.561**	**0.638**	**-0.023**	**0.095**	0.009	

This table reports the correlation matrix for the dependent and independent variable in the main regression models, with Pearson correlations below the diagonal and Spearman correlations above the diagonal.

Panel A presents the matrix for the early forecast period sample and panel B presents the matrix for the late forecast sample.

Correlation coefficients in bold are significant at the 5% level at least.

Variable definitions:

See Table 5-5 for variable definitions.

5.3   Regression results

Petersen (2009) emphasises the importance of correcting for cross-sectional and time-series dependence in finance panel data sets. Relatedly, Gow et al. (2010) demonstrate that correcting for both types of dependence substantially affects inferences in the accounting literature. Since I use panel data that are potentially influenced by both types of dependence, all the following regression tests correct standard errors for clusters in both firm and quarter dimensions.

As noted earlier, the main tests are conducted separately for the early and late periods. Accordingly, I present results from each test for the early and late periods side by side. Also, I use three variables (including both dichotomous and continuous variables) to measure business cycles. Within the early or late periods, I display results using all three business cycle variables. In the following subsections, I focus mainly on the dichotomous measures (recessions versus expansions).

5.3.1   Uncertainty and business cycles: H1a

Table 5-8 reports the results from the regressions of uncertainty on the business cycle and control variables as per Equation (4.4). Columns 3 through 5 of the table present coefficients and t-statistics using three different business cycle variables for the early forecast period, and columns 6 through 8 for the late forecast period, respectively.

Table 5-8 Analysis of uncertainty in relation to the business cycle

$$V_t = \alpha_0 + \alpha_1 CY_t + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \qquad (4.4)$$

Coefficient (t-statistic)	Exp Sign	Early forecast period (underreaction to earnings surprise)			Late forecast period (underreaction to returns)		
1	2	3	4	5	6	7	8
Variable		*NBER_Rec*	*CFNAI_Rec*	*CFNAI_Ind*	*NBER_Rec*	*CFNAI_Rec*	*CFNAI_Ind*
Intercept		-0.0033**	-0.0034**	-0.0032**	-0.0021***	-0.0021***	-0.0019***
		(-2.32)	(-2.35)	(-2.14)	(-4.40)	(-4.40)	(-3.99)
CY_t	+	0.0058***	0.0056***	0.0032***	0.0028**	0.0023**	0.0016***
		(3.57)	(3.64)	(4.40)	(2.98)	(2.54)	(5.05)
MEMD		0.3156***	0.3154***	0.3075***	0.1092***	0.1101***	0.1062***
		(9.87)	(9.84)	(9.52)	(9.72)	(9.80)	(9.48)
LOGSALES		0.0030***	0.0030***	0.0031***	0.0015***	0.0015***	0.0015***
		(9.58)	(9.45)	(9.74)	(12.97)	(12.85)	(13.55)
LOGFLLW		0.0039***	0.0039***	0.0040***	0.0010***	0.0010***	0.0010***
		(5.30)	(5.25)	(5.45)	(4.69)	(4.67)	(4.66)
CV		0.0001	0.0001	0.0002	-0.0000	-0.0000	-0.0000
		(0.64)	(0.59)	(0.95)	(-0.44)	(-0.58)	(-0.20)
INDROA		-0.0376***	-0.0376***	-0.0376***	-0.0052***	-0.0053***	-0.0051***
		(-8.86)	(-8.87)	(-8.92)	(-3.94)	(-3.97)	(-3.91)
LOSS		0.0023*	0.0023*	0.0024*	0.0027***	0.0027***	0.0027***
		(1.71)	(1.70)	(1.83)	(6.03)	(6.02)	(6.09)
LOGTV		-0.0030***	-0.0030***	-0.0031***	-0.0011***	-0.0010***	-0.0011***
		(-7.47)	(-7.27)	(-7.97)	(-8.07)	(-7.94)	(-8.96)
DS		0.0050***	0.0050***	0.0049***	0.0020***	0.0020***	0.0019***
		(9.18)	(9.21)	(9.29)	(10.22)	(10.25)	(10.29)
DR					-0.0002	-0.0002	-0.0001
					(-1.06)	(-1.02)	(-0.70)
Adj R-Sq		0.057	0.057	0.059	0.045	0.044	0.047
No_Obs		41,309	41,309	41,309	57,180	57,180	57,180

This table reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of uncertainty on the business cycle and control variables.

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Variable definitions:

V_t (uncertainty) is calculated based on the Barron et al. (1998) model using forecast dispersion, error in the mean forecast, and the number of forecasts.

CY_t (business cycles) includes three measures:

NBER_Rec is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise;

CFNAI_Rec is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise;

CFNAI_Ind is a continuous variable being CFNAI-MA3 multiplied by -1.

See Table 5-5 for remaining variable definitions.

The coefficient α_1 for the business cycle variable CY_t is significantly positive for both early and late forecast periods across all business cycle proxies, indicating that uncertainty is greater during recessionary periods than expansionary periods. The economic interpretation is that when the economic condition changes from an expansionary period to a recessionary period, all else remaining unchanged, uncertainty increases on average by 0.0058 or 0.0056 (0.0028 or 0.0023) during the early (late) forecast period based on the NBER or CFNAI measure. The effect of the business cycle on uncertainty is economically significant as the change in uncertainty from an expansion to a recession, on average, is about half the size of the mean uncertainty over the whole sample period (0.013 for the early and 0.004 for the late period as shown in Table 5-5).

Regarding the firm-level control variables, uncertainty is significantly positively associated with *MEMD*, *LOGSALES*, *LOGFLLW*, *LOSS*, *DS*, and negatively associated with *INDROA* and *LOGTV*. These results mean that the level of information uncertainty is higher for firms with more skewed earnings, larger size, more analyst following, loss, bad earnings news, lower profitability, and lower previous trading volume.

In short, the findings support Hypothesis 1a, i.e., uncertainty about future earnings is greater in recessionary periods than in expansionary periods.

5.3.2   Asymmetric reputation cost and business cycles: H1b

Table 5-9 presents the results from the estimation of Equation (4.5), where underreaction coefficient *Beta* is regressed on the business cycle measure, the scaled uncertainty measure, and an interaction term between the scaled uncertainty and the business cycle measures. Columns 3 through 5 (6 through 8) report the results for the early (late) forecast period.

DATA AND RESULTS

Table 5-9 Analysis of asymmetric reputation cost in relation to the business cycle

$$Beta_t = \alpha_0 + \alpha_1 CY_t + \alpha_2 r_t + \alpha_3(r_t * CY_t) + \varepsilon_t \tag{4.5}$$

Coefficient (t-statistic)	Exp. Sign	Early forecast period (underreaction to earnings surprise)			Late forecast period (underreaction to returns)		
1	2	3	4	5	6	7	8
Variable		*NBER_Rec*	*CFNAI_Rec*	*CFNAI_Ind*	*NBER_Rec*	*CFNAI_Rec*	*CFNAI_Ind*
Intercept		0.1987***	0.1974***	0.1990***	0.0951***	0.0956***	0.0858***
		(6.67)	(6.56)	(7.37)	(4.16)	(4.09)	(4.00)
CY_t		-0.2104*	-0.1860*	-0.1354***	-0.1475*	-0.1328*	-0.0816*
		(-1.88)	(-1.74)	(-3.23)	(-1.79)	(-1.77)	(-1.76)
r_t		-0.0002	-0.0002	-0.0002*	0.0050**	0.0050**	0.0036*
		(-1.54)	(-1.64)	(-1.76)	(2.37)	(2.37)	(1.93)
$r_t * CY_t$	-	-0.0010**	-0.0010**	-0.0003	-0.0141**	-0.0138**	-0.0042
		(-2.10)	(-2.10)	(-1.31)	(-2.10)	(-2.15)	(-1.33)
Adj_R-Sqr		0.072	0.061	0.132	0.050	0.045	0.046
No_Obs		41,309	41,309	41,309	57,180	57,180	57,180

This table reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of underreaction on the business cycle measure, the scaled uncertainty measure, and an interaction term between the scaled uncertainty and the business cycle measures.

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Variable definitions:

$Beta_t$ (underreaction) is the quarterly cross-sectional estimate of underreaction to earnings surprise β_S from Equation (4.1) or underreaction to returns β_R from Equation (4.2).

CY_t (business cycles) includes three measures:

NBER_Rec is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise;

CFNAI_Rec is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise;

CFNAI_Ind is a continuous variable being CFNAI-MA3 multiplied by -1.

r_t (scaled uncertainty) is the uncertainty V_t calculated from Equation (4.3) scaled by the absolute value of *Sur* or *Ret*.

As discussed in subsection 4.3.2, the coefficient of interest is α_3 ($r_t * CY_t$), which is an estimate of the change in the asymmetric reputation cost across business cycles. Recall that the value of α_2 or $\alpha_2 + \alpha_3$ is not a direct estimate of the asymmetric reputation cost. Rather, α_2 ($\alpha_2 + \alpha_3$) measures the function of asymmetric reputation cost $\frac{a-1}{a+1}$ in expansions (recessions). Because $\frac{a-1}{a+1}$ moves in the same direction as a (i.e., the asymmetric reputation

cost per unit of absolute forecast error), α_3 is able to capture the change in the asymmetric reputation cost between recessionary periods and expansionary periods.

The table shows that α_3 is significantly negative for both periods when using the NBER (columns 3 and 4) or CFNAI (columns 6 and 7) recession measure. The negative value implies that the asymmetric reputation cost is greater during expansionary periods ($CY = 0$) compared to recessionary periods ($CY = 1$). While there is lack of significance when using the continuous CFNAI indices, the results nonetheless provide evidence supporting the alternative form of Hypothesis1b, i.e., asymmetric reputation cost is greater during expansions than recessions.

5.3.3   Underreaction and business cycles: H1c

Table 5-10 reports the results from the estimation of Equations (4.6) and (4.7), where forecast errors are regressed on the news variables (earnings surprise for the early forecast period, stock returns and earnings surprise for the late forecast period), the business cycle variable, two-way interaction terms between the news and the business cycle variables, and control variables.

Table 5-10   Analysis of underreaction in relation to the business cycle

$$FE_t^E = \alpha_0 + \beta_0 CY_t + \beta_{S1} Sur_t + \beta_{S2}(Sur_t * CY_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \tag{4.6}$$

$$FE_t^L = \alpha_0 + \beta_0 CY_t + \beta_{R1} Ret_t + \beta_{R2}(Ret_t * CY_t) + \beta_{S1} Sur_t + \beta_{S2}(Sur_t * CY_t) \tag{4.7}$$
$$+ \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

Coefficient (*t*-statistic)	Exp. Sign	Early forecast period (Eq. 4.6) (underreaction to earnings surprise)			Late forecast period (Eq. 4.7) (underreaction to returns)		
1	2	3	4	5	6	7	8
Variable		NBER_Rec	CFNAI_Rec	CFNAI_Ind	NBER_Rec	CFNAI_Rec	CFNAI_Ind
Intercept		-0.0025***	-0.0025***	-0.0025***	-0.0001*	-0.0001*	-0.0001*
		(-12.45)	(-12.31)	(-12.49)	(-1.90)	(-1.94)	(-1.71)
CY		-0.0005*	-0.0005**	-0.0002	0.0002	0.0002**	0.0001
		(-1.71)	(-2.01)	(-1.64)	(1.64)	(2.01)	(1.22)
Sur		0.3008***	0.3013***	0.3009***	0.1742***	0.1743***	0.1738***
		(18.84)	(18.60)	(19.86)	(19.63)	(19.67)	(19.62)
*Sur*CY*	?	-0.0980**	-0.0919**	-0.0495***	-0.0135	-0.0142	-0.0111
		(-2.46)	(-2.45)	(-3.00)	(-0.55)	(-0.58)	(-0.45)
Ret					0.0436***	0.0453***	0.0411***
					(8.24)	(8.58)	(8.41)
*Ret*CY*	?				-0.0261*	-0.0298**	-0.0116
					(-1.94)	(-2.38)	(-1.36)
MEMD		-0.0361***	-0.0359***	-0.0356***	0.0037	0.0037	0.0037
		(-9.28)	(-9.18)	(-9.20)	(1.61)	(1.59)	(1.63)
LOGSALES		0.0001***	0.0001***	0.0001***	0.0000***	0.0001***	0.0000***
		(4.31)	(4.29)	(4.22)	(3.65)	(3.66)	(3.66)
LOGFLLW		0.0004***	0.0004***	0.0004***	-0.0001**	-0.0001**	-0.0001**
		(4.16)	(4.17)	(4.13)	(-2.12)	(-2.08)	(-2.17)
CV		0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
		(3.05)	(3.00)	(2.96)	(3.39)	(3.40)	(3.40)
INDROA		0.0110***	0.0110***	0.0110***	0.0032***	0.0032***	0.0032***
		(14.53)	(14.54)	(14.55)	(10.96)	(10.89)	(11.00)
LOSS		0.0002	0.0002	0.0002	-0.0001	-0.0001	-0.0001
		(0.97)	(0.96)	(0.91)	(-1.39)	(-1.44)	(-1.39)
LOGTV		0.0001	0.0001	0.0001	0.0001***	0.0001***	0.0001***
		(1.32)	(1.30)	(1.47)	(2.97)	(2.84)	(3.15)
Adj_R-Sqr		0.098	0.098	0.098	0.042	0.043	0.042
No_Obs		41,309	41,309	41,309	57,180	57,180	57,180

Table 5-10 (Continued) Analysis of underreaction in relation to the business cycle

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This table reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of forecast errors on earnings surprise or stock returns, the business cycle variables, two-way interaction terms between surprise/returns and the business cycle variables, and control variables.

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Variable definitions:

FE_t^E (FE_t^L) is actual quarterly earnings per share minus the median of all analysts' forecasted earnings issued in the early (late) forecast period, deflated by the stock price at the beginning of the quarter.

CY_t (business cycles) includes three measures:

NBER_Rec is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise;

CFNAI_Rec is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise;

CFNAI_Ind is a continuous variable being CFNAI-MA3 multiplied by -1.

Sur (earnings surprise) is the late forecast error from the previous quarter.

Ret (stock returns) is the average daily stock price changes within the period between 31 days after the last quarterly earnings announcement and 31 days before one-quarter-ahead earnings announcement.

MEMD (earnings skewness) is the mean-median difference of I/B/E/S actual earnings per share over the past eight quarters (requiring a minimum of four observations) deflated by the beginning period stock price.

LOGSALES (firm size) is the natural log of quarterly sales at the beginning of the quarter.

LOGFLLW (analyst following) is the natural log of the number of analysts issuing annual forecasts.

CV (earnings predictability) is the coefficient of variation of earnings per share over the past eight quarters (requiring a minimum of four observations).

INDROA (industry-adjusted ROA) is the firm's realised return on asset, calculated by income before extraordinary items over the 12 months following the forecast quarter divided by the average of quarterly total assets during the 12-month period, minus the median return on assets over the same period of all firms by the same two-digit SIC industry code.

LOSS is a dummy variable that equals 1 if the consensus earnings forecast is negative and 0 otherwise.

LOGTV (trading volume) is the natural log of the sum of monthly trading volume over the 12-month period before the latest earnings announcement.

With respect to forecast bias, the intercept is -0.0025 with a high level of significance for the early forecasts period across all regressions, implying a strong presence of analysts' optimism bias in the early forecast period. However, when we move to the late forecast period, the intercept is -0.0001 with the significance only at the 10% level. That is, optimism is lower both in magnitude and significance. This confirms the documented "walk down" pattern in earnings forecasts (discussed in 5.2) even when the analyses distinguish optimism bias and underreaction effects. The business cycle intercept (*CY*) is significantly negative with the exception of column 5 using the CFNAI index continuous measure for the early period. This means early forecasts are more optimistic in the recessionary period, consistent with the earlier argument that recessions are associated with heightened conflicts of interest in analysts' forecasts. However, in the late period, the business cycle intercept is no longer

significantly negative. In one regression using *CFNIA_Rec*, it is even significantly positive. While the results from the late period are indecisive, it is obvious that the impact of macroeconomic conditions on forecast optimism bias appears to be strong only during the early forecast period.

Turning attention to analysts' underreaction, the results from Table 5-10 show significantly positive coefficients for *Sur* and *Ret* for all business cycle variables and for both periods. This is consistent with the previous finding that analysts underreact to both earnings news and other earnings news reflected in returns. Looking further at the differential underreaction across business cycles, for the early period, the coefficient β_{S2} for *Sur*CY* for all business cycle variables are significantly negative. This means analysts' underreaction to earnings surprise is lower when the economy is weaker. For instance, using the NBER recession measure (column 3 *NBER_Rec*), the underreaction to earnings surprise in the early forecast period is 0.3008 (β_{S1} for *Sur*) for expansions and 0.2028 (β_{S1} for *Sur*+β_{S2} for *Sur*CY*, i.e., 0.3008-0.0980) for recessions.

Moving to the late forecast period where the focus is on the differential underreaction to the more recent news (i.e., stock returns), the coefficient β_{R2} for *Ret*CY* is significantly negative for the NBER and CFNAI recession variables. Again, taking *NBER_Rec* as an example (column 6), the underreaction to returns is 0.0436 (β_{R1} for *Ret)* during expansions and 0.0175 (β_{R1} for *Ret* + β_{R2} for *Ret*CY*, i.e., 0.0436-0.0261) during recessions. Underreaction to returns is weaker during recessions than during expansions, consistent with the findings from the early forecast period. With respect to the underreaction to earnings news in the late forecast period, the results show that analysts' underreaction to earnings surprise still exists during expansions but with a smaller magnitude, e.g., 0.1742 for the late period versus 0.3008 for the early period under column 6. It is consistent with Raedy et al.'s (2006) theory and their empirical findings of horizon-dependent underreaction. As

uncertainty decreases in the late forecast period, underreaction is consequently reduced, holding asymmetric reputation cost unchanged for a given stage of the business cycle. Also, the coefficient β_{S2} for *Sur*CY* becomes insignificant, meaning that the underreaction to earnings surprise in the late forecast period no longer has any significant difference between recessionary periods and expansionary periods.

These findings are consistent with the alternative form of hypothesis 1c that analysts' underreaction in general does depend upon economic conditions. Specifically, analysts' underreaction to information in earnings surprises and stock returns is stronger in expansionary periods compared to recessionary periods. Combined with the results from H1a and H1b, i.e., expansions are associated with greater asymmetric reputation cost and lower uncertainty, the findings imply that the asymmetric reputation cost effect, rather than the uncertainty effect, drives analysts' underreaction. This implication is important to the literature as it shows that uncertainty is not the only factor leading to underreaction. Given the positive impact of uncertainty on underreaction documented in the literature, analysts would have underreacted to information in a more pronounced manner during recessions where uncertainty is higher. The finding shows otherwise, which clearly demonstrates that there is more than just uncertainty that leads to analysts' underreaction.

Regarding the control variables, size, earnings variability, industry adjusted ROA, and trading volume are positively associated with forecast errors, consistent with the prior studies. Analyst following is negative for the late period, a possible result from its correlation with size. A puzzle is the earnings skewness variable. Opposite to Gu and Wu (2003)'s skewness and bias hypothesis and findings, the coefficient for earnings skewness is negatively associated with forecasts in the early period. This is, however, consistent with Louis et al. (2010) who find a negative association between initial analyst forecast errors and earnings skewness. As this is not the focus of my study, I leave it open for future research.

5.3.4   Asymmetric underreaction and business cycles: H2

Table 5-11 presents the results from the estimation of Equations (4.8) through (4.11) with the bad news indicator and interaction terms among the surprise or returns variable, the business cycle variable, and the bad news indicator as additional explanatory variables. Equations (4.8) and (4.9) estimate differential underreaction to good versus bad news for the early and late forecast, respectively, without taking business cycles into consideration. Equations (4.10) and (4.11) fully test for the difference in the differential underreaction to good versus bad news between expansionary periods and recessionary periods.

First, I discuss the results in Table 5-11 for Equations (4.8) and (4.9) that focus on the difference between good news and bad news (columns 3 and 7). Then, I review the results for the full Equations (4.10) and (4.11) for the early forecast period (columns 4 through 6) and the late forecast period (columns 8 through 10), respectively.

With respect to optimism, columns 3 and 7 show the intercept from Equations (4.8) and (4.9) is significantly negative for both early and late forecast periods, with a reduction in magnitude and significance in the late period. The coefficient for the negative earnings surprise indicator (DS) is strongly significant and negative for both periods. This means analysts tend to be more optimistic towards firms with bad news, confirming the findings from Francis and Philbrick (1993) and Raedy et al. (2006). Similar to the intercept, the magnitude and significance of the bad news coefficient are greater in the early period than the late period. However, for the late period, the coefficient for the negative returns indicator (DR) is not significant, meaning that the direction of the news embedded in returns does not affect analyst forecast bias.

Table 5-11   Analysis of asymmetric underreaction and business cycles

$$FE_t^E = \alpha_0 + \beta_{S1}DS_t + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * DS_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \qquad (4.8)$$

$$FE_t^L = \alpha_0 + \beta_{R1}DR_t + \beta_{R2}Ret_t + \beta_{R3}(Ret_t * DR_t) + \beta_{S1}DS_t + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * DS_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \qquad (4.9)$$

$$FE_t^E = \alpha_0 + \beta_0 CY_t + \beta_{S1}DS_t + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * DS_t) + \beta_{S4}(Sur_t * CY_t) + \beta_{S5}(DS_t * CY_t) + \beta_{S6}(Sur_t * DS_t * CY_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \qquad (4.10)$$

$$FE_t^L = \alpha_0 + \beta_0 CY_t + \beta_{R1}DR_t + \beta_{R2}Ret_t + \beta_{R3}(Ret_t * DR_t) + \beta_{R4}(Ret_t * CY_t) + \beta_{R5}(DR_t * CY_t) + \beta_{R6}(Ret_t * DR_t \qquad (4.11)$$

$$* CY_t) + \beta_{S1}DS_t + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * DS_t) + \beta_{S4}(Sur_t * CY_t) + \beta_{S5}(DS_t * CY_t) + \beta_{S6}(Sur_t * DS_t * CY_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

Coefficient (t-statistic)	Exp. Sign	Early forecast period (underreaction to earnings surprise)				Late forecast period (underreaction to returns)			
		Eq. 4.8	Eq. 4.10			Eq. 4.9	Eq. 4.11		
1	2	3	4	5	6	7	8	9	10
Variable			NBER_Rec	CFNAI_Rec	CFNAI_Ind		NBER_Rec	CFNAI_Rec	CFNAI_Ind
Intercept		-0.0022***	-0.0022***	-0.0022***	-0.0022***	-0.0001*	-0.0001	-0.0001	-0.0001
		(-10.65)	(-10.99)	(-11.01)	(-11.06)	(-1.72)	(-1.58)	(-1.57)	(-1.58)
CY			-0.0004*	-0.0003*	-0.0001		0.0001	0.0001	0.0001
			(-1.72)	(-1.80)	(-1.09)		(0.46)	(0.63)	(1.28)
DS		-0.0005***	-0.0005***	-0.0004***	-0.0004***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
		(-6.45)	(-5.84)	(-5.69)	(-5.77)	(-3.41)	(-2.95)	(-2.70)	(-2.76)
Sur	+	0.1901***	0.2193***	0.2252***	0.2253***	0.1691***	0.1707***	0.1723***	0.1711***
		(7.16)	(8.74)	(9.21)	(9.69)	(12.83)	(12.80)	(12.72)	(13.52)
*Sur*DS*	?	0.0784**	0.0725*	0.0639*	0.0674*	-0.0219	-0.0172	-0.0141	-0.0161
		(2.13)	(1.79)	(1.75)	(1.76)	(-0.93)	(-0.70)	(-0.57)	(-0.68)
*Sur*CY*			-0.1199	-0.1377*	-0.0742**		-0.0200	-0.0258	-0.0164
			(-1.38)	(-1.65)	(-2.17)		(-0.43)	(-0.58)	(-0.77)
*DS*CY*			-0.0003	-0.0003	-0.0003**		-0.0002	-0.0002	-0.0002***
			(-0.97)	(-1.18)	(-2.04)		(-1.12)	(-1.47)	(-3.55)
*Sur*DS*CY*	?		0.0011	0.0388	0.0082		-0.0171	-0.0335	-0.0148
			(0.01)	(0.39)	(0.22)		(-0.22)	(-0.45)	(-0.40)

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Table 5-11 (Continued) Analysis of asymmetric underreaction and business cycles

Coefficient (*t*-statistic)	Exp. Sign	Early forecast period (underreaction to earnings surprise)				Late forecast period (underreaction to returns)			
		Eq. 4.8	Eq. 4.10			Eq. 4.9	Eq. 4.11		
1	2	3	4	5	6	7	8	9	10
Variable			NBER_Rec	CFNAI_Rec	CFNAI_Ind		NBER_Rec	CFNAI_Rec	CFNAI_Ind
DR						-0.0000	-0.0000	-0.0000	-0.0000
						(-1.00)	(-0.83)	(-0.73)	(-0.54)
Ret						0.0484***	0.0437***	0.0432***	0.0457***
						(5.38)	(4.74)	(4.56)	(5.16)
Ret*DR	?					-0.0302**	-0.0080	-0.0027	-0.0118
						(-2.17)	(-0.54)	(-0.18)	(-0.85)
Ret*CY							0.0248	0.0240	0.0067
							(0.93)	(0.97)	(0.59)
DR*CY							0.0000	0.0000	-0.0001
							(0.31)	(0.25)	(-0.75)
Ret*DR*CY	?						-0.0529***	-0.0599***	-0.0504***
							(-2.58)	(-3.00)	(-3.02)
MEMD		-0.0346***	-0.0338***	-0.0335***	-0.0334***	0.0038	0.0035	0.0035	0.0035
		(-9.13)	(-8.95)	(-8.79)	(-8.85)	(1.61)	(1.56)	(1.55)	(1.58)
LOGSALES		0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
		(4.43)	(4.28)	(4.25)	(4.20)	(3.70)	(3.94)	(3.93)	(3.96)
LOGFLLW		0.0004***	0.0004***	0.0004***	0.0004***	-0.0001**	-0.0001**	-0.0001**	-0.0001**
		(3.94)	(4.15)	(4.16)	(4.13)	(-2.29)	(-2.12)	(-2.09)	(-2.18)
CV		0.0001***	0.0001***	0.0001***	0.0001***	0.0000***	0.0001***	0.0001***	0.0001***
		(3.34)	(3.10)	(3.01)	(2.99)	(2.98)	(3.37)	(3.39)	(3.38)
INDROA		0.0108***	0.0108***	0.0108***	0.0108***	0.0032***	0.0032***	0.0032***	0.0032***
		(14.59)	(14.51)	(14.49)	(14.52)	(11.13)	(11.06)	(11.00)	(11.08)
LOSS		0.0002	0.0002	0.0002	0.0002	-0.0001	-0.0001	-0.0001	-0.0001
		(1.16)	(1.12)	(1.10)	(1.06)	(-1.46)	(-1.47)	(-1.50)	(-1.48)
LOGTV		0.0000	0.0000	0.0000	0.0001	0.0001***	0.0001***	0.0001***	0.0001***
		(0.09)	(1.06)	(1.05)	(1.19)	(2.82)	(2.74)	(2.64)	(2.90)
Adj_R-Sqr		0.097	0.099	0.100	0.100	0.042	0.043	0.043	0.043
No_Obs		41,309	41,309	41,309	41,309	57,180	57,180	57,180	57,180

Table 5-11 (Continued) Analysis of asymmetric underreaction and business cycles

Combination of regression coefficients for underreaction to news in returns – Equation 4.11 NBER Recession:		Value of coefficient:
Underreaction coefficient to good news in returns for expansionary periods		
βRet	0.0437*Ret	0.0437
Underreaction coefficient to bad news in returns for expansionary periods		
$\beta Ret + \beta Ret * DR$	(0.0437-0.0080)*Ret	0.0357
Underreaction coefficient to good news in returns for recessionary periods		
$\beta Ret + \beta Ret * CY$	(0.0437+0.0248)*Ret	0.0685
Underreaction coefficient to bad news in returns for recessionary periods		
$\beta Ret + \beta Ret * DR + \beta Ret * CY + \beta Ret * DR * CY$	(0.0437-0.0080+0.0248-0.0529)*Ret	0.0076

This table reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of forecast errors on earnings surprise or stock returns, the bad news indicator, the business cycle variables, two-way and three-way interaction terms for surprise/returns, the bad news indicator, and the business cycle variables, and control variables (the entire sample).

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Variable definitions:

FE_t^E (FE_t^L) is actual quarterly earnings per share minus the median of all analysts' forecasted earnings issued in the early (late) forecast period, deflated by the stock price at the beginning of the quarter.

CY_t (business cycles) includes three measures:

NBER_Rec is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise;

CFNAI_Rec is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise;

CFNAI_Ind is a continuous variable being CFNAI-MA3 multiplied by -1.

DS (earnings surprise dummy) is 1 if earnings surprise is negative and 0 otherwise.

Sur (earnings surprise) is the late forecast error from the previous quarter.

DR (returns dummy) is 1 if stock return is negative and 0 otherwise.

Ret (stock returns) is the average daily stock price changes within the period between 31 days after the last quarterly earnings announcement and 31 days before one-quarter-ahead earnings announcement.

MEMD (earnings skewness) is the mean-median difference of I/B/E/S actual earnings per share over the past eight quarters (requiring a minimum of four observations) deflated by the beginning period stock price.

LOGSALES (firm size) is the natural log of quarterly sales at the beginning of the quarter.

LOGFLLW (analyst following) is the natural log of the number of analysts issuing annual forecasts.

CV (earnings predictability) is the coefficient of variation of earnings per share over the past eight quarters (requiring a minimum of four observations).

INDROA (industry-adjusted ROA) is the firm's realised return on asset, calculated by income before extraordinary items over the 12 months following the forecast quarter divided by the average of quarterly total assets during the 12-month period, minus the median return on assets over the same period of all firms by the same two-digit SIC industry code.

LOSS is a dummy variable that equals 1 if the consensus earnings forecast is negative and 0 otherwise.

LOGTV (trading volume) is the natural log of the sum of monthly trading volume over the 12-month period before the latest earnings announcement.

Moving to columns 4 through 6 where Equation (4.10) includes the business cycle variable, the intercept and the coefficient for *CY* are both significantly negative, indicating forecasts are on average optimistic during expansions and the optimism is more pronounced during recessions. The coefficient for *DS*CY* is significantly negative for the business cycle measure *CFNAI_Ind* (Column 6), providing some evidence that the bad-news induced optimism is more pronounced in the recessionary periods. In comparison, for the late forecast period (columns 8 through 10), the intercept and the coefficient for *CY* are both insignificant, consistent with previous results that forecasts issued during the late periods are not optimistically biased during expansions, and that there is no difference during recessions than expansions. In addition, the coefficients for *DR* and *DR*CY* are insignificant, providing no evidence of optimism in relation to bad news embedded in returns in late forecasts. In contrast, the coefficients for *DS* (for all regressions) and *DS*CY* (only for column 6) remain significant and negative. These results confirm that during both early and late forecast periods, firms with bad news in their earnings surprises are associated with relatively more optimistic forecasts, and this is heightened in the recessionary period. This evidence is consistent with the notion that analysts have greater short-term economic incentives to forecast optimistically during recessions.

With respect to asymmetric underreaction between good news and bad news, the incremental underreaction coefficient β_{S3} for negative earnings surprise (*Sur*DS*) is significantly positive for the early forecast period (column 3), meaning that underreaction is more pronounced for firms with a negative earnings surprise. This is consistent with findings from prior literature (e.g., Francis and Philbrick, 1993; Raedy et al. 2006). For the late forecast period (column 6), there is no difference in underreaction between good and bad news in earnings surprises, suggested by the insignificant coefficient β_{S3} for *Sur*DS*. On the

contrary, the asymmetric underreaction coefficient β_{R3} for stock returns (*Ret*DR*) is significant but negative, suggesting analysts underreact less to bad news in returns.

For the full estimation Equations (4.10) and (4.11), the variables of interest are the three-way interaction terms *Sur*DS*CY* and *Ret*DR*CY*. The coefficients on these terms indicate whether there is asymmetric underreaction to bad news versus good news, particularly during recessionary periods. For the early forecast period, the coefficient β_{S6} for *Sur*DS*CY* is not significant in all regressions (columns 4 through 6), suggesting that analysts do not show any difference in excessive underreaction to bad news during recessionary periods relative to expansionary periods. This finding is inconsistent with the short-term incentive hypothesis where analysts are expected to show more pronounced excessive underreaction to bad news during recessionary periods due to stronger short-term economic incentives.

Moving to the late forecast period, while the coefficient β_{S6} for *Sur*DS*CY* remains insignificant in all regressions, the coefficient β_{R6} for *Ret*DR*CY* is significantly negative for all business cycle proxies (columns 8 through 10). Combined with the negative but insignificant coefficient for *Ret*DR*, this means analysts do not underreact excessively to bad news during expansionary periods, and appear to respond more to bad news during recessions than expansions. Table 5-11 reports the combined coefficients from the results under column 8, for good news and bad news in expansions and recessions, respectively. Of these four possible situations, the table shows that analysts' underreaction is the least pronounced for bad news in recessions. This evidence is consistent with the interpretation that bad news is more likely to happen in the near future in recessions, hence analysts feel more confident when they incorporate bad news (compared with good news) in their forecasts. In short, the findings from both early and late forecast periods reject the short-term economic incentive hypothesis in favour of the reputation-building incentive hypothesis.

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While the three-way interaction allows a direct test for Hypothesis 2 with statistical significance using the entire sample, the results are relatively hard to understand. To provide more insight into the asymmetric underreaction to bad versus good news in relation to business cycles, I estimate Equations (4.8) and (4.9) for expansionary observations and recessionary observations separately, an alternative to Equations (4.10) and (4.11) that include a three-way interaction. As in previous tests, I use the NBER and CFNAI index to identify expansions and recessions. Table 5-12 presents results of these separate regressions, labelled as NBER recessions, NBER expansions, CFNAI recessions, CFNAI expansions for each equation. For the purpose of comparison, the full sample results are also included.

As noted previously, early forecasts display a significantly excessive underreaction to bad news in the full sample (column 3), as suggested by the coefficient β_{S3} for *Sur*DS* (0.0784). However, separated results show that the significantly excessive underreaction to bad news only occurs during the NBER/CFNAI expansions (columns 5 and 7) but not the recessions (columns 4 and 6). This evidence is important in terms of identifying which type of incentives as the driving factor of such behaviour. The short-term economic incentives drive analysts' behaviour causing excessive underreaction to bad news, especially during recessionary periods when these incentives are stronger. In contrast, the asymmetric reputation cost theory predicts more underreaction to bad news in expansions but less underreaction to bad news in recessions. Clearly, the evidence favours the reputation argument.

With respect to late forecasts, differential underreaction to earnings surprise is no longer significant for the full sample or either subsample. Importantly, for the underreaction to returns, analysts show less underreaction to bad news than good news in the full sample (column 8). In particular, separate analyses show that this result is solely driven by the recessionary subsample, indicated by the significant coefficient β_{R3} for *Ret*DR* (-0.077) for

NBER and CFNAI recessions (columns 9 and 11), but insignificant coefficients for expansions (columns 10 and 12). Again, the evidence of less underreaction to bad news in recessions supports the reputation-building incentive argument. but not the short-term economic incentive argument.

Table 5-12 Analysis of asymmetric underreaction and business cycles – separate regressions

$$FE_t^E = \alpha_0 + \beta_{S1}DS_t + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * DS_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \tag{4.8}$$

$$FE_t^L = \alpha_0 + \beta_{R1}DR_t + \beta_{R2}Ret_t + \beta_{R3}(Ret_t * DR_t) + \beta_{S1}DS_t + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * DS_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \tag{4.9}$$

Coefficient (t-statistic)	Exp. Sign	Early forecast period (underreaction to earnings surprise) - Eq. 4.8					Late forecast period (underreaction to returns) - Eq. 4.9				
1	2	3	4	5	6	7	8	9	10	11	12
Variable		Full sample	NBER recessions	NBER expansions	CFNAI recessions	CFNAI expansions	Full sample	NBER recessions	NBER expansions	CFNAI recessions	CFNAI expansions
Intercept		-0.0022***	-0.0033***	-0.0020***	-0.0031***	-0.0020***	-0.0001*	-0.0006**	-0.0001	-0.0005*	-0.0001
		(-10.65)	(-4.54)	(-10.28)	(-4.61)	(-10.33)	(-1.72)	(-2.17)	(-0.68)	(-1.92)	(-0.73)
DS	-	-0.0005***	-0.0007***	-0.0005***	-0.0007***	-0.0004***	-0.0001***	-0.0003**	-0.0001***	-0.0003**	-0.0001***
		(-6.45)	(-2.56)	(-5.96)	(-2.93)	(-5.82)	(-3.41)	(-2.03)	(-2.86)	(-2.47)	(-2.60)
Sur	+	0.1901***	0.0999	0.2202***	0.0885	0.2260***	0.1691***	0.1394***	0.1734***	0.1343***	0.1755***
		(7.16)	(1.33)	(8.84)	(1.21)	(9.36)	(12.83)	(3.71)	(13.18)	(3.80)	(13.15)
*Sur*DS*	?	0.0784**	0.0771	0.0696*	0.1049	0.0613*	-0.0219	-0.0099	-0.0227	-0.0211	-0.0211
		(2.13)	(0.91)	(1.74)	(1.23)	(1.83)	(-0.93)	(-0.16)	(-0.93)	(-0.36)	(-0.85)
DR	-						-0.0000	0.0000	-0.0000	0.0000	-0.0000
							(-1.00)	(0.10)	(-0.83)	(0.05)	(-0.73)
Ret	+						0.0484***	0.0612**	0.0440***	0.0588**	0.0436***
							(5.38)	(2.19)	(4.77)	(2.29)	(4.60)
*Ret*DR*	?						-0.0302**	-0.0771**	-0.0091	-0.0767**	-0.0047
							(-2.17)	(-2.27)	(-0.62)	(-2.42)	(-0.32)
MEMD		-0.0346***	-0.0341***	-0.0341***	-0.0336***	-0.0338***	0.0038	0.0162**	0.0011	0.0146**	0.0010
		(-9.13)	(-4.63)	(-7.92)	(-4.67)	(-7.76)	(1.61)	(2.02)	(0.59)	(1.98)	(0.55)
LOGSALES		0.0001***	0.0001	0.0001***	0.0001	0.0001***	0.0001***	0.0000	0.0001***	0.0000	0.0001***
		(4.43)	(0.76)	(4.48)	(0.76)	(4.61)	(3.70)	(0.87)	(4.26)	(0.91)	(4.21)
LOGFLLW		0.0004***	0.0006*	0.0003***	0.0005*	0.0003***	-0.0001**	0.0002	-0.0001***	0.0002	-0.0001***
		(3.94)	(1.72)	(4.12)	(1.83)	(4.14)	(-2.29)	(0.96)	(-3.31)	(0.84)	(-3.23)
CV		0.0001***	0.0001	0.0001***	0.0002	0.0001***	0.0000***	0.0000	0.0001***	0.0000	0.0001***
		(3.34)	(1.5)	(2.73)	(1.43)	(2.68)	(2.98)	(0.09)	(4.16)	(0.08)	(4.21)

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Table 5-12 (Continued) Analysis of asymmetric underreaction and business cycles – separate regressions

Coefficient (*t*-statistic)	Exp. Sign	Early forecast period (underreaction to earnings surprise) - Eq. 4.8					Late forecast period (underreaction to returns) - Eq. 4.9				
1	2	3	4	5	6	7	8	9	10	11	12
Variable		Full sample	NBER recessions	NBER expansions	CFNAI recessions	CFNAI expansions	Full sample	NBER recessions	NBER expansions	CFNAI recessions	CFNAI expansions
INDROA		0.0108***	0.0113***	0.0106***	0.0111***	0.0107***	0.0032***	0.0017*	0.0034***	0.0015*	0.0035***
		(14.59)	(4.53)	(15.10)	(4.90)	(14.84)	(11.13)	(1.77)	(12.52)	(1.74)	(12.65)
LOSS		0.0002	0.0006	0.0001	0.0005	0.0001	-0.0001	-0.0003	-0.0001	-0.0001	-0.0001
		(1.16)	(1.22)	(0.49)	(1.03)	(0.60)	(-1.46)	(-1.61)	(-1.11)	(-0.87)	(-1.44)
LOGTV		0.0000	0.0001	0.0000	0.0001	0.0000	0.0001***	0.0000	0.0001***	0.0000	0.0000***
		(0.09)	(0.81)	(0.72)	(0.82)	(0.69)	(2.82)	(0.31)	(2.97)	(0.39)	(2.82)
Adj_R-Sqr		0.097	0.073	0.105	0.073	0.105	0.042	0.029	0.047	0.027	0.048
No_Obs		41,309	6,431	34,878	7,219	34,090	57,180	7,645	49,535	8,525	48,655

This table reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of forecast errors on earnings surprise or stock returns, the business cycle variables, two-way interaction terms between surprise/returns and the business cycle variables, and control variables (separately for the recessionary subsample and the expansionary subsample, respectively).

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Variable definitions:

FE_t^E (FE_t^L) is actual quarterly earnings per share minus the median of all analysts' forecasted earnings issued in the early (late) forecast period, deflated by the stock price at the beginning of the quarter.

DS (earnings surprise dummy) is 1 if earnings surprise is negative and 0 otherwise.

DR (return dummy) is 1 if stock return is negative and 0 otherwise.

Sur (earnings surprise) is the late forecast error from the previous quarter.

Ret (stock returns) is the average daily stock price changes within the period between 31 days after the last quarterly earnings announcement and 31 days before one-quarter-ahead earnings announcement.

MEMD (earnings skewness) is the mean-median difference of I/B/E/S actual earnings per share over the past eight quarters (requiring a minimum of four observations) deflated by the beginning period stock price.

LOGSALES (firm size) is the natural log of quarterly sales at the beginning of the quarter.

LOGFLLW (analyst following) is the natural log of the number of analysts issuing annual forecasts.

CV (earnings predictability) is the coefficient of variation of earnings per share over the past eight quarters (requiring a minimum of four observations).

INDROA (industry-adjusted ROA) is the firm's realised return on asset, calculated by income before extraordinary items over the 12 months following the forecast quarter divided by the average of quarterly total assets during the 12-month period, minus the median return on assets over the same period of all firms by the same two-digit SIC industry code.

LOSS is a dummy variable that equals 1 if the consensus earnings forecast is negative and 0 otherwise.

LOGTV (trading volume) is the natural log of the sum of monthly trading volume over the 12-month period before the latest earnings announcement.

5.4   Robustness tests

5.4.1   Uncertainty and underreaction

Findings from section 5.3 suggest that uncertainty is smaller during expansionary periods than during recessionary periods, and that analysts' underreaction is greater during expansionary periods than recessionary periods. That is, underreaction does not appear to move with uncertainty in this context. To make sure that this result is driven by some factor other than uncertainty, but not by an inverse relation between underreaction and uncertainty, I check the relationship between uncertainty and analysts' underreaction in my sample data. Based on Equations (4.1) and (4.2), I add the uncertainty measure and a two-way interaction variable between uncertainty and prior news, as shown at the top of Table 5-13.

A positive coefficient on the interaction variables (*V*Sur* or *V*Ret*) in both models indicates a positive association between uncertainty and underreaction. Consistent with the asymmetric reputation cost theory and evidence from previous studies, the results reported in Table 5-13 show that the coefficients for all interaction variables are significantly positive for both types of news in both early and late periods. These results provides empirical evidence from my sample data that at the firm level, analysts' underreaction is greater when the uncertainty level is higher, ruling out the possibility of any irregular relation between underreaction and uncertainty that may contribute to the findings in section 5.3.

In short, the results of this rest are consistent with my inference that it is the asymmetric reputation cost factor (rather than the uncertainty factor) that plays a dominant role in driving analysts' underreaction.

Table 5-13   Analysis of uncertainty and underreaction

$$FE_t^E = \alpha_0 + \beta_0 V_t + \beta_{S1} Sur_t + \beta_{S2}(V_t * Sur_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

$$FE_t^L = \alpha_0 + \beta_0 V_t + \beta_{R1} Ret_t + \beta_{R2}(V_t * Ret_t) + \beta_{S1} Sur_t + \beta_{S2}(V_t * Sur_t)$$
$$+ \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

Coefficient (t-statistic)	Exp. Sign	Early forecast period (underreaction to earnings surprise)	Late forecast period (underreaction to returns)
Variable			
Intercept		-0.0025***	-0.0001
		(-11.88)	(-1.01)
V		-0.0470***	-0.0059**
		(-22.49)	(-2.23)
Sur	+	0.2138***	0.1060***
		(17.08)	(14.19)
*V *Sur*	+	1.5437***	6.2687***
		(3.99)	(8.73)
Ret	+		0.0247***
			(5.44)
*V *Ret*	+		2.0933**
			(3.00)
MEMD		-0.0203***	0.0040
		(-5.89)	(1.68)
LOGSALES		0.0003***	0.0000**
		(9.23)	(3.14)
LOGFLLW		0.0005***	-0.0001**
		(5.51)	(-2.47)
CV		0.0001***	0.0001**
		(3.18)	(3.11)
INDROA		0.0092***	0.0032***
		(14.10)	(11.33)
LOSS		0.0003	-0.0001
		(1.63)	(-1.13)
LOGTV		-0.0001*	0.0001**
		(-1.70)	(3.03)
Adj R-Sq		0.206	0.056
No_Obs		41,309	57,180

This table reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of forecast errors on uncertainty, earnings surprise or stock returns, two-way interaction terms between surprise/returns and uncertainty, and control variables.
***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.
Variable definitions:
See Table 5-5 for variable definitions.

5.4.2   Underreaction estimation

5.4.2.1 Firm intercept effect

      Raedy et al. (2006) point out a potential problem with estimating underreaction using pooled cross-sectional data. If optimism or pessimism bias differs systematically across firms, a pooled cross-sectional regression can generate a significant slope coefficient even when analysts do not misreact to news. To mitigate the problem, Raedy et al. (2006) run regressions at the firm level and then estimate an average coefficient across firms. However, their method is not applicable to this study, because running regressions at the firm level over time eliminates the variation in forecast errors caused by business cycles. Instead, I add a firm intercept α_i (i.e., the firm dummy variable) in Equations (4.6) and (4.7) for the main tests of underreaction. This way, the firm intercept captures the potential systematic firm-specific bias, and the slope coefficient on news variables is able to capture average underreaction across firms during different stages of the business cycle.

      Table 5-14 reports the results for Equations (4.6) and (4.7) with an additional firm fixed effect. For brevity, the table omits firm intercepts and the control variables.

      The results show that the coefficient for *Sur*CY* is negative and statistically significant at least the 0.10 level for all business cycle variables in the early forecast period. Similarly, in the late forecast period, the coefficient for *Ret*CY* is significantly negative for all business cycle variables except the *CFNAI_Ind*. There is no significant difference from results in Table 5-10, suggesting that the issue raised by Raedy et al. (2006) does not affect the underreaction estimates in the main tests.

Table 5-14   Analysis of underreaction in relation to the business cycle - firm fixed effect

$$FE_t^E = \alpha_0 + \alpha_i + \beta_0 CY_t + \beta_{S1}Sur_t + \beta_{S2}(Sur_t * CY_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \qquad (4.6)$$

$$FE_t^L = \alpha_0 + \alpha_i + \beta_0 CY_t + \beta_{R1}Ret_t + \beta_{R2}(Ret_t * CY_t) + \beta_{S1}Sur_t + \beta_{S2}(Sur_t * CY_t) \qquad (4.7)$$
$$+ \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

Coefficient (*t*-statistic)	Exp. Sign	Early forecast period (Eq. 4.6) (underreaction to earnings surprise)			Late forecast period (Eq. 4.7) (underreaction to returns)		
Variable		NBER_Rec	CFNAI_Rec	CFNAI_Ind	NBER_Rec	CFNAI_Rec	CFNAI_Ind
Intercept		-0.0042***	-0.0042***	-0.0043***	-0.0012***	-0.0012***	-0.0012***
		(-8.09)	(-8.02)	(-8.41)	(-5.36)	(-5.37)	(-5.33)
CY		-0.0007***	-0.0007***	-0.0004**	0.0001*	0.0001**	0.0001
		(-2.81)	(-3.15)	(-2.57)	(1.86)	(1.99)	(1.14)
Sur	+	0.2064***	0.2078***	0.2109***	0.0875***	0.0875***	0.0870***
		(12.89)	(12.94)	(13.71)	(8.28)	(8.28)	(8.23)
*Sur*CY*	-	-0.0957*	-0.0931*	-0.0578**	-0.0379	-0.0376	-0.0347
		(-1.73)	(-1.81)	(-2.46)	(-0.94)	(-0.93)	(-0.86)
Ret	+				0.0375***	0.0386***	0.0353***
					(7.56)	(7.67)	(7.51)
*Ret*CY*	-				-0.0192*	-0.0214*	-0.0076
					(-1.72)	(-1.81)	(-0.96)
…							
Adj_R-Sqr		0.211	0.212	0.212	0.127	0.127	0.127
No_Obs		41,309	41,309	41,309	57,180	57,180	57,180

This table reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of forecast errors on earnings surprise or stock returns, the business cycle variables, two-way interaction terms for surprise/returns and the business cycle variables, control variables, and firm intercepts.

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Results regarding the control variables and firm intercepts are not reported for the sake of brevity.

Variable definitions:

FE_t^E (FE_t^L) is actual quarterly earnings per share minus the median of all analysts' forecasted earnings issued in the early (late) forecast period, deflated by the stock price at the beginning of the quarter.

CY_t (business cycles) includes three measures:

NBER_Rec is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise;

CFNAI_Rec is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise;

CFNAI_Ind is a continuous variable being CFNAI-MA3 multiplied by -1.

Sur (earnings surprise) is the late forecast error from the previous quarter.

Ret (stock returns) is the average daily stock price changes within the period between 31 days after the last quarterly earnings announcement and 31 days before one-quarter-ahead earnings announcement.

5.4.2.2 Adding inverse of price as a control variable

In subsection 4.2.1, I discuss the potential problem associated with deflating forecast errors by price. According to Cheong and Thomas' (2011) findings, price-deflated forecast errors are negatively associated with price. This problem may cause researchers to draw biased inferences if the test variables are also related to price. One remedy suggested by the authors is to include the inverse of price as an additional control variable when using scaled measures of forecast errors.

Thus, I construct an inverse of the price variable and include it when estimating Equations (4.6) and (4.7). Untabulated results show no significant differences from that of the main tests reported in Table 5-10.

5.4.2.3 Different cut-offs for forecast periods

As defined in section 4.1, I divide a between-earnings-announcement quarter equally into three parts: the first 30 days are the early forecast period, and the last 30 days are the late forecast period. In this robustness test, I follow Raedy et al. (2006) to re-define the forecast timeline. Specifically, the early forecast period includes the 20 days immediately following the last quarterly earnings announcement, whereas the late forecast period includes the 40 days immediately preceding the one-quarter-ahead earnings announcement. The idea is to generate more balanced subsamples because forecasts are more concentrated in the days following the latest earnings announcement than later in the period. Using the new definition for forecast periods, I re-estimate Equations (4.6) and (4.7). Untabulated results are qualitatively similar to the results of the main tests documented in Table 5-10.

5.4.3   Alternative measurement

5.4.3.1 Alternative measure for uncertainty

      With respect to the test for Hypothesis 1a, I estimate Equation (4.4) using an

alternative measure of uncertainty – forecast dispersion *(Disp)*. Replacing the Barron et al.

(1998) uncertainty measure with the dispersion measure does not change the significance of

the results (untabulated). This is consistent with the significantly positive correlation between

Disp and the recession measures reported in Table 5-7. Thus, this test provides further

evidence supporting the alternative form of Hypothesis 1a. That is, uncertainty about a firm's

future earnings is greater when the macroeconomy is worse.

5.4.3.2 Alternative measure for stock returns

      In Equation (4.7) that estimates the underreaction to earnings news in returns, I now

consider market-adjusted returns, i.e., returns minus the returns on the value-weighted market

portfolio for the same period. Table 5-15 reports the results from Equation (4.7) using the

market-adjusted returns as a proxy for earnings-related news.

      Table 5-15 shows that the coefficient for *Ret*CY* is significantly negative for all

business cycle variables except the *CFNAI_Ind*, similar to the results reported in Table 5-10.

Therefore, the results are robust whether the stock returns variable is market-adjusted or not.

Table 5-15   Analysis of underreaction in relation to the business cycle for the late forecast period using market-adjusted returns

$$FE_t^L = \alpha_0 + \beta_0 CY_t + \beta_{R1} Ret_t + \beta_{R2}(Ret_t * CY_t) + \beta_{S1} Sur_t + \beta_{S2}(Sur_t * CY_t) \qquad (4.7)$$
$$+ \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t$$

Coefficient (*t*-statistic)	Exp. Sign	Late forecasts (underreaction to market-adjusted returns)		
Variable		NBER_Rec	CFNAI_Rec	CFNAI_Ind
Intercept		-0.0001*	-0.0001*	-0.0001
		(-1.68)	(-1.70)	(-1.55)
CY		0.0001	0.0002*	0.0001
		(1.36)	(1.65)	(0.99)
Sur	+	0.1743***	0.1745***	0.1741***
		(19.65)	(19.70)	(19.64)
*Sur*CY*	-	-0.0138	-0.0145	-0.0120
		(-0.56)	(-0.58)	(-0.48)
Ret	+	0.0015***	0.0015***	0.0014***
		(8.58)	(8.35)	(8.27)
*Ret*CY*	-	-0.0012**	-0.0012**	-0.0004
		(-1.98)	(-2.09)	(-1.54)
…				
Adj_R-Sqr		0.042	0.042	0.042
No_Obs		57,180	57,180	57,180

This table reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of forecast errors on the market-adjusted returns, earnings surprises, the business cycle variables, two-way interaction terms between returns/earnings surprises and the business cycles variables, and control variables.

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Results regarding control variables are not reported for the sake of brevity.

Variable definitions:

FE_t^E (FE_t^L) is actual quarterly earnings per share minus the median of all analysts' forecasted earnings issued in the early (late) forecast period, deflated by the stock price at the beginning of the quarter.

CY_t (business cycles) includes three measures:

NBER_Rec is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise;

CFNAI_Rec is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise;

CFNAI_Ind is a continuous variable being CFNAI-MA3 multiplied by -1.

Sur (earnings surprise) is the late forecast error from the previous quarter.

Ret (market-adjusted stock returns) is the average daily stock price changes within the period between 31 days after the last quarterly earnings announcement and 31 days before one-quarter-ahead earnings announcement, minus the returns on the value-weighted market portfolio for the same period.

5.5 Summary

This chapter describes I/B/E/S sample selection process and reports data and results from regression tests. The results show that the two factors leading to underreaction in asymmetric reputation cost theory vary oppositely with macroeconomic conditions. Specifically, asymmetric reputation cost increases when the economy improves whereas uncertainty increases when the economy weakens. The results also show that analysts underreact to both earnings surprise and returns, and the underreaction is more pronounced during good times than bad times. A series of tests suggest that the results are robust.

These findings indicate that asymmetric reputation cost is not constant over time. It varies with macroeconomic conditions. Further, the asymmetric reputation cost has a dominant effect on underreaction. This is important to the literature because the results show that uncertainty is not the only factor that drives analysts to underreact to earnings news.

I also find that optimism bias is greater in recessionary periods, consistent with prior findings. Combined with the evidence from analysts forecasting activity in relation to the business cycle, the findings support the conjecture that short-term economic incentives are greater in bad times. However, I do not find evidence suggesting that analysts trade-off their reputations against short-term gains through underreaction. In fact, the results show that analysts appear to respond more pronouncedly to bad news (versus good news) during recessions than expansions. In other words, the evidence is consistent with the reputation cost minimising theory.

Collectively, this chapter provides evidence on the reputation-building incentive explanation for analysts' underreaction. In the situation where analysts have to incorporate new information in the forecasts, their decisions appear to be largely affected by reputation concerns rather than short-term opportunism.

So far, I have focused on the cyclical variation in analysts' underreaction and its determining factors. While the estimation models include control variables at the firm level, I do not consider the cross-sectional variation in underreaction simultaneously. It is widely known that certain factors vary across industries and firms. Analysts may behave differently towards firms with different characteristics, holding the economic conditions constant. In the following chapter, I further study the impact of certain industry- or firm-specific attributes on the association between underreaction and the business cycle.

CHAPTER 6

FURTHER STUDY

The previous chapter documents evidence suggesting that analysts' underreaction varies with the business cycle. This time variation in underreaction is consistent with the theory of the asymmetric reputation cost associated with analysts' earnings forecast inaccuracy. In this chapter, I further test the asymmetric reputation cost theory by simultaneously considering cross-sectional variations in certain industry- and firm-specific factors. Specifically, I examine the impact of (1) earnings cyclicality, (2) earnings quality, and (3) analyst following, on the association between underreaction and the business cycle in the following sections.

6.1   Earnings cyclicality

Not all industries are equally sensitive to economic fluctuations (Bodie, Kane, and Marcus, 2001, p. 396). Industries that provide capital equipment and durable items are highly sensitive to the state of economy, because businesses and consumers can defer spending on these items, and hence, the demand for these items is determined by the level of income. These industries are referred to as cyclical industries. In contrast, industries that provide staples such as food, drugs, and medical services show little sensitivity to the business cycle, because the demand for these necessities is a small part of consumers' budgets and the products and services from these industries are needed in economic downturns as well as economic upturns. As a result, sales of these industries are less sensitive to the business cycle. These industries are referred to as non-cyclical industries.

In this section, I consider the variation in earnings cyclicality across industries while examining the association between analysts' underreaction and the business cycle. Intuitively,

as cyclical (non-cyclical) industries are more sensitive (insensitive) to economic fluctuations, one would expect a strong (weak) association between underreaction and the business cycle in cyclical (non-cyclical) industries.

6.1.1 Hypothesis development

In subsection 3.1.2, I explain that investors' loss aversion is greater during expansionary periods because investors suffer relatively more deprivation from losses when other investors enjoy gains. When the fear of losses increases, investors will impose higher implicit reputation costs on an analyst if subsequent information creates a reversal of their expectations about the firm based on that analyst's forecasts. I predict that analysts underreact more to earnings news during expansionary periods in order to reduce greater asymmetric reputation cost. The findings from Chapter 5 are consistent with this prediction.

If an industry is non-cyclical, i.e., its performance is relatively independent of the business cycle, then investors will not expect firms in that industry to perform as well as those in cyclical industries during good times. Accordingly, investors' loss aversion and analysts' asymmetric reputation cost would vary little across business cycles for non-cyclical industries. In contrast, cyclical industries perform better during booming periods. Investors' expectation to gain from these cyclical industries becomes higher. Since their sensitivity to losses increases when others enjoy gains from these industries, they become more adverse to losses in expansionary periods. Accordingly, the asymmetric reputation cost for analysts, which arises when later news contradicts the views implied by their earlier forecasts, will increase. Thus, given the validity of the asymmetric reputation cost theory, I predict greater analyst underreaction to news during expansionary periods, particularly for cyclical industries.

One condition for this prediction is that analysts understand the cyclicality of industries and incorporate it in their forecasts. Textbooks implore forecasting that considers

the relationship between industrial activity and business cycles. Reilly (1979), in his recommendations of earnings forecasting procedures, states that "the first of which is deriving an estimate of sales per share based upon an analysis of relationship between sales of the given industry and aggregate sales for some relevant economic series" (p. 323). In a similar vein, Reilly and Brown (2006) recommend that the first step of macro-analysis of the industry is to "determine how this industry relates to the business cycle and what economic variables drive this industry" (p. 463). Analysts can obtain knowledge about an industry and its relation to the business cycle by modelling the relation between industrial activity and macroeconomic variables using historical data. Given its important role in earnings forecasting process, it is reasonable to expect that analysts understand the degree of cyclicality of their assigned industry. Thus, I hypothesise:

H3:   *Analysts' differential underreaction during recessions versus expansions is more strongly associated with cyclical industries than non-cyclical industries.*

6.1.2   Research design

To test this hypothesis, I focus on analysts' underreaction to earnings surprise using data from the early forecast period. I partition the sample firms into a cyclical industry subsample and a non-cyclical industry subsample. Then, I run Equation (4.6) separately for each subsample. If H3 is true, then the coefficient β_{S2} for *Sur*CY* will be more significantly negative for the cyclical industry subsample compared to the non-cyclical subsample.

I use two methods to identify cyclical industries. The first method relies on publicly available indices of cyclicality (e.g., Yahoo Finance) based on the cyclical or non-cyclical nature of an industry's sales volume (hereafter the cyclical-sales industry measure). For example, Yahoo Finance identifies 'Consumer Cyclical' industries, including apparel/accessories, appliance and tool, and auto and truck manufacturing. Industries such as

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real estate, industrial, technology, and transportation are also cyclical because they represent expensive consumer items or capital equipment that can have their purchase deferred during hard times (Gitman and Joehnk, 1999, p. 192). Non-cyclical industries include industries identified as "Consumer Non-Cyclical" by Yahoo Finance, such as beverages, crops, food processing, office supplies, personal and household products, and tobacco. Other industries such as bank and finance, insurance, healthcare, energy and utilities are also non-cyclical industries because these sectors are subject to regulation that protect them from business cycle fluctuations (Higgins, 2002a). These industries tend to underperform the market during periods of economic growth, but outperform the market during economic downturns (Taylor, 1998). Accordingly, I assign 1 to an industry if it is cyclical and 0 otherwise, based on its four-digit SIGC (sector industry group code) in I/B/E/S.

It is worth noting that although sales is an important determinant of firm earnings, earnings sensitivity to economic conditions is also affected by other factors, such as operating leverage and financial leverage. High operating leverage and high financial leverage lead to high levels of fixed costs that would increase the sensitivity of profits to business cycles, because fixed costs are harder to reduce than variable costs in hard times (Bodie et al., 2001). Earnings management is a potential factor as well, because management discretion (e.g., to smooth earnings) clearly affects earnings sensitivity to business cycles.

Therefore, in the second method, I consider the correlation between earnings growth and the business cycle proxies (hereafter the cyclical-earnings industry measure). This is a direct way to identify whether an industry is cyclical in terms of its earnings variation with the business cycle. The earnings growth is the growth rate of I/B/E/S actual earnings of the current quarter relative to the corresponding quarter of the last year to take into account any seasonal variations. Then, I compute the correlation coefficient between the earnings growth and the business cycle variable within an industry using the four-digit SIGC industry code.

An industry is assigned a code of 1 (cyclical industry) if the correlation coefficient is significantly negative at the 0.10 level (because the business cycle is measured inversely), and 0 (non-cyclical industry) otherwise.

6.1.3   Results

Table 6-1 and Table 6-2 report results of industry analysis based on the cyclical-sales industry measure and the cyclical-earnings industry measure, respectively. For brevity, both tables omit coefficients for the control variables. I employ all three business cycle measures defined in subsection 4.2.4, and present results for cyclical industries and non-cyclical industries side by side.

The results in both tables show a remarkable difference between the two subsamples. For cyclical industries (columns 2 through 4), the differential underreaction coefficient for *Sur*CY* is significantly negative in all regressions, consistent with findings in Table 5-10. In contrast, non-cyclical industries do not show any significant coefficient for *Sur*CY* for all the business cycle measures (columns 5 through 7). That is, for non-cyclical industries, analysts do not underreact to earnings surprise differently across business cycles. In addition, the coefficients for non-cyclical industries are smaller in magnitude than cyclical industries. For example, in Table 6-1, the coefficient is -0.08 for non-cyclical industries (column 5) but -0.18 for cyclical industries (column 2) when the NBER measure is used. To confirm the difference in magnitude in a statistical sense, I conduct a Wald Chi-Squared test to compare the coefficients for the differential underreaction between the two groups. The results show that the difference is statistically significant, particularly when the cyclical-earnings industry measure is used in Table 6-2.

Table 6-1 Cyclical/non-cyclical industry analysis of underreaction in relation to
the business cycle (using the cyclical-sales industry measure)

$$FE_t^E = \alpha_0 + \beta_0 CY_t + \beta_{S1} Sur_t + \beta_{S2}(Sur_t * CY_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \qquad (4.6)$$

Coefficient (*t*-statistic)	Cyclical Industries			Non-cyclical Industries		
Variable	*NBER_Rec*	*CFNAI_Rec*	*CFNAI_Ind*	*NBER_Rec*	*CFNAI_Rec*	*CFNAI_Ind*
1	2	3	4	5	6	7
Intercept	-0.0024***	-0.0024***	-0.0024***	-0.0019***	-0.0019***	-0.0019***
	(-8.41)	(-8.18)	(-8.25)	(-5.76)	(-5.71)	(-5.71)
CY	-0.0004	-0.0006	-0.0003	-0.0002	-0.0001	-0.0001
	(-1.17)	(-1.66)	(-1.44)	(-0.51)	(-0.42)	(-0.57)
Sur	0.3190***	0.3228***	0.3171***	0.3032***	0.3078***	0.3005***
	(12.98)	(13.03)	(13.56)	(11.62)	(11.66)	(12.17)
*Sur*CY*	-0.1771**	-0.1777**	-0.0865***	-0.0794	-0.0894	-0.0360
	(-2.95)	(-3.23)	(-3.51)	(-1.47)	(-1.70)	(-1.42)
…						
Adj_R-Sqr	0.102	0.103	0.103	0.087	0.087	0.087
No_Obs	16,620	16,620	16,620	18,028	18,028	18,028

Chi Squared test for difference in the coefficient for *Sur*CY* between the two subsamples:

Chi2	2.66	2.33	3.41*
P-value	0.1028	0.1271	0.065

This table reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of forecast errors on earnings surprise, the business cycle variables, a two-way interaction between earnings surprise and the business cycle variables, and control variables. The regressions are estimated for the cyclical subsample and the noncyclical subsample separately.

An industry is cyclical when the industry's sales are positively correlated with business cycles and non-cyclical otherwise.

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Results regarding control variables are not reported for the sake of brevity.

Variable definitions:

FE_t^E is actual quarterly earnings per share minus the median of all analysts' forecasted earnings issued in the early forecast period, deflated by the stock price at the beginning of the quarter.

CY_t (business cycles) includes three measures:

NBER_Rec is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise;

CFNAI_Rec is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise;

CFNAI_Ind is a continuous variable being CFNAI-MA3 multiplied by -1.

Sur (earnings surprise) is the late forecast error from the previous quarter.

Table 6-2 Cyclical/non-cyclical industry analysis of underreaction in relation to
the business cycle (using the cyclical-earnings industry measure)

$$FE_t^E = \alpha_0 + \beta_0 CY_t + \beta_{S1} Sur_t + \beta_{S2}(Sur_t * CY_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \tag{4.6}$$

Coefficient (*t*-statistic)	Cyclical Industries			Non-cyclical Industries		
Variable	*NBER_Rec*	*CFNAI_Rec*	*CFNAI_Ind*	*NBER_Rec*	*CFNAI_Rec*	*CFNAI_Ind*
1	2	3	4	5	6	7
Intercept	-0.0033***	-0.0032***	-0.0031***	-0.0020***	-0.0021***	-0.0021***
	(-10.28)	(-9.76)	(-10.00)	(-8.99)	(-9.65)	(-9.73)
CY	-0.0006*	-0.0007**	-0.0004**	-0.0004	-0.0004	-0.0001
	(-1.84)	(-2.25)	(-2.37)	(-1.44)	(-1.51)	(-1.01)
Sur	0.3409***	0.3417***	0.3432***	0.2746***	0.2822***	0.2807***
	(12.22)	(10.54)	(11.72)	(14.68)	(16.64)	(17.03)
*Sur*CY*	-0.1663***	-0.1538***	-0.0887***	-0.0545	-0.0631	-0.0300
	(-3.32)	(-2.62)	(-3.57)	(-1.23)	(-1.59)	(-1.55)
…						
Adj_R-Sqr	0.124	0.125	0.128	0.084	0.084	0.084
No_Obs	15,263	15,099	15,099	26,046	26,210	26,210

Chi Squared test for difference in the coefficient for *Sur*CY* between the two subsamples:

Chi2	3.19*	2.16	4.11**
P-value	0.074	0.142	0.043

This table reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of forecast errors on earnings surprise, the business cycle variables, a two-way interaction between earnings surprise and the business cycle variables, and control variables.

The regressions are estimated for cyclical group and noncyclical group separately.

An industry is cyclical when the industry's earnings are significantly positively correlated with business cycles at the 0.10 level, and non-cyclical otherwise.

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Results regarding control variables are not reported for the sake of brevity.

Variable definitions:

FE_t^E is actual quarterly earnings per share minus the median of all analysts' forecasted earnings issued in the early forecast period, deflated by the stock price at the beginning of the quarter.

CY_t (business cycles) includes three measures:

NBER_Rec is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise;

CFNAI_Rec is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise;

CFNAI_Ind is a continuous variable being CFNAI-MA3 multiplied by -1.

Sur (earnings surprise) is the late forecast error from the previous quarter.

Considering the difference in underreaction during expansions between the cyclical

and non-cyclical industry group, I compare the ratio of the underreaction coefficients during

recessions relative to expansions, i.e., $(\beta_{S1} + \beta_{S2})/\beta_{S1}$, between the two subsamples. Statistically, I rely on the Delta method (Casella and Berger, 2002) and the Fieller's interval (Fieller, 1954) to estimate and compare confidence intervals of the coefficient ratios. Caskey and Peterson (2009) use the same methods to estimate a ratio measure based on the Basu (1997) model for accounting conservatism. Table 6-3 reports the estimate of the underreaction coefficient ratio during recessions relative to expansions and 90% confidence intervals using the Fieller and Delta methods.

Panel A (B) of Table 6-3 shows the ratio and the confident intervals based on the results in Table 6-1 (Table 6-2) that uses the cyclical-sales (cyclical-earnings) industry measure to identify cyclical/non-cyclical industries. Except for one instance when the cyclical-earnings and the CFNAI recession measures are used, the difference in the underreaction coefficient ratios is statistically significant between the two subsamples.

In short, the results show a significant difference in analysts' underreaction across business cycles between the cyclical and non-cyclical industries. The findings support Hypothesis 3 that the incremental underreaction in expansionary periods is associated with cyclical industries solely, consistent with the notion that analysts' differential underreaction is a rational behaviour driven by the reputation building incentives. The less significant result for the cyclical-earnings measure than the cyclical-sales measure also suggests that investors and analysts rely more on the traditional notion of the cyclical industries, rather than the cyclical behaviour of earnings.

Table 6-3 Cyclical/non-cyclical industry difference in underreaction coefficient ratio during recessions relative to expansions – Fieller and Delta method

Panel A: Ratio comparison based on the cyclical-sales industry measure

Business Cycle	Cyclical Industries			Non-cyclical Industries		
	Ratio	Fieller intervals	Delta Intervals	Ratio	Fieller intervals	Delta Intervals
NBER_Rec	0.441	[0.303,0.583]	[0.301,0.580]	0.766	[0.643,0.895]	[0.640,0.891]
Difference	-0.325**					
CFNAI_Rec	0.486	[0.355,0.622]	[0.353,0.620]	0.760	[0.642,0.885]	[0.639,0.882]
Difference	-0.274*					

Panel B: Ratio comparison based on the cyclical-earnings industry measure

Business Cycle	Cyclical Industries			Non-cyclical Industries		
	Ratio	Fieller intervals	Delta Intervals	Ratio	Fieller intervals	Delta Intervals
NBER_Rec	0.512	[0.383,0.647]	[0.381,0.644]	0.802	[0.682,0.927]	[0.680,0.924]
Difference	-0.290*					
CFNAI_Rec	0.550	[0.427,0.679]	[0.425,0.676]	0.777	[0.664,0.894]	[0.661,0.892]
Difference	-0.227					

This table reports the estimate of ratio of underreaction coefficients during recessions relative to expansions, i.e., $(\beta_{S1} + \beta_{S2})/\beta_{S1}$, from Equation (4.6), and 90% confidence interval using the Fieller interval and the Delta method.

Panel A (B) shows the ratio and confident intervals based on the results in Table 6-1 (6-2) that uses the cyclical-sales (cyclical-earnings) measure to identify cyclical/non-cyclical industries.

An industry is cyclical when the industry's sales or earnings are significantly positively correlated with business cycles, and non-cyclical otherwise

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Variable definitions:

NBER_Rec is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise;

CFNAI_Rec is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise.

6.1.4   Additional tests

The analyses in subsection 6.1.3 distinguish the cyclical and non-cyclical industries

with an emphasis on the pro-cyclicality. Among the non-cyclical industries, some industries

can be truly counter-cyclical, i.e., their financial performance is negatively correlated to the

overall state of the economy. An example would be an outplacement agency that earns

revenues from finding jobs for laid-off workers. This type of firm has more business

opportunities during recessions than expansions. While the number of counter-cyclical industries is limited, it is interesting to see whether analysts' behaviour regarding these industries is different.

Based on the cyclical-earnings industry measure, I separate the counter-cyclical industries from the non-cyclical industries. An industry is counter-cyclical when the earnings-business cycle correlation coefficient is significantly positive at the 0.10 level. An industry is non-cyclical when the correlation is insignificant. Only a few industries are identified as counter-cyclical: the tobacco and truck manufacturing industries under the NBER recession measure, and the tobacco and textile industries under the CFNAI measure.

Table 6-4 reports the regression results for the non- and counter-cyclical industries. I also provide the results for the pro-cyclical industries (same as in Table 6-2) for the purpose of comparison. The coefficient of *Sur*CY* is negative and significant for the pro-cyclical industries only (columns 2 through 4). For non-cyclical and counter-cyclical industry groups, the coefficient of differential underreaction is statistically insignificant (columns 5 through 10). Hence, there is no evidence suggesting that analysts treat the counter-cyclical industries differently than the non-cyclical industries. Of course, the small sample size and lack of statistical power may be a factor in these tests.

Table 6-4 Cyclical/non-cyclical industry analysis of underreaction in relation to the business cycle
(distinguishing counter-cyclical industries based on the cyclical-earnings industry measure)

$$FE_t^E = \alpha_0 + \beta_0 CY_t + \beta_{S1} Sur_t + \beta_{S2}(Sur_t * CY_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \qquad (4.6)$$

Coefficient (t-statistics)	Pro-cyclical Industries			Non-cyclical Industries			Counter-cyclical Industries		
Variable	NBER_Rec	CFNAI_Rec	CFNAI_Ind	NBER_Rec	CFNAI_Rec	CFNAI_Ind	NBER_Rec	CFNAI_Rec	CFNAI_Ind
1	2	3	4	5	6	7	8	9	10
Intercept	-0.0033***	-0.0032***	-0.0031***	-0.0020***	-0.0020***	-0.0021***	-0.0027	-0.0060**	-0.0061**
	(-10.28)	(-9.76)	(-10.00)	(-9.16)	(-9.60)	(-9.71)	(-0.81)	(-2.10)	(-2.08)
CY	-0.0006*	-0.0007**	-0.0004**	-0.0004	-0.0004	-0.0002	0.0014	0.0013	0.0001
	(-1.84)	(-2.25)	(-2.37)	(-1.49)	(-1.60)	(-1.05)	(1.37)	(1.38)	(0.26)
Sur	0.3409***	0.3417***	0.3432***	0.2755***	0.2847***	0.2835***	0.6838***	0.6573***	0.6172***
	(12.22)	(10.54)	(11.72)	(15.08)	(17.61)	(18.13)	(5.97)	(4.26)	(4.15)
*Sur*CY*	-0.1663***	-0.1538***	-0.0887***	-0.0530	-0.0597	-0.0291	-0.4431	-0.4091	0.1086
	(-3.32)	(-2.62)	(-3.57)	(-1.19)	(-1.40)	(-1.43)	(-1.16)	(-1.20)	(0.46)
…									
Adj_R-Sqr	0.124	0.125	0.128	0.083	0.084	0.084	0.340	0.215	0.209
No_Obs	15,263	15,099	15,099	25,862	26,025	26,025	184	185	185

This table reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of forecast errors on earnings surprise, the business cycle variables, a two-way interaction between earnings surprise and the business cycle variables, and control variables.

The regressions are estimated for the pro-cyclical, non-cyclical, and counter-cyclical industry subsamples separately.

An industry is pro-cyclical when the earnings-business cycle correlation coefficient is significantly positive; non-cyclical when the correlation coefficient is insignificant; counter-cyclical when the correlation coefficient is significantly negative.

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Variable definitions:

See Table 6-1 for variable definitions.

6.2   Earnings quality

In this section, I investigate the effect of firm-specific earnings quality on (1) analysts' underreaction and (2) differential underreaction across business cycles.

6.2.1   Hypothesis development

In a recent review of the earnings quality literature, Dechow, Ge, and Schrand (2010) discuss analyst forecasting as one of the consequences of earnings quality. Under the assumption of analyst efficiency, several studies examine forecast accuracy as a function of earnings quality, and infer that certain accounting methods, accounting standard sets, or earnings formats are of higher quality (Brown, 1983; Elliott and Philbrick, 1990; Ashbaugh and Pincus, 2001; Bhattacharya, Black, Christensen, and Larson, 2003). However, given the evidence against the assumption of analyst efficiency, many studies investigate analysts' ability to anticipate and adjust for the effect of firms' earnings management incentives in various contexts. That is, when firms manage earnings away from their true financial performance due to various incentives of the managers, forecast inefficiency may result from analysts' inability to anticipate and incorporate the effect of earnings management. For example, Abarbanell and Lehavy (2003) document a correlation between forecast errors and extreme unexpected accruals.

Several studies suggest that analysts show some degree of rationality in anticipating firms' incentives to manage earnings in order to maximise bonus compensation (Kim and Schroeder, 1990) and to avoid reporting losses (Burgstahler and Eames, 2003). However, Burgstahler and Eames (2003) find no evidence that analysts can anticipate *which* firms will manage earnings. Other studies further show evidence suggesting that analysts, in their forecasts, fail to incorporate the implications of accruals (Elliott and Philbrick, 1990; Bradshaw et al., 2001), the aggressive accrual behavior in pre-merger reports by acquiring

firms (Louis, 2004), and restructuring charges (Chaney, Hogan, and Jeter, 1999). Shane and Stock (2006) find little evidence that analysts anticipate or adjust for the earnings effects of firms' incentives to shift income from higher to lower tax rate years in the context of the Tax Reform Act of 1986. Finally, Givoly, Hayn, and Yoder (2010) examine whether analysts anticipate earnings management and if so, whether they predict unmanaged or managed earnings. They identify firms that manage earnings through earnings restatements and accrual behaviour around earnings thresholds. Their findings suggest that analysts focus on predicting firms' actual reported earnings (i.e., the managed earnings number). However, they further find that in the wake of upward earnings management, analysts issue more optimistic forecasts and recommendations that are not supported by firms' subsequent performance. In short, while the evidence is somewhat mixed, the literature generally suggests that analysts' ability to predict earnings management is limited.

Rather than examining analyst efficiency in anticipating certain incentives for or certain types of earnings management, I investigate whether earnings quality affects analysts' efficiency from a reputation-related incentive perspective. Specifically, I examine whether earnings quality affects analysts' underreaction to earnings news. For firms with low quality earnings, managers are more likely to manage earnings when certain incentives are present. There is a higher degree of uncertainty associated with these firms' future earnings. If analysts are able to gauge the quality of a firm's reported earnings based on its historical behaviour, they will take the earnings quality factor into consideration when responding to earnings news. Then the asymmetric reputation cost theory would predict that, given a certain level of the asymmetric reputation cost, analysts' underreaction is more (less) pronounced for firms with lower (higher) quality earnings due to the higher (lower) degree of uncertainty for these firms. I hypothesise:

H4a: Analysts' underreaction is more pronounced for firms with lower quality earnings

than firms with higher quality earnings.

The above hypothesis assumes the effects of the business cycle and earnings quality on underreaction are additive. It is interesting to study whether the two effects are interactive, i.e., whether the impact of the business cycle on underreaction depends on earnings quality. In the previous chapter, I document that analysts underreact more due to the increased reputation costs during expansionary periods. I conjecture that for firms with lower (higher) quality earnings, analysts are less (more) confident in predicting these earnings, and hence, the increased reputation costs will have more (less) marginal effect on underreaction than they would for firms with higher (lower) quality earnings. That is, the differential underreaction across business cycles will be more (less) pronounced for firms with lower (higher) quality earnings. I hypothesise:

H4b: Analysts' differential underreaction across business cycles is more pronounced for

firms with lower quality earnings than firms with higher quality earnings.

6.2.2   Research design

I choose a modified version of the Dechow and Dichev (2002) model to measure the earnings quality. The Dechow and Dichev (2002) model embodies the intuition that firms recognise accruals to adjust for cash flow timing problems in earnings and better reflects economic performance. Since accruals are based on assumptions and estimates, the quality of accruals and earnings is a decreasing function of accrual estimation errors. The empirical measure of accruals quality is based on the residuals from firm-specific regressions of changes in working capital accruals on lagged, current and future cash flows from operations. Following Dhaliwal, Naiker, and Navissi (2010), I include change in sales (employed in the Jones's (1991) model) and three quarterly dummy variables (to control for any possible

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seasonality effects) as additional explanatory variables. Because accrual quality is

systematically related to industry characteristics (e.g., operating cycle length and operation

variability), I estimate the regression model at the industry level based on the 3-digit SIC

industry code. Lastly, I adopt a rolling window method to run regressions over the 12-quarter

period prior to the latest earnings announcement (requiring a minimum of eight observations

per firm). This way, the estimated earnings quality measure is comparative among firms

within a certain industry and is relevant to analysts' earnings forecasting. The modified

model follows:

$$\Delta WC_t = \alpha_0 + \alpha_1 CFO_{t-1} + \alpha_2 CFO_t + \alpha_3 CFO_{t+1} + \alpha_4 \Delta Sales_t \tag{6.1}$$

$$+ \sum_{k=1}^{3} \alpha_{4+k} QTR_k + \varepsilon_t$$

where ΔWC_t is the change in working capital accruals of firm i in quarter t, measured using

data from the statement of cash flows scaled by average assets (ATQ),[19] CFO_t is the cash

flow from operations of firm i in quarter t ($OANCFY$) scaled by average assets, $\Delta Sales_t$ is the

change in sales of firm i in quarter t ($SALEQ$) scaled by average assets, QTR_k is a dummy

variable that takes a value of 1 when the observation is from fiscal quarter k *(1, 2, or 3)* and 0

otherwise, and ε_t is the residual of firm i in quarter t. COMPUSTAT presents quarterly cash

flow data as year-to-date periodic figures. Therefore, ΔWC_t and CFO_t are adjusted to the

corresponding quarterly change only.

The sample is restricted to firms with complete data for assets, cash flows from

operations, changes in accounts receivable and changes in inventory, and at least eight

quarters of data. I obtain quarterly residuals ε_t for each firm from Equation (6.1) over the 12-

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[19] Specifically, change in working capital accruals is increase in accounts receivable plus increase in inventory
plus the decrease in accounts payable and accrued liabilities plus decreases in taxes accrued plus increase
(decrease) in other assets (liabilities). In Compustat, WC= - (recchy+invchy+apalchy+txachy+aolochy).

quarter period prior to the latest earnings announcement from 1988 through 2009.[20] These

quarterly residuals are unrelated to cash flow realisations, thus represent abnormal changes in

working capital accruals (Dechow and Dichev, 2002). Similar to Dechow and Dichev (2002),

I measure earnings quality by calculating the standard deviation of firm i's estimated

residuals from Equation (6.1).[21] A higher standard deviation (higher volatility in abnormal

accruals) signifies lower quality of accruals and earnings. Hence, I multiply the standard

deviation by -1 to make the measure increase with earnings quality.

I use the following estimation equations to test the relation between earnings quality

and underreaction while controlling for the effect of the business cycle on underreaction,

along with other control variables:

$$FE_t^E = \alpha_0 + \beta_0 CY_t + \beta_1 Quality_t + \beta_{S2} Sur_t + \beta_{S3}(Sur_t * Quality_t) \tag{6.2}$$

$$+ \beta_{S4}(Sur_t * CY_t) + \sum_{k=1}^{n} \beta_{1+k} Controls_k + \varepsilon_t$$

$$FE_t^L = \alpha_0 + \beta_0 CY_t + \beta_1 Quality_t + \beta_{R2} Ret_t + \beta_{R3}(Ret_t * Quality_t) \tag{6.3}$$

$$+ \beta_{R4}(Ret_t * CY_t) + \beta_{S2} Sur_t + \beta_{S3}(Sur_t * Quality_t)$$

$$+ \beta_{S4}(Sur_t * CY_t) + \sum_{k=1}^{n} \beta_{1+k} Controls_k + \varepsilon_t$$

where *Quality* is negative of the standard deviation of residuals from regressions of changes

in working capital accruals on lagged, current and future cash flows from operations based on

the modified Dechow and Dichev's (2002) model, i.e., Equation (6.1), other variables are

defined in previous equations, and ε_t is the error term.

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[20] Statement of Cash Flows is required by SFAS No. 95 for fiscal years ending after July 15, 1988.
[21] This measure is based on the time-series mechanics of accruals and on the intuition that any large positive abnormal accruals will be offset by future negative abnormal accruals.

The interaction term *Sur*CY* (*Ret*CY*) controls for the net effect of the business cycle on analysts' underreaction, jointly determined by the level of uncertainty and asymmetric reputation cost. The coefficient of interest is β_{S3} (β_{R3}) for the interaction term *Sur*Quality* (*Ret*Quality*), which captures the effect of earnings quality on analysts' underreaction to earnings surprises (stock returns). Recall that in a basic model that estimates underreaction (e.g., Equation 2.1), a positive coefficient for earnings news implies that analysts underreact to the news. Also, the measure *Quality* increases with earnings quality. Hence, for the early forecast period in Equation (6.2), if analysts' underreaction to earnings surprises is more pronounced for firms with low quality earnings, then the coefficient β_{S3} for the interaction term *Sur*Quality* will be significantly negative. Likewise, for the late forecast period in Equation (6.3), if analysts' underreaction to stock returns is more pronounced for firms with low quality earnings, then the coefficient β_{R3} for *Ret*Quality* will be significantly negative. To statistically test H4a, I employ *t*-tests of the following null and alternative hypothesis:

H^0_{4a}: $\beta_{S3} = 0$, H^A_{4a}: $\beta_{S3} < 0$ for the early forecast period,

H^0_{4a}: $\beta_{R3} = 0$, H^A_{4a}: $\beta_{R3} < 0$ for the late forecast period.

To test Hypothesis 4b, i.e., whether the impact of the business cycle on underreaction depends on earnings quality, I add a three-way interaction onto the previous equations:

$$FE^E_t = \alpha_0 + \beta_0 CY_t + \beta_1 Quality_t + \beta_{S2} Sur_t + \beta_{S3}(Sur_t * Quality_t) \qquad (6.4)$$

$$+ \beta_{S4}(Sur_t * CY_t) + \beta_{S5}(Quality_t * CY_t) + \beta_{S6}(Sur_t * CY_t$$

$$* Quality_t) + \sum_{k=1}^{n} \beta_{1+k} Controls_k + \varepsilon_t$$

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$$FE_t^L = \alpha_0 + \beta_0 CY_t + \beta_1 Quality_t + \beta_{R2} Ret_t + \beta_{R3}(Ret_t * Quality_t) \qquad (6.5)$$

$$+ \beta_{R4}(Ret_t * CY_t) + \beta_{R5}(Ret_t * Quality_t * CY_t) + \beta_{S2} Sur_t$$

$$+ \beta_{S3}(Sur_t * Quality_t)$$

$$+ \beta_{S4}(Sur_t * CY_t) + \beta_{S5}(Quality_t * CY_t) + \beta_{S6}(Sur_t * CY_t * Quality_t)$$

$$+ \sum_{k=1}^{n} \beta_{1+k} Controls_k + \varepsilon_t$$

where all variables are defined in previous equations.

In Equation (6.4), the coefficient of interest is β_{S6} for *Sur*CY*Quality*. H4b hypothesises the differential underreaction across business cycles is more pronounced for firms with low quality earnings, i.e., a negative association between earnings quality and the incremental underreaction during expansions (versus recessions). As the incremental underreaction during expansions versus recessions in the regression model means a negative coefficient for *Sur*CY*, if H4b is true, then the coefficient β_{S6} will be positive. Likewise, in Equation (6.5), if H4b is true, the coefficient β_{R5} will be positive.

To statistically test H4b, I employ *t*-tests of the following null and alternative hypothesis:

H^0_{4b}: $\beta_{S6} = 0$, H^A_{4b}: $\beta_{S6} > 0$ for the early forecast period,

H^0_{4b}: $\beta_{R5} = 0$, H^A_{4b}: $\beta_{R5} > 0$ for the late forecast period.

6.2.3   Data and results

Table 6-5 panel A reports descriptive statistics of earnings quality (*Quality*) for the early forecast subsample. After the data requirements for earnings quality are met, the final sample size is reduced to 14,795 firm-quarter observations in the early forecast period. The mean of the earning quality measure is -0.01.

Table 6-5 Analysis of earnings quality and the underreaction/business cycle relation
for the early forecast period

Panel A. Distribution of the earnings quality variable (*Quality*) in the early forecast subsample

N	Mean	STD	Min	Q1	Median	Q3	Max
14,795	-0.01	0.0067	-0.0420	-0.0127	-0.0081	-0.0053	-0.0004

Panel B. The association between earnings quality and the underreaction/business cycle relation

$$FE_t^E = \alpha_0 + \beta_0 CY_t + \beta_1 Quality_t + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * Quality_t) + \beta_{S4}(Sur_t * CY_t) \qquad (6.2)$$
$$+ \sum_{k=1}^{n} \beta_{1+k} Controls_k + \varepsilon_t$$

$$FE_t^E = \alpha_0 + \beta_0 CY_t + \beta_1 Quality_t + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * Quality_t) \qquad (6.4)$$
$$+ \beta_{S4}(Sur_t * CY_t) + \beta_{S5}(Quality_t * CY_t) + \beta_{S6}(Sur_t * CY_t * Quality_t)$$
$$+ \sum_{k=1}^{n} \beta_{1+k} Controls_k + \varepsilon_t$$

Coefficient (*t*-statistic)	Exp. Sign	Equation (6.2)			Equation (6.4)		
1	2	3	4	5	6	7	8
Variable		NBER_Rec	CFNAI_Rec	CFNAI_Ind	NBER_Rec	CFNAI_Rec	CFNAI_Ind
Intercept		-0.0021***	-0.0021***	-0.0021***	-0.0020***	-0.0020***	-0.0020***
		(-7.02)	(-6.83)	(-6.80)	(-6.59)	(-6.43)	(-6.50)
CY		-0.0003	-0.0004	-0.0002	-0.0008*	-0.0008**	-0.0004*
		(-0.93)	(-1.31)	(-0.94)	(-1.89)	(-2.06)	(-1.85)
Quality		0.0075	0.0079	0.0081	0.0170*	0.0164*	0.0156*
		(0.81)	(0.85)	(0.84)	(1.95)	(1.86)	(1.86)
Sur	+	0.2717***	0.2776***	0.2779***	0.2628***	0.2558***	0.2569***
		(6.52)	(6.41)	(6.57)	(5.38)	(5.21)	(5.46)
*Sur*Quality*	-	-3.2848	-3.2444	-2.9779	-4.0921	-5.1618	-4.7283
		(-1.09)	(-1.07)	(-0.99)	(-1.10)	(-1.47)	(-1.41)
*Sur*CY*	-	-0.1302**	-0.1438**	-0.0651***	-0.1032**	-0.0675**	-0.0274***
		(-2.22)	(-2.45)	(-3.04)	(-2.19)	(-2.13)	(-2.86)
*CY*Quality*					-0.0508*	-0.0408	-0.0235*
					(-1.77)	(-1.51)	(-1.94)
*Sur*CY* Quality*	+				3.0190	7.7356	4.0248**
					(0.68)	(1.36)	(1.98)
…							
Adj_R-Sqr		0.093	0.094	0.094	0.095	0.096	0.096
No_Obs		14,795	14,795	14,795	14,795	14,795	14,795

Table 6-5 (Continued) Analysis of earnings quality and the underreaction/business cycle relation for the early forecast period

Panel A of this table reports the distribution of the modified Dechow and Dichev earnings quality variable.

Panel B reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of forecast errors on earnings surprise, the business cycle, earnings quality, two-way and three-way interactions among earnings surprise, the business cycle, and earnings quality variables, and control variables.

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Results regarding control variables are not reported for the sake of brevity.

Variable definitions:

FE_t^E is actual quarterly earnings per share minus the median of all analysts' forecasted earnings issued in the early forecast period, deflated by the stock price at the beginning of the quarter.

CY_t (business cycles) includes three measures:

NBER_Rec is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise;

CFNAI_Rec is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise;

CFNAI_Ind is a continuous variable being CFNAI-MA3 multiplied by -1.

Sur (earnings surprise) is the late forecast error from the previous quarter.

Quality (earnings quality) is negative of the standard deviation of residuals from regressions of changes in working capital accruals on lagged, current and future cash flows from operations.

In panel B, columns 3 through 5 report the results from Equation (6.2), the regression model that controls for the business cycle effect on underreaction without considering the interaction effect of earnings quality and the business cycle on underreaction. The results show a significantly positive coefficient for *Sur* and a negative coefficient for *Sur*CY* in all regressions, consistent with the previous findings. However, the coefficient of interest β_{S3} for *Sur*Quality* is insignificant, which does not support H4a.

Columns 6 through 8 show the results from Equation (6.4) that considers the potential interaction effect of earnings quality and the business cycle on underreaction. With respect to the impact of earnings quality on forecast bias, the coefficient for *Quality* is significantly positive in all regressions. This means that forecast errors are positively associated with earnings quality in expansionary periods. Moving on to the interaction term *CY*Quality*, the coefficient is significantly negative with a greater absolute value than that of *Quality*. This implies that forecast errors are negatively associated with earnings quality in recessionary periods (i.e., the combination of *Quality* and *CY*Quality*). These results suggest that analysts

appear to be more pessimistic (optimistic) about high earnings quality firms compared to low quality firms during the expansionary (recessionary) periods.

With respect to underreaction, the coefficient for *Sur*Quality* is not significant in all regressions. Similarly, the coefficient for *Sur*CY*Quality* is not significant for the dichotomous business cycle measures. However, in the regression that uses the CFNAI index measure (column 8), the coefficient is significantly positive, consistent with H4b.

Table 6-6 reports the results for the late forecast subsample. Panel A shows the final sample includes 19,197 firm-quarter observations after data requirements for earnings quality, slightly larger than the early forecast subsample reported in Table 6-5. The summary statistics of earnings quality are similar to those reported in Table 6-5.

In panel B, columns 3 through 5 report the results from Equation (6.3), the regression model that considers the additive effects of the business cycle and earnings quality on underreaction. The results show a significantly positive coefficient for *Ret* and a negative coefficient for *Ret*CY* in all regressions, consistent with the previous findings. The coefficient of interest β_{R3} for *Ret*Quality* is insignificant. Interestingly, while the coefficient for *Sur*CY* is insignificant in all regressions, the coefficient β_{S3} for *Sur*Quality* is negative and significant at the 0.1 level. The latter finding is consistent with Hypothesis 4a that analysts feel more uncertain about firms with low earnings quality and, hence, underreact more to earnings surprise in order to protect themselves. This finding, combined with the results in Table 6-5, provide some evidence indicating that analysts shift their focus from the business cycle effect on earnings surprise in the early forecast period to the earnings quality effect in the late forecast period.

Table 6-6 Analysis of earnings quality and the underreaction/business cycles relation for the late forecast period

Panel A. Distribution of the earnings quality variable (*Quality*) in the late forecast subsample

N	Mean	STD	Min	Q1	Median	Q3	Max
19,197	-0.01	0.0066	-0.0422	-0.012	-0.0081	-0.0053	-0.0004

Panel B. The association between earnings quality and the underreaction/business cycle relation

$$FE_t^L = \alpha_0 + \beta_0 CY_t + \beta_1 Quality_t + \beta_{R2} Ret_t + \beta_{R3}(Ret_t * Quality_t) + \beta_{R4}(Ret_t * CY_t) \quad (6.3)$$
$$+ \beta_{S2} Sur_t + \beta_{S3}(Sur_t * Quality_t) + \beta_{S4}(Sur_t * CY_t) + \sum_{k=1}^{n} \beta_{1+k} Controls_k$$
$$+ \varepsilon_t$$

$$FE_t^L = \alpha_0 + \beta_0 CY_t + \beta_1 Quality_t + \beta_{R2} Ret_t + \beta_{R3}(Ret_t * Quality_t) \quad (6.5)$$
$$+ \beta_{R4}(Ret_t * CY_t) + \beta_{R5}(Ret_t * Quality_t * CY_t) + \beta_{S2} Sur_t$$
$$+ \beta_{S3}(Sur_t * Quality_t) + \beta_{S4}(Sur_t * CY_t) + \beta_{S5}(Quality_t * CY_t) + \beta_{S6}(Sur_t$$
$$* CY_t * Quality_t) + \sum_{k=1}^{n} \beta_{1+k} Controls_k + \varepsilon_t$$

Coefficient (*t*-statistic)	Exp. Sign	Equation (6.3)			Equation (6.5)		
1	2	3	4	5	6	7	8
Variable		NBER_Rec	CFNAI_Rec	CFNAI_Ind	NBER_Rec	CFNAI_Rec	CFNAI_Ind
Intercept		-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
		(-0.27)	(-0.24)	(-0.12)	(-0.20)	(-0.16)	(-0.06)
CY		0.0002*	0.0002*	0.0001*	0.0001	0.0001	0.0001
		(1.66)	(1.72)	(1.26)	(0.74)	(0.75)	(0.56)
Quality		0.0036	0.0038	0.0036	0.0046	0.0049	0.0046
		(0.91)	(0.94)	(0.93)	(1.18)	(1.24)	(1.22)
Sur	+	0.1242***	0.1259***	0.1220***	0.1356***	0.1390***	0.1338***
		(4.77)	(4.80)	(4.72)	(5.07)	(5.13)	(5.21)
*Sur*Quality*	-	-3.4394*	-3.4128*	-3.4841*	-2.4342	-2.2615	-2.4909
		(-1.86)	(-1.84)	(-1.88)	(-1.29)	(-1.18)	(-1.40)
*Sur*CY*	-	-0.0250	-0.0297	-0.0099	-0.0737	-0.0829	-0.0390
		(-0.64)	(-0.77)	(-0.52)	(-1.26)	(-1.45)	(-1.53)
*CY*Quality*					-0.0080	-0.0081	-0.0043
					(-0.80)	(-0.84)	(-1.20)
*Sur*CY* Quality*	+				-4.6806	-5.1370	-2.8137
					(-0.99)	(-1.11)	(-1.34)
Ret	+	0.0358***	0.0370***	0.0281**	0.0389***	0.0388***	0.0287**
		(2.85)	(2.92)	(1.94)	(2.99)	(2.90)	(2.13)

Table 6-6 (Continued) Analysis of earnings quality and the underreaction/business cycle relation for the late forecast period

Coefficient (*t*-statistic)	Exp. Sign	Equation (6.3)			Equation (6.5)		
1	2	3	4	5	6	7	8
Ret*Quality	-	-0.4392	-0.4819	-0.5333	-0.1764	-0.3308	-0.4924
		(-0.47)	(-0.52)	(-0.55)	(-0.17)	(-0.31)	(-0.51)
Ret*CY	-	-0.0490**	-0.0510***	-0.0165	-0.0673**	-0.0642**	-0.0201
		(-2.54)	(-2.70	(-1.47)	(-2.06)	(-2.02)	(-1.53)
Ret*CY* Quality	+				-1.8252	-1.3333	-0.3485
					(-0.83)	(-0.63)	(-0.28)
…							
Adj_R-Sqr		0.034	0.035	0.034	0.035	0.036	0.035
No_Obs		19,197	19,197	19,197	19,197	19,197	19,197

Panel A of this table reports the distribution of the modified Dechow and Dichev earnings quality variable for the late forecast period.

Panel B reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of forecast errors on earnings surprise, the business cycle, earnings quality, two-way and three-way interactions among earnings surprise, the business cycle, and earnings quality variables, and control variables.

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Results regarding control variables are not reported for the sake of brevity.

Variable definitions:

FE_t^L is actual quarterly earnings per share minus the median of all analysts' forecasted earnings issued in the late forecast period, deflated by the stock price at the beginning of the quarter.

CY_t (business cycles) includes three measures:

NBER_Rec is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise;

CFNAI_Rec is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise;

CFNAI_Ind is a continuous variable being CFNAI-MA3 multiplied by -1.

Sur (earnings surprise) is the late forecast error from the previous quarter.

Ret (stock returns) is the average daily stock price changes within the period between 31 days after the last quarterly earnings announcement and 31 days before one-quarter-ahead earnings announcement.

Quality (earnings quality) is negative of the standard deviation of residuals from regressions of changes in working capital accruals on lagged, current and future cash flows from operations.

Columns 6 through 8 of Table 6-6 panel B show the results from Equation (6.5) that considers the potential interaction effect of earnings quality and the business cycle on underreaction. The coefficients for both interaction terms *Sur*CY*Quality* and *Ret*CY*Quality* are insignificant in all regressions, which does not suggest that the differential underreaction across business cycles depends on earnings quality. Thus, the results from the late forecast subsample provide no evidence supporting H4b.

Overall, there is some evidence suggesting that earnings quality has an effect on analysts' underreaction. While the underreaction to earnings surprise in the early forecast period and the underreaction to stock returns in the late forecast period do not depend on earnings quality, there is weak evidence suggesting that earnings quality has an effect on underreaction to earnings surprise in the late forecast period. Specifically, analysts underreact more to earnings surprise for firms with low quality earnings, for a given level of reputation concern. This is consistent with the uncertainty argument in the asymmetric reputation cost theory framework. In the previous chapter, the analyses at the business cycle level show that the asymmetric reputation cost factor, rather than the uncertainty factor, is dominant in determining analysts' underreaction. The analyses in this section provide complementary evidence that when the asymmetric reputation cost is controlled for, underreaction increases with uncertainty (low earnings quality) at a firm level. In addition, there is weak evidence suggesting that earnings quality and the business cycle have an interaction effect on analysts' underreaction. Specifically, relative to recessions, analysts' incremental underreaction during expansions is more pronounced for firms with low quality earnings.

The lack of strong evidence could be explained by analyst' limited ability to distinguish earnings quality, which has been documented in previous studies (e.g., Elliott and Philbrick, 1990; Bradshaw et al., 2001). Given this explanation, the evidence on the differential impact of earnings quality on forecast bias across business cycles is consistent with the interpretation that firms with high earnings quality are less likely to manipulate earnings downwards (upwards) during good (bad) times, resulting in a positive (negative) association between forecast errors and earnings quality in expansions (recessions). This interpretation is also consistent with findings from the earnings quality literature. Dechow et al. (2010) document that the standard deviation of residuals measure (also in the inverse form) is significantly and negatively associated with earnings smoothness measures. In other words,

high quality earnings firms (determined by the standard deviation of residuals measure) are less likely to smooth earnings, e.g., more likely to have greater earnings in expansions, resulting in reported earnings greater than forecast earnings, i.e., a positive forecast error.

6.3   Analyst following

In this section, I examine whether the underreaction and the differential underreaction across business cycles depend on analyst following.

6.3.1   Hypothesis development

As discussed in subsection 2.3.2, Raedy et al.'s (2006) asymmetric reputation cost theory argues that analysts' reputation capital suffers less (more) when new information leads to a forecast revision or forecast error in the same (opposite) direction as the immediately prior forecast revision. Due to reputation concerns, analysts are incentivised to underreact to news when faced with uncertainty. Hence, underreaction is a mechanism that analysts use to protect themselves from having to reverse their revision and incur a higher reputation penalty from investors.

An important assumption underlying this theory, as noted by Raedy et al. (2006), is that market frictions prevent market prices from immediately unravelling underreaction in analysts' forecasts. Only when the market does not completely unravel analyst underreaction, investors who buy (sell) stock on the basis of upward (downward) earnings forecast revisions are rewarded when subsequent earnings announcements or other information confirms the news in the prior forecast revision. These investors have incentives to prefer analyst underreaction to information about future earnings. On the contrary, if market frictions do not prevent rational investors from immediately unravelling analysts' underreaction, then market prices would immediately adjust. In this situation, investors are all price takers but not

arbitragers. Hence, the market would not impose the asymmetric reputation penalty on analysts, and analysts would not underreact to information due to their reputation concerns as suggested in the theory.

Theories and empirical evidence from the literature suggest that investors face sizable market frictions. Numerous studies document that market prices do not immediately respond to available information (e.g., the post-earnings-announcement drift) due to a variety of market frictions, including incomplete information (Hirshleifer, 1988), asymmetric information (Easley, Hvidkjaer, and O'Hara, 2002), short-sale constraints (Jones and Lamont, 2002), transactions costs (Arbel, Carvell, and Strebel, 1983; Ke and Ramalingegowda, 2004), lack of liquidity (Pástor and Stambaugh, 2003), investor recognition (Merton, 1987; Shapiro, 2002), or sentiment risk (DeLong, Shleifer, Summers, and Waldmann, 1990).

More related to the market friction assumption in the context of underreaction in analysts' forecasts, Stickel (1991) demonstrates that stock prices do not immediately reflect analysts' earnings forecast revisions. He explains that this is not necessarily due to investors' irrationality, but could be due to the costs of gathering and processing information substantial enough to sustain the market inefficiency. Stickel's findings and explanation are consistent with the assumption that market frictions prevent the market from immediately unravelling underreaction.

The literature documents that market frictions have a significant effect on cross-sectional stock return predictability (e.g., Hou and Moskowitz, 2005). However, the ability to exploit the effect may be severely limited, and hence, inefficiencies may persist in markets (Shleifer and Vishny, 1997). For instance, Ke and Ramalingegowda (2004) provide empirical evidence that transaction costs create impediments that prevent sophisticated investors from arbitraging away post-earnings-announcement drift. Slezak (2003) finds equilibrium conditions where irrational investors who underreact to information create

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market inefficiencies that persist even in the presence of fully rational investors and frictionless trading opportunities.

In short, theories and evidence from the literature support the assumption that market frictions prevent the market from immediately unravelling underreaction in analysts' earnings forecasts and prevent market prices from efficiently reflecting unbiased estimates of future earnings. Due to the market frictions, investors prefer analysts' underreaction and impose the asymmetric reputation cost on analysts. In other words, whether analysts use the underreaction as a mechanism to maximise their reputation capital would depend on the market frictions. Small market frictions lead to relatively more efficient market prices, which is less likely to induce investors to impose the asymmetric penalty. Consequently, analysts cannot rely on underreaction to reduce reputation loss, but rather concentrate more on the forecast accuracy itself. This results in less underreaction. Vice versa, analysts' underreaction would be greater for firms that are more severely affected by market frictions. Therefore, I hypothesise:

H5a: *Analysts' underreaction is more pronounced for firms that are more severely affected*
         by market frictions than firms that are less severely affected by market frictions.

The above hypothesis focuses on the variation in underreaction caused by the variation in market frictions. Considering the variation in asymmetric reputation cost, one would expect that market frictions will not have much impact on analysts' underreaction if the asymmetric reputation cost is low, because the level of underreaction is low to begin with. Stated differently, the impact of market frictions on underreaction increases with the amount of asymmetric reputation cost. In Chapter 5, I find evidence suggesting that underreaction is stronger during expansionary periods where the asymmetric reputation cost is higher than during recessionary periods. Hence, the impact of market frictions on analysts' underreaction will be stronger during expansionary periods. As a result, I hypothesise:

H5b: *The positive association between analysts' underreaction and market frictions is more*

         pronounced during expansionary periods where the asymmetric reputation cost is

         higher than recessionary periods where the asymmetric reputation cost is lower.

6.3.2   Research design

Hou and Moskowitz (2005) construct a parsimonious measure for severity of market frictions affecting a stock: the average delay with which its share price responds to information. This measure captures the impact of all the potential frictions on the market prices. They find that post-earnings-announcement drift is monotonically increasing in the price delay measure and that the drift is nonexistent among non-delayed firms. They use this measure to test the association between market frictions and a variety of proxies for the sources of frictions. The finding is that investor recognition, rather than traditional liquidity price impact and transaction cost measures, is more consistent in explaining market frictions. Specifically, market friction is negatively associated with investor recognition. This is consistent with the prior literature that the process of information diffusion is slow for less visible firms (e.g., Arbel et al., 1983; Merton, 1987; Hirshleifer, 1988)

Based on Hou and Moskowitz (2005) who find an association between analyst following and the delay in market price adjustments (a measure of market frictions), I use analyst following as a proxy for market frictions. If analyst following is greater, then investor recognition is greater and market frictions are smaller. Hence, analyst following is an inverse measure of market frictions. To test Hypothesis 5a, I employ the following regression models based on Equations (4.1) and (4.2) for the early and the late forecast subsamples, respectively:

$$FE_t^E = \alpha_0 + \beta_1 LOGFLLW_t + \beta_{S2} Sur_t + \beta_{S3}(Sur_t \tag{6.6}$$

$$* LOGFLLW_t) + \sum_{k=1}^{n} \beta_{1+k} Controls_k + \varepsilon_t$$

$$FE_t^L = \alpha_0 + \beta_1 LOGFLLW_t + \beta_{R2} Ret_t + \beta_{R3}(Ret_t \tag{6.7}$$

$$* LOGFLLW_t) + \beta_{S2} Sur_t + \beta_{S3}(Sur_t * LOGFLLW_t)$$

$$+ \sum_{k=1}^{n} \beta_{1+k} Controls_k + \varepsilon_t$$

where all variables are defined in the previous equations.

As discussed above, the analysts following measure (LOGFLLW) decreases with market frictions. Recall again that underreaction means a positive coefficient β_{S2} or β_{R2} for the news variable. If market frictions are positively related with underreaction, as predicted in Hypothesis 5a, then β_{S3} (β_{R3}) for the interaction term between the analyst following and the news variable *Sur*LOGFLLW* (*Ret*LOGFLLW*) will be significantly negative, meaning that underreaction decreases with analyst following (i.e., increases with market frictions).

To statistically test H5a, I employ *t*-tests of the following null and alternative hypothesis:

H^0_{5a}: $\beta_{S3} = 0$, H^A_{5a}: $\beta_{S3} < 0$ for the early forecast period,

H^0_{5a}: $\beta_{R3} = 0$, H^A_{5a}: $\beta_{R3} < 0$ for the late forecast period.

One concern is that analyst following may have a mechanical relation with firm-specific uncertainty due to the way in which the uncertainty measure is constructed in Equation (4.3) based on the Barron et al. (1998) model. In particular, the uncertainty measure increases with analyst following.[22] Subsection 5.3.2 presents results from a regression of uncertainty on the business cycle and other firm-level variables in Table 5-8. It shows that uncertainty indeed increases with analyst following (the coefficient is significantly positive). As underreaction increases with uncertainty, more analyst following (through the mechanical relation with uncertainty) would lead to more underreaction, which works against the

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[22] This is consistent with the idea that analyst following reflects firms' innate factors. Firms with larger size and more complexity are likely to attract more analysts. Even though more analysts may provide greater amount of information, the level of uncertainty may remain higher due to firms' size and complexity, particularly in a cross-sectional setting.

prediction in Hypothesis 5a. It would make it more difficult to find significant results that support the hypothesis.

With respect to Hypothesis 5b, I add a three-way interaction term among the news, the analyst following, and the business cycle variables on Equations (6.6) and (6.7) to examine whether the impact of analyst following on analysts' underreaction depends on the business cycle.

$$FE_t^E = \alpha_0 + \beta_0 CY_t + \beta_1 LOGFLLW_t + \beta_{S2} Sur_t + \beta_{S3}(Sur_t * LOGFLLW_t) \qquad (6.8)$$

$$+ \beta_{S4}(Sur_t * CY_t) + \beta_{S5}(LOGFLLW_t * CY_t) + \beta_{S6}(Sur_t$$

$$* LOGFLLW_t * CY_t) + \sum_{k=1}^{n} \beta_{1+k} Controls_k + \varepsilon_t$$

$$FE_t^L = \alpha_0 + \beta_0 CY_t + \beta_1 LOGFLLW_t + \beta_{R2} Ret_t + \beta_{R3}(Ret_t * LOGFLLW_t) \qquad (6.9)$$

$$+ \beta_{R4}(Ret_t * CY_t) + \beta_{R5}(LOGFLLW_t * CY_t) + \beta_{R6}(Ret_t$$

$$* LOGFLLW_t$$

$$* CY_t) + \beta_{S2} Sur_t + \beta_{S3}(Sur_t * LOGFLLW_t)$$

$$+ \beta_{S4}(Sur_t * CY_t) + \beta_{S5}(Sur_t * LOGFLLW_t * CY_t)$$

$$+ \sum_{k=1}^{n} \beta_{1+k} Controls_k + \varepsilon_t$$

where all variables are defined in the previous equations.

H5b predicts that the positive impact of market frictions on analysts' underreaction will be stronger during expansions than recessions. That is, the association between underreaction and analyst following will be more negative during expansions than recessions. As the dichotomous measure of the business cycle takes the value of 1 if an observation is in a recessionary period and 0 otherwise, if H5b is true, then the coefficient β_{S6} or β_{R6} for the three-way interaction term *Sur*LOGFLLW*CY* or *Ret*LOGFLLW*CY* will be significantly positive in Equation (6.8) or (6.9).

To statistically test H5b, I employ *t*-tests of the following null and alternative hypothesis:

H^0_{5b}: $\beta_{S6}= 0$, H^A_{5b}: $\beta_{S6} > 0$ for the early forecast period,

H^0_{5b}: $\beta_{R6}= 0$, H^A_{5b}: $\beta_{R6} > 0$ for the late forecast period.

6.3.3   Results

Table 6-7 presents the results from the estimation Equations (6.6) through (6.9) with interaction terms among the surprise or returns variable, the analyst following variable, and the business cycle variable. Equations (6.6) and (6.7) estimate the impact of analyst following on underreaction for the early and late forecast periods, respectively, without taking business cycles into consideration. Equations (6.8) and (6.9) examine the difference in the underreaction-analyst following association between expansionary periods and recessionary periods.

First, I discuss the results in Table 6-7 for Equations (6.6) and (6.7) that correspond to Hypothesis 5a. For the early forecast period (column 3), there is no significant result regarding the coefficient for *Sur*LOGFLLW*. In contrast, column 7 for the late forecast period shows significantly negative coefficients β_{S3} for *Sur*LOGFLLW* (-0.024) and β_{R3} for *Ret*LOGFLLW* (-0.014). This means that analysts underreact more to information in both earnings announcements and stock returns when there are fewer analysts following the firm. This evidence supports Hypothesis 5a, i.e., analysts' underreaction is stronger for firms that are followed by fewer analysts and, hence, more severely affected by market frictions.

Table 6-7 Analysis of analyst following and the underreaction/business cycle relation

$$FE_t^E = \alpha_0 + \beta_{S1}LOGFLLW_t + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * LOGFLLW_t) + \sum_{k=1}^{n}\beta_k Controls_k + \varepsilon_t \tag{6.6}$$

$$FE_t^L = \alpha_0 + \beta_1 LOGFLLW_t + \beta_{R2}Ret_t + \beta_{R3}(Ret_t * LOGFLLW_t) + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * LOGFLLW_t) + \sum_{k=1}^{n}\beta_k Controls_k + \varepsilon_t \tag{6.7}$$

$$FE_t^E = \alpha_0 + \beta_0 CY_t + \beta_1 LOGFLLW_t + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * LOGFLLW_t) + \beta_{S4}(Sur_t * CY_t) + \beta_{S5}(LOGFLLW_t * CY_t) + \beta_{S6}(Sur_t * LOGFLLW_t$$
$$* CY_t) + \sum_{k=1}^{n}\beta_k Controls_k + \varepsilon_t \tag{6.8}$$

$$FE_t^L = \alpha_0 + \beta_0 CY_t + \beta_1 LOGFLLW_t + \beta_{R2}Ret_t + \beta_{R3}(Ret_t * LOGFLLW_t) + \beta_{R4}(Ret_t * CY_t) + \beta_{R5}(LOGFLLW_t * CY_t) + \beta_{R6}(Ret_t * LOGFLLW_t$$
$$* CY_t) + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * LOGFLLW_t) + \beta_{S4}(Sur_t * CY_t) + \beta_{S5}(Sur_t * DLOGFLLW_t * CY_t) + \sum_{k=1}^{n}\beta_k Controls_k + \varepsilon_t \tag{6.9}$$

Coefficient (t-statistic)	Exp. Sign	Early forecast period (underreaction to earnings surprise)				Late forecast period (underreaction to returns)			
		Eq. (6.6)	Eq. (6.8)			Eq. (6.7)	Eq. (6.9)		
1	2	3	4	5	6	7	8	9	10
Variable			NBER_Rec	CFNAI_Rec	CFNAI_Ind		NBER_Rec	CFNAI_Rec	CFNAI_Ind
Intercept		-0.0026***	-0.0024***	-0.0024***	-0.0025***	-0.0001*	-0.0001	-0.0001	-0.0001
		(-11.84)	(-12.02)	(-11.78)	(-12.73)	(-1.87)	(-1.33)	(-1.52)	(-1.39)
CY			-0.0012	-0.0013	-0.0006*		-0.0004	-0.0002	-0.0003
			(-1.49)	(-1.62)	(-1.67)		(-1.07)	(-0.71)	(-1.29)
Sur	+	0.3792***	0.4859***	0.4770***	0.4673***	0.2280***	0.2385***	0.2475***	0.2347***
		(5.30)	(6.95)	(6.69)	(7.06)	(7.87)	(7.83)	(8.16)	(8.03)
LOGFLLW		0.0004***	0.0004***	0.0004***	0.0004***	-0.0001**	-0.0001**	-0.0001**	-0.0001**
		(4.11)	(4.18)	(4.16)	(4.25)	(-2.13)	(-2.55)	(-2.38)	(-2.52)
Sur* LOGFLLW	-	-0.0378	-0.0717***	-0.0679***	-0.0644***	-0.0235**	-0.0271**	-0.0299**	-0.0257**
		(-1.64)	(-2.81)	(-2.61)	(-2.61)	(-2.03)	(-2.25)	(-2.49)	(-2.22)
Sur*CY	-		-0.4722***	-0.3979**	-0.1933***		-0.0696	-0.1163	-0.0283
			(-3.05)	(-2.56)	(-3.04)		(-0.69)	(-1.20)	(-0.56)
LOGFLLW *CY			0.0003	0.0003	0.0001		0.0002*	0.0002	0.0001**
			(1.14)	(1.19)	(1.40)		(1.83)	(1.51)	(2.05)
Sur*LOG FLLW*CY	+		0.1501**	0.1211*	0.0577**		0.0228	0.0384	0.0087
			(2.26)	(1.86)	(2.03)		(0.55)	(0.98)	(0.42)

Table 6-7 (Continued) Analysis of analyst following and the underreaction/business cycle relation

Coefficient (*t*-statistic)	Exp. Sign	Early forecasts period (underreaction to earnings surprise)				Late forecast period (underreaction to returns)			
		Eq. (6.6)	Eq. (6.8)			Eq. (6.7)	Eq. (6.9)		
1	2	3	4	5	6	7	8	9	10
Variable			NBER_Rec	CFNAI_Rec	CFNAI_Ind		NBER_Rec	CFNAI_Rec	CFNAI_Ind
Ret	+					0.0738***	0.0992***	0.1019***	0.0841***
						(3.22)	(4.19)	(4.22)	(3.67)
*Ret*LOG FLLW*	-					-0.0144*	-0.0238***	-0.0242***	-0.0188**
						(-1.82)	(-2.95)	(-2.91)	(-2.36)
*Ret*CY*	-						-0.1739***	-0.1704***	-0.0590
							(-2.81)	(-3.07)	(-1.53)
*Ret*LOG FLLW*CY*	+						0.0581***	0.0555***	0.0184
							(2.71)	(2.90)	(1.47)
MEMD		-0.0351***	-0.0339***	-0.0338***	-0.0334***	0.0040*	0.0038	0.0037	0.0038*
		(-9.94)	(-9.59)	(-9.53)	(-9.53)	(1.65)	(1.63)	(1.62)	(1.65)
LOGSALES		0.0001***	0.0001***	0.0001***	0.0001***	0.0000***	0.0001***	0.0001***	0.0001***
		(4.46)	(4.32)	(4.27)	(4.24)	(3.26)	(3.72)	(3.72)	(3.78)
CV		0.0001***	0.0001***	0.0001***	0.0001***	0.0000***	0.0001***	0.0001***	0.0001***
		(3.18)	(2.88)	(2.83)	(2.78)	(3.07)	(3.35)	(3.35)	(3.37)
INDROA		0.0111***	0.0110***	0.0110***	0.0110***	0.0032***	0.0032***	0.0032***	0.0032***
		(14.42)	(14.41)	(14.41)	(14.42)	(11.04)	(10.96)	(10.90)	(10.98)
LOSS		0.0002	0.0002	0.0002	0.0002	-0.0001	-0.0001	-0.0001	-0.0001
		(0.90)	(0.91)	(0.89)	(0.87)	(-1.34)	(-1.34)	(-1.37)	(-1.31)
LOGTV		0.0000	0.0001	0.0001	0.0001	0.0001***	0.0001***	0.0001***	0.0001***
		(0.33)	(1.38)	(1.37)	(1.54)	(3.27)	(2.95)	(2.83)	(3.12)
Adj_R-Sqr		0.095	0.098	0.098	0.099	0.042	0.043	0.043	0.043
No_Obs		41,309	41,309	41,309	41,309	57,180	57,180	57,180	57,180

Table 6-7 (Continued) Analysis of analyst following and the underreaction/business cycle relation

This table reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of forecast errors on earnings surprise or stock returns, analyst following, the business cycle variables, two-way and three-way interaction terms for earnings surprise/returns, analyst following, and the business cycle variables, and control variables.

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Variable definitions:

FE_t^E (FE_t^L) is actual quarterly earnings per share minus the median of all analysts' forecasted earnings issued in the early (late) forecast period, deflated by the stock price at the beginning of the quarter.

LOGFLLW (analyst following) is the natural log of the number of analysts issuing annual forecasts.

Sur (earnings surprise) is the late forecast error from the previous quarter.

Ret (stock returns) is the average daily stock price changes within the period between 31 days after the last quarterly earnings announcement and 31 days before one-quarter-ahead earnings announcement.

CY_t (business cycles) includes three measures:

NBER_Rec is a dummy variable being 1 if most of the time in that period falls in a NBER recession and 0 otherwise;

CFNAI_Rec is a dummy variable being 1 if the CFNAI-MA3 in that period is less than -0.7 and 0 otherwise;

CFNAI_Ind is a continuous variable being CFNAI-MA3 multiplied by -1.

MEMD (earnings skewness) is the mean-median difference of I/B/E/S actual earnings per share over the past eight quarters (requiring a minimum of four observations) deflated by the beginning period stock price.

LOGSALES (firm size) is the natural log of quarterly sales at the beginning of the quarter.

CV (earnings predictability) is the coefficient of variation of earnings per share over the past eight quarters (requiring a minimum of four observations).

INDROA (industry-adjusted ROA) is the firm's realised return on asset, calculated by income before extraordinary items over the 12 months following the forecast quarter divided by the average of quarterly total assets during the 12-month period, minus the median return on assets over the same period of all firms by the same two-digit SIC industry code.

LOSS is a dummy variable that equals 1 if the consensus earnings forecast is negative and 0 otherwise.

LOGTV (trading volume) is the natural log of the sum of monthly trading volume over the 12-month period before the latest earnings announcement.

With respect to Hypothesis 5b, for the early forecast period, columns 4 through 6 in Table 6-7 show that the coefficient β_{S6} for *Sur*LOGFLLW*CY* is significantly positive for all regressions. Also, when the three-way interaction term is included, the negative coefficient for *Sur*LOGFLLW* becomes significant as well. For the late forecast period, columns 8 and 9 show that the coefficient β_{R6} for *Ret*LOGFLLW*CY* is significantly positive when the dichotomous business cycle measures are used (although not for the CFNAI index measure under column 10). Thus, there is strong evidence suggesting that the negative relationship between underreaction and analyst following is stronger during expansions than recessions, consistent with Hypothesis 5b.

The coefficient for the three-way interaction captures the difference in the underreaction-analyst following relation across business cycles. I now consider the coefficients for the interaction between underreaction and analyst following in expansions and in recessions. For the early forecast period using *NBER_Rec* (column 4), while the interaction coefficient is -0.07 (*Sur*LOGFLLW*) during expansions, it is +0.08 (*Sur*LOGFLLW* + *Sur*LOGFLLW*CY*) during recessions. Column 5 shows similar results. Likewise, the coefficients for *Ret*LOGFLLW* have opposite directions during expansions compared to recessions (columns 8 and 9). It appears that analyst following negatively affects underreaction in expansions, but positively affects underreaction in recessions. However, no conclusion can be drawn based on this puzzling finding, because it is not clear whether the combined coefficient (*Sur*LOGFLLW* + *Sur*LOGFLLW*CY*) is significant or not.

To further study this, I run estimation Equations (6.6) and (6.7) for expansions and recessions separately. As in previous tests, I use the NBER and CFNAI classifications to identify expansions and recessions, respectively. Table 6-8 reports the results for the separate regressions, labelled as NBER recessions, NBER expansions, CFNAI recessions, and CFNAI

expansions for each equation. For the purpose of comparison, the full sample results are also included.

For the early forecast period, the coefficient for *Sur*LOGFLLW* is insignificant during recessionary periods in both regressions (columns 4 and 6), i.e., the same as reported in the full sample. However, the coefficient is strongly significantly negative during expansionary periods (columns 5 and 7). Interestingly, while the full sample for the late forecasts has a significantly negative coefficient for *Sur*LOGFLLW*, there is a similar pattern in the separate regressions: the coefficient is significant during expansions (columns 10 and 12) but insignificant during recessions (columns 9 and 11). Likewise, the significant coefficient for *Ret*LOGFLLW* in the full sample is driven mainly by the expansionary observations (columns 8 through 12). These findings suggest that the impact of analyst following on underreaction is strong during expansions but is rather unnoticeable during recessions. Again, the results are consistent with Hypothesis 5b.

Table 6-8 Analysis of analyst following and the underreaction/business cycle relation – separate regressions

$$FE_t^E = \alpha_0 + \beta_{S1}LOGFLLW_t + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * LOGFLLW_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \qquad (6.6)$$

$$FE_t^L = \alpha_0 + \beta_1 LOGFLLW_t + \beta_{R2}Ret_t + \beta_{R3}(Ret_t * LOGFLLW_t) + \beta_{S2}Sur_t + \beta_{S3}(Sur_t * LOGFLLW_t) + \sum_{k=1}^{n} \beta_k Controls_k + \varepsilon_t \qquad (6.7)$$

Coefficient (t-statistic)	Exp. Sign	Early forecasts period (underreaction to earnings surprise) - Eq. (6.6)					Late forecast period (underreaction to returns) - Eq. (6.7)				
1	2	3	4	5	6	7	8	9	10	11	12
Variable		Full sample	NBER recessions	NBER expansions	CFNAI recessions	CFNAI expansions	Full sample	NBER recessions	NBER expansions	CFNAI recessions	CFNAI expansions
Intercept		-0.0026***	-0.0037***	-0.0024***	-0.0037***	-0.0024***	-0.0001*	-0.0006**	-0.0001	-0.0005*	-0.0001
		(-11.84)	(-4.74)	(-12.03)	(-5.05)	(-11.91)	(-1.87)	(-2.02)	(-1.32)	(-1.68)	(-1.46)
Sur	+	0.3792***	0.0146	0.4843***	0.0805	0.4754***	0.2280***	0.1769*	0.2376***	0.1401	0.2461***
		(5.30)	(0.10)	(6.95)	(0.58)	(6.68)	(7.87)	(1.96)	(7.82)	(1.63)	(8.13)
LOGFLLW		0.0004***	0.0006*	0.0004***	0.0006*	0.0004***	-0.0001**	0.0002	-0.0001***	0.0002	-0.0001***
		(4.11)	(1.74)	(4.28)	(1.92)	(4.25)	(-2.13)	(1.07)	(-3.04)	(0.92)	(-2.91)
Sur* LOGFLLW	-	-0.0378	0.0780	-0.0711***	0.0525	-0.0672***	-0.0235**	-0.0063	-0.0268**	0.0059	-0.0296**
		(-1.64)	(1.27)	(-2.79)	(0.88)	(-2.59)	(-2.03)	(-0.17)	(-2.24)	(0.17)	(-2.47)
Ret	+						0.0738***	-0.0694	0.1025***	-0.0632	0.1046***
							(3.22)	(-1.17)	(4.48)	(-1.24)	(4.46)
Ret* LOGFLLW	-						-0.0144*	0.0338	-0.0235***	0.0307*	-0.0238***
							(-1.82)	(1.64)	(-2.90)	(1.74)	(-2.86)
MEMD		-0.0351***	-0.0354***	-0.0339***	-0.0354***	-0.0335***	0.0040*	0.0163**	0.0013	0.0147*	0.0012
		(-9.94)	(-4.58)	(-8.58)	(-4.82)	(-8.38)	(1.65)	(1.97)	(0.70)	(1.96)	(0.64)
LOGSALES		0.0001***	0.0001	0.0001***	0.0001	0.0001***	0.0000***	0.0000	0.0001***	0.0000	0.0001***
		(4.46)	(0.95)	(4.45)	(0.89)	(4.60)	(3.26)	(0.54)	(4.19)	(0.53)	(4.19)
CV		0.0001***	0.0001	0.0001***	0.0001	0.0001***	0.0000***	0.0000	0.0001***	0.0000	0.0001***
		(3.18)	(1.15)	(2.65)	(1.14)	(2.62)	(3.07)	(0.05)	(4.24)	(0.05)	(4.27)

Table 6-8 (Continued) Analysis of analyst following and the underreaction/business cycle relation – separate regressions

Coefficient (*t*-statistic)	Exp. Sign	Early forecasts period (underreaction to earnings surprise) - Eq. (6.6)					Late forecast period (underreaction to returns) - Eq. (6.7)				
1	2	3	4	5	6	7	8	9	10	11	12
Variable		Full sample	NBER recessions	NBER expansions	CFNAI recessions	CFNAI expansions	Full sample	NBER recessions	NBER expansions	CFNAI recessions	CFNAI expansions
INDROA		0.0111***	0.0115***	0.0109***	0.0113***	0.0109***	0.0032***	0.0018*	0.0034***	0.0015*	0.0035***
		(14.42)	(4.56)	(14.94)	(4.93)	(14.70)	(11.04)	(1.76)	(12.52)	(1.72)	(12.67)
LOSS		0.0002	0.0006	0.0001	0.0004	0.0001	-0.0001	-0.0003	-0.0001	-0.0001	-0.0001
		(0.90)	(1.27)	(0.26)	(0.96)	(0.43)	(-1.34)	(-1.63)	(-0.98)	(-0.83)	(-1.33)
LOGTV		0.0000	0.0001	0.0000	0.0001	0.0000	0.0001***	0.0000	0.0001***	0.0000	0.0001***
		(0.33)	(0.86)	(1.15)	(0.91)	(1.10)	(3.27)	(0.43)	(3.25)	(0.52)	(3.08)
Adj_R-Sqr		0.095	0.070	0.104	0.070	0.104	0.042	0.028	0.047	0.026	0.048
No_Obs		41,309	6,431	34,878	7,219	34,090	57,180	7,645	49,535	8,525	48,655

This table reports coefficients and t statistics (in parentheses) from 2-way cluster (firm and quarter) and heteroscedasticity adjusted regressions of forecast errors on earnings surprise or stock returns, analyst following, two-way interaction terms for surprise/returns and analyst following, and control variables.

***, **, and * denote that the coefficient is statistically significant different from zero at the 0.01, 0.05, and 0.10 levels in a two-tailed test, respectively.

Variable definitions:

FE_t^E (FE_t^L) is actual quarterly earnings per share minus the median of all analysts' forecasted earnings issued in the early (late) forecast period, deflated by the stock price at the beginning of the quarter.

LOGFLLW (analyst following) is the natural log of the number of analysts issuing annual forecasts.

Sur (earnings surprise) is the late forecast error from the previous quarter.

Ret (stock returns) is the average daily stock price changes within the period between 31 days after the last quarterly earnings announcement and 31 days before one-quarter-ahead earnings announcement.

MEMD (earnings skewness) is the mean-median difference of I/B/E/S actual earnings per share over the past eight quarters (requiring a minimum of four observations) deflated by the beginning period stock price.

LOGSALES (firm size) is the natural log of quarterly sales at the beginning of the quarter.

CV (earnings predictability) is the coefficient of variation of earnings per share over the past eight quarters (requiring a minimum of four observations).

INDROA (industry-adjusted ROA) is the firm's realised return on asset, calculated by income before extraordinary items over the 12 months following the forecast quarter divided by the average of quarterly total assets during the 12-month period, minus the median return on assets over the same period of all firms by the same two-digit SIC industry code.

LOSS is a dummy variable that equals 1 if the consensus earnings forecast is negative and 0 otherwise.

LOGTV (trading volume) is the natural log of the sum of monthly trading volume over the 12-month period before the latest earnings announcement.

6.4   Summary

In this chapter, I examine how (1) industry-specific earnings cyclicality, (2) firm-specific earnings quality, and (3) firm-specific analyst following, affect the impact of the business cycle on analysts' underreaction.

In section 6.1, I argue that the performance of non-cyclical industries is not sensitive to the business cycle. For these industries, there is no business cycle-related variation in investor's loss aversion and, hence, no business cycle-related variation in the asymmetric reputation penalty imposed on analysts. Therefore, there will be no business cycle-related variation in underreaction due to reputation concerns. I predict and find that the impact of the business cycle on underreaction is more pronounced for cyclical industries than for non-cyclical industries. In particular, the difference in underreaction across business cycles is found to be significant for cyclical industries but not non-cyclical industries. Results from comparing the coefficient magnitude and comparing the coefficient ratio confirm that analysts' underreaction across business cycles is significantly different between cyclical and non-cyclical industries. In short, the findings are consistent with the reputation-building incentives.

Further analyses also suggest that investors and analysts rely more on the traditional notion of the cyclical industries, rather than the cyclical behaviour of earnings. There is no evidence suggesting that counter-cyclical industries have any impact on the business cycle-underreaction relation.

In section 6.2, I argue that firms with lower quality earnings are associated with a higher level of uncertainty. Given a certain level of the asymmetric reputation cost, analysts' underreaction will be more pronounced for firms with lower quality earnings due to the higher uncertainty for these firms. Also, for firms with higher quality earnings, analysts are more confident in predicting these earnings, and hence, any increase in asymmetric reputation

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cost (e.g., from a recession to an expansion) will have less marginal effect on analysts' underreaction than they would for firms with lower quality earnings. While the results are not prevalently significant, there is some evidence suggesting that (1) analysts underreact more to earnings surprise for firms with low quality earnings when the asymmetric reputation cost is controlled for and (2) analysts' incremental underreaction during expansions versus recessions is more pronounced for firms with lower quality earnings, consistent with my predictions.

In section 6.3, I examine the assumption underlying the asymmetric reputation cost theory, i.e., market frictions prevent market prices from immediately unravelling the underreaction in analysts' forecasts. Whether analysts use the underreaction as a mechanism to maximise their reputation capital would depend on the market frictions. Accordingly, I predict that (1) analysts' underreaction would be greater (lower) for firms that are more (less) severely affected by market frictions and (2) the impact of market frictions on underreaction is greater when the asymmetric reputation cost is higher. Following the prior literature, I use analyst following as an inverse measure for market frictions. The results show strong evidence that supports both predictions.

Overall, this chapter examines the interaction effect of the business cycle (time variation) and certain industry- and firm-specific attributes (cross-sectional variation) on analysts' underreaction. The findings provide supplemental evidence suggesting that analysts underreact to information due to reputation concerns, driven by the asymmetric reputation cost of inaccuracy for inconsistent versus consistent consecutive forecast revisions and forecast errors.

CHAPTER 7

CONCLUSION

As prominent information intermediaries, sell-side financial analysts play an important role to help ensure efficient pricing and resource allocation in capital markets. However, recent scandals have intensified public concerns about conflicts of interest leading to overly optimistic earnings forecasts and stock recommendations emanating from analyst research. A series of regulatory changes in the US were enacted to address the conflicts of interest. The increased concerns for analyst integrity and the consequent regulatory changes have motivated numerous studies on optimism bias in relation to analysts' short-term economic incentives. A stream of these studies suggests that reputation effects, rather than regulations aimed at eliminating certain short-term economic incentives, may be more successful in mitigating analysts' opportunistic attempts to adopt overly optimistic forecasting and recommendation strategies aimed at achieving short-term economic benefits.

This thesis contributes to the literature by examining the relation between analyst reputation and another form of forecast bias, i.e., underreaction. Prior research suggests that the reputation effect reduces optimism in earnings forecasts and, hence, increases forecast accuracy (i.e., an aspect of high quality forecasts). In contrast, my research suggests that the reputation effect leads to analyst underreaction. Specifically, when faced with uncertainty, analysts employ underreaction as a mechanism to maximise the likelihood of their forecast revisions having the same direction as subsequent news (i.e., another aspect of high quality forecasts), so as to protect analysts from incurring higher reputation costs.

Within the reputation framework, I examine the asymmetric reputation cost theory, which predicts that underreaction increases with uncertainty and asymmetric reputation cost. I contextualise my study in the business cycle where both factors change. Using a sample of

US firms with quarterly data collected from I/B/E/S, COMPUSTAT, and CRSP databases, I confirm the prior findings that analysts underreact to information in both earnings surprises and stock returns. Using macroeconomic information collected from the NBER and the CFNAI, I predict and find that uncertainty is greater during recessions than expansions whereas asymmetric reputation cost is greater during expansions than recessions (i.e., reputation concerns are greater during expansions). Further, I find that analysts' underreaction is greater during expansions than recessions. The implication is that the asymmetric reputation cost, rather than the uncertainty, drives analyst underreaction. Combined, my findings support the asymmetric reputation cost theory, i.e., analysts underreact to information due to reputation concerns.

Next, I examine the differential underreaction to good news versus bad news. Prior literature considers the excessive underreaction to bad news versus good news as an opportunistic behaviour due to analysts' short-term economic incentives, because this type of behaviour results in an optimistic outcome on balance. Hence, I investigate the differential underreaction in relation to short-term economic incentives and the reputation-building incentives simultaneously. Again, I use the business cycle as a setting because the two types of incentives cause the asymmetric underreaction to vary between business cycles. If analysts put more emphasis on short-term gains, they will underreact more to bad news than good news, particularly during recessions where the short-term economic incentives are heightened. On the contrary, if analysts are more concerned with their reputations, they will underreact less (more) to bad news than good news during recessions (expansions), because bad (good) news is more likely to follow in bad (good) times and, accordingly, they can incorporate the current bad (good) news with greater confidence.

My findings suggest that the differential underreaction depends on the business cycle. However, there is no evidence suggesting that analysts excessively underreact to bad news in

recessions as predicted by the short-term incentive argument. In fact, I only find evidence showing that analysts underreact more to bad news than good news contained in earnings surprise during expansions. Furthermore, analysts only show less underreaction to bad news than to good news reflected in stock returns during recessions. Both findings are consistent with the reputation-building incentive theory, but inconsistent with the short-term incentive theory.

Hence, the findings in my main study support the theory that analysts' underreaction is due to reputation concerns. I conduct additional tests for robustness checks. First, I test the association between underreaction and uncertainty at the firm level in my sample data. Given the evidence indicating that uncertainty alone cannot explain the cyclical variation in underreaction, a possible reason might be an irregular relation between underreaction and uncertainty. The test confirms that, using my sample data, analysts' underreaction is greater when the uncertainty level is higher at the firm level. Second, I address some potential issues in estimating analysts' underreaction by adding firm intercept effect, the inverse of price as a control variable, and using different cut-offs to define the early and late forecast periods. Results from all the tests are consistent with my main findings. Third, I use alternative measures for uncertainty and information in stock returns and find the results are robust.

While the main study focuses on the business cycle related variations, in further research, I examine the reputation cost theory by simultaneously considering cross-sectional variations in certain industry- and firm-specific factors. I find evidence that the interaction between the business cycle and industry/firm specific information affects underreaction. Based on the asymmetric reputation cost framework, I predict and find that the business cycle impacts underreaction only for cyclical industries and not for non-cyclical industries. Second, I argue that analyst uncertainty decreases with the quality of earnings. I hypothesise, and find some evidence suggesting, that (1) underreaction is more pronounced and (2) differential

underreaction across business cycles is more pronounced for firms with low quality earnings. Third, I examine the assumption underlying the asymmetric reputation cost theory, i.e., the presence of market frictions. Without market frictions, market prices will include all information immediately and investors will not benefit from analysts' underreaction. Using analyst following as an inverse measure of market frictions, I find that (1) analyst underreaction is greater for firms that are more severely affected by market frictions and (2) the impact of market frictions on underreaction is greater during expansions when the asymmetric reputation cost is higher.

While evidence regarding underreaction suggests that analysts, as a whole, are driven by reputation-building incentives, it does not imply that short-term economic incentives have no effect on analyst behaviour. In my main study, the results regarding forecast optimism show that optimism bias is greater on average during recessions than expansions. This is consistent with the link between optimism and the short-term economic incentives suggested in the prior literature and consistent with my conjecture of greater short-term economic incentives during recessions. Prior studies document that an analyst faces a conflict between reputation-building incentives and short-term economic incentives. The findings from this thesis show that such conflict is also present in analysts' forecasts at the aggregate level.

This study differs from prior studies. First, prior studies focus on the impact of analysts' incentives on forecast accuracy or optimism. This study separates optimism bias and underreaction and examines the impact of multiple incentives on underreaction. Second, prior literature on reputation focuses on the cross-sectional variation in reputation effect, i.e., how reputation effect works differently between reputable analysts and non-reputable analysts. This study examines the time variation in reputation concerns, testing whether the reputation effect works on analysts as a group and whether analysts' reputation concerns at the aggregate level vary with the business cycle.

As a result, this thesis makes several important contributions to the literature. First, the thesis contributes to the economic incentives-based research on analyst efficiency. It is among the first to offer a reputation-related, incentive-based explanation for what appears to be inefficient forecasting behaviour. The thesis provides evidence for an empirical link between reputation and underreaction, which to my best knowledge has not been established in the literature. Moreover, the thesis proposes a new dimension of forecast quality that investors may value: the consistency between the implications of analysts' forecasts and subsequent news.

In addition, the thesis finds that uncertainty is not the only factor that affects underreaction. The existing literature widely accepts uncertainty as a determinant of underreaction. However, uncertainty alone cannot explain the variation in underreaction in the context of the business cycle. The thesis demonstrates a more important factor affecting underreaction, i.e., asymmetric reputation cost of forecast inaccuracy.

Furthermore, the thesis contributes to the literature in terms of several methodological issues. First, the thesis demonstrates that the business cycle is a natural setting that easily allows for variations in different testing variables and competing incentives that can lead to different theoretical predictions. As a consequence, it allows more powerful tests and more credible inferences. Second, the thesis develops an indirect measure for asymmetric reputation cost that might be useful for future research. Third, the thesis finds evidence suggesting that analysts' reputation incentives and short-term economic incentives vary with the business cycle, and consequently, analysts' underreaction varies with the business cycle. These results highlight the importance of including macroeconomic variables omitted from prior studies of analyst forecasting behaviour. Fourth, the thesis provides evidence for an interaction between the business cycle and the industry- or firm-specific information that

affects underreaction, and hence shows the importance for researchers to consider this interaction when developing their design for similar types of research.

Finally, the thesis has implications for several groups. First, the findings suggest that the reputation mechanism is effective for analysts at the aggregate level, which has implications for regulators. A successful way to minimise conflicts of interest may be to enforce more regulations that help increase the reputation effect and allow investors to better monitor individual analyst's forecasting performance. The variation of reputation concerns across business cycles also may be relevant for regulators and policy makers. In addition, academics can include the cyclical variation in earnings forecasts in relevant research designs and can emphasise the impact of business cycles when teaching financial analysis and security valuation. Lastly, investors may improve their investment performance by allowing for the cyclical variation in the optimism bias and underreaction in analysts' earnings forecasts.

A caveat to my findings is that I do not use a direct measure for the asymmetric reputation cost. In future studies, this could be measured directly. Some candidates include the *Institutional Investor* All-American designation and market responses to individual analysts' forecast revisions. Changes in these measures capture the effect of reputation costs cross-sectionally. Second, I do not empirically test the links (1) between analysts' underreaction and the consistency between analysts' opinions and subsequent news, and (2) between that consistency and investors' reaction to analyst' forecast revisions and forecast errors. A possible way to test it is to examine whether analysts that underreact produce forecasts that are more consistent with immediately subsequent news, and whether these analysts have a larger market price impact than other analysts. Third, I do not consider the impact of the recent regulatory changes on reputation-related incentives. Future research

might consider separating the sample data into a pre-regulations group and post-regulations group, with hypotheses and tests of differences between the two groups.

The role of reputation in analysts' research is an important issue that warrants further study. First, while I examine interactions between aggregate and firm-specific information on underreaction, future research could investigate the interaction effect between both cross-period and cross-sectional variations in reputations when examining earnings forecasts. Second, studies could investigate the consistency of analysts' opinions and future news in other analyst outputs such as stock recommendations and long-term earnings growth forecasts. It will be more interesting to consider analysts' multiple outputs simultaneously while testing the consistency, e.g., whether analysts sending consistent signals through earnings forecasts have more consistent long-term earnings growth forecasts, more profitable recommendations, and so on. Third, future research could evaluate the relation between reputation and multiple forecast properties at the same time, such as accuracy, timeliness, frequency, consistency in prior forecast errors, and consistency between forecast revisions and future news, and investigate which properties matter more to analyst reputation, i.e., whether analysts, driven by reputation concerns, sacrifice some properties for other more important properties in certain contexts.

REFERENCES

Abarbanell, J. 1991. Do analysts' earnings forecasts incorporate information in prior stock

    price changes? *Journal of Accounting and Economics* 14: 147-165.

Abarbanell, J., and V. Bernard. 1992. Tests of analysts' overreaction/underreaction to

    earnings information as an explanation for anomalous stock price behavior. *Journal of*

    finance 47(3): 1181-1207.

Abarbanell, J., and R. Lehavy. 2003. Biased forecasts or biased earnings? The role of

    reported earnings in explaining apparent bias and over/underreaction in analysts'

    earnings forecasts. *Journal of Accounting and Economics* 36(1-3): 105-146.

Abdellaoui, M., H. Bleichrodt, and C. Paraschiv. 2007. Loss aversion under prospect theory:

    a parameter-free measurement. *Management Science* 53: 1659-1674.

Abdolmohammadi, M., R. Simnett, J. C. Thibodeau, and A. M. Wright. 2006. Sell-side

    analysts' reports and the current external reporting model. *Accounting Horizons* 20(4):

    375-389.

Ackert, L. F., and W. C. Hunter. 1995. Rational expectations and security analysts' earnings

    forecasts. *Financial Review* 30(3): 427-443.

Ahmad, N. 2005. Two essays in busniess cycle theory. Univerisy of New Orleans. A doctoral

    dissertation (Financial Economics).

Ali, A., A. Klein, and J. Rosenfeld. 1992. Analysts' use of information about permanent and

    transitory earnings components in forecasting annual EPS. *The Accounting Review*

    67(1): 183-198.

Arbel, A., S. Carvell, and P. Strebel. 1983. Giraffes, institutions and neglected firms.

    Financial Analysts Journal 39(3): 57-63.

Ashbaugh, H., and M. Pincus. 2001. Domestic accounting standards, international accounting standards, and the predictability of earnings. *Journal of Accounting Research* 39(3): 417-434.

Ball, R., and E. Bartov. 1996. How naive is the stock market's use of earnings information. *Journal of Accounting and Economics* 21: 319-338.

Ball, R., and P. Brown. 1968. An empirical evaluation of accounting numbers. *Journal of Accounting Research* 6: 159-178.

Bandyopadhyay, S., L. Brown, and G. Richardson. 1995. Analysts' use of earnings forecasts in predicting stock returns: forecast horizon effects. *International Journal of Forecasting* 11: 429-445.

Barber, B., R. Lehavy, M. McNichols, and B. Trueman. 2006. Buys, holds, and sells: The distribution of investment banks' stock ratings and the implications for the profitability of analysts' recommendations. *Journal of Accounting and Economics* 41: 87-117.

Barberis, N., M. Huang, and T. Santos. 2001. Prospect theory and asset prices. *Quarterly Journal of Economics* 116(1): 1-53.

Barron, O. E., O. Kim, S. C. Lim, and D. E. Stevens. 1998. Using analysts' forecasts to measure properties of analysts' information environment. *The Accounting Review* 73: 421.

Barron, O. E., M. H. Stanford, and Y. Yu. 2009. Further evidence on the relation between analysts' forecast dispersion and stock returns. *Contemporary Accounting Research* 26(2): 329-357.

Barron, O. E., and P. S. Stuerke. 1998. Dispersion in analysts' earnings forecasts as a measure of uncertainty. *Journal of Accounting, Auditing and Finance* 13: 245-270.

Basu, S. 1997. The conservatism principle and the asymmetric timeliness of earnings. *Journal of Accounting and Economics* 24(1): 3-37.

Basu, S., S. Markov, and L. Shivakumar. 2010. Inflation, earnings forecasts, and post-earnings announcement drift. *Review of Accounting Studies* 15(2): 403-440.

Beaver, W., B. Cornell, W. R. Landsman, and S. R. Stubben. 2008. The impact of analysts' forecast errors and forecast revisions on stock prices. *Journal of Business Finance and Accounting* 35(5-6): 709-740.

Bergman, N. K., and S. Roychowdhury. 2008. Investor sentiment and corporate disclosure. *Journal of Accounting Research* 46(5): 1057-1083.

Bernard, V., and J. Thomas. 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics* 13: 305-340.

Bernstein, W. J., and R. D. Arnott. 2003. Earnings growth: The two percent dilution. *Financial Analysts Journal* 59(5): 47–55.

Beyer, A., and I. Guttman. 2011. The effect of trading volume on analysts' forecast bias. *The Accounting Review* 86(2): 451.

Bhattacharya, N., E. L. Black, T. E. Christensen, and C. R. Larson. 2003. Assessing the relative informativeness and permanence of pro forma earnings and GAAP operating earnings. *Journal of Accounting and Economics* 36(1-3): 285.

Biddle, G. C., and W. E. Ricks. 1988. Analyst forecast errors and stock price behavior near the earnings announcement dates of LIFO adopters. *Journal of Accounting Research* 26(2): 169-194.

Bodie, Z., A. Kane, and A. J. Marcus. 2001. *Essentials of Investments (*4th*).* McGraw-Hill Irwin.

186

Bradshaw, M. 2002. The use of target prices to justify sell-side analysts' stock recommendations. *Accounting Horizons* 16: 27-40.

Bradshaw, M. 2004. How do analysts use their earnings forecasts in generating stock recommendations? *The Accounting Review* 16: 27-40.

Bradshaw, M. 2011. Analysts' forecasts: What do we know after dacades of work? Working paper. Available at SSRN: http://ssrn.com/abstract=1880339. .

Bradshaw, M., S. Richardson, and R. Sloan. 2001. Do analysts and auditors use information in accruals? *Journal of Accounting Research* 39: 45-74.

Brown, L. 1983. Accounting changes and the accuracy of analyst's earnings forecasts. *Journal of Accounting Research* 21(2): 432-443.

Brown, L. 1993. Earnings forecasting research: Its implications for capital markets research. *International Journal of Forecasting* 9: 295-320.

Brown, L. 2001b. A temporal analysis of earnings surprises: Profits and losses. *Journal of Accounting Research* 39: 221-241.

Brown, L., P. Griffin, R. Hagerman, and M. Zmijewski. 1987. Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings. *Journal of Accounting and Economics* 9: 61-87.

Brown, L., and K. Sivakumar. 2003. Comparing the value relevance of two operating income measures. *Review of Accounting Studies* 8: 561-572.

Brown, P., G. Foster, and E. Noreen. 1985. *Security analyst multi-year earnings forecasts and the capital market*. Sarasota, Florida: American Accounting Association.

Burgstahler, D. C., and M. J. Eames. 2003. Earnings management to avoid losses and earnings decrease: Are analysts fooled? *Contemporary Accounting Research* 20(2): 253-294.

Carter, R., F. H. Dark, and A. K. Singh. 1998. Underwriter reputation, initial returns, and the long-run performance of IPO stocks. *Journal of Finance* 53: 285-311.

Carter, R., and S. Manaster. 1990. Initial public offerings and underwriter reputation. *Journal of Finance* 45: 1045-1064.

Casella, G., and R. L. Berger. 2002. *Statistical Inference, 2nd ed.* Pacific Grove, CA: Thomson Learning.

Caskey, J. A., and K. Peterson. 2009. On the estimation of the asymmetric timeliness of earnings: Inference and bias corrections. Working paper. Available at SSRN: http://ssrn.com/paper=1266787.

Chan, L. K. C., J. Karceski, and J. Lakonishok. 2007. Analysts' conflicts of interest and biases in earnings forecasts. *Journal of Financial and Quantitative Analysis* 42(4): 893-913.

Chaney, P. K., C. E. Hogan, and D. C. Jeter. 1999. The effect of reporting restructuring charges on analysts' forecast revisions and errors. *Journal of Accounting and Economics* 70(261-284).

Cheong, F. S., and J. Thomas. 2011. Why do EPS forecast error and dispersion not vary with scale? Implications for analyst and managerial behavior. *Journal of Accounting Research* 49(2): 359-401.

Chopra, V. K. 1998. Why so much error in analysts' earnings forecasts? *Financial Analysts Journal* 54(6): 35-42.

Chordia, T., and L. Shivakumar. 2002. Earnings, business cycle and stock returns. Working paper.

Chugh, L. C., and J. W. Meador. 1984. The stock valuation process: The analysts' view. *Financial Analysts Journal* 40(6): 41-48.

Clement, M. B., J. Hales, and Y. Xue. 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., and S. Y. Tse. 2003. Do investors respond to analysts' forecast revisions as if forecast accuracy is all that matters? *The Accounting Review* 78(1): 227-249.

Cohen, D. A., and P. Zarowin. 2007. Earnings management over the business cycle. working paper. New York University.

Conrad, J., B. Cornell, and W. R. Landsman. 2002. When is bad news really bad news? *The Journal of Finance* 57(6): 2507-2532.

Cowen, A., B. Groysberg, and P. Healy. 2006. Which types of analyst firms are more optimistic? *Journal of Accounting and Economics* 41(1–2): 119-146.

Das, S., C. Levine, and K. Sivaramakrishnan. 1998. Earnings predictability and bias in analysts' earnings forecasts. *The Accounting Review* 73: 277-294.

De Zwart, G., and D. Van Dijk. 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., W. Ge, and C. Schrand. 2010. Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics* 50(2/3): 344-401.

Dechow, P., A. Hutton, and R. Sloan. 2000. The relation between analysts' forecasts of long-term earnings growth and stock price performance following equity offerings. *Contemporary Accounting Research* 17: 1-32.

Dechow, P. M., and I. D. Dichev. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77(4): 35.

DeLong, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. 1990. Noise trader risk in financial markets. *Journal of Political Economy* 98: 703-738.

Dhaliwal, D., V. Naiker, and F. Navissi. 2010. The association between accruals quality and the characteristics of accounting experts and mix of expertise on audit committees. *Contemporary Accounting Research* 27(3): 787-827.

Diamond, D. 1989. Reputation acquisition in debt markets. *Journal of Political Economy* 97: 828-862.

Diamond, D. 1991. Monitoring and reputation: the choice between bank loans and directly placed debt. *Journal of Political Economy* 99: 689-721.

Ding, D. K., C. Charoenwong, and R. Seetoh. 2004. Prospect theory, analyst forecasts, and stock returns. *Journal of Multinational Financial Management* 14(4-5): 425-442.

Dugar, A., and S. Nathan. 1995. The effect of investment banking relationships on financial analysts' forecasts and investment recommendations. *Contemporary Accounting Research* 11: 131-160.

Easley, D., S. Hvidkjaer, and M. O'Hara. 2002. Is information risk a determinant of asset returns? *The Journal of Finance* 57(5): 2185-2221.

Easterwood, J. C., and S. R. Nutt. 1999. Inefficiency in analyst's earnings forecasts: Systematic misreaction or systematic optimism? *Journal of Finance* 54: 1777-1797.

Elliott, J., D. Philbrick, and C. Weidman. 1995. Evidence from archival data on the relation between security analysts' forecast errors and prior forecast revisions. *Contemporary Accounting Research* 11: 919-938.

Elliott, J. A., and D. R. Philbrick. 1990. Accounting changes and earnings predictability. *The Accounting Review* 65(1): 157-174.

Elton, E. J., M. J. Gruber, and M. N. Gultekin. 1984. Professional expectations: Accuracy and diagnosis of errors. *The Journal of Financial and Quantitative Analysis* 19: 351-363.

Fama, E. F. 1980. Agency problems and the theory of the firm. *The Journal of Political Economy* 88(2): 288-307.

Fang, L., and A. Yasuda. 2009. The effectiveness of reputation as a disciplinary mechanism in sell-side research. *The Review of Financial Studies* 22(9): 3735-3777.

Fang, L. H. 2005. Investmentbank reputation and the price and quality of underwriting services. *Journal of Finance* 60: 2729-2761.

Fieller, E. 1954. Some problem in interval estimation. *Journal of Royal Statistical Society Series B* 16(2): 175-185.

Francis, J., and D. Philbrick. 1993. Analysts' decisions as products of a multi-task environment. *Journal of Accounting Research* 31: 216-230.

Francis, J., and R. H. Willis. 2000. A multivariate test of incentive, selection and judgmental explanations for analyst bias. *Working Paper, Duke University*.

Fried, D., and D. Givoly. 1982. Financial analysts' forecasts of earnings: A better surrogate for market expectations. *Journal of Accounting and Economics* 4(2): 85-107.

Gintschel, A., and S. Markov. 2004. The effectiveness of Regulation FD. *Journal of Accounting and Economics* 37(3): 293-314.

Gitman, L. J., and M. D. Joehnk. 1999. *Fundamental of Investing (*7th*).* Addison-Wesley.

Givoly, D., C. Hayn, and T. Yoder. 2010. What do analysts really predict? Inferences from earnings restatements and managed earnings. Working paper.

Gomme, P., and J. Greenwood. 1995. On the cyclical allocation of risk. *Journal of Economic Dynamics and Control* 19(1-2): 91-124.

Gow, I. D., G. Ormazabal, and D. J. Taylor. 2010. Correcting for cross-sectional and time-series dependence in accounting research. *The Accounting Review* 85(2): 483-512.

Gu, Z., and J. S. Wu. 2003. Earnings skewness and analyst forecast bias. *Journal of Accounting and Economics* 35(1): 5-29.

Hamilton, J. D., and G. Lin. 1996. Stock market volatility and the business cycle. *Journal of Applied Econometrics* 11(5): 573-593.

Hayes, R. 1998. The impact of trading commission incentives on analysts' stock coverage decisions and earnings forecasts. . *Journal of Accounting Research* 36: 299-320.

Higgins, H. N. 2002a. Analyst earnings forecasts for recession periods. Working paper.

Higgins, H. N. 2002b. Analysts' forecasts of Japanese firms' earnings: additional evidence. *The International Journal of Accounting* 37(4): 371-394.

Hilary, G., and C. Hsu. 2012. Analyst forecast consistency. *Journal of Finance* Forthcoming. Available at SSRN: http://ssrn.com/abstract=1991062.

Hirshleifer, D. 1988. Residual risk, trading costs, and commodity futures risk premia. *The Review of Financial Studies* 1(2): 173-193.

Hong, H., and J. D. Kubik. 2003. Analyzing the analysts: Career concerns and biased earnings forecasts. *Journal of Finance* 58(1): 313-351.

Hong, H., J. D. Kubik, and D. Solomon. 2000. Security analysts' career concerns and herding of earnings forecasts. *Rand Journal of Economics* 31: 121-144.

Hong, H., T. Lim, and J. Stein. 2000. Bad news travels slowly: Size, analyst coverage and the profitability of momentum strategies. *Journal of Finance* 55(1): 265-296.

Hou, K., and T. J. Moskowitz. 2005. Market frictions, price delay, and the cross-section of expected returns. *The Review of Financial Studies* 18(3): 981-1020.

Hugon, A., and V. Muslu. 2010. Market demand for conservative analysts. *Journal of Accounting and Economics* 50(1): 42-57.

Hunter, W. C., and L. F. Ackert. 1993. Business cycles and analysts' forecasts: Further evidence of rationality. *Economic Review-Federal Reserve Bank of Atlanta* 78(6): 13-22.

Hwang, L. S., C. L. Jan, and S. Basu. 1996. Loss firms and analysts' earnings forecast errors. *Journal of Financial Statement Analysis* 1: 18-30.

Hwang, S., and S. E. Satchell. 2010. How loss averse are investors in financial markets? *Journal of Banking and Finance* 34(10): 2425-2438.

Irvine, P. 2004. Analysts' forecasts and brokerage-firm trading. *The Accounting Review* 79(125-149).

Jackson, A. R. 2005. Trade generation, reputation, and sell-side analysts. *Journal of Finance* 60(2): 673-717.

Jacob, J., S. Rock, and D. Weber. 2008. Do non-investment bank analysts make better earnings forecasts? *Journal of Accounting, Auditing and Finance* 23(1): 23.

Jenkins, D. S., G. D. Kane, and U. Velury. 2009. Earnings conservatism and value relevance across the business cycle. *Journal of Business Finance and Accounting* 36: 1041-1058.

Jin, Q. 2005. Business cycle, accounting behavior and earnings management. Hong Kong University of Science and Technology (Hong Kong). A doctoral dissertation (Accounting).

Johnson, M., F. . 1999. Business cycles and the relation between security returns and earnings. *Review of Accounting Studies* 4(2): 93-117.

Jones, C., and O. Lamont. 2002. Short-sale constraints and stock returns. *Journal of Financial Economics* 66: 207-239.

Jones, J. J. 1991. Earnings management during import relief investigations. *Journal of Accounting Research* 29(2): 193-228.

Kadan, O., L. Madureira, R. Wang, and T. Zach. 2009. Conflicts of interest and stock recommendations: The effects of the Global Settlement and related regulations. *Review of Financial Studies* 22(10): 4189-4217.

Kahneman, D., and A. Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* 47(2): 263-291.

Kahneman, D., and A. Tversky. 1992. Advances in prospect theory: cumulative representation of uncertainty. *Journal of Risk and Uncertainty* 5: 297-323.

Ke, B., and S. Ramalingegowda. 2004. Do institutional investors exploit the post-earnings announcement drift? *Journal of Accounting and Economics* 39(1): 25-53.

Ke, B., and Y. Yu. 2006. The effect of issuing biased earnings forecasts on analysts' access to management and survival. *Journal of Accounting Research* 44(5): 965-999.

Khurana, I., X. Martin, R. Pereira, and K. Raman. 2006. Economic state-varying incentives and the timely recognition of economic losses. Working paper presented at the American Accounting Association annual meeting (August 2006).

Kim, K., and D. A. Schroeder. 1990. Analysts' use of managerial bonus incentives in forecasting earnings. *Journal of Accounting and Economics* 13(1): 3-23.

King, R. G., and S. Rebelo. 2000. Resuscitating real business cycles. NBER working paper 7543.

Klein, A., and C. A. Marquardt. 2006. Fundamentals of accounting losses. *The Accounting Review* 81(1): 179-206.

Koller, T., M. Goedhart, and D. Wessels. 2005. *Valuation: Measuring and Managing the Value of Companies (*4th ed.*).* Hoboken, N.J.: John Wiley & Sons, Inc.

Kothari, S. P., J. Lewellen, and J. B. Warner. 2006. Stock returns, aggregate earnings surprises, and behavioral finance. *Journal of Financial Economics* 79(3): 537–568.

Krainer, R. E. 2003. *Corporate finance, governance, and business cycles: Theory and international comparisons*. Amesterdam, The Netherlands: Elsevier Science B.V.

Kreps, D., and R. Wilson. 1982. Reputation and imperfect information. *Journal of Economic Theory* 27: 253-279.

Kross, W., B. Ro, and D. Schroeder. 1990. Earnings expectations: the analysts' information advantage. *The Accounting Review* 65: 461-476.

Lang, M., and R. J. Lundholm. 1993. Cross-sectional determinants of analyst rating of corporate disclosures. *Journal of Accounting Research* 31(2): 246-271.

Lemmon, M., and E. Portniaguina. 2006. Consumer confidence and asset prices: Some empirical evidence. *The Review of Financial Studies* 19(4): 1499-1529.

Leone, A. J., and J. S. Wu. 2007. What does it take to become a superstar? Evidence from institutional investor rankings of financial analysts. Simon School of Business Working Paper No. FR 02-12. Available at SSRN: http://ssrn.com/abstract=313594 or doi:10.2139/ssrn.313594.

Libby, R., J. Hunton, H. Tan, and N. Seybert. 2008. Relationship incentives and the optimistic/pessimistic pattern in analysts' forecasts. *Journal of Accounting Research* 46(1): 173-198.

Lim, T. 2001. Rationality and analysts' forecast bias. *Journal of Finance* 56: 369-385.

Lin, H., and M. McNichols. 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics* 25: 101-127.

Loh, R., and G. Mian. 2006. Do accurate earnings forecasts facilitate superior investment recommendations? *Journal of Financial Economics* 80(2): 455-483.

Louis, H. 2004. Earnings management and the market performance of acquiring firms. *Journal of Financial Economics* 74: 121-148.

Louis, H., T. Lys, and A. X. Sun. 2008. Conservatism and analyst earnings forecast bias. Working paper.

Lucas, R. E. 1977. Understanding Business Cycles. In K. Brunner and A. H. Meltzer, *Stabilization of the Domestic and International Economy*. Amsterdam: North-Holland Publishing Company.

Lundholm, R. J., and R. G. Sloan. 2007. *Equity valuation and analysis with eVal (*2nd ed.*).* Boston, Mass.: McGraw-Hill/Irwin.

Lys, T., and S. Sohn. 1990. The association between revisions of financial analysts' earnings forecasts and security-price changes. *Journal of Accounting and Economics* 13: 341-363.

Mayew, W. J. 2006. Evidence of management discrimination among analysts during earnings conference calls. *Journal of Accounting Research* 46(3): 627-659.

McLean, R. D., and M. Zhao. 2011. The business cycle, investor sentiment, and costly external finance. Working paper. Available at SSRN: http://ssrn.com/abstract=1475663.

McNichols, M., and P. O'Brien. 1997. Self-selection and analyst coverage. *Journal of Accounting Research* 35: 167-199.

Mendenhall, R. 1991. Evidnence of possible underweighting of earnings-related information. *Journal of Accounting Research* 29: 170-180.

Merton, R. C. 1987. A simple model of capital market equilibrium with incomplete information. *The Journal of Finance* 42(3): 483-510.

Michaely, R., and K. Womack. 1999. Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies* 12: 653-686.

Mikhail, M. B., B. R. Walther, and R. H. Willis. 1999. Does forecast accuracy matter to security analysts? *The Accounting Review* 74 185-200.

Mikhail, M. B., B. R. Walther, and R. H. Willis. 2003. The effect of experience on security analyst underreaction. *Journal of Accounting and Economics* 35(1): 101-116.

Naes, R., J. A. Skjeltorp, and B. A. Odegaard. 2011. Stock market liquidity and the business cycle. *Journal of Finance* 66(1): 139-176.

Narayanan, V. K., and L. Fahey. 2001. *Macroenvironmental Analysis: Understanding the Environment Outside the Industry (*2nd ed.*)*. New York: John Wiley & Sons, Inc.

Nocera, J. 1997. Who really moves the market? *Fortune* October 27: 90-110.

Olsen, R. A. 1997. Prospect theory as an explanation of risky choice by professional investors: Some evidence. *Review of Financial Economics* 6(2): 225-232.

Pae, J., and D. Thornton. 2010. The association between accounting conservatism and analysts' forecast inefficiency. *Asia-Pacific Journal of Financial Studies* 39(2): 171-197.

Palepu, K. G., P. M. Healy, and V. L. Bernard. 2004. *Business analysis & valuation using financial statements: text & cases (*3rd ed.*)*. Mason, Ohio: Thomson/South-Western.

Pástor, Ľ., and Robert F. Stambaugh. 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111(3): 642-685.

Payne, J., and B. Thomas. 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.

Petersen, M. A. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22(1): 435-480.

Philbrick, D., and W. Ricks. 1991. Using value line and IBES analyst forecasts in accounting research. *Journal of Accounting Research* 29: 397-417.

Previts, G. J., R. J. Bricker, T. R. Robinson, and S. J. Young. 1994. A content analysis of sell-side financial analyst company reports. *Accounting Horizons* 8(2): 55-70.

Qiu, L., and I. Welch. 2004. Investor sentiment measures. NBER Working Paper No. 10794.

Raedy, J. S., P. Shane, and Y. Yang. 2006. Horizon-dependent underreaction in financial analysts' earnings forecasts. *Contemporary Accounting Research* 23(1): 291-322.

Ramnath, S., S. Rock, and P. Shane. 2005. Value line and I/B/E/S earnings forecasts. *International Journal of Forecasting* 21: 185-198.

Ramnath, S., S. Rock, and P. Shane. 2008a. A review of research related to financial analysts' forecasts and stock recommendations. *Foundations and Trends in Finance* 2(4): 311-420.

Ramnath, S., S. Rock, and P. Shane. 2008b. 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., and K. C. Brown. 2006. *Investment Analysis and Portfolio Management (*8th ed.*)*. Mason, Ohio: Thomson/South-Western.

Richardson, S., S. Teoh, and P. Wysocki. 2004. The walk-down to beatable analyst forecasts: The role of equity issuance and insider trading incentives. *Contemporary Accounting Research* 21(4): 885-924.

Rogers, R. K., and J. Grant. 1997. Content analysis of information cited in reports of sell-side financial analysts. *Journal of Financial Statement Analysis* 3(1): 17-30.

Schipper, K. 1991. Analysts' forecasts. *Accounting Horizons* 5(4): 105-131.

Shane, P. B., and T. Stock. 2006. Security analyst and stock market efficiency in anticipating tax-motivated income shifting. *The Accounting Review* 81(1): 227-250.

Shapiro, A. 2002. Theinvestor recognition hypothesis in a dynamic general equilibrium: Theory and evidence. *The Review of Financial Studies* 15(1): 97-141.

Shefrin, H., and M. Statman. 1985. The disposition to sell winners too early and ride losers too long: theory and evidence. *Journal of Finance* 40: 777-790.

Shleifer, A., and R. W. Vishny. 1997. The limits of arbitrage. *The Journal of Finance* 52(1): 35-55.

Slezak, S. 2003. On the impossibility of weak-form efficient markets. *Journal of Financial and Quantitative Analysis* 38(3): 523-554.

Soffer, L., and R. Soffer. 2003. *Financial Statement Analysis: A Valuation Approach*. Upper Saddle River, New Jersey: Prentice Hall.

Statman, M., and K. L. Fisher. 2002. Consumer confidence and stock returns. Santa Clara University Dept. of Finance Working Paper No. 02-02. Available at SSRN: http://ssrn.com/abstract=317304.

Stickel, S. E. 1989. The timing of and incentives for annual earnings forecasts near interim earnings announcements. *Journal of Accounting and Economics* 11(2-3): 275-292.

Stickel, S. E. 1990. Predicting individual analyst earnings forecasts. *Journal of Accounting Research* 28(2): 409-417.

Stickel, S. E. 1991. Common stock retums surrounding eamings forecasts revisions: More puzzling evidence. *The Accounting Review* 66 (2): 402-416.

Stickel, S. E. 1992. Reputation and performance among security analysts. *Journal of Finance* 47(5): 1811-1836.

Taylor, J. G. 1998. *Investment Timing and the Business Cycle*. Canada: John Wiley & Sons, Inc.

Thaler, R. H., and E. J. Johnson. 1990. Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice. *Management Science* 36(6): 643-660.

Trueman, B. 1990. On the incentives for security analysts to revise their earnings forecasts. *Contemporary Accounting Research* 7: 203-222.

Zhang, W., and W. Semmler. 2009. Prospect theory for stock markets: Empirical evidence with time-series data. *Journal of Economic Behavior and Organization* 72(3): 835-849.

Zhang, X. F. 2006. Information uncertainty and analyst forecast behavior. *Contemporary Accounting Research* 23: 565-590.