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Essays on Mutual Funds

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A thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy in Finance

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New Zealand

ABSTRACT

Mutual funds are unmatched by most other investment products in terms of assets under management and popularity. Academics have long addressed the question whether there is more behind the glossy brochures with eye-glazing graphs and tables. But much of the evidence in the finance literature suggests that most actively managed funds are not able to provide added value. Successful funds might beat their competition but very few beat the market (Fisher, 2014), and those that do tend to be rather lucky than truly skilled. Proponents of the efficient market hypothesis understand this as a natural consequence of correctly priced assets. By argumentum e contrario active investing should hence be more beneficial in markets that are perceived to be less efficient. In chapter 1 I show that funds predominantly investing in emerging market equities generate higher reward-to-risk ratios compared to their benchmarks. Adjusted for common stock factors, emerging market funds outperform before costs, but not after expenses. Local funds seem to have an edge over their foreign counterparts, outperforming them by approximately 1.8% annually. Chapter 2 examines late trading in mutual fund shares in European markets. This practice was common and widespread in the US until 2003, but it is startling to find evidence of this in the most recent past. Even more so after the European watchdog completed an investigation in 2004 reassuring that there are no indications with respect to late trading in their member states. I find that late trading accounts for up to 10% of daily flow. In chapter 3 I propose a flow-based explanation for two long-standing empirical regularities in finance – the Sell in May and the January effect. Flow exhibits a strong winter-summer seasonal that is consistent with both anomalies. After controlling for flow, there is no seasonality left in stock returns. Both of these effects appear to be mainly driven by retail money flow.

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Moritz Wagner

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PART I

INTRODUCTION

Mutual funds are one of the financial sector's great success stories, at least as seen from the provider's point of view. The industry has enjoyed a sweeping 10% annual compounded growth rate in assets under management over the past 20 years.[1] A period that includes several major financial crises such as the Asian and the Russian crisis, the collapse of LTCM, the technology bubble, and the recent global financial crisis and Eurozone sovereign debt crisis. With trillions of dollars in assets under management and being available to the general public, mutual funds are unmatched by most other investment products.[2] In the US net purchases in fund shares exceeded those in stocks for the first time in 1954.[3] Today, about one in two US households invests either directly or indirectly in mutual funds. Because of the industry's remarkable growth, importance and of course due to the large amount of data available, academics have produced a vast body of studies on mutual funds. A large part of it is devoted to the question whether and how investors and the overall economy share into this success story. The first and foremost question, how funds perform, has been at the centre of the debate. The mere number of academic studies is a reflection of the large interest in this area, but it also makes providing a comprehensive overview a tough task.[4] Some of the more influential early papers, Sharpe (1966) and Jensen (1968), painted a less favourable picture about active investing, documenting negative average fund alphas net of expenses.[5] And several follow-up papers report similar results, e.g. Elton et al. (1993), Malkiel (1995) and Carhart (1997). However, with

[1] Growth rate is based on worldwide total net assets of mutual funds. All figures about the fund industry presented in this paragraph are taken from the Investment Company Institute (ICI) Fact Books. The growth of the mutual funds industry has slowed down over recent years partially due to the growing importance of exchange traded funds (ETF) and hedge funds. However, mutual funds remain the primary investment vehicle for most investors.
[2] At the end of 2014 worldwide total net assets of mutual funds were USD 31.4 trillion.
[3] See the Investment Company Institute (ICI) Fact Book 2015.
[4] A good review on performance measurement and evidence for the US and UK is provided in Cuthbertson et al. (2010).
[5] My discussion here mainly focuses on equity mutual funds.

increasing samples and novel statistical methods empirical evidence on the performance of mutual funds has become more and more mixed. For instance, Kosowski (2011) find that funds on average weather downturns and provide positive risk-adjusted returns during recession periods. Similarly, Kacperczyk et al. (2012) propose a theoretical model of time-varying fund manager skills that change with the overall state of the economy. Evidence for this model is reported in Kacperczyk et al. (2014) indicating that managers who possess time-varying skills outperform the market. Using a bootstrap technique, Kosowski et al. (2006) also show that some funds do outperform the market. The large variation in the cross-section of fund alphas and the difficulty to pick winning funds has inspired research that tries to separate luck from skill. Cuthbertson et al. (2008), Barras et al. (2010) and Fama and French (2010), report that most funds in the right tails of the performance distribution are there due to luck rather than skill. By contrast, most funds on the other side of the distribution appear to be truly unskilled rather than simply unfortunate. Cremers and Petajisto (2009) introduce a new measure of active portfolio management based on the portfolio holdings of funds. They document that funds with the highest active share outperform their benchmarks even net of expenses and exhibit strong performance persistence, which might be at least partially the result of skill.[6] Similarly, Amihud and Goyenko (2013) show superior performance of funds with the lowest R^2 in multifactor market models. That means funds holding portfolios that differ the most from their (passive) benchmarks tend to perform better.

This rather brief discussion of the past and recent performance literature on mutual funds highlights that the debate is still unsettled and ongoing. The first essay contributes to this literature by analysing the performance of actively managed funds investing in emerging

[6] Active share is further discussed in Frazzini et al. (2015) and Petajisto (2015).

market economies (EM funds). This is motivated by (1) the fact that most of the existing studies focus on the US, (2) there is now much improved data availability for EMs and (3) EMs provide a natural alternative for testing the implications of the efficient market hypothesis (EMH). The latter follows from the prediction that active management should be more fruitful in markets that are less efficient. I find that similar to their counterparts in advanced economies, funds in emerging markets hold portfolios that are close to the market portfolio. And contrary to the concerns outlined in Harvey (1995), standard asset pricing models explain most of the fund returns.[7] More specifically, I use a global factor model, which assumes complete integration of capital markets, but also local factor models. Overall, EM funds outperform their benchmarks before expenses. After costs, aggregate fund alpha is zero. This is noticeably better than the results reported for funds in the US which, on aggregate, underperform by the size of their expenses.

Besides trying to generate high returns, mutual funds generally provide liquidity, economies of scale, access to diversified portfolios and enable investments in assets or markets which might be otherwise too difficult or costly to do. Because mutual funds are collective investments, fund managers also have fiduciary duties. This is important to emphasize since mutual funds have become an integral element of retirement savings schemes in many countries, including New Zealand.[8] Hence, it is important that investors can trust fund managers act in their best interests and according to law. Something so obvious might have come into question for many, considering the numerous scandals in the financial services sector in the recent past. Just over the last five to six years, the world has experienced incidents of fraud and blank criminal behaviour unseen in number and scale

[7] Note, Harvey identified market segmentation on the likely reason that standard pricing models failed to explain the cross section of EM returns which was fairly plausible at the time but may not be the case anymore.
[8] In New Zealand the saving scheme is called KiwiSaver, in the US and UK similar pension schemes are called 401K and BritSaver.

with the largest investment scam in history run by Bernhard Madoff leading the way. Good old insider trading has also experienced a kind of revival, with several cases plaguing the hedge funds industry. But the manipulation of benchmark rates (LIBOR) and the rigging of currency exchange rates, involving all major international banks, brought financial market scandals truly up to another level. These two episodes have potential adverse effects for individuals financing consumer goods or properties, international payment transactions, business borrowing and government finance. And it is disheartening that serious question about the integrity of the financial markets come so soon after promises of improvement and change made by banks following their involvement in the actions that led to the global financial crisis. Should we now be concerned that many of these banks are also major providers of mutual funds?

The second essay investigates the incidence of late trading in mutual fund shares in Europe. Late trading is a form of stale price arbitrage that allows certain investors to buy and sale fund shares after the official cutoff time. But unlike other arbitrage strategies, late trading is prohibited by law because it favours a small number of investors to the detriment of all other investors in the funds. Zitzewitz (2006) estimated the loss due to late trading in the US where it was common and widespread until 2003 to USD 400 million per year. Perhaps it comes with surprise to find evidence of this practice in two European markets not long after the US scandal, but I also understand the lure of easy money particularly in the world of finance where the winner usually takes it all. My findings suggest that investors that are allowed to trade late can earn up to 35% per annum and this with substantially lower risk than simply buying a fund and holding it. These findings, however, are not able to indicate whether fund managers, banks or other intermediaries are directly or indirectly the culprits in this trading.

In my third essay I take a different perspective and analyse the relation between mutual fund flow and seasonalities in stock returns. Calendar anomalies have probably been around since the opening of the first stock exchange.[9] Many of these have disappeared not long after they were discovered whereas others remain highly questionable. The focus of this essay is on the Sell in May and January effects. Both are rather pervasive and popular among investors and in the media. As usual when dealing with anomalies, some sceptics might argue that there were none in the first place. However, previous research provides more supporting than opposing evidence for these anomalies, and regularities are also present in my data.[10] The explanations offered in the literature for the Sell in May effect are not convincing and are incomplete for the January effect. The main explanations for the Sell in May effect are based on investor behaviour and psychology, while for the January effect risk, window dressing and tax-loss selling are suggested. I propose and provide evidence that both effects are at least partially driven by mutual fund flows. This builds on the contemporaneous relation between flow and returns documented in the literature and a distinct winter-summer seasonality I find in mutual fund flows.[11] More specifically, in most years flow is higher during winter than during summer months. And in years where this is not the case, i.e. when summer flow is higher than winter flow, the Sell in May effect is negative. The standard dummy tests for both, the Sell in May and the January effect, become insignificant when we control for retail fund flow. These results are consistent with the price-pressure hypothesis as one of the possible explanations for the co-movement

[9] The Amsterdam Stock Exchange (today Euronext Amsterdam) opened in the early 1600's and is considered to be the world's oldest, e.g. see Petram (2011). Besides calendar anomalies, finance literature has also discussed anomalies related to fundamentals (e.g. value or size effect, high dividend yield or low price-to-sales ratios) or technical anomalies such as momentum.

[10] I discuss the literature in more detail below.

[11] For example, Warther (1995), Edelen and Warner (2001) and Boyer and Zheng (2009) all document a positive relation between market returns and mutual fund flows. I expand on this and the main hypotheses discussed as explanation below.

between market returns and fund flow, which has received strong support in recent papers such as Coval and Stafford (2007) and Lou (2012).

The rest of the thesis is organized as follows. Part II contains the three essays on mutual funds. Chapter 1 analyses the performance of mutual funds specifically investing in emerging market equities. Chapter 2 examines the practice of late trading in European markets, while Chapter 3 uses fund flow to explain long-standing anomalies in stock returns. Part III concludes.

PART II

ESSAYS ON MUTUAL FUNDS

Chapter 1

ALL ABOUT FUN(DS) IN EMERGING MARKETS? THE CASE OF ACTIVELY MANAGED EQUITY FUNDS

ABSTRACT

The aggregate portfolio of actively managed mutual funds that predominantly invest in emerging market equities is close to the market portfolio. We find that actively managed funds produce higher reward-to-risk ratios compared to market indices. However, relative to common stock factors funds add value only before expenses. After expenses, only growth-oriented and China funds seem to generate benchmark-adjusted returns that more than recoup their costs. Classifying funds based on their investment style further suggests growth beats value. We also find that funds located within their geographical investment focus outperform their foreign counterparts by 1.8% after costs annually. Foreign funds tend to invest more cautiously in small and growth firms. We do not find much evidence that equity funds in emerging markets pursue a market timing strategy, those that do seem to have rather poor market timing skills. Similarly, we do not find that common measures of stock market efficiency are related to performance.

1.1 Introduction

In this essay, we examine the performance of actively managed mutual funds that predominantly invest in emerging market equities (henceforth EM funds). Much evidence in the finance literature suggests that even if fund managers have stock-picking skills, they tend to deliver mediocre returns, at best, to their clients (e.g., Jensen (1968), Malkiel (1995),

Gruber (1996), Carhart (1997), Barras et al. (2010), Fama and French (2010)). However, recent studies which account for different economic states find that funds are able to provide added value when it arguably matters the most for investors, during economic downturns (e.g., Moskowitz (2000), Kosowski (2011), Turtle and Zhang (2012), De Souza and Lynch (2012), Avramov and Wermers (2006)). Most of these studies focus on US mutual funds or those in other advanced economies. Our motivation to examine funds which invest in emerging markets comes from the simple consideration that active management should be more beneficial in markets that are perceived to be less efficient. In practice selecting a portfolio involves a combination of data and judgment. For example, if information is not evenly distributed and readily available, information might not be instantaneously and/or correctly priced that in turn might provide opportunities for sophisticated investors. There is ample evidence suggesting that stock markets in emerging economies (EME) display indeed a lower level of (informational) efficiency than in advanced economies (e.g., Lim and Brooks (2008, 2010), Morck et al. (2000), Jin and Myers (2006), Fernandes and Ferreira (2007, 2008), Griffin et al. (2007, 2009), Bekaert and Harvey (2002), Khandakera and Heaney(2009)).[12] Moreover, this sector of the fund industry has tremendously grown over the last two decades and with the term BRIC formed in 2001,[13] emerging market equities are established for all times as distinct asset class or investment strategy. Yet, academic evidence about the most important question from an investor's point of view, how funds in these markets perform, is thin and inconclusive. For example, Eling and Faust (2010) find that hedge funds perform better than mutual funds in EMEs with most of the latter underperforming traditional benchmarks. For 55 diversified

[12] Informational efficiency refers to the general definition provided by Fama (1970) who defined a market to be informational efficient if prices at any point in time incorporate all available information for price formation.

[13] Confer O'Neill, "The World Needs Better Economic BRICs", written for Goldman Sachs' Global Economic Paper Series.

EM funds, Michelson et al. (2008) document that larger and less actively trading funds tend to perform better. This is contrary to Gottesman and Morey (2006) who find that expense ratio is the only attribute variable that consistently predicts future fund performance. Pomerleano (1998) shows that US-based equity mutual funds investing in EMEs outperform two broad market benchmarks after costs.

The short literature review highlights how less attention mutual funds in emerging countries have received unlike, for example, their counterparts in the US.[14] This paper extends the current literature by providing comprehensive evidence about the performance of mutual funds that mainly invest in EMEs. Using Morningstar we overcome data-related limitations of most prior research and obtain data on 5,175 equity funds over the period July 1992 through October 2012.[15] This sample allows us to examine the performance of actively managed mutual funds in most countries that are considered as emerging. The time period covers the entire life of most of the funds and starts right after the financial liberalization in most emerging countries. Bekaert and Harvey (2000) date the opening of equity markets in those countries around the end of the 80s and beginning of the 90s. In terms of mean monthly returns and Sharpe's (1966) ratio, we find that equally-weighted (EW) and value-weighted (VW) portfolios of all funds outperform traditional market benchmarks before and after expenses. The aggregate portfolio of the funds is close to the market portfolio. The standard CAPM already explains 93% of the variance of monthly EW and VW fund returns. On aggregate, the sample funds have negative (positive) exposure to the size (value) factor and do not have much exposure to momentum returns.

[14] Besides the mentioned articles, there are a few country-specific studies we have discussed in an earlier version of this paper (e.g. see Swinkels and Rzezniczak (2009) and Bialkowski and Otten (2011) for Poland funds, Sehgal and Jhanwar (2007, 2008), Miglani (2011) and Kundu (2009) for India funds, Eid and Rochman (2006) for Brazilian funds).

[15] The sample period varies across our different tests mainly depending on data availability.

We further find that actively managed funds in emerging markets have some skill to add value relative to common stock factors, but only before expenses. The annualized intercept in a regression with the market, size, value and momentum factor using EW gross returns is 2.64% with a *t*-statistic of 3.06. Using returns before expenses provides some evidence for fund managers' skills. However, regressions using net returns indicate that fund managers on average are rather not sufficiently skilled to recoup their costs. Yet, the mainly non-negative intercepts also suggest it does not hurt to invest in EM funds.

To mitigate potential issues arising from the question if or to what extent asset pricing is integrated throughout different countries, we also use local benchmark versions of asset pricing models. As pointed out by Griffin (2002), stock returns in all countries should be explained by the same factors if capital markets are fully integrated. However, he finds lower average pricing errors for local than international models. Similarly, Fama and French (2012) show that local specifications of pricing models perform better in describing average returns. Forming portfolios of country-specific mutual funds also allows evaluating the performance of active management in different countries or regions. More specifically, we form EW portfolios of mutual funds that mainly invest in equities listed in one of the following countries: South Africa, Brazil, Chile, China, India, Indonesia, Israel, South Korea, Malaysia, Mexico, Poland, Russia, Taiwan and Thailand. The market slopes range between 0.57 and 0.96 with *t*-statistics from 17.00 to 54.48. Apart from Brazil and China funds, all fund portfolios show exposure to the size but only a few to the value factor. The exposure to momentum returns is mixed. In terms of gross returns the four-factor intercepts of China, India, Russia and Taiwan funds range between 0.41 to 0.71 with *t*-statistics between 1.91 and 2.69, respectively. After expenses however, only active managers in China seem to be able to generate returns that are large enough to more than recoup their costs. The annualized three- and four-factor intercepts for EW net returns in China are a

whopping 7.2% and 6.72% per year with *t*-statistics of 1.93 and 1.82, respectively. This is contrary to most of the evidence reported on US equity funds which on average underperform the market by about the size of their expenses. On the other hand, there is not much reason to party for investors of Brazil and Chile funds, which underperform their four-factor benchmarks after expenses by around 7.00% per annum.

Since investment style has mainly been neglected in the context of emerging markets, we also form style portfolios of mutual funds using Morningstar's style classification method. This is based on actual portfolio holdings rather than the investment style mentioned in the funds' prospectuses, allowing us to track a fund's investment style through time. This is important as mutual funds tend to change their investing style over time due to various reasons. For example, a change in management often brings along a change in style. Style drift or style chasing behaviour has also been documented in literature (e.g., Froot and Teo (2008), Brown et al. (2011), Wermers (2012), Frijns et al. (2015)). We use a classification that results in nine distinct style portfolios, a combination of large/mid/small and value/blend/growth. The portfolios are rebalanced monthly. In terms of average monthly returns large beats small, but in terms of benchmark-adjusted returns it is the other way round. Moreover, growth funds tend to perform better than value funds and provide most added value to investors. This is even more interesting, since small stocks and growth stocks seems to have lower average returns compared to large and value stocks. The annualized four-factor intercept of EW net returns on growth funds is a staggering 6.72% with a *t*-statistic of 3.58. None of the investment style portfolios of active mutual funds has much exposure to momentum returns.

We use Treynor and Mazuy's (1966) and Henriksson and Merton's (1981) proposed timing factors to account for the fact that fund returns can also be the result of a portfolio manager's ability to time the market in the sense of predicting the likely direction of price

movements in addition to finding and trading mispriced securities. However, we do not find much evidence that actively managed funds in emerging markets pursue a market timing strategy. For an EW portfolio of small cap oriented funds and eight out of 14 EW portfolios of country-specific funds, we rather find evidence of poor market timing skills. In four of these portfolios, the fund managers' good selection skills remain unnoticed in performance measures not accounting for market timing.

Next, we discriminate between funds that are located within (local investors) and those located outside their geographical investment focus (foreign investors). We find that based on raw returns local investors outperform foreign investors by approximately 2.0% before and 1.8% after costs annually. Foreign investors are on average the larger funds and tend to invest more cautiously in small cap firms than local investors. Considering the different investment styles, we only find a significant domicile effect for EW value funds. Over the sample period, local value funds outperformed their foreign counterparts by 6.36% on average per annum.

In a panel setting, we finally test whether direct measures of stock market efficiency are related to fund performance. For the test to work, we increase the cross section of country-specific fund portfolios from above by EW portfolios of actively managed funds that predominantly invest in one of the following countries: France, Germany, Italy, Japan, Norway, Spain, Sweden, Switzerland, United Kingdom and the US. However, we do not find evidence that common measures of a stock market's efficiency level are related to alpha.

The remainder of the essay is organized as follows. Section 1.2 describes the data. Section 1.3 presents our empirical findings, and we conclude in Section 1.4.

1.2 Data on Actively Managed Mutual Funds

Data on mutual funds are obtained from Morningstar. This is one of the industry's most comprehensive investment databases, covering thousands of investments worldwide. The core competency of Morningstar is to provide data on open- and closed-end funds, equities, ETFs, hedge funds, insurances, separate accounts, stocks and fund ownership and public filings. Morningstar covers a total of 170.000+ open-end funds worldwide. The main area of interest for the present study is actively managed mutual funds that invest in emerging market economies. Hence, all funds in the Global Category of Emerging Equities are included in the sample. The broad categories in Morningstar are Africa Equity, Brazil Equity, Emerging Market Equity (diversified funds), Greater China Equity, India Equity, Israel Equity, Korea Equity, Latin America Equity, Mexico Equity, South American Equity, Taiwan Equity, Thailand Equity and Thailand Equity Large Cap. These categories are further broken up into more detailed, country specific categories (Morningstar Categories). We specify a total of 39 search items to determine the funds' geographical investment focus and to retrieve all funds from Morningstar that invest in emerging markets. This search returns more than 25,200 funds, including dead funds.[16]

All index funds and all but a fund's oldest share class are then excluded from the sample. This procedure should omit most of the passively managed funds and keeps only a fund's main share class in cases where a fund has more than one share classes. It is not unusual that a fund offers different share classes to different groups of investors, with different cost structures and/or for tax purposes. However, all classes refer to the same underlying portfolio. This is identified by different security or fund IDs having the same portfolio ID. Applying these additional search criteria leaves around 8,300 funds. Fund of funds are also

[16] Including dead funds removes any potential survivorship bias.

excluded, since they only invest in other funds without holding an own portfolio of emerging market equities. Furthermore, investors essentially pay double for expenses at the level of the fund directly invested in and at the level of the funds of the fund. Not excluding them would probably bias the overall performance of the sample downwards. The search is further limited to only certain investment types or legal structures, so that closed-end funds, hedge funds, separate accounts and so forth are not included. Our final sample contains 5,175 actively managed equity mutual funds that invest in EMEs. These funds are domiciled around the world. Particularly in the context of emerging markets, data availability has been a major constraint for more research so far. Our data set is substantially larger than in any other study, allowing us to examine mutual funds throughout the emerging world.

1.2.1 Overview and Summary Statistics

Table 1.1 provides an overview of the data. The number of active funds has increased from 113 in 1992 to over 5,000 at the end of 2012. And, it has become more expensive to invest in EM funds, as shown by the movement in the average expense ratio over time. Since we are looking at equity funds, average fund size moves closely together with the overall stock market as shown in Figure 1.1. The graph also shows that the co-movement between stock markets in emerging countries and the developed world has increased over time. The correlation coefficient between the MSCI EM Index and S&P 500 is 0.05 before and 0.75 after 2000.[17] From a portfolio management point of view, this will have direct implications on the diversification benefits of investing in equities from EMEs. From Table

[17] The correlation coefficient over the full sample period is 0.70.

1.1 we further see that various financial crises are reflected in the funds' net assets and average monthly net flows. During the Mexican (1994-1995), Asian (1997-1998) and Russian (1998) crises, net assets decreased from previous years. Fund assets also decreased between 2000-2002, a period in which Turkey (2000-2001) and Argentina (2002) suffered from a public debt and currency crisis and in which the well-known technology bubble burst (2000-2001). Average net assets peaked at USD 337m in 2007 and dropped sharply with the global financial crisis (GFC) in 2008. The decrease in fund assets in 2011 coincides with increased investor risk aversion associated with the sovereign debt and banking crisis in Europe. A similar pattern emerges for average monthly net flows. During the Mexican and Asian crises, investors pulled more than USD 1bn out of emerging market funds. A lot of this capital moved back to the US to fuel the IT bubble. In the subsequent years, net flow greatly increased and peaked in 2007 when more than USD 113bn was invested in EMEs through active funds.

Table 1.1: Overview of Actively Managed Emerging Markets Funds

This table provides an overview of active mutual funds that predominantly invest in equities of emerging countries available from Morningstar. Date refers to the 31 December of each year. The second column shows the number of funds for which net returns are available. Average net assets are measured across mutual funds at the end of each year. Column four shows monthly net flow averaged across funds during the year specified in the date column. Sum of monthly net flow is the aggregate amount of the funds' monthly net flows during the year specified in the date column. Net expense ratio is the annual report net expense ratio averaged across funds. The sample period is January 1992 through December 2012.

Date	Number of Funds	Average Net Assets (USD)	Monthly Average Net Flow	Sum of Monthly Net Flow	Net Expense Ratio
1992	113	58,458,877	3,187,809	761,886,393	-
1993	188	263,355,966	20,916,711	8,805,935,174	-
1994	297	187,886,696	7,637,484	6,163,449,757	1.68
1995	391	139,302,772	-798,725	-1,060,706,766	1.72
1996	479	143,952,979	2,319,999	3,920,798,497	1.63
1997	607	136,611,800	2,251,603	4,809,423,132	1.58
1998	728	87,041,381	-503,426	-1,314,445,436	1.73
1999	867	99,761,424	780,960	2,682,596,586	1.66
2000	1015	58,212,200	55,347	284,871,230	1.60
2001	1130	50,875,353	249,692	1,663,450,594	1.54
2002	1253	46,952,426	528,811	4,068,143,959	1.82
2003	1360	80,539,820	1,386,111	11,901,150,363	1.70
2004	1605	98,327,146	1,597,511	16,240,295,685	1.72
2005	1946	147,582,526	3,812,004	50,082,113,224	1.92
2006	2361	197,356,764	2,395,692	42,926,010,449	1.99
2007	2941	336,586,343	4,712,519	113,519,872,432	2.16
2008	3540	121,826,757	78,721	2,484,286,782	2.05
2009	3898	201,000,608	2,108,383	75,235,544,930	2.14
2010	4380	206,337,272	1,473,588	58,912,585,859	2.19
2011	4845	144,390,660	5,974	259,828,189	2.01
2012	5175	151,708,565	494,161	22,872,721,152	1.82

Figure 1.1 Equity Fund Net Assets and the Overall Stock Market

The graph plots average monthly total net assets of active mutual funds that predominantly invest in equities of emerging countries against the MSCI Emerging Market Index and the S&P 500. The funds' total net assets are given in USD. All three time-series are adjusted for capital distributions and cash dividends (re-invested). The time period is January 1992 through December 2012.

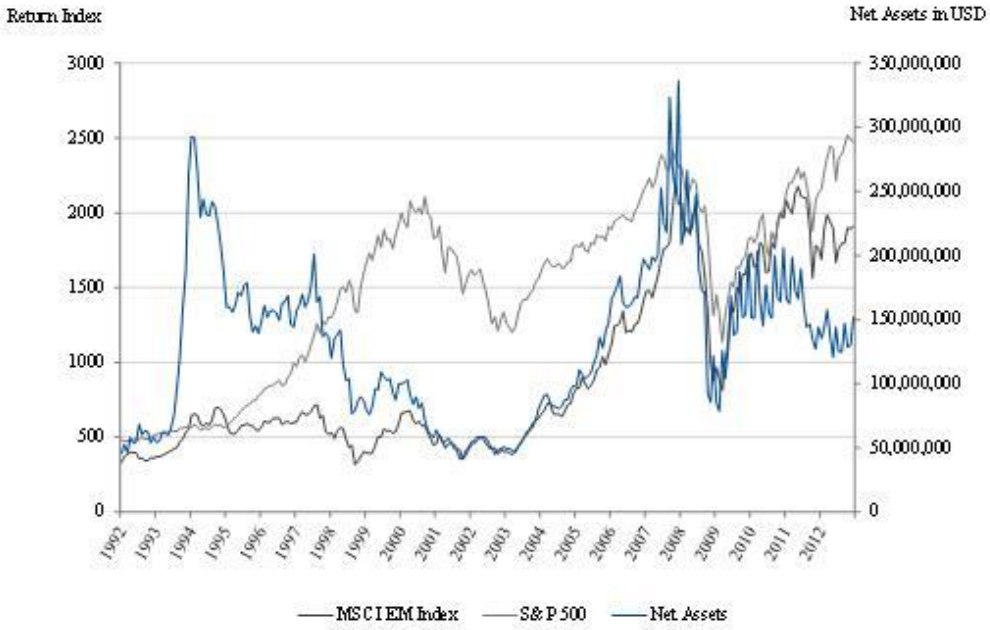


Table 1.2 presents summary statistics for EW and VW portfolios of the sample funds compared to broad equity indices.[18] These indices are commonly used by academics and practitioners to measure the overall stock market performance of emerging countries. Both, the funds' EW and VW average monthly gross returns are above the average monthly returns on all four market benchmarks. After costs, this is true in three out of four cases. The average annual return difference between the funds' EW net return and Russell's

[18] We have repeated the analysis over a longer sample period from July 1992 to October 2012 using the MSCI EM Index, S&P EM BMI and FTSE Emerging Markets Index obtaining the same results as presented in Table 1.2.

market index is 1.44%, but -0.12% compared to the S&P BMI Index. It has been widely documented that evaluating performance by such simple measures is sensitive to the benchmark. Taking risk into account, the assessment becomes more consistent but overall a similar picture can be drawn. The funds' Sharpe ratios based on EW and VW portfolios are before and after costs in all but one case above those of the benchmark indices. Not shown in Table 1.2 are higher moments of the return distributions. Monthly net returns across all funds are somewhat negatively skewed (-0.20), while excess kurtosis (2.4) suggests a peaked distribution.

Table 1.2: Summary Statistics for EM Funds and Market Benchmarks

This table presents summary statistics for equally- and value-weighted portfolios of mutual funds and broad equity indices designed to measure the overall stock market performance of global emerging countries. The sample period is August 1996 to October 2012 (Russell's Emerging Markets Index is not available before August 1996).

	All EM Funds		MSCI EM Index	Russell Emrg Mkts	S&P EM BMI Index	FTSE Emerging Mkts
	gross	net				
Mean *(EW portfolio)*	1.13	0.96	0.88	0.84	0.97	0.89
Mean *(VW portfolio)*	1.08	0.91				
SD *(EW portfolio)*	6.71	6.62	7.31	7.31	7.28	7.37
SD *(VW portfolio)*	6.94	6.90				
Sharpe Ratio *(EW portfolio)*	1.61	1.32	1.07	1.02	1.22	1.08
Sharpe Ratio *(VW portfolio)*	1.48	1.20				

1.2.2 Investment Style

So far, investment style considerations have mainly been neglected in the context of emerging markets analyses, yet style is important from an investor's point of view, in particular because investment style assists in setting long-term expectations of returns. Financial theory and empirical evidence tell us that a style combination of small and value has, on average, the highest return potential relative to other combinations (not considering risk).[19] However, it is not clear whether this stylistic analysis carries over into emerging markets when considering the performance of actively managed mutual funds. To shed light on this, we group the sample funds into nine distinct categories based on their investment style without any overlap. Morningstar assigns style categories to funds based on their actual portfolio holdings rather than just their prospectus style. This is important since a fund's investment style often changes over time due to changes in management, investment objective or changes in market conditions. Style drift or style chasing behaviour has also been documented in literature (e.g., Froot and Teo (2008), Brown et al. (2011), Wermers (2012), Frijns et al. (2015)). In our sample, the funds report holdings at different frequencies monthly, quarterly or semi-annually. Each of the funds' portfolios is accompanied by a style classification in Morningstar that allows tracking a fund's investment style over time. For example, if a fund reports on a quarterly basis, we keep its style classification until the new holdings are obtained and a new classification is assigned. Every month we put the sample funds into one out of nine distinct portfolios according to their style categories, a combination of large/mid/small and value/blend/growth.[20] The

[19] See for example Rosenberg et al. (1985) and Fama and French (1992, 2007).

[20] According to Morningstar, the classification begins at the individual stock level based on three market capitalization breakpoints (large, mid and small) and value and growth characteristics as well as a core style (stocks for which neither value nor growth characteristics dominate). The style attributes of the stocks are then used to determine the style classification of equity portfolios (blend style represents the core style in case of portfolios).

portfolios are rebalanced monthly. Figure 1.2 is a graphical representation of the performance of our mutual fund style portfolios using monthly gross and net returns. The shading indicates whether the performance measures for the fund portfolios are above (light shading) or below (dark shading) those of respective market benchmarks.[21] The benchmarks are chosen from Russell Investments' index family, since it provides style indices without any gaps or overlaps.[22]

[21] Using individual fund months instead of equally-weighted fund returns does not change the results.
[22] We have repeated the analysis using indices from MSCI and S&P but the overall picture does not change.

Figure 1.2: Performance Grids of Mutual Fund Style Portfolios

Panel A (B) reports the average monthly gross (net) returns and Sharpe ratios of EW mutual fund portfolios based on investment style. Style is determined by the funds' actual portfolio holdings according to three market capitalization breakpoints and value and growth characteristics as well as a blend category of individual equity holdings. The sample period is August 1996 to October 2012. The shading indicates whether the performance measures are above (light) or below (dark) of respective market benchmarks.

Panel A

Gross Return	Large	Mid	Small
Value	1.12	0.94	1.06
Blend	1.01	1.15	1.13
Growth	1.21	1.28	1.12

Sharpe Ratio	Large	Mid	Small
Value	1.45	1.32	1.61
Blend	1.34	1.61	1.60
Growth	1.68	2.00	1.32

Panel B

Net Return	Large	Mid	Small
Value	0.94	0.78	0.85
Blend	0.83	0.95	0.90
Growth	1.02	1.06	0.89

Sharpe Ratio	Large	Mid	Small
Value	1.17	1.05	1.19
Blend	1.05	1.32	1.26
Growth	1.38	1.60	1.02

By comparing the first with the last column and the top and the bottom row of the performance grids in Figure 1.2, we can see that on average large beats small and growth actually value. This is even more interesting, considering that small stocks and growth stocks seem to have lower average returns compared to large and value stocks as shown in

Figure 1.3.[23] Furthermore, the dark shadings in Panel A and B indicate that mutual funds pursuing a value strategy generally underperform their style benchmarks. On the other hand, investors would have gained most over the sample period by investing in growth funds. These funds outperform their style benchmarks pre and after costs. Similarly, average monthly returns on small-cap-blend and small-cap-growth funds are higher than those on corresponding style indices. Assuming that Morningstar's style classifications are correct, growth funds may be simply better in selecting stocks which is also indicated by the results reported in Table 1.5 below.[24]

Figure 1.3: Performance Grids for Style Benchmarks

This figure reports average monthly returns (total returns adjusted for dividends and splits) and Sharpe ratios of Russell Emerging Markets style indices. The sample period is August 1996 to October 2012.

Total Return	Large	Mid	Small
Value	1.17	1.02	0.98
Blend	0.88	0.81	0.79
Growth	0.60	0.59	0.56

Sharpe Ratio	Large	Mid	Small
Value	1.52	1.33	1.22
Blend	1.06	0.98	0.92
Growth	0.59	0.60	0.54

[23] This is also reflected in the negative (positive) premium on the global size (value) factor computed for the specified set of emerging market equities described below.
[24] We do not find evidence of superior market timing skills for any style class (please see Table 1.8 below).

Overall, value stocks in emerging markets have on average higher returns than growth stocks. It is surprising that mutual funds investing in those equities seem to underperform funds which invest in lower return stocks. A *t*-test for the difference between the mean returns of value and growth funds is statistically significant at the 1% level.[25]

1.3 Empirical Results of Benchmark-Adjusted Returns

1.3.1 Methodology

In this section we use standard asset pricing models to evaluate the performance of actively managed funds in emerging markets. Our main model is Fama and French's (1993) three-factor and the extended four-factor time-series regression of Carhart (1997).

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{mt} - R_{ft}) + s_i SMB_t + v_i HML_t + m_i MOM_t + e_{it} \qquad (1.1)$$

The left-hand side of the equation is the return on sample fund *i* for month *t*, R_{it}, in excess of the risk-free rate, R_{ft} (the 3-month US Treasury bill rate). R_{mt} is the market return, SMB_t and HML_t are the returns on portfolios of small minus large cap stocks and value minus growth stocks. MOM_t is Carhart's (1997) momentum return, the return difference of winner minus loser stocks based on prior 1-year returns. α_i is the average return left unexplained by the regression model that is generally interpreted to come from active management or security selection skills (omitted factors not considered). e_{it} is the usual error term. Equation (1.1) nests alternative benchmark models. Using the market factor as the only term on the right-hand side is the standard CAPM. Including the first three explanatory variables is Fama-French's three-factor and the full model specification is Carhart's four-factor model.

[25] The difference in means of value minus growth funds is about -19 basis points (*t* value = -5.39).

For evaluating the performance of the sample funds we use factors computed from global emerging market equities.[26] The market return is the value-weighted return on a portfolio of all listed stocks in the specified set of emerging countries sourced from Datastream and Worldscope.[27] The construction of the size (SMB_t), value (HML_t) and momentum (MOM_t) factor follows Fama and French (1993, 2012). The only difference is the size breakpoint for the 2 x 3 sorts of stocks on size and B/M or size and momentum to construct the explanatory returns. Big (small) stocks are those in the top 20% (bottom 80%) of market cap. Fama and French (2012) use a 90:10 partition of market cap to avoid too much weight on micro stocks for the construction of their global factors.

A downside of using this data is the relatively short time period starting in July 1995 and ending in June 2011. Nevertheless, this period covers most of the funds in the sample over their entire life, since only a few existed before 1995. Table 1.3 reports summary statistics for the independent variables used to estimate equation (1.1). The value factor has the highest average return, 1.78% per month with a *t*-statistic of 5.37, followed by the average monthly momentum and market premium, 1.07% and 0.59% with *t*-statistics of 2.12 and 1.29, respectively. The size factor has a negative monthly average of -0.11% with an insignificant *t*-statistic of -0.52. This might be due to the different size breakpoints for constructing these factors, but Fama and French (2012) also do not find a size premium for any of their regions outside the US.[28]

[26] Available at <http://www.jasonhsu.org/research-data.html>. The code for producing these global emerging market factors has been calibrated by replicating the factors for the US market available from French's data library with a correlation of 1.

[27] Global emerging markets include Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Israel, Korea (South), Malaysia, Morocco, Mexico, Pakistan, Peru, Philippines, Poland, Russian Federation, South Africa, Thailand, Turkey, and Taiwan.

[28] SMB for the period 11/1990-03/2011 in Europe -0.06 (t = -0.38), Japan -0.09 (t = -0.42) and Asia Pacific -0.21 (t = -1.05).

Table 1.3: Summary Statistics of Global Emerging Market Regression Factors (R_m - R_f, *SMB, HML* and *MOM*)

R_m is the value-weighted return on the market portfolio of all listed stocks in Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Israel, South Korea, Malaysia, Morocco, Mexico, Pakistan, Peru, Philippines, Poland, Russian Federation, South Africa, Thailand, Turkey, and Taiwan (the specified set of emerging countries) obtained from Datastream and Worldscope. R_f is the 3-month US Treasury bill rate. The construction of *SMB*, *HML* and *MOM* follows mainly Fama and French (1993, 2012). The stocks are sorted into two size (big and small stocks based on market cap) and three book-to-market equity (B/M) groups (growth are bottom 30%, neutral are middle 40% and value are top 30% B/M stocks), rebalanced at the end of June each year. Big (small) stocks are those in the top 20% (bottom 80%) of market cap. The momentum return is defined as the B/M sort just based on prior 1-year returns and rebalanced monthly instead of annually. *SMB*, *HML* and *MOM* are the return differences between the monthly average returns on the (double sorted) three small stock and the three big stock portfolios, the two value stock and the two growth stock portfolios, and the two high momentum minus the average of the returns on the two low momentum portfolios, respectively. The table shows the mean, standard deviation and *t*-statistic for the global market $R_m - R_f$ (market), *SMB* (size), *HML* (value) and *MOM* (momentum) factors. The sample period is from July 1995 to June 2011.

	R_m-R_f	*SMB*	*HML*	*MOM*
Average Return	0.59	-0.11	1.78	1.07
Standard Deviation	6.32	2.95	4.58	6.98
t-statistic	1.29	-0.52	5.37	2.12

1.3.2 Regression Results for EW and VW Portfolios of EM Funds

Table 1.4 shows the results of equation (1.1) estimated for our full sample of mutual funds over the period July 1995 to June 2011. Funds are weighted by their net assets in USD in the VW and equally each month in the EW portfolio.[29] The models are estimated using both gross (before expenses) and net returns (after expenses). Morningstar computes gross returns by backing out a fund's expenses, provided information about a fund's

[29] There is a loss in observations associated with forming VW portfolios since Morningstar does not have net assets for all funds in the sample. For example, at the end of 2012 Morningstar has net assets for 4,079 funds, but net returns for 5,175 funds.

expenses is available. Typically, there are fewer observations of gross than net returns. We do not replace missing gross return values by, for example, adding average expenses of all funds in the sample to net return values, in order to avoid measurement issues.[30] Regressing the return on funds over SMB_t, HML_t and MOM_t adjusts the fund returns by common factors in stock returns. The regression intercept measures the average return or added value provided by the funds as the result of active management (security selection skills).

The market slopes in Table 1.4 are all close to 1 and highly significant. The model specification of equation (1.1) with $R_m - R_f$ as the only explanatory variable (CAPM) already explains about 93% of the variance of the monthly EW and VW fund returns.[31] The coefficients on HML_t are around 0.10 with *t*-statistics above 4.0. On aggregate, funds load negatively on the size factor. The coefficient on SMB_t for the VW portfolio of funds is -0.29 with a *t*-statistic of -7.43 which is approximately twice the estimate of the SMB_t coefficient for the EW portfolio. With coefficients on MOM_t close to zero, the funds show little exposure to the momentum factor.[32] A possible explanation is that momentum funds are simply underrepresented in our sample and because value and momentum returns are usually negatively correlated (e.g. see Cakici et al., 2013), most value funds will have a negative exposure to momentum.[33] But regardless of the sample, Table 1.3 shows that the value factor is more pronounced in emerging markets than momentum, which is consistent with the findings reported by Hanauer and Linhart (2015). Hence, value investing might be preferred by some of the funds.

[30] The difference is negligible and results are not affected when we only use net return observations with equivalent gross return observations.
[31] This is consistent with findings reported for equity funds in the US. For example, Fama and French (2010) show that the market model already explains about 96% of the variance of aggregate mutual fund returns.
[32] We cannot test whether these results are robust to different momentum specifications by using the data from Jason Hsu.
[33] Table 1.5 also reports negative loadings on MOM_t for value funds.

Table 1.4: Benchmark Regression Estimates for EW and VW Portfolios of Actively Managed Emerging Market Funds

This table reports the intercepts, regression coefficients on $R_m - R_f$ (b), *SMB* (s), *HML* (v) and *MOM* (m) together with the associated t-statistics and adj. R^2 measures for the one-, three- and four-factor version of equation (1.1). The regressions are estimated for EW and VW gross and net returns of emerging market funds. The sample period is from July 1995 to June 2011.

	Gross	Net	b	s	v	m	R^2
EW Returns							
Coef	0.34	0.18	1.00				0.94
(t-stat)	3.06	1.59	56.68				
Coef	0.17	0.00	0.97	-0.12	0.10		0.95
(t-stat)	1.53	0.04	57.53	-3.33	4.22		
Coef	0.22	0.05	0.96	-0.14	0.10	-0.04	0.95
(t-stat)	2.00	0.49	56.09	-3.76	4.23	-2.74	
VW Returns							
Coef	0.31	0.12	1.04				0.93
(t-stat)	2.26	0.91	48.69				
Coef	0.07	-0.11	0.99	-0.29	0.13		0.95
(t-stat)	0.61	-0.99	55.45	-7.44	5.25		
Coef	0.08	-0.09	0.98	-0.29	0.13	-0.01	0.95
(t-stat)	0.70	-0.81	53.55	-7.43	5.23	-0.57	

The regression intercepts based on fund returns before expenses are positive and in case of EW returns for the CAPM and full specification of equation (1.1) statistically significant. Annualized CAPM and four-factor intercepts are 4.11% and 2.64%, with t-statistics of 3.06 and 2.00, respectively. However, the intercepts from regressions using EW net returns are close to zero. Considering the large R^2 measures, it seems common stock factors do not leave much unexplained of the return on funds (even in the global context). In other words, the average fund does not add much value after expenses if

anything, but the non-negative intercepts also suggest it does not hurt to invest in EM equity funds. Though, aggregate wealth is better represented by VW returns (Fama and French, 2010). The regression intercepts using VW net returns are negative (-0.11 and -0.09) yet not significant with *t*-statistics of -0.99 and -0.81, respectively.

Overall, Table 1.4 shows the sample funds hold portfolios that are close to the market. The results further provide some hints that on aggregate actively managed funds in emerging economies have some skill to add value relative to common stock factors, but only before expenses. The intercepts in equation (1.1) for EW and VW net returns, however, indicate that average managers, though maybe skilled, are rather not sufficiently skilled to recoup (more than) their costs. The results in Table 1.4 are mainly confirmed in a sub period analysis.[34] For 1995-2001, a period with many crises in the emerging world, intercepts and coefficient estimates of equation (1.1) are very similar to the ones shown in the table above. However, none of the intercepts is more than two standard errors away from zero. This is also the case for the sub periods 2001-2006, a fairly stable time characterized by economic growth in most countries and 2006-2011, a period including two major crises of the western world the GFC and sovereign debt crisis.[35] The only interesting difference is that in the most recent period the three- and four-factor intercepts for the EW fund portfolio are negative, but positive when we estimate equation (1.1) for the VW fund portfolio.

[34] The results are not presented but are available from the authors.
[35] We have tested various partitions of the sample period, all yielding similar results.

1.3.3 Regression Results for EW Style Portfolios of EM Funds

Table 1.5 reports results of equation (1.1) for EW style portfolios of mutual funds. For this test, we condense the 3x3 sort from Figure 1.2 to a 2x2 sort basically dropping all funds following a mid-cap(-blend) strategy.[36] $(R_{mt} - R_{ft})$ is the excess return on either Russell EM Large Cap, Small Cap, Growth or Value Index.[37] The market betas in Table 1.5 are all around 0.90 and highly significant in statistical terms. Growth funds show the best performance over the sample period. The three- and four-factor intercepts of EW gross and net returns are positive and more than two standard errors away from zero. For example, the annualized four-factor intercept of EW net returns is a staggering 6.72% with a *t*-statistic of 3.58. All style portfolios seem to have some exposure to small stocks, including large cap funds which have about the same coefficients on SMB_t as value funds. The coefficient estimates are around 0.25 with *t*-statistics above 4.0. Growth funds have approximately half as much of the exposure to the size factor in magnitude (0.12 and 0.13, with *t*-statistics of 2.14 and 2.42, respectively). Somewhat surprising, the coefficients of small cap funds on the SMB_t factor are -0.20 and -0.19 with *t*-statistics of -2.68 and -2.44. Similarly, value funds do not seem to have much exposure to HML_t (0.05 and 0.05 with *t*-statistics of 1.38 and 1.39). Though, both effects might be already captured (at least to some extend) by the market factor, which are the time series of excess returns on a small cap and a value benchmark. For example, when we use the excess return on the VW portfolio of all stocks in emerging markets as market factor (not included in Table 1.5), the coefficients on HML_t in the three and four factor specification of equation (1.1) are 0.20 with *t*-statistics > 5.00. The coefficients on HML_t of growth and small cap funds

[36] We have also estimated equation (1.1) for each of the nine style groups described in Figure 1.2, mainly confirming the results presented in Table 1.5.

[37] Using the excess return on the value-weighted average of all emerging market stocks for $(R_{mt} - R_{ft})$ does not change the conclusions drawn from Table 1.5.

are close to zero. The coefficients on HML_t of large cap funds are 0.07 with t-statistics of 2.51. None of the investment style portfolios of active funds has much exposure to momentum returns.

Table 1.5: Benchmark Regression Estimates for EW Style Portfolios of Emerging Market Funds

The table reports the intercepts, regression coefficients on $R_m - R_f$, *SMB*, *HML* and *MOM* with the associated *t*-statistics and adj. R^2 measures for the one-, three- and four-factor version of equation (1.1). The regressions are estimated for EW gross and net returns on actively managed emerging market funds. The investment styles large cap, small cap, growth and value are determined by the characteristics of the funds' underlying equity holdings. A fund's style classification is specified monthly, quarterly or semi-annually depending on how frequent a fund reports its holdings. A fund can move across the different style portfolios when the main characteristics of its equity holdings change. For the EW portfolio of large cap (small cap) funds, $R_m - R_f$ is the excess return on Russell EM Large Cap (Small Cap) Index. For the EW portfolio of growth (value) funds, $R_m - R_f$ is the excess return on Russell EM Growth (Value) Index. The sample period is from August 1996 to June 2011.

	Gross	Net	*b*	*s*	*v*	*m*	R^2		Gross	Net	*b*	*s*	*v*	*m*	R^2
Large cap funds								*Small cap funds*							
Coef	0.33	0.15	0.90				0.94	Coef	0.49	0.35	0.82				0.81
(t-stat)	2.50	1.19	50.91					*(t-stat)*	2.24	1.43	27.44				
Coef	0.21	0.03	0.93	0.25	0.07		0.94	Coef	0.56	0.49	0.81	-0.20	-0.04		0.81
(t-stat)	1.57	0.26	50.46	5.45	2.51			*(t-stat)*	2.38	1.84	25.93	-2.68	-0.87		
Coef	0.20	0.03	0.93	0.25	0.07	0.00	0.94	Coef	0.49	0.41	0.83	-0.19	-0.05	0.05	0.82
(t-stat)	1.49	0.22	48.09	5.38	2.51	0.26		*(t-stat)*	2.08	1.54	25.30	-2.44	-0.90	1.57	
Growth funds								*Value funds*							
Coef	0.77	0.58	0.87				0.91	Coef	0.02	-0.09	0.90				0.89
(t-stat)	5.17	4.00	43.33					*(t-stat)*	0.13	-0.56	37.56				
Coef	0.81	0.60	0.89	0.12	-0.02		0.92	Coef	-0.07	-0.18	0.92	0.28	0.05		0.90
(t-stat)	5.09	3.91	41.18	2.14	-0.55			*(t-stat)*	-0.40	-1.04	36.71	4.74	1.38		
Coef	0.77	0.56	0.90	0.13	-0.02	0.04	0.92	Coef	-0.04	-0.16	0.92	0.27	0.05	-0.02	0.90
(t-stat)	4.75	3.58	40.07	2.42	-0.51	1.64		*(t-stat)*	-0.21	-0.91	34.68	4.48	1.39	-1.00	

1.3.4 Regression Results for Country-Specific EW Portfolios of EM Funds

In this section we form EW portfolios of our sample funds based on their geographical investment focus. These are portfolios of actively managed mutual funds that predominantly invest in equities of one particular country or region. This allows evaluating the performance of active management in different countries and regions. More specifically, we form portfolios of mutual funds that mainly invest in equities listed in one of the following countries: South Africa, Brazil, Chile, China, India, Indonesia, Israel, South Korea, Malaysia, Mexico, Poland, Russia, Taiwan and Thailand. Karolyi (2015) shows that developing countries are often very different rather than a homogenous group of markets. While not directly addressing differences in the underlying investment conditions, forming country-specific fund portfolios takes differences at least implicitly into account.

To estimate the different variants of equation (1.1) we use domestic or local $(R_{mt} - R_{ft})$, SMB_t, HML_t and MOM_t factors which are constructed largely following the methodology of Fama and French (1993).[38] Using local factors should mitigate potential issues arising from the question if or to what extent asset pricing is integrated throughout different countries. As put forward in Griffin (2002) under the assumption of full or perfect market integration, returns in all countries should be explained by the same factors. However, Griffin finds lower average pricing errors for local than international models, and thus, concludes performance evaluations are best performed on a country-specific level. The findings in Fama and French (2012) also suggest that local specifications of equation (1.1) that use local explanatory returns compared to global versions of equation (1.1), that use

[38] Available at <http://www.sandylai-research.com/html/research___data.html>;see also Hau and Lai (2011) and Eun et al. (2010).

global explanatory returns, perform better in describing average stock returns. Similar results for emerging markets are reported in Hanauer and Linhart (2015) and Cakici et al. (2013) suggesting emerging markets segmentation. Table 1.6 provides summary statistics for local explanatory returns for the three-factor and four-factor models.

Table 1.6: Summary Statistics of Local Emerging Market Regression Factors ($R_m - R_f$, *SMB*, *HML* and *MOM*)

For each of the following countries South Africa, Brazil, Chile, China, India, Indonesia, Israel, South Korea, Malaysia, Mexico, Poland, Russia, Thailand and Taiwan R_m is the return on the MSCI country market index obtained from Datastream. R_f is the 1-month US Treasury bill rate. The construction of *SMB, HML* and *MOM* follows mainly Fama and French (1993). For each of the aforementioned countries stocks are sorted into two size (big and small stocks based on market cap) and three book-to-market equity (B/M) groups (growth are bottom 30%, neutral are middle 40% and value are top 30% B/M stocks), rebalanced at the end of June each year. Big (small) stocks are those in the upper 50% (lower 50%) of market cap. The momentum return is defined as the B/M sort just based on prior 1-year returns and rebalanced monthly. *SMB*, *HML* and *MOM* are the return differences between the monthly average returns on the (double sorted) three small stock and the three big stock portfolios, the two value stock and the two growth stock portfolios, and the two high momentum minus the average of the returns on the two low momentum portfolios respectively. The table shows the mean (premium), standard deviation and *t*-statistic for the local market, size, value and momentum factors. The sample period is from July 1992 to December 2010.

	Premium				Standard Deviation				*t*-statistic			
Countries	R_m-R_f	*SMB*	*HML*	*MOM*	R_m-R_f	*SMB*	*HML*	*MOM*	R_m-R_f	*SMB*	*HML*	*MOM*
ZA	1.15	-0.34	0.88	1.70	8.11	3.47	4.64	4.12	2.09	-1.45	2.80	6.06
BR	1.67	-0.45	1.29	0.52	11.44	6.46	6.74	7.01	2.33	-0.14	2.34	0.61
CL	1.02	0.05	1.01	1.27	6.88	3.49	4.20	4.29	2.15	0.20	3.50	4.28
CN	0.58	0.63	0.55	0.09	10.95	5.40	6.46	4.57	0.69	1.55	1.13	0.27
IN	1.17	0.25	0.45	0.75	9.06	5.08	6.62	8.64	1.87	0.72	0.99	1.26
ID	1.17	0.53	1.56	-0.63	13.44	8.85	13.23	10.41	1.29	0.89	1.76	-0.91
IS	0.75	0.25	-0.11	1.10	7.55	4.60	5.32	6.14	1.14	0.61	-0.23	2.05
KO	0.76	-0.12	0.38	0.42	11.40	6.21	5.06	8.39	1.47	-0.64	0.86	0.82
MY	0.69	-0.17	0.83	0.27	8.56	5.03	4.06	7.40	1.16	-0.65	3.40	-0.06
MX	1.09	-0.54	0.78	0.82	8.92	4.14	4.76	4.50	1.76	-1.88	2.39	2.64
PL	1.03	0.59	1.24	1.74	10.42	5.52	4.85	6.44	1.16	1.25	3.01	3.17
RU	1.46	-0.75	1.43	-0.63	11.33	7.05	6.63	8.90	1.05	-0.87	1.75	-0.58
TH	0.77	-0.34	1.40	0.21	11.51	6.09	4.83	6.88	0.98	-0.71	3.90	0.46
TW	0.38	-0.06	0.26	0.18	8.78	4.36	6.57	6.42	0.60	-0.20	0.56	0.40

The market slopes of the EW portfolios of country-specific mutual funds range between 0.57 and 0.96 with *t*-statistics from 17.00 to 54.48 (Table 1.7). Apart from Brazil and China funds, all fund portfolios have some exposure to SMB_t. The four-factor coefficients on HML_t of Brazil, Malaysia and Taiwan funds are 0.11, 0.19 and -0.18 with *t*-statistics of 2.58, 3.15 and -5.67, respectively. The other EW portfolios of funds do not show much exposure to the value factor (coefficients are close to zero). The coefficients on MOM_t are mixed. Taiwan funds have the largest exposure to momentum returns (0.25 with a *t*-statistic of 7.23), but the estimated momentum premium in Taiwan (0.18% per month) is rather low relative to the other countries in the sample.

The intercepts in Table 1.7 summarize the average performance of the EW portfolios of country-specific funds. In terms of gross returns the performance of China, India, Russia and Taiwan funds stand out. The four-factor intercepts range between 0.41 to 0.71 with *t*-statistics between 1.91 and 2.69. After expenses however, only the intercept estimates for the EW portfolio of funds investing in China are more than two standard errors away from zero. The annualized three- and four-factor intercepts for EW net returns over the period July 1996 to December 2010 are 7.25% and 6.78% per year with *t*-statistics of 1.93 and 1.82, respectively. Active managers in China seem to be able to generate returns that are large enough to more than recoup their costs. This is contrary to most of the evidence reported for US equity funds which, on aggregate, underperform the market by about the size of their expenses (e.g., Carhart 1997).

At the other end of the performance distribution are Brazil and Chile funds, which underperform their benchmarks before and after expenses. The EW net return intercepts are -0.66 (t = -2.53) and -0.51 (t = -3.16) in the 3-factor and -0.63 (t = -2.47) and -0.56 (t = -3.40) in the four-factor specification of equation (1.1). Hence, the average active fund in

Brazil and Chile underperform the market benchmark by around 7.00% per annum. The intercept estimates of the other EW fund portfolios are mainly indistinguishable from zero.

Table 1.7: Benchmark Regression Estimates for EW Portfolios of Country-Specific Emerging Market Funds

The table reports the intercepts, regression coefficients on $R_m - R_f$, *SMB*, *HML* and *MOM* with the associated *t*-statistics and adj. R^2 measures for the three- and four-factor version of equation (1.1). The regressions are estimated for EW gross and net returns of actively managed emerging market funds. The portfolios are formed based on the funds' geographical investment focus. No gross returns are available for funds that primarily invest in equities listed in Israel; hence only net returns are analysed. The sample periods are between July 1992 and December 2010.

	Number of Funds (Sample period)		Gross	Net	*b*	*s*	*v*	*m*	R^2
Africa	243	*Coef*	0.23	0.12	0.80	0.17	-0.05		0.85
	(Jan 1993 - Dec 2010)	*(t-stat)*	1.25	0.66	29.77	2.52	-1.14		
		Coef	0.09	-0.02	0.80	0.18	-0.05	0.09	0.85
		(t-stat)	0.43	-0.10	30.03	2.67	-1.09	1.95	
Brazil	78	*Coef*	-0.35	-0.66	0.92	0.05	0.09		0.93
	(Aug 1994 - Dec 2010)	*(t-stat)*	-1.11	-2.53	29.25	0.92	2.10		
		Coef	-0.38	-0.63	0.93	0.04	0.11	-0.11	0.94
		(t-stat)	-1.25	-2.47	29.98	0.76	2.58	-2.35	
Chile	48	*Coef*	-0.08	-0.51	0.92	0.13	0.06		0.88
	(Jul 1993 - Dec 2010)	*(t-stat)*	-0.47	-3.16	35.27	2.52	1.71		
		Coef	-0.13	-0.56	0.92	0.13	0.06	0.05	0.88
		(t-stat)	-0.80	-3.40	35.33	2.44	1.57	1.34	
China	974	*Coef*	0.75	0.60	0.59	0.02	0.02		0.72
	(Jul 1996 - Dec 2010)	*(t-stat)*	2.44	1.93	19.19	0.42	0.32		
		Coef	0.71	0.56	0.61	0.07	-0.01	0.14	0.73
		(t-stat)	2.33	1.82	19.02	1.12	-0.19	1.86	
India	707	*Coef*	0.44	0.22	0.90	0.31	0.01		0.93
	(Jul 1993 - Dec 2010)	*(t-stat)*	2.93	1.44	53.99	10.54	0.24		
		Coef	0.41	0.17	0.90	0.32	0.01	0.04	0.94
		(t-stat)	2.69	1.16	54.48	10.84	0.45	2.28	
Indonesia	84	*Coef*	0.11	0.35	0.86	0.12	-0.04		0.92
	(Jul 1992 - Dec 2010)	*(t-stat)*	0.51	1.51	50.10	3.93	-1.94		
		Coef	0.09	0.34	0.88	0.14	-0.01	0.09	0.93
		(t-stat)	0.42	1.47	49.57	4.50	-0.45	3.42	
Israel	108	*Coef*	-	-0.10	0.81	0.14	0.09		0.71
	(Jul 1999 - Dec 2010)	*(t-stat)*	-	-0.27	17.00	1.80	1.39		
		Coef	-	0.18	0.80	0.17	0.18	-0.24	0.74
		(t-stat)	-	0.54	17.68	2.27	2.68	-4.23	

Table 1.7 – Continued

	Number of Funds (Sample period)		Gross	Net	*b*	*s*	*v*	*m*	R^2
Korea	609	*Coef*	0.08	-0.03	0.80	0.08	-0.02		0.92
	(Jul 1992 - May 2010)	*(t-stat)*	0.41	-0.18	50.89	2.70	-0.50		
		Coef	0.06	-0.04	0.81	0.09	-0.01	0.03	0.92
		(t-stat)	0.32	-0.22	49.37	2.91	-0.37	1.14	
Malaysia	104	Coef	0.12	0.00	0.64	0.14	0.22		0.75
	(Jul 1992 - Dec 2010)	*(t-stat)*	0.49	0.01	22.48	2.86	3.58		
		Coef	0.14	0.02	0.63	0.11	0.19	-0.06	0.75
		(t-stat)	0.57	0.09	21.80	2.27	3.15	-1.80	
Mexico	40	Coef	-0.06	-0.24	0.97	0.30	0.07		0.87
	(Jul 1993 - Dec 2010)	*(t-stat)*	-0.26	-1.11	29.52	4.24	1.54		
		Coef	0.02	-0.16	0.97	0.30	0.08	-0.11	0.87
		(t-stat)	0.11	-0.74	29.53	4.20	1.83	-2.24	
Poland	49	Coef	0.19	-0.06	0.81	0.29	0.07		0.93
	(Jul 1999 - Dec 2010)	*(t-stat)*	0.96	-0.33	42.67	8.08	1.86		
		Coef	0.20	-0.05	0.81	0.28	0.08	-0.01	0.93
		(t-stat)	0.98	-0.24	41.48	7.95	1.86	-0.21	
Russia	108	Coef	0.55	0.35	0.94	0.18	0.04		0.96
	(Jul 2005 - Dec 2010)	*(t-stat)*	1.92	1.26	37.09	4.32	0.97		
		Coef	0.55	0.36	0.94	0.19	0.05	0.02	0.96
		(t-stat)	1.91	1.25	35.69	4.33	1.05	0.59	
Thailand	194	Coef	0.28	0.15	0.83	0.17	-0.02		0.93
	(Jul 1992 - Dec 2010)	*(t-stat)*	1.67	0.85	38.14	4.23	-0.47		
		Coef	0.15	0.01	0.87	0.20	0.04	0.15	0.94
		(t-stat)	0.94	0.07	41.05	5.19	1.35	6.17	
Taiwan	160	Coef	0.51	0.38	0.92	0.35	-0.22		0.86
	(Jul 1994 - Dec 2010)	*(t-stat)*	2.23	1.64	34.88	6.54	-6.11		
		Coef	0.45	0.31	0.96	0.45	-0.18	0.25	0.89
		(t-stat)	2.20	1.54	39.85	9.02	-5.67	7.23	

1.3.5 Market Timing

The main focus of emerging market studies has been the evaluation of fund managers' stock selection skills, i.e. finding and trading mispriced securities. Most studies have not examined the skill of timing the market in the sense of predicting the direction of price movements. Evidence in existing studies shows that fund managers do not have much

market timing skills (e.g., Treynor and Mazuy (1966), Henriksson and Merton (1984), Graham and Harvey (1996), Bollen and Busse (2001), Jiang (2003) and Romacho and Cortez (2006)).[39] The two models below extend equation (1.1) to capture market timing.

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{mt} - R_{ft}) + s_i SMB_t + v_i HML_t + m_i MOM_t + b_i^{sq}(R_{mt} - R_{ft})^2 + e_{it} \qquad (1.2)$$

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{mt} - R_{ft}) + s_i SMB_t + v_i HML_t + m_i MOM_t + b_i^{max}\{max = [0, (R_{mt} - R_{ft})]\} + e_i \qquad (1.3)$$

Following Treynor and Mazuy (1966) equation (1.2) adds the squared market return, $(R_{mt} - R_{ft})^2$, to the four-factor specification of equation (1.1) in order to test for market timing skills. Basis of this term is the expectation that skilled fund managers will hold portfolios with a higher market exposure when the market does well and a lower exposure otherwise. Consistent with this, the relationship between the funds returns and the market should be convex rather than linear. The quadratic regression specification has the purpose of picking up market timing ability. However, it does not separate between the effects security selection and timing skills may have on fund performance. To overcome this limitation, equation (1.3) adds a term proposed by Henriksson and Merton (1981). $max = [0, (R_{mt} - R_{ft})]$ proxies for the expected returns from a simple but very stringent market timing strategy. It provides for a payoff similar to an option, and either equals the return on the market (in excess of the risk free rate) or is zero in case the market return is negative.[40] Hence, it is more restrictive than the squared market return and does not account for the fact that most dedicated equity funds must probably, at least to some degree, always

[39] The mentioned studies mainly use return-based methodologies to test for market timing. Another strand of literature makes use of portfolio holdings (e.g., see Jiang et al. (2007) who find more supportive evidence).
[40] Merton (1981) shows that the pattern of returns from a successful market timing strategy is similar to the pattern of returns from an (protective put) option strategy.

be invested in equities according to their charters. By including this term, fund performance is decomposed into security selection, as measured by α, and market timing, as measured by b^{max}. Although not perfect, the additional terms in equations (1.2) and (1.3) provide an appealing and simple proxy for market timing and are widely used within the mutual fund performance literature. The main advantage is that it only requires the time-series returns of the funds and the market. There is no need for the funds' portfolio holdings, which are not available for our sample. In both equations, a positive (negative) and significant timing coefficient, b^{sq} and b^{max}, indicates successful (poor) market timing. Generally, if funds on average have good (poor) market timing skills alpha will be overstated (understated) in models that do not account for market timing.[41]

[41] For example Grant (1977) explains how alpha estimates in empirical tests can be affected by market timing. See also Jensen (1972) or Grinblatt and Titmann (1989).

Table 1.8: Market Timing and Security Selection Skills of Emerging Market Funds – Aggregate and Investment Style Portfolios

This table reports the intercepts, regression coefficients on $R_m - R_f$, $(R_{mt} - R_{ft})^2$ (b^{sq}), *SMB*, *HML*, *MOM* and $max[(0, (R_{mt} - R_{ft})]$ (b^{max}) with the associated *t*-statistics and adj. R^2 measures of equations (1.2) and (1.3). For Panel A the regressions are estimated for EW and VW gross and net returns of all emerging market funds. For Panel B the regressions are estimated for EW portfolios based on the funds' investment styles (large cap, small cap, growth or value stocks). Global versions of the explanatory variables are used. The sample period in Panel A is from July 1995 through June 2011 and from August 1996 to June 2011 in Panel B.

Panel A

	Gross	Net	b	s	v	m	b^{sq}	b^{max}	R^2
EW Returns									
Coef	0.20	0.03	0.96	-0.14	0.10	-0.04	0.00		0.95
(t-stat)	1.60	0.23	53.08	-3.75	4.18	-2.64	0.38		
Coef	0.24	0.07	0.96	-0.14	0.10	-0.04		-0.01	0.95
(t-stat)	1.47	0.42	34.74	-3.73	4.22	-2.72		-0.18	
VW Returns									
Coef	0.13	-0.06	0.98	-0.29	0.13	-0.01	0.00		0.95
(t-stat)	1.00	-0.44	50.37	-7.41	5.27	-0.69	-0.81		
Coef	0.26	0.05	1.02	-0.29	0.13	-0.01		-0.07	0.95
(t-stat)	1.46	0.29	34.23	-7.37	5.33	-0.78		-1.33	

Panel B

	Gross	Net	b	s	v	m	b^{sq}	b^{max}	R^2
EW Returns large cap									
Coef	0.00	-0.16	0.95	0.26	0.07	0.02	0.00		0.95
(t-stat)	-0.01	-1.10	46.26	5.75	2.35	0.83	2.61		
Coef	-0.11	-0.25	0.88	0.26	0.07	0.01		0.11	0.95
(t-stat)	-0.54	-1.28	31.20	5.65	2.41	0.70		2.05	
EW Returns small cap									
Coef	0.83	0.73	0.80	-0.19	-0.04	0.03	-0.01		0.82
(t-stat)	3.09	2.38	23.53	-2.50	-0.70	0.89	-2.54		
Coef	1.30	1.22	0.95	-0.19	-0.04	0.03		-0.28	0.82
(t-stat)	3.72	3.05	18.78	-2.55	-0.72	0.89		-3.08	
EW Returns growth									
Coef	0.79	0.59	0.90	0.13	-0.02	0.03	0.00		0.92
(t-stat)	4.14	3.18	37.35	2.37	-0.51	1.53	-0.22		
Coef	0.80	0.61	0.90	0.13	-0.02	0.03		-0.01	0.92
(t-stat)	3.22	2.54	26.09	2.38	-0.51	1.56		-0.16	
EW Returns value									
Coef	-0.21	-0.32	0.93	0.27	0.05	-0.02	0.00		0.90
(t-stat)	-0.99	-1.63	33.19	4.56	1.15	-0.64	1.65		
Coef	-0.31	-0.41	0.88	0.28	0.05	-0.02		0.09	0.90
(t-stat)	-1.12	-1.54	21.80	4.57	1.28	-0.72		1.31	

Table 1.8 shows the regression results of equations (1.2) and (1.3) estimated for EW and VW returns of actively managed EM funds and EW returns on our investment style portfolios from above. The coefficients on $(R_{mt} - R_{ft})^2$ and $max[(0, (R_{mt} - R_{ft})]$ in Panel A are close to zero with *t*-statistics between -1.33 and 0.38. In line with most evidence in the finance literature, this tells us that, on aggregate, active funds in emerging markets do not pursue a market timing strategy. However, market timing strategies may be hindered by restrictions on the use of leverage and derivatives imposed on mutual funds, or the non-availability of such instruments in emerging markets. For example, index derivatives are common instruments to increase or decrease market exposure. Moreover, our tests are based on monthly returns while Bollen and Busse (2001) show that mutual funds exhibit significant timing ability more often in daily tests. This follows Goetzmann et al. (2000) who discuss that monthly data might simply fail to capture timing activities that fall between the monthly reporting dates.

Panel B shows similar results for our EW growth and value fund portfolios. The coefficients on $(R_{mt} - R_{ft})^2$ for the portfolios of large cap and small cap oriented funds are also essentially zero, but more than two standard errors away from zero. The coefficients on the timing factor in equation (1.3), $max[(0, (R_{mt} - R_{ft})]$, are 0.11 and -0.28 with *t*-statistics of 2.05 and -3.08, respectively. Hence, if anything, active large cap funds are better in timing the market than small cap funds. The increase (decrease) in the intercept estimates in equation (1.3) compared to the four-factor version of equation (1.1) in Table 1.4 and Table 1.5 is associated with the decomposition of performance into security selection, reflected in the regression intercept or α, and timing skills as shown by the coefficient estimate on $max[(0, (R_{mt} - R_{ft})]$. In other words, the negative or positive effect of market timing is removed from α. For example, the intercept estimates of small cap funds

using net returns in Table 1.5 is indistinguishable from zero, but are 0.73 and 1.22 with *t*-statistics of 2.38 and 3.05 in Table 1.8.

We obtain similar results from equations (1.2) and (1.3) estimated for EW country-specific fund portfolios (Table 1.9). For eight out of the 14 portfolios the parameter estimates on both timing factors are significant in statistical terms. Though, the coefficients on $(R_{mt} - R_{ft})^2$ are all zero with *t*-statistics from -2.21 to -5.09. The coefficients on $max[(0, (R_{mt} - R_{ft})]$ are negative and larger in magnitude ranging between -0.13 and -0.23 with *t*-statistics between -1.87 and -2.91. As before, the intercepts increase in regressions when the coefficients on the timing factors are negative. This is the case of EW portfolios of South Africa, Indonesia, South Korea and Poland funds. The intercepts gross and net of expenses are only more than two standard errors away from zero in regressions that account for market timing, equations (1.2) and (1.3). One way to interpret these results is that the fund manager's good security selection skills are obscured by poor market timing.

In summary, the results for the aggregate portfolio of mutual funds suggest active equity funds in emerging markets do not pursue a market timing strategy. However, for an EW portfolio of small cap oriented funds and eight out of 14 EW portfolios of country-specific funds, we find evidence of poor market timing skills. In four of these portfolios, the fund managers' good selection skills remain unnoticed in performance measures not accounting for market timing. Complementary to the findings in section 1.2.2 the results in Table 1.8 also show that in terms of benchmark-adjusted returns small cap funds seem to perform better compared to large cap funds.

Table 1.9: Market Timing and Security Selection Skills of Emerging Market Funds

The table reports the intercepts, regression coefficients on $R_m - R_f$, $(R_{mt} - R_{ft})^2$, *SMB*, *HML*, *MOM* and $max[(0, (R_{mt} - R_{ft})]$ with the associated *t*-statistics and adj. R^2 measures of equations (1.2) and (1.3). The regressions are estimated for EW gross and net returns of actively managed emerging market funds. The portfolios are formed based on the funds' geographical investment focus. No gross returns are available for funds that primarily invest in equities listed in Israel; hence only net returns are analysed. Local versions of the explanatory variables are used. The sample periods are between July 1992 and December 2010.

	Number of Funds (Sample Period)		Gross	Net	b	s	v	m	b^{sq}	b^{max}	R^2
Africa	243	Coef	0.53	0.46	0.79	0.17	-0.06	0.07	-0.01		0.86
	(Jan 1993 - Dec 2010)	*(t-stat)*	2.31	2.05	30.06	2.60	-1.41	1.68	-3.72		
		Coef	0.75	0.72	0.90	0.17	-0.06	0.07		-0.20	0.86
		(t-stat)	2.49	2.38	21.20	2.55	-1.36	1.72		-2.91	
Brazil	78	Coef	-0.36	-0.58	0.93	0.04	0.11	-0.11	0.00		0.93
	(Aug 1994 - Dec 2010)	*(t-stat)*	-0.99	-1.96	29.73	0.74	2.53	-2.32	-0.11		
		Coef	-0.18	-0.42	0.96	0.04	0.10	-0.11		-0.05	0.93
		(t-stat)	-0.36	-1.07	16.78	0.68	2.45	-2.33		-0.52	
Chile	48	Coef	-0.18	-0.61	0.92	0.13	0.05	0.05	0.00		0.88
	(Jul 1993 - Dec 2010)	*(t-stat)*	-1.00	-3.36	35.02	2.46	1.46	1.26	0.66		
		Coef	-0.11	-0.54	0.92	0.12	0.06	0.05		-0.01	0.88
		(t-stat)	-0.46	-2.22	20.93	2.42	1.57	1.34		-0.11	
China	974	Coef	1.01	0.89	0.63	0.09	0.00	0.15	0.00		0.73
	(Jul 1996 - Dec 2010)	*(t-stat)*	3.06	2.66	19.19	1.41	-0.06	2.00	-2.21		
		Coef	1.31	1.22	0.69	0.08	-0.01	0.14		-0.15	0.73
		(t-stat)	2.97	2.73	12.52	1.25	-0.24	1.89		-1.87	
India	707	Coef	0.37	0.16	0.90	0.32	0.01	0.04	0.00		0.94
	(Jul 1993 - Dec 2010)	*(t-stat)*	2.04	0.86	53.61	10.70	0.48	2.29	0.36		
		Coef	0.42	0.17	0.90	0.32	0.01	0.04		0.00	0.94
		(t-stat)	1.63	0.66	25.80	10.47	0.44	2.23		-0.08	

Table 1.9 - Continued

	Number of Funds (Sample Period)		Gross	Net	b	s	v	m	b^{sq}	b^{max}	R^2
Indonesia	84	Coef	0.53	0.67	0.89	0.14	-0.02	0.06	0.00		0.93
	(Jul 1992 - Dec 2010)	*(t-stat)*	2.28	2.70	51.76	4.84	-0.98	2.42	-4.39		
		Coef	0.75	0.82	0.95	0.14	-0.02	0.07		-0.14	0.93
		(t-stat)	2.36	2.46	30.82	4.75	-0.78	2.77		-2.82	
Israel	108	Coef	0.04	0.04	0.80	0.16	0.18	-0.25	0.00		0.74
	(Jul 1999 - Dec 2010)	*(t-stat)*	0.11	0.11	17.66	2.13	2.63	-4.29	0.73		
		Coef	0.09	0.09	0.78	0.17	0.18	-0.24		0.03	0.74
		(t-stat)	0.18	0.18	9.66	2.23	2.63	-4.22		0.25	
Korea	609	Coef	0.36	0.28	0.84	0.07	-0.02	0.03	0.00		0.93
	(Jul 1992 - May 2010)	*(t-stat)*	1.99	1.43	49.61	2.36	-0.46	1.50	-5.09		
		Coef	0.57	0.47	0.88	0.07	-0.01	0.02		-0.13	0.93
		(t-stat)	2.19	1.68	27.06	2.49	-0.31	1.07		-2.71	
Malaysia	104	Coef	0.41	0.29	0.64	0.12	0.20	-0.10	0.00		0.76
	(Jul 1992 - Dec 2010)	*(t-stat)*	1.57	1.15	22.32	2.51	3.25	-2.77	-2.81		
		Coef	0.68	0.56	0.72	0.12	0.19	-0.08		-0.17	0.76
		(t-stat)	1.97	1.66	14.59	2.47	3.21	-2.32		-2.22	
Mexico	40	Coef	0.34	0.16	0.94	0.27	0.08	-0.10	0.00		0.87
	(Jul 1993 - Dec 2010)	*(t-stat)*	1.36	0.62	26.76	3.81	1.80	-2.18	-2.48		
		Coef	0.58	0.39	1.03	0.28	0.08	-0.11		-0.16	0.87
		(t-stat)	1.65	1.11	23.03	3.95	1.71	-2.28		-2.02	
Poland	49	Coef	0.60	0.35	0.81	0.27	0.07	-0.02	0.00		0.94
	(Jul 1999 - Dec 2010)	*(t-stat)*	2.50	1.49	42.72	7.74	1.81	-0.51	-3.06		
		Coef	0.86	0.62	0.89	0.27	0.07	-0.01		-0.16	0.93
		(t-stat)	2.72	1.98	25.45	7.71	1.81	-0.40		-2.70	
Russia	108	Coef	1.07	0.90	0.93	0.16	0.05	-0.03	0.00		0.96
	(Jul 2005 - Dec 2010)	*(t-stat)*	3.36	2.92	36.45	3.81	1.10	-0.84	-3.07		
		Coef	1.55	1.44	1.05	0.16	0.04	-0.02		-0.23	0.96
		(t-stat)	3.49	3.37	23.50	3.88	0.96	-0.64		-2.85	

Table 1.9 - Continued

	Number of Funds (Sample Period)		Gross	Net	b	s	v	m	b^{sq}	b^{max}	R^2
Thailand	194	Coef	0.27	0.12	0.86	0.18	0.05	0.15	0.00		0.94
	(Jul 1992 - Dec 2010)	*(t-stat)*	1.53	0.70	40.57	4.60	1.53	5.84	-1.56		
		Coef	0.23	0.07	0.88	0.19	0.05	0.15		-0.02	0.94
		(t-stat)	1.02	0.30	31.93	5.01	1.38	6.01		-0.51	
Taiwan	160	Coef	0.57	0.43	0.96	0.44	-0.18	0.24	0.00		0.89
	(Jul 1994 - Dec 2010)	*(t-stat)*	2.28	1.74	39.38	8.90	-5.72	6.96	-0.83		
		Coef	0.64	0.51	0.99	0.44	-0.18	0.24		-0.06	0.89
		(t-stat)	1.86	1.47	20.09	8.90	-5.67	7.07		-0.69	

1.3.6 Foreign Versus Local Investors

In this section we contribute to the debate among academics and practitioners whether and why there might be a difference in the investment behaviour and performance between foreign and local investors. For example, the home bias phenomenon is well documented in literature.[42] Analysing equity holdings of mutual funds in 26 different countries, Chan et al. (2005) find an almost omnipresent home bias. With respect to performance, Shukla and van Inwegen (1995) show that UK funds investing in US equities underperform US funds investing in domestic equities. However, based on a more comprehensive dataset Otten and Bams (2007) do not find much evidence of a meaningful difference in the performance of US and UK funds investing in US stocks. Our sample allows evaluating whether there is a difference in performance between foreign and local investors in the context of emerging market equities around the world. Many EMEs are considered to be at least partially intransparent, partially closed for foreign investors and research intensive. Informational advantages of local investors, transaction costs, currency risk and legal or institutional constraints, amongst others, that are discussed as possible explanations for potential differences between foreign and local investors, might be more prevalent in those markets.

We follow general practice and categorize the sample funds as local investors when they are domiciled within and foreign investors when they are domiciled outside their geographical investment focus. This classification procedure is based on either the funds' or the fund management companies' domicile. The latter is used in case they deviate from each other as many funds are based offshore or in countries such as Luxembourg or Ireland (mainly for tax purposes), while the actual fund managers are located somewhere else. For country-specific funds this is straightforward. Diversified or internationally investing EM

[42] For an overview of this literature see Karolyi and Stulz (2003) and Lewis (1999).

funds are classified as local when they are domiciled within one country of their investment focus and foreign otherwise.[43] 2,533 funds are classified as foreign and 2,592 as local investors. Table 1.10 provides summary statistics of active mutual funds classified as either foreign or local investors. The sample period July 1992 through October 2012 covers most funds over their entire life. On average, local investors outperform foreign investors by approximately 2.0% before and 1.8% after costs annually.[44] Although investing from *outside* foreign investors do not seem to have higher costs in terms of expense ratios that could have served as a possible explanation for the return difference. Foreign investors are on average the larger funds. Though, the dispersion in net assets is very wide. Net assets of foreign (local) investors range from about USD 16bn (USD 3.6bn) for the largest to as little as USD 10k (USD 10k) for the smallest funds.[45]

[43] Excluding those funds from the sample does not change the results noticeably in this section.
[44] The difference between foreign minus local investors is statistically significant (*t*-statistic gross return = -5.5 and *t*-statistic net return = -5.7).
[45] One standard deviation in size is about USD 800m for foreign and USD 260m for local funds.

Table 1.10: Overview and Summary Statistics of Foreign and Local Investors

This table provides an overview of active mutual funds classified into foreign and local investors. The funds are categorized as foreign when they are domiciled within and local when they are domiciled outside their geographical investment focus. The classification procedure is based on either the funds' or the fund management companies' domicile. The latter is being used in case they deviate from each other. From the entire sample 2,533 funds are categorized as foreign and 2,592 as local investors. The period is July 1992 through October 2012.

Investor Type	Number of Funds[1]	Number of Fund Months	Mean Return (gross)	Mean Return (net)	Standard Deviation	Sharpe Ratio[2] (p.a.)	Average Size[3] (net assets)	Average Expense Ratio[4]
Foreign	2,533	212,663	1.02%	0.82%	8.46	0.95	193,910,378	1.95
Local	2,592	217,808	1.18%	0.96%	8.51	1.16	105,549,293	2.06

[1] number of funds for which net returns are available in Morningstar at the end of the sample period

[2] based on net returns

[3] based on net assets at the end of Q3 2012

[4] based on yearly expense ratios (1992-2012)

For the test reported in Table 1.11 we include slope and intercept terms of a dummy variable on the right-hand side of equation (1.1) in order to assess statistically differences, if any, between EW portfolios of foreign and local mutual funds. The estimated model is specified as:

$$R_{it} - R_{ft} = \propto + b\left(R_{mt} - R_{ft}\right) + sSMB_t + vHML_t + mMOM_t + \delta D_i + \delta_b D * \left(R_{mt} - R_{ft}\right) + \delta_s D * SMB_t + \delta_v D * HML_t + \delta_m D * MOM_t + \varepsilon \quad (1.4)$$

The dummy variable D takes the value of 1 for the return observations of funds domiciled in the country of their investment focus and 0 otherwise. Hence, δD_i indicates the incremental effect on the intercept for funds domiciled within compared to outside of their geographical investment focus. Similarly, the interaction terms capture the

incremental effect on the factor coefficients in comparison to the baseline specification (foreign investors).

Table 1.11: Foreign versus Local Investors

This table reports intercepts, regression coefficients on $R_m - R_f$, *SMB*, *HML*, *MOM*, the effects of a domicile dummy *D* and associated interaction terms on the intercept and coefficients respectively, *t*-statistics and adj. R^2 measures of equation (1.4). The regression is estimated for EW gross returns on foreign and local investors. *D* takes the value of 1 when a fund is domiciled in the country of its investment focus and 0 otherwise. Global versions of the explanatory variables are used. The period is July 1995 to June 2011.

	Gross	b	s	v	m	δD	δb	δs	δv	δm	R^2
Coef	0.12	0.99	-0.28	0.15	-0.03	0.22	-0.06	0.29	-0.12	-0.02	0.92
(*t*-stat)	0.85	43.51	-5.83	4.73	-1.65	1.04	-1.83	4.15	-2.68	-0.83	

The intercept of equation (1.4) summarizes the average performance of foreign investors before expenses and is estimated at 0.12 with a *t*-statistic of 0.85. The coefficient estimate of δD is 0.22 and has a *t*-statistic of 1.04.[46] This tells us, that local investors might outperform foreign investors based on raw returns (see Table 1.10) but not in risk-adjusted terms.[47] The coefficient on $(R_{mt} - R_{ft})$ for foreign investors is one and highly significant. Local investors have a slightly lower exposure to the market factor with a coefficient estimate of about 0.93. Thus, it seems local funds hold portfolios that are less equal to the

[46] The intercept of equation (1.4) estimated for EW net returns on the sample funds is -0.03 (t = -0.24), δ_i is 0.21 with *t*-statistic 1.05.

[47] If we estimate equation (1.4) for individual fund months the intercept for foreign investors is 0.02 (t = 0.68) and δD is 0.14 (t = 6.38). Excluding all diversified or internationally investing funds does not change the results in Table 1.11 noticeably. The estimate of δD is also indistinguishable from zero when we fit equation (1.4) for VW portfolios of the sample funds.

general market than foreign funds.[48] The coefficient on SMB_t for foreign investors is -0.28 with a *t*-statistic of -5.83. The incremental exposure to the size factor for local investors is 0.29 with a *t*-statistic of 4.15. This is an indication that foreign investors are more cautious about investing in the small cap market segment and consistent with general evidence that foreign investors invest more in large cap stocks. Small cap firms are generally more research intensive particularly in the context of equity markets in emerging countries where many small cap firms are probably micro-cap firms. Furthermore, foreign funds tend to value invest more than local funds as shown by the coefficient estimate of 0.15 on HML_t with a *t*-statistic of 4.73 and -0.12 on the value interaction term with a *t*-statistic of -2.68, respectively. Both fund groups do not display much exposure to momentum. Including $log(net\ assets)_t$ on the right-hand side of equation (1.4) to control for a possible size effect does not change the results in Table 1.11 noticeably.[49] We also find similar results estimating equation (1.4) using EW returns on our investment style portfolios (not presented in Table 1.11). The domicile effect is only significant in statistical terms for the EW portfolio of value funds. The estimate of δD is 0.53 with a *t*-statistic of 1.82. This means local value funds outperform foreign value funds by 6.36% on average per year. The estimates of δD for EW portfolios of large cap, small cap and growth funds are not distinguishable from zero. Also not reported in Table 1.11 are the results of equation (1.4) estimated for country-specific funds.[50] Apart from Indonesia, Korea and Malaysia funds, the estimates of δD using individual fund months are, except for Thailand funds, all positive

[48] This is also confirmed in separate regressions for both portfolios. The R^2 of the four-factor model using returns on foreign funds is 0.78, while it is 0.65 in the regression for local funds.
[49] These results are not presented but are available upon request.
[50] Results are available upon request.

and more than two standard errors away from zero. However, the domicile effect mostly disappears when we estimate equation (1.4) for EW portfolios of country-specific funds.[51]

We find a significant difference between gross and net returns of foreign and local mutual funds in emerging markets. On average, local funds outperform foreign funds by approximately 2.0% before and 1.8% after costs per annum. However, the performance differential disappears on a risk-adjusted basis. Foreign investors tend to be more cautious with their stock selection, investing less in small cap and more in value shares. Considering different investment styles, we only find a significant domicile effect for EW value funds. Over the sample period, local value funds outperformed foreign value funds by 6.36% on average per year. For country-specific funds we only find a domicile effect when we use individual fund months. This effect largely disappears when we form EW portfolios of the funds.

1.3.7 Stock Market Efficiency and Alpha

So far we have looked at alpha estimates for gross and net returns on individual, EW and VW portfolios of actively managed mutual funds that predominantly invest in emerging market equities. Alpha is the intercept in the variants of equations (1.1) to (1.4) and in the present context is interpreted as a performance measure of active management. In this section we contribute to the discussion of how underlying investment conditions are related to performance. For example, Ferreira et al. (2012) study how country characteristics are related to the performance of domestically investing mutual funds. They find some evidence that funds in liquid stock markets with strong legal institutions tend to

[51] Only for EW Africa and EW Thailand fund portfolios the domicile effect is significant in statistical terms. The estimates of δD are -0.63 and -0.51 with t-statistics of -1.68 and -2.01 respectively.

perform better. In the subsequent analysis, we test how the efficiency of equity markets is related to our alpha estimates. Finance literature has not come up with a standard definition of market efficiency, but according to the widely-quoted EMH from Fama (1965a, 1965b) a market is considered as efficient when stock prices fully reflect all available information. This implies that the more efficient a market is, the more difficult it becomes for active managers to achieve abnormal returns. Because perfect efficiency is unlikely to hold in practice, it is debatable to what degree financial markets are efficient. The main reason for this is that the proposed EMH itself is not a well-defined and empirically refutable hypothesis (Lo, 2007). As a result, stock market efficiency is measured in different ways.[52] We use the market model R^2 statistic proposed by Morck et al. (2000)[53] and an autocorrelation-based measure to assess efficiency. Our goal is not to test the EMH per se, we rather fit this test around its arguments. Following the notion of relative efficiency active management should be more fruitful in countries with less efficient stock markets, where for instance prices walk less randomly and hence are more predictable. Therefore, if anything, one would expect a stock market's efficiency to be inversely related to the performance of mutual funds in a cross country analysis. Using panel regression methods we test whether efficiency measures are related to the alpha estimates of EW portfolios of country-specific mutual funds.

The market model R^2 statistic or stock price synchronicity measure from MYY is used to distinguish between firm-specific from market wide price movements based on regressions such as equation (1.5) given below. It measures the firm-level return variation explained by a local and the US market index. The idea here is the closer a firm's stock return moves with the market return, the less firm-specific information is priced. Hence,

[52] A good overview about different measures of stock market efficiency is provided in Lim and Brooks (2010).
[53] Henceforth MYY.

this is an inverse measure of informational efficiency, with higher R^2 estimates being associated with lower efficiency. Although not unchallenged this measure has become widely accepted in the finance literature.

$$R_{it} = \alpha_i + \beta_{1i} R_{m,jt} + \beta_{2i}[R_{US,t} + FX_{jt}] + e_{it} \qquad (1.5)$$

R_{it} is the return on stock i in month t. $R_{m,jt}$ is the return on a local market index of country j. $R_{US,t}$ is the return on the S&P 500 index and FX_{jt} is the exchange rate per USD, converting the USD denominated return series into local currency terms. MYY include the US market index, as a proxy for the world index, to account for all information that enters stock prices. Monthly returns are used to overcome thin trading problems that might be the case for many emerging market equities.

We carry out this market efficiency test using a cross section that includes firms from emerging market economies and firms from developed countries. These include: South Africa, Chile, China, India, Indonesia, South Korea, Malaysia, Mexico, Poland, Thailand, Taiwan (emerging economies); and France, Germany, Italy, Japan, Norway, Spain, Sweden, Switzerland, United Kingdom and the US (advanced economies). We obtain monthly returns for all firms covered by Datastream over the sample period including firms that are no longer traded (dead, merged or delisted firms). To account for time zone differences we follow MYY and lag US returns by one day when necessary. Estimating equation (1.5) for each firm and aggregating the regressions' R^2_{ij} across firms is the synchronicity or efficiency measure for country j.[54] Figure 1.4 plots the mean R^2 over the

[54] We only use R^2 coefficients from regressions with degrees of freedom > 30 to ensure meaningful estimates. MYY aggregate the regressions' R^2_{ij} across firms using variance weights $R_j^2 = \frac{\sum_i R_{ij}^2 * SST_{ij}}{\sum_i SST_{ij}}$.

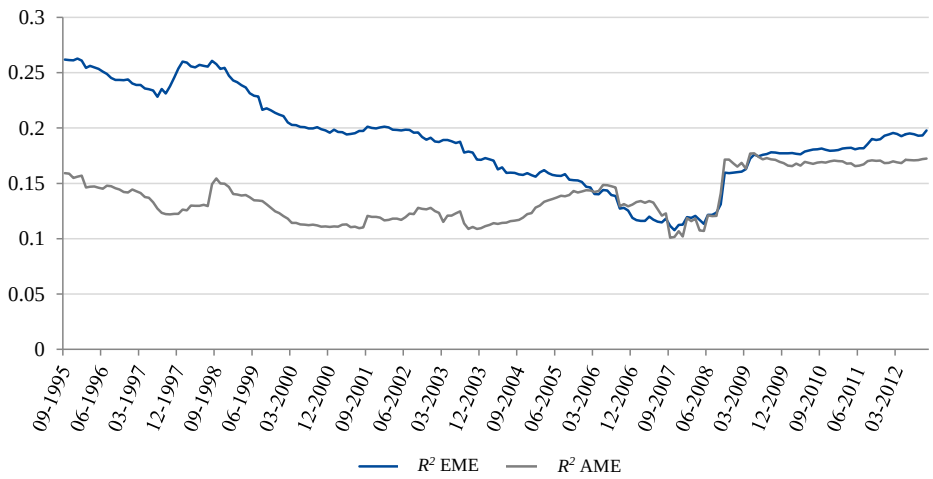
Jin and Myers (2006) have not found that this measure is much different to the equally-weighted average.

complete period September 1995 to October 2012. Mean R^2 of stock markets in both emerging and advanced economies has decreased until the GFC. This decreasing trend is in line with the evidence reported in MYY, Campbell et al. (2001) and Jin and Myers (2006).[55] Since then, stock prices have become more synchronous. Mean R^2 has increased from approximately 10% to 19% for equity markets in emerging and to 16% for equity markets in advanced economies by the end of 2012. Figure 1.4 shows a similar pattern around 1997 and 1998 possibly associated with the Asia or Russia crises in the case of emerging markets and around 1998 and 1999 possibly linked to the LTCM collapse in the case of US market equities, respectively. But theses jumps are substantially smaller compared to the increase during the GFC. The burst of the technology bubble does not seem to have affected the R^2 measures. It is not surprising that the variation in returns of individual firms explained by the market increases during periods of crises since most stocks are affected by major market shocks proportionately more than by changes in firm-specific information (at least over the short or medium run). This reflects the current state where stock markets seem to be more driven by macroeconomic news especially news concerning government budgets and monetary policies than by firm specific news. However, we are not trying to explain the R^2 statistic itself. The purpose of Figure 1.4 is to illustrate that stock markets in emerging countries appear to be less efficient relative to equity markets in advanced economies over most of the sample especially the period leading up to the GFC. Somewhat puzzling, the negative trend in mean R^2 of equity markets in emerging countries has changed into a slight positive trend after the onset of the GFC.

[55] A trend line fitted through the data for emerging markets has a slope coefficient of -0.0004 with *t*-statistic = -12.4. The coefficient of a trend line for the mean R^2 of equity markets in advanced economies over the entire sample period is 0.0001 with *t*-statistic 4.03 and -0.0002 with *t*-statistic = -7.83 for the decreasing trend up to the GFC.

Figure 1.4: Change of Mean R^2 between 1994 and 2012

The graph shows the equally-weighted R^2 for equity markets in 11 emerging and 10 advanced economies. R^2 is estimated by equation (1.5) mainly following MYY over a rolling window using 60 monthly observations moving forward one month at a time. The period is September 1995 through October 2012.



As an alternative efficiency measure, we estimate first-order autocorrelation coefficients for the 21 country market indices. This measure provides a very simple yet direct test for the random walk hypothesis which is closely related to weak-form market efficiency.[56] We estimate the first-order autocorrelation in the same way as the R^2 statistic. Lastly, the dispersion of monthly index returns proxies for the underlying risk in the different stock markets. Both measures are based on monthly returns on value-weighted MSCI market indices adjusted for dividends and capital distributions. For the US market total returns on the S&P 500 are used. Panel A of Table 1.12 provides summary statistics of the data including the variation along the time series and cross sectional dimension.

[56] For example see Lo (2013), Encyclopaedia of Finance.

To test the relation between stock market efficiency and fund performance unaffected by any unobserved constant fund or country effects, we estimate a panel regression with fixed effects (FE), equation (1.6). This allows factoring in arbitrary correlations between time-invariant effects such as a country's legal system and its institutions and the explanatory variables.[57] Time-demeaning transformation cancels out these effects. The null hypothesis of random effects (RE) is rejected by Hausman's specification test.[58] The FE model takes the form

$$\alpha_{it} = u_i + v_t + \beta_1 Rsquared_{it} + \beta_2 Correl_{it} + \beta_3 SD_{it} + \varepsilon_i \qquad (1.6)$$

where α_{it} is the (time-demeaned) intercept estimate in the four-factor specification of equation (1.1) of the EW fund portfolio of country i in month t.[59] u_i are the fixed group and v_t the fixed time effects. Group effects capture differences in the cross section that are constant over time, and time effects capture differences over time that are common to all groups respectively. $Rsquared_{it}$, $Correl_{it}$ and SD_{it} are the described explanatory variables for each cross sectional unit i in month t.

Panel B of Table 1.12 reports coefficient estimates for univariate and multivariate specifications of equation (1.6) with t-statistics corrected for serial correlation and heteroscedasticity.[60] The F-tests for no FE clearly show pooled OLS would not give reasonable results. The coefficient of $Rsquared_{it}$ is -0.41 but with a t-statistic of -0.36

[57] For instance, MYY find that higher firm-specific return variation is related with stronger property rights. Ferreira et al. (2012) report funds perform better in countries with strong legal institutions.
[58] More precisely, under the null hypothesis both estimators from a RE (β_o) and a FE (β_1) regression are consistent but only β_o is asymptotically efficient, while under the alternative only β_1 is consistent. The m-statistic of a Hausman test for the difference in coefficients of a RE and a FE model with all three regressors is 15.33 with Pr > m = 0.0013.
[59] Estimating equation (1.6) using individual fund alphas does not change the results reported in Table 1.12.
[60] Using daily returns in month t to compute correlation coefficients and standard deviations for month t does not change the results reported in Table 1.12. Results are available from the authors.

indistinguishable from zero. Recalling that a higher R^2 signifies lower firm-specific return variation it is less surprising that this measure might be negatively related to fund alpha estimates, since it leaves less room for active management to add value. The coefficients of $Correl_{it}$ and SD_{it} are -0.12 and -0.04 and with *t*-statistics of -0.29 and -1.22, respectively, also indistinguishable from zero. Overall, we do not find evidence that stock market efficiency is directly related to our alpha estimates.

Table 1.12: The Efficiency of Stock Markets and Fund Performance

Panel A reports summary statistics of *Alpha*, *Rsquared*, *Correl* and *SD*. Panel B reports regression coefficients on *Rsquared*, *Correl* and *SD* with associated *t*-statistics in parentheses and R^2 measures of different variants of (1.6). Dependent and explanatory variables are computed over a 60 month window rolling forward one month at a time. We omit all estimates based on less than 30 observations throughout the computation process. The dependent variable is the intercept of the four-factor specification of equation (1.1) with local versions of $R_m - R_f$, *SMB*, *HML*, *MOM* as the regressors estimated using EW net returns of country-specific mutual funds. Using gross returns, does not change the results noticeably as reported below (not presented). *Rsquared* is MYY's stock price synchronicity measure. *Correl* and *SD* are the monthly first-order autocorrelation coefficient and standard deviation of VW MSCI market indices, and the S&P 500 Index for the US market. We estimate the variables for a cross section of 21 countries: South Africa, Chile, China, India, Indonesia, South Korea, Malaysia, Mexico, Poland, Thailand, Taiwan (emerging economies); and France, Germany, Italy, Japan, Norway, Spain, Sweden, Switzerland, United Kingdom and the US (advanced economies). The time period is December 1997 through December 2010. Standard errors are corrected for serial correlation and heteroscedasticity (Newey-West). *F* tests for no FE are at the bottom of the table.

Panel A

Variable		Mean	Std. Dev.	Min	Max	Observations	
Alpha	overall	0.0021	0.3819	-1.5108	2.9436	N	3302
	between		0.2833	-0.8186	0.4205	n	21
	within		0.2634	-0.9672	2.8194	t	157
Rsquared	overall	0.1547	0.0885	0.0001	0.6315	N	3302
	between		0.0756	0.0641	0.3768	n	21
	within		0.0487	-0.0200	0.4094	t	157
Correl	overall	0.0527	0.1256	-0.3160	0.5310	N	3302
	between		0.0615	-0.0535	0.1571	n	21
	within		0.1105	-0.3017	0.5526	t	157
SD	overall	7.7834	3.4218	2.4600	20.7860	N	3302
	between		2.7596	3.9482	13.9015	n	21
	within		2.1213	1.2208	14.6678	t	157

Table 1.12 – Continued

Panel B

	(1)	(2)	(3)	(4)
Rsquared	-1.37			-0.41
(t-stat)	(-1.56)			(-0.36)
Correl		-0.44		-0.12
(t-stat)		(-1.05)		(-0.29)
SD			-0.05	-0.04
(t-stat)			(-1.87)	(-1.22)
R^2	0.60	0.58	0.61	0.61
Pr > F for no FE	<.0001	<.0001	<.0001	<.0001

1.4 Conclusion

This essay provides empirical evidence about the performance of mutual funds that invest in markets that are considered as economically developing. Using data from Morningstar Direct allows us to evaluate a large sample of equity funds over a period that covers most of the funds over their entire life. On aggregate, EM funds hold a portfolio that is close to the market. Our results show that EM funds outperform market indices in terms of raw returns and produce higher reward-to-variability ratios than traditional benchmarks. We also find that actively managed funds in emerging markets have some skill to add value relative to common stock factors, but only before expenses. After expenses, the usual alpha estimates are indistinguishable from zero. Compared to US funds which, on average, underperform the market by the size of their expenses our results are more than just a silver lining for investors. And, we would not get such results on the aggregate level if there are not at least some funds with above average positive returns. For example, the annualized four-factor intercepts for EW net returns on growth-oriented funds and mutual funds that

predominantly invest in China equities are a staggering 6.72% per annum. Less reason to celebrate have investors of Brazil and Chile funds which, on average, underperform their four-factor benchmarks after expenses by about 7.00% annually. Furthermore, we find that funds located within their geographical investment focus outperform their foreign counterparts by 1.8% after costs annually. Foreign funds tend to invest more cautiously in small and growth firms. We do not find much evidence that funds in emerging markets pursue a market timing strategy, those that do seem to have rather poor market timing skills. In some occasions poor market timing masks the fund managers' good security selection skills. Similarly, general proxies for market efficiency do not seem to be related to fund performance. Some readers may be concerned about the effect of the financial liberalization process in the emerging world. However, Bekaert and Harvey (2000) date the opening of equity markets in most emerging countries around the end of the 80s or beginning of the 90s, and hence before the start of our sample period. A 5-year sub period analysis reveals average fund performance in these countries does not show a certain trend over time as countries become more advanced and integrated.

Chapter 2

LATE TRADING IN MUTUAL FUND SHARES – THE SEQUEL

ABSTRACT

This paper provides new evidence of late trading activities in the mutual fund markets of France and Germany. We find that investors who are allowed to trade late can earn substantial returns between 18% and 35% annually. Late trading accounts for up to 10% of daily flow. Evidence of such illicit and abusive trading practices was uncovered in 2003 during a large scandal in the US fund industry. Our findings suggest that late trading may still persist in European markets.

2.1 Introduction

The tip-off from a whistle blower in 2003 unfolded what became the largest scandal in mutual fund history. Several major asset management companies, hedge funds and brokerage firms in the US engaged in abusive trading activities including market timing, mispricing, insider trading and late trading. The latter allows some investors to trade mutual fund shares after market close, resulting in profitable opportunities at the expense of other

investors. This practice evolved from the way mutual funds are priced. For example, US-based funds calculate their net asset value per share (NAV) once a day usually at the close of the stock exchange at 4pm Eastern Standard Time (EST). This is the price at which investors can purchase and redeem fund shares. US statutory law requires trades in open-ended mutual fund shares to be processed at a price following the order (forward pricing).[61] Accordingly, orders received before 4pm are executed at current day's NAV, while orders received after 4pm must be executed at next day's NAV. However, some investors were allowed to place orders after 4pm at current day's price (backward pricing). By doing so, these investors could place orders after market close and profit by exploiting the likely direction of the price movement the following day based on information revealed after market close. Thus the exercise of stale price arbitrage provides an opportunity to some investors to reap short-term gains at almost no extra risk to the detriment of long-term (mainly small) investors.[62] The additional expenses incurred by these trades are shared by all investors at the fund level, while the profits are reserved for only those who actually trade late. Zitzewitz (2006) estimated losses to late trading incurred by long term investors at about USD 400m per annum.

Late trading was often facilitated by brokerage firms or dealers which colluded with investors. But fund companies have also allowed this practice for a fee or in exchange for 'sticky assets', whereby investors engaging in late trading place additional funds into other high fee investments under management. New York State Attorney General Eliot Spitzer,

[61] So called forward pricing rule 22c-1, adopted by SEC in 1968.

[62] Late trading was often practiced together with market timing or frequent trading of mutual fund shares in an attempt to exploit stale prices. The rules surrounding market timing vary from fund to fund and such practice is either prohibited or deemed unethical since it violates the fund's fiduciary duty to act in its shareholders' best interests. In the words of former New York State Attorney General Eliot Spitzer "Allowing timing is like a casino saying that it prohibits loaded dice, but then allowing favored gamblers to use loaded dice, in return for a piece of the action."

who led the investigation into the mutual fund trading scandal in 2003, compared such illegal trading schemes to *"betting on a horse race after the horses have crossed the finish line"*.[63] By the end of 2004, numerous institutions had settled the alleged trading charges with payments totalling over USD 3bn.[64] Settlements included civil penalties, investor restitutions and lower future management fees. Among those institutions were firms like Janus Capital Group, Franklin Templeton, Bank of America, Bank One, Alliance Bernstein, Putnam, Old Mutual PLC, Sun Life Financial, Canary Capital Partner LLC and many more. Since then, the fund industry has grown from USD 16.2 trillion in assets under management in 2004 to USD 31.4 trillion in 2014, half of which is held by US funds.[65] Almost every second household in the US owns mutual funds either directly or indirectly.

In the wake of the US scandal, regulators in other countries became concerned about potential misconduct in the fund industry of their own jurisdiction. For example, the Committee of European Securities Regulators (CESR) conducted regulatory and supervisory investigative work towards the end of 2003 and in 2004 to assess the state of affairs in the European fund industry.[66] The investigation was mainly done by sending out questionnaires to fund companies designed to detect possible malpractices related to late trading and market timing. In some instances the investigation involved on-site inspections or special audits. The investigation concluded that there was no prima facie evidence of abusive trading practices in the member states, despite some alarming findings in their

[63] Eliot Spitzer was New York State Attorney General from 1998 until the end of 2006. See also "State Investigation Reveals Mutual Fund Fraud: Secret Trading Schemes Harmed Long-Term Investors", Press Release Office of New York State Attorney General Eliot Spitzer, September 3, 2003. <http://www.oag.state.ny.us/press/2003/sep/sep03a_03.html>.
[64] See Houge and Wellman (2005) for more details on the charges and settlements.
[65] US equity mutual funds held USD 8.3 trillion in total net assets in 2014. See Investment Company Institute Fact Book 2015, < http://www.ici.org/pdf/2015_factbook.pdf>.
[66] See the Committee of European Securities Regulators (CESR) Report "Investigations of Mis-Practises in the European Investment Fund Industry", CESR/40-407, November 2004. CESR was replaced by the European Securities and Market Authority (ESMA) in 2011.

report. Among others, compliance with cutoff times used to determine whether an order gets processed at current or next day's price could not be verified in all cases, mainly due to inadequate record keeping.[67] And this regardless of the fact that the cutoff times are clearly defined in the prospectus of all investment funds according to the CESR report. Also, poor organisational structures lacking clarity in responsibilities and procedures were identified in a number of cases, with the ramification that can be prone to trading abuses and business practices, e.g. favouring special clients. Some fund managers even reported they had been approached by hedge funds specifically asking for late trading or market timing facilities. Yet, the actions taken by European regulators were relatively meagre. Policies to hinder late trading or market timing were largely implemented through self-regulatory codes of best practices in cooperation with national fund industry associations. The upshot of all this was that fund companies had to do not much more than tighten their internal control mechanisms.

There are only a handful of academic studies addressing the alleged trading abuses and associated consequences related to the mutual fund scandal in the US. For example, Peterson (2010) and Frankel (2006-2007) evaluate the conditions and structures that led to such trading abuses, mainly the regulatory environment in general and lack of transparency. Houge and Wellman (2005) as well as Choi and Kahan (2007) examine investor reactions by measuring capital flows, assets under management and fund performance. Not surprisingly, funds that were involved in the investigation suffered substantial outflows and underperformed their peers in the period following the scandal. Shichor (2012) studies the scandal from a criminologist point of view and highlights the failure of US regulators and supervisors but also the funds' internal control mechanisms to prevent such kind of

[67] Such problems were identified as being somewhat alarming in France but not in Germany.

misconduct. Davis, Payne and McMahan (2007) assess the relationship between fund management fees and control structures and illegal activities. They show that higher levels of management fees decrease the likelihood of illegal behaviour, most likely as a result of reduced financial incentives to engage in malpractices.

In this essay, we examine the incidence and extent of late trading in European markets. Our approach follows closely the methodology used by Zitzewitz (2006) with some notable differences. First, we include market return volatility as a general limit to this arbitrage strategy.[68] A model only accounting for potential gains while ignoring the risk involved in such arbitrage opportunities might lead to spurious results. Since our empirical tests to unravel late trading are based on the changes in futures prices, the volatility of these changes is a direct proxy for risk. Furthermore, Cao et al. (2008) document a negative relation between contemporaneous response of flow to shocks in high frequency market-wide volatility. Hence, to the extent that market volatility serves as a proxy for investor sentiment, a large drop in investor confidence might greatly constrain a fund manager's ability to engage in arbitrage trading on late information even if profitable opportunities exist. In addition, Busse (1999) showed that mutual funds time market volatility with funds decreasing market exposure when volatility is high. Other limits to late trading are legal constraints and implementation costs. As late trading is prohibited by law, the legal constraints are obvious. The opportunity of stale price arbitrage in the form discussed here should not exist. As a result, the coefficients on the variables that capture late trading should all be zero. Implementation costs can be largely ignored because funds can be traded at virtually no costs and because late traders are unlikely to incur sales charges. Second, we

[68] Limits of arbitrage are discussed in Shleifer and Vishny (1997), Gromb and Vayanos (2002) and Barberis and Thaler (2003). A recent survey of the limits of arbitrage literature can be found in Gromb and Vayanos (2010).

address the question of who is more likely to trade late. We distinguish between different types of funds based on style, size and clientele types, in an attempt to identify likely investment vehicles that can be used to conceal late trading practices and hence gain a better understanding of how widespread late trading practices have been. In particular, we investigate the incidence of late trading across retail and institutional funds, small and large funds, and small cap versus large cap orientation funds. Third, we complement the literature by providing estimates of the amount of flow accounted for by late trading and the potential gains from this practice.

Europe, the second largest mutual fund industry in terms of assets under management after the US, provides an interesting case arising from the nature of the CESR investigation and, in particular, its findings that we believe warrant further scrutiny. Because we require futures contracts to be traded long enough after the market close of equities and due to limited data availability for mutual funds, we focus our study on France and Germany. Despite a cutoff time of 12pm for most funds in the sample for France, our results show that net flow of French mutual funds is correlated with market movements after the market close of 5.30pm Central European Time (CET). [69] Some of the trades are placed as late as between 8pm and 10pm. Similarly, net flow of German equity funds, with a cutoff time of usually 3pm, is correlated with changes in futures prices between 5.30pm and 7pm and during the last hour of futures trading between 9pm and 10pm. Moreover, we find this correlation pattern to hold for both retail and institutional funds.[70] Distinguishing between large and small funds based on assets under management reveals that only the flow of larger funds is correlated with "after-hour" market movements. Based on investment style, we

[69] All time designations hereinafter refer to CET unless otherwise stated.
[70] In the case of French mutual funds, we find a correlation for retail funds but not for institutional funds. In the case of German funds the flow of both, retail and institutional funds is correlated with price changes after the market close for trading in equities.

find evidence of late trading in the flow of large cap and small cap oriented funds in the sample of French mutual funds. In the case of German funds, only the flow of large cap funds appears to be correlated with post-cutoff price changes.

Overall, our evidence suggests that the net flow of equity mutual funds is to some extent correlated with market movements after the official cutoff times with late trading accounting for approximately 10% of daily flow. We find that investors who are allowed to trade late can earn between 18% and 31% annually with a minimum number of trades following large market movements and as much as 35% per annum at the highest trading frequency. These returns come with lower risk compared to a buy-and-hold strategy. Our results demonstrate why late trading has been so widespread and why it is still likely to persist.

The remainder of the essay is organized as follows. Section 2.2 describes the data. Sections 2.3 and 2.4 present the empirical findings and we conclude in section 2.5.

2.2 Data

We use daily net flow and fund assets data from Morningstar. Net flow is estimated from a fund's prior day assets, current day assets and the daily return as:

$$FLOW_{it} = TNA_{it} - TNA_{it-1}(1 + r_{it}) \tag{2.1}$$

TNA_{it} is the fund's daily total net assets and r_{it} is the fund's total return. Hence, equation (2.1) is simply the difference between current and prior day's assets that is not accounted for by daily return. We obtain estimated share class flow and net assets by share class rather than fund-level data. As pointed out by Greene and Hodges (2002) there is no

a priori reason to assume that flow into different share classes of a fund would be the same. Rather flow is affected by the different fee structures and purchase and redemption restrictions of the various share classes. Using share classes also allows us to distinguish between retail and institutional investors. Lastly, investors can only trade share classes of funds and hence share class flow directly resembles investor flow. Working with daily flow usually gives rise to questions about the timeliness of the data. For example, it has been found that some funds report assets pre- instead of post-flow.[71] For these funds, flow of day *t* is actually flow of day *t-1*. Since we do not have access to balance sheet data of European funds, we cannot test for this potential data issue, and hence we do not adjust flow. However, if some funds do report with a time lag this would bias the results against finding evidence of late trading, while making false corrections would bias the results in the opposite direction.

To proxy for movements in the market we use changes in near-month futures contracts from Thomson Reuters Tick History (TRTH) obtained through Sirca. This enables us to compute intraday price changes throughout and, more importantly, after continuous trading in equities ends. Trading hours for futures contracts vary across European countries but these contracts are generally not traded over night. However, we require that futures are traded long enough after the market close of equities in order to capture sufficient post cutoff information. This ensures price changes in futures contracts can be used as a general predictor for next day's market return and trading signal by late traders. Because of this and due to limited data availability on assets and flow of mutual funds, we focus our analysis on France and Germany where trading in futures contracts ends at 10pm. We use price changes of futures on the CAC 40 in the case of French funds and price changes of futures

[71] This is known in the industry as *t*-plus-one-accounting. See Edelen and Warner (2001), Greene and Hodges (2002) and Zitzewitz (2003) for a discussion.

on the DAX 30 in the case of German mutual funds. These futures contracts are traded every week day from 8am (CAC) and 9am (DAX) until 10pm.[72]

For French mutual funds data is available from June 2008 and for German funds from June 2006. Both samples go through to the end of July 2014. Because of better data availability we restrict our sample to equity mutual funds. We delete a small number of observations that are related to the inception of a fund, mergers between funds or obvious data entry errors. Table 2.1 reports summary statistics of aggregate mutual fund flow normalised by prior day's total net assets of all funds in each sample.

Table 2.1: Summary Statistics of Aggregate Daily Flow of French and German Mutual Funds

The table reports summary statistics of aggregate daily net flow for a sample of 351 French and 255 German mutual funds that invest in domestic equities. The sample periods vary depending on data availability and start from June 2008 and June 2006, respectively, through to July 2014. Net flow, inflow and outflow are normalised by previous day's aggregate TNAs of the sample funds.

	N	Mean (bps)	Median (bps)	Std (bps)	Max (%)	Min (%)
Panel A: French mutual funds						
Net flow	1,563	-2.49	-2.21	49.08	8.51	-8.03
Inflow	492	12.32	2.61	61.59	8.51	0.00
Outflow	1,071	-9.30	-3.99	40.37	0.00	-8.03
Panel B: German mutual funds						
Net flow	2,080	-2.43	-1.95	15.23	1.78	-3.35
Inflow	780	7.46	4.09	11.55	1.78	0.00
Outflow	1,300	-8.37	-5.00	14.05	0.00	-3.35

[72] Our initial sample also included the UK. However, we did not find statistical evidence in support of late trading practices for British mutual funds.

Panel A reports the characteristics of aggregate net flow of French mutual funds. The mean net flow over the sample period is -2.52 basis points per day and the median daily net flow is -2.25 basis points. The standard deviation is 49.08 basis points. Average daily net flow of German funds is also slightly negative, -2.43 basis points, and the standard deviation around the mean is 15.23. These measures are influenced by the significant outflow during the global financial crisis (GFC) and the sovereign debt crisis (SDC) both of which occurred during the sample period. Investors withdrew more capital than they invested in equity mutual funds in over 60% of the trading days. Yet, average daily inflow is greater than outflow in the case of French mutual funds, 12.31 basis points compared to -9.30 basis points, respectively. But for German mutual funds average daily inflow is 7.46 basis points and hence smaller than average outflow of -8.37 basis points.

2.3 Methodology and Empirical Results

2.3.1 Methodology

In this section we use standard regression analysis to test for late trading. Equation (2.2) is an example of a regression where the cutoff time for processing redemption and subscription orders is assumed to be 12pm midday, while regular trading in stocks ends at 5.30pm. This allows measuring the correlation of daily net flow with market movements after the official cutoff time and after market close as:

$$\begin{aligned} FLOW_{it} &= \alpha_{it} + \beta_1 \Delta FUT_t^{9am-12pm} + \beta_2 \Delta FUT_t^{12pm-5:30pm} + \beta_3 \Delta FUT_t^{5:30pm-10pm} \\ &+ \sum_{k=1}^{K} \gamma_k F_{kt} + \delta_1 Volatility_t + \delta_2 Bond\,\mathrm{Re}t_t + \varepsilon_{it} \end{aligned} \tag{2.2}$$

$FLOW_{it}$ is the fund's net flow normalised by prior day net assets. The right-hand side variables of interest are log changes in the near-month futures contract price. The first term controls for market movements driven by information emerging before the cutoff or valuation point. The second and third terms capture post-cutoff information and hence late trading. Normal trading in futures ends at 10pm. Most futures contracts in Europe are not traded over night.[73] F is a vector that controls for lagged flow and lagged fund returns. The former is included to account for persistence in the time series of flow whereas the latter accounts for the return chasing behaviour of investors. Since late trading is just an arbitrage strategy, and risk represents one of the major limits to arbitrage, we also include volatility as a control variable. More specifically, we include the realized volatility of five minute intraday returns defined as:

$$\sigma_t = \sqrt{\sum_{i=1}^{N} (r_{ti})^2} \quad , \tag{2.3}$$

where, σ_t denotes daily market volatility based on five-minute returns on day t, r_{ti} are log changes of the futures contracts on the market index over the five-minute interval. We calculate intraday returns including the time period after continuous trading in securities has stopped, i.e. after 5.30pm. This is important since it is the post-cutoff and after market close price changes that are the main predictors of next day's market return and thus the main drivers of stale-price arbitrage.[74] This measure is based on the high-frequency

[73] Note that 9pm was the latest trading time stated in the civil complaint brought in 2003 by the Attorney General of the State of New York to the State Supreme Court against Canary Capital Partners LLC, a hedge fund that collaborated with different brokers and asset management companies, including among others the Bank of America (Nations funds), to trade hundreds of funds late (after 4pm).

[74] For example, consider there was a large increase in stock prices after the cutoff until market close, say between 12pm (3pm) and 5.30pm in the case of French (German) funds. Buying a fund at the prevailing (stale) price would be profitable even if next day's return did not prove to be as high as expected.

volatility estimator proposed by Andersen et al. (2001) who argue that a five minute interval is long enough to avoid measurement errors and short enough to avoid microstructure biases.[75] Conditioning on market volatility is also important to account for the market turmoil and swings in investor sentiment during the GFC 2007-2009 and the deepening of the SDC in Europe at the end of 2011 that are spanned by our sample period. Lastly, bond returns, $Bond\ Ret_t$, are included because investors might shift between shares and bonds, particularly during crises. We obtain the return series on 10-year government bonds of France and Germany from Thomson Reuters Datastream. Equation (2.2) is estimated by OLS and the estimated standard errors are double clustered in the fund (i) and time (t) dimensions. Hence they are robust to both cross-sectional dependence and serial correlation in the residuals.

2.3.2 French Mutual Funds

Table 2.2 shows the results of different variants of equation (2.2) estimated for French mutual funds that invest in domestic equities.[76] The legislation in France does not specify a particular time at which fund shares are to be priced; rather each fund company has to determine a valuation point in its prospectus. We have viewed numerous fund documents and unlike the US, where funds price their shares usually at 4pm market close EST, cutoff time for most funds in France is 12pm. Regular trading hours for equities at the Euronext Paris are from 9am through 5.30pm, while futures contracts on the CAC 40 are traded from

[75] The results reported below are qualitatively the same if we use other volatility measures such as standard deviation or intervals of 15 minutes.
[76] In all tests reported in this paper, we include only funds that have more than 100 observations. We find similar results for equally weighted portfolios of funds.

8am through 10pm. Therefore, our first regression specification is identical to the form given by equation (2.2) above.

Table 2.2: French Mutual Funds

The table reports regression estimates of different variants of equation (2.2). The dependent variable is normalised daily net flow of 351 mutual funds domiciled either in France or Luxembourg that invest in French equities. All funds are registered and available for sale in France. The independent variables are log changes in the price of futures contracts on the CAC 40 index, Δ*FUT*, lagged flow, *Flow*, and lagged fund returns, *Ret*, realized volatility over 5-minute intraday returns, *Volatility*, and the returns on 10-year government bonds, *Bond Ret*. Columns one and two report results for the full sample, while column three comprises trading days with post cutoff price changes in the futures market of 1% or more. Standard errors are clustered by fund and year. Corresponding *t*-statistics are reported in parentheses. The time period is June 2008 through July 2014.

	Full Sample:					
	Morning, Afternoon and Evening		Hourly Price Changes		Large Price Changes	
	(1)		(2)		(3)	
Intercept	0.00	(1.15)	0.00	(1.19)	0.00	(-1.20)
$\Delta FUT^{9am\ to\ 12pm}$	0.01	(0.93)	0.01	(1.04)	**0.02**	**(2.46)**
$\Delta FUT^{12pm\ to\ 5.30pm}$	0.01	(1.11)	0.00	(0.86)	**0.04**	**(3.25)**
$\Delta FUT^{5.30pm\ to\ 10pm}$	0.01	(1.49)				
$\Delta FUT^{5.30pm\ to\ 6pm}$			0.00	(0.20)	**0.04**	**(1.77)**
$\Delta FUT^{6pm\ to\ 7pm}$			0.00	(-0.12)	**0.10**	**(3.22)**
$\Delta FUT^{7pm\ to\ 8pm}$			-0.01	(-0.71)	0.04	(0.94)
$\Delta FUT^{8pm\ to\ 9pm}$			**0.02**	**(2.12)**	**0.07**	**(4.16)**
$\Delta FUT^{9pm\ to\ 10pm}$			**0.02**	**(2.05)**	**0.08**	**(4.62)**
$Flow_{t-1}$	**0.02**	**(1.76)**	**0.02**	**(1.75)**	0.02	(1.24)
$Flow_{t-2}$	**0.02**	**(3.11)**	**0.02**	**(3.11)**	**0.02**	**(3.80)**
$Flow_{t-3}$	**0.02**	**(5.29)**	**0.02**	**(5.35)**	**0.04**	**(2.19)**
$Flow_{t-4}$	**0.01**	**(3.20)**	**0.01**	**(3.20)**	0.01	(1.01)
Ret_{t-1}	0.01	(1.59)	0.01	(1.62)	0.01	(0.71)
Ret_{t-2}	0.01	(1.52)	0.01	(1.49)	**0.01**	**(1.82)**
Ret_{t-3}	-0.01	(-0.66)	-0.01	(-0.70)	0.01	(1.08)
Ret_{t-4}	0.00	(-0.92)	0.00	(-0.92)	0.00	(0.16)
Volatility	-0.03	(-1.20)	-0.03	(-1.25)	**-0.04**	**(-6.22)**
Bond Ret	0.00	(-1.29)	0.00	(-1.39)	0.00	(-0.16)
R^2	0.01		0.01		0.03	
N	438,427		407,695		68,874	

The coefficient estimates in columns one and two of Table 2.2 show that flow is correlated with market movements after market close between 8pm and 10pm. This effect remains largely unnoticed in a regression that includes intraday time intervals for the morning, afternoon and evening rather than hourly price changes.[77] The coefficients on $\Delta FUT^{8pm\text{-}9pm}$ and $\Delta FUT^{9pm\text{-}10pm}$, the last two hours of futures trading, are both equal to 0.02 with *t*-statistics of 2.12 and 2.05, respectively. Post market close price movements are probably more important for late traders than price movements during the afternoon, because those changes are naturally better predictors of next day's market returns. All coefficient estimates on lagged flow are statistically significant, illustrating persistence in the flow series.[78] By contrast, none of the estimates on lagged returns are more than two standard errors away from zero. The negative coefficient on volatility, -0.03, is in line with Cao et al. (2008) who document a negative relation between fund flow and market volatility. However, the estimate is not significant in statistical terms. Similarly, bond returns are negatively but insignificantly related to fund flow. To account for the possibility that fund companies have become more careful after the scandal in the US, we assume they engage in or knowingly allow late trading, if at all, only when it appears to be most profitable. For this reason, the results shown in column three include observations only when the change in futures prices between 12pm and 10pm is equal to or larger than one percent.[79] We do not find meaningful differences in the results if we condition on smaller

[77] The main reason for this is that the regression includes both retail and institutional funds. However, we only find that flow of retail funds is correlated with post-cutoff market movements. We discuss separate results for both fund groups in detail below. If we only include retail funds for the regression in column one, the coefficient of $\Delta FUT^{5.30pm\text{-}10pm}$ is 0.01 with a *t*-statistic of 1.75.

[78] We include four lags to cover one week of trading. However our results are not affected by the number of lags.

[79] Consistent with the view that late trading is primarily used for profit maximization rather than loss avoidance or minimization, the alternative condition of market movements equal to or less than minus 1 percent may not work as well. Saying that we recognize that 'stale price arbitrage' may involve both buying at the stale price while expecting a gain on the next day and selling when the market is expected to decline.

or larger price changes (e.g. 0.5% or 1.5%). In comparison to column two, the results in column three highlight the much stronger impact of market information on net flow. Flow is correlated with market movements pre-cutoff between 9am and 12pm and again with movements post-cutoff between 12 noon and 10pm. The coefficient on price changes during the morning, $\Delta FUT^{9am\text{-}12pm}$, is 0.02 with a *t*-statistic of 2.46. The coefficient on price changes during the afternoon, $\Delta FUT^{5.30pm\text{-}10pm}$, is 0.02 with a *t*-statistic of 3.25. Moreover, apart from price changes between 7pm and 8pm all coefficients on hourly price changes after continuous trading in equities has stopped are positive and statistically significant. The coefficients on $\Delta FUT^{5.30pm\text{-}6pm}$ and $\Delta FUT^{6pm\text{-}7pm}$ are 0.04 and 0.10 with *t*-statistics of 1.77 and 3.22, respectively. And the coefficients on $\Delta FUT^{8pm\text{-}9pm}$ and $\Delta FUT^{9pm\text{-}10pm}$ are 0.07 and 0.08 with *t*-statistics of 4.16 and 4.62, respectively. The results in column three show that all coefficient estimates on price changes after the official cutoff are larger in magnitude than for price changes in futures during the morning, up to the order processing time. Similarly, the increase in *t*-values from morning to afternoon to evening highlights the increased importance of the information reflected by price changes towards the end of the day, which are also expected to be the best predictors for next day's returns. The coefficient on volatility is -0.04 and is highly significant with a *t*-statistic of -6.22 even after controlling for past returns. Besides confining late trading to days on which post cutoff price changes are large, it might be that such practices are as profitable during periods with a high degree of value-relevant information. To test this hypothesis, we re-estimate our models including only quarterly earnings announcement periods. We obtain similar results

For French mutual funds, the results are mixed when we test for the latter by conditioning on price changes in futures prices (after cutoff) of minus 0.5% or minus 1%.

as in Table 2.2 regardless of different time window lengths around the end of a calendar quarter.[80]

In summary, we find evidence of late trading in French mutual funds. Our results are robust when we control for the GFC and SDC by introducing intercept and interaction dummies to capture the respective periods of extreme market turmoil.[81] Our results are also broadly consistent with the report of the CESR investigation of French fund companies in 2004, stating:

"Despite the fact that the cutoff time is clearly defined in the prospectus of all investment funds, its enforcement is variable depending on the different parties involved in the processing of these subscriptions/redemptions."

Indeed non-compliance with cutoff times is the core of late trading schemes and conflicting reports on enforcement practices during the CESR investigation should have raised questions necessitating further scrutiny.

2.3.3 German Mutual Funds

Table 2.3 reports pooled regression results for German equity mutual funds. As before, no particular cutoff time is legally set, but according to the annotation of German statutory

[80] In order to conserve space, the results are not included in the paper but are available upon request from the authors.
[81] Again these results are not reported but are available upon request.

law this should normally be 3pm.[82] The 3pm cutoff also corresponds to the time stated in most prospectuses we have viewed.

[82] See German securities law, annotation to sec. 36 par. 1 InvG (Investmentgesetz), Berger, Steck and Luebbehuesen, C.H. Beck, Muenchen 2010, p. 351 marginal number 6. Note in the context of implementing a European Directive (so-called AIFM-Directive) the InvG was replaced by the KAGB (Kapitalanlagegesetzbuch) in July 2013, which takes over the regulations of the InvG and other acts.

Table 2.3: German Mutual Funds

The table reports regression estimates of different variants of equation (2.2). The dependent variable is normalised daily net flow of 255 mutual funds domiciled either in Germany, Ireland or Luxembourg that invest in German equities. All funds are registered and available for sale in Germany. The independent variables are log changes in the price of futures contracts on the DAX 30 index, ΔFUT, lagged flow, *Flow*, and lagged fund returns, *Ret*, realized volatility over 5-minute intraday returns, *Volatility*, and the returns on 10-year government bonds, *Bond Ret*. Columns one and two report results for the full sample, while column three comprises trading days with post cutoff price changes in the futures market of 1% or more. Standard errors are clustered by fund and year. Corresponding *t*-statistics are reported in parentheses. The time period is June 2006 through July 2014.

	Full Sample:					
	Morning, Afternoon and Evening		Hourly Price Changes		Large Price Changes	
	(1)		(2)		(3)	
Intercept	**0.00**	**(2.80)**	**0.00**	**(2.91)**	**0.00**	**(1.94)**
$\Delta FUT^{9am\ to\ 12pm}$	0.01	(0.99)	0.01	(1.00)	-0.01	(-0.76)
$\Delta FUT^{12pm\ to\ 5.30pm}$	0.00	(-0.71)	0.00	(-0.68)	-0.05	(-1.62)
$\Delta FUT^{5.30pm\ to\ 10pm}$	**0.02**	**(2.28)**				
$\Delta FUT^{5.30pm\ to\ 6pm}$			**0.05**	**(1.92)**	**0.12**	**(1.69)**
$\Delta FUT^{6pm\ to\ 7pm}$			**0.03**	**(2.20)**	0.08	(1.32)
$\Delta FUT^{7pm\ to\ 8pm}$			0.00	(-0.10)	-0.07	(-1.04)
$\Delta FUT^{8pm\ to\ 9pm}$			0.02	(1.12)	-0.03	(-0.59)
$\Delta FUT^{9pm\ to\ 10pm}$			**0.03**	**(2.02)**	-0.02	(-0.91)
$Flow_{t-1}$	**0.05**	**(5.16)**	**0.05**	**(5.16)**	**0.02**	**(3.19)**
$Flow_{t-2}$	**0.03**	**(6.62)**	**0.03**	**(6.61)**	**0.04**	**(3.76)**
$Flow_{t-3}$	**0.02**	**(3.03)**	**0.02**	**(3.03)**	**0.01**	**(1.91)**
$Flow_{t-4}$	**0.03**	**(2.66)**	**0.03**	**(2.67)**	**0.03**	**(3.45)**
Ret_{t-1}	**0.02**	**(3.20)**	**0.02**	**(3.16)**	**0.03**	**(2.55)**
Ret_{t-2}	**0.02**	**(2.76)**	**0.02**	**(2.76)**	0.01	(0.58)
Ret_{t-3}	0.00	(-0.38)	0.00	(-0.39)	**0.03**	**(3.80)**
Ret_{t-4}	**0.01**	**(1.72)**	**0.01**	**(1.69)**	**0.01**	**(1.89)**
Volatility	**-0.05**	**(-3.04)**	**-0.05**	**(-3.26)**	**-0.04**	**(-1.78)**
Bond Ret	-0.01	(-1.63)	**-0.01**	**(-1.65)**	0.00	(-0.18)
R^2	0.05		0.05		0.05	
N	246,951		246,817		25,710	

The results in column 1 show that fund flow is correlated with market movements between 5.30pm and 10pm. The coefficient estimate on $\Delta FUT^{5.30pm\text{-}10pm}$ is 0.02 with a *t*-statistic of 2.28. The coefficients on price changes during the morning and afternoon are not statistically significant. As in the case of French mutual funds, information emerging after the market close for trading in equities seems to be more important for net flow of equity funds than compared to information emerging before and up to the valuation point. Using the results in column one, we can estimate the amount of flow accounted for by presumed late trading. Since we include log changes in futures prices on the right-hand side, the effect of a change in $\Delta FUT^{5.30pm\text{-}10pm}$ can be calculated as $\beta_3 * ln(1+\Delta)$, where β_3 is the coefficient estimate reported in column one and Δ is the percentage change in $\Delta FUT^{5.30pm\text{-}10pm}$. Because the dependent variable is flow as percent of TNA, we can say for one standard deviation increase in $\Delta FUT^{5.30pm\text{-}10pm}$ orders in the volume of about 1.5 basis points of TNA are traded late. Compared to one standard deviation in daily flow, this equates to approximately 9.5% of flow.[83]

Column 2 indicates that late trading occurs mainly between 5.30pm and 7pm and during the last hour of futures trading. The coefficient estimates on $\Delta FUT^{5.30pm\text{-}6pm}$, $\Delta FUT^{6pm\text{-}7pm}$ and $\Delta FUT^{9pm\text{-}10pm}$ are 0.05, 0.03 and 0.03 with *t*-statistics of 1.92, 2.20 and 2.02, respectively. All coefficients on lagged flow are positive and significant on the one percent level, again demonstrating persistence in daily fund flow. Three of the four coefficients on lagged returns are also positive and statistically significant. Hence, the performance over the immediate previous days seems to be an important determinant of flow in the case of German mutual funds. Realized volatility on day *t* is negatively correlated with flow. The

[83] The standard deviation of average flow is reported in Table 2.1 and is 15.23 basis points. In case of French mutual funds late trading accounts for approximately 1.9% of daily flow. This is based on the coefficient estimate reported in footnote 17 and compared to a one standard deviation in aggregate daily flow of French mutual funds as reported in Table 2.1.

coefficient on $Volatility_t$ is -0.05 with a *t*-statistic of -3.04 in column one and -3.26 in column two. Bond returns are also negatively correlated with flow. The estimate on $Bond\ Ret_t$ is -0.01 and has a *t*-statistic of -1.65 in column two. Column three shows the results for the subsample where we include observations only when the futures return between 3pm and 10pm is one percent or more. We cannot find as strong evidence of late trading as in the case of French mutual funds. Only the coefficient on price changes around the close of the market for continuous trading in equities is statistically significant. The estimate on $\Delta FUT^{5.30pm\text{-}6pm}$ is 0.12 and has a *t*-statistic of 1.69. The relatively large coefficient suggests late orders were mainly placed to exploit the observed changes in NAV, rather than speculating on next day's price changes. These findings highlight the limits of late trading arbitrage. Because most of the large post cutoff price movements in the German sample occur around the collapse of Lehman Brothers during autumn 2009, the peak of the GFC, and during the deepening of the SDC in late 2011, such profitable opportunities may be offset by constraints to arbitrage induced by large swings in investor sentiment, run-like behaviour and liquidity shortages.[84] Price changes in the futures market might generally indicate the direction of the market for the following day, but owing to the turmoil in the markets, this direction is far from guaranteed. Fundamental risk, the arrival of new bad information and noise trader risk, both identified as general limits of arbitrage, are substantially higher during such times of major market turmoil. The coefficient on $Volatility_t$ is -0.04 and has a *t*-statistic of -1.78, consistent with a reduced investor appetite for risk and higher outflows associated with higher volatility.

[84] In the case of France, large price changes ($\Delta FUT^{12pm\text{-}10pm} \geq 1\%$) are evenly spread across the sample period.

2.4. Robustness

2.4.1 Institutional Funds versus Retail Funds

To further investigate how widespread late trading practices may have been, we first distinguish between institutional and retail funds. Funds with a minimum investment of EUR 100,000 or more are usually classified as institutional and generally aim at corporations, pension funds, and other large investors. On the other hand, retail funds focus on private individual investors. The results in Table 2.4 for French mutual funds show that only flow of retail funds is correlated with market movements after the cutoff. The coefficients on $\Delta FUT^{8pm\text{-}9pm}$ and $\Delta FUT^{9pm\text{-}10pm}$ are 0.03 and 0.02 with *t*-statistics of 3.49 and 1.90. None of the coefficients on price changes in futures is statistically significant in the case of institutional funds. This suggests the culprits may be hiding their illicit trades among the frequent subscription and redemption orders of retail investors. It may also indicate that retail fund managers may have more flexibility to exploit late trade opportunities compared to institutional funds who act on predetermined flow orders, or that institutional investors monitor funds closer than retail investors and thus prevent them from engaging in illicit trades. However, in the case of German mutual funds the results show that the flow of both, institutional and retail funds is correlated with after-hour market movements. The coefficients on $\Delta FUT^{5.30pm\text{-}6pm}$, $\Delta FUT^{9pm\text{-}10pm}$ (institutional funds) and on $\Delta FUT^{6pm\text{-}7pm}$ (retail funds) are 0.04, 0.07 and 0.03 with *t*-statistics of 3.84, 5.21 and 2.09, respectively. The coefficients on $Volatility_t$ are -0.10 and -0.04 with *t*-statistics of -2.35 and -3.42. The lack of significant coefficients on lagged returns in columns one and three are consistent with prior research showing that portfolio choice, investor behaviour and the flow-performance relation between both fund types are different. For example, Del Guercio and Tkac (2002), James and Karceski (2006), and

Salganik (2015) show that clients of institutional funds tend to use more sophisticated performance measures such as risk-adjusted return measures or tracking error and do not display the same return chasing behaviour as their retail counterparts.

Table 2.4: Institutional Funds versus Retail Funds

This table reports regression estimates of equation (2.2) for institutional and retail funds by country. Funds with a minimum investment of EUR 100,000 or more are classified as institutional, all other funds as retail funds. In case of French (German) mutual funds, $\Delta FUT^{morning}$ are log changes in futures prices between 9am and 12pm (3pm). $\Delta FUT^{afternoon}$ are log changes in future prices between 12pm (3pm) and 5.30pm. Standard errors are clustered by fund and year. Corresponding *t*-statistics are reported in parentheses. The time period for French mutual funds is June 2008 and for German mutual funds June 2006 through July 2014.

	Institutional Funds				Retail Funds			
	France		Germany		France		Germany	
Intercept	0.00	(0.82)	**0.00**	**(3.17)**	0.00	(1.17)	**0.00**	**(2.71)**
$\Delta FUT^{morning}$	0.01	(0.23)	0.01	(0.53)	0.01	(1.17)	0.00	(0.62)
$\Delta FUT^{afternoon}$	0.02	(0.76)	0.00	(0.16)	0.00	(0.63)	-0.01	(-0.73)
$\Delta FUT^{5.30pm\ to\ 6pm}$	-0.06	(-1.61)	**0.04**	**(3.84)**	0.01	(0.51)	0.01	(0.29)
$\Delta FUT^{6pm\ to\ 7pm}$	-0.24	(-1.61)	0.04	(0.39)	0.01	(0.49)	**0.03**	**(2.09)**
$\Delta FUT^{7pm\ to\ 8pm}$	0.12	(1.03)	0.09	(1.10)	-0.01	(-1.34)	-0.02	(-0.44)
$\Delta FUT^{8pm\ to\ 9pm}$	-0.08	(-0.63)	0.12	(1.47)	**0.03**	**(3.49)**	0.01	(0.45)
$\Delta FUT^{9pm\ to\ 10pm}$	-0.01	(-0.17)	**0.07**	**(5.21)**	**0.02**	**(1.90)**	0.02	(1.49)
$Flow_{t-1}$	**0.05**	**(3.46)**	**0.04**	**(3.39)**	0.01	(1.12)	**0.05**	**(4.04)**
$Flow_{t-2}$	**0.04**	**(2.05)**	**0.02**	**(2.55)**	**0.02**	**(2.22)**	**0.03**	**(6.22)**
$Flow_{t-3}$	**0.02**	**(2.70)**	**0.02**	**(2.33)**	**0.02**	**(4.90)**	**0.02**	**(2.80)**
$Flow_{t-4}$	0.01	(1.14)	0.00	(0.79)	**0.01**	**(3.04)**	**0.04**	**(2.70)**
Ret_{t-1}	0.01	(0.60)	0.02	(0.59)	0.01	(1.35)	**0.02**	**(2.89)**
Ret_{t-2}	-0.02	(-0.86)	0.01	(0.37)	**0.01**	**(2.44)**	**0.02**	**(2.99)**
Ret_{t-3}	0.01	(0.57)	-0.04	(-1.47)	-0.01	(-0.80)	0.00	(0.29)
Ret_{t-4}	0.02	(0.83)	-0.03	(-1.01)	-0.01	(-1.44)	**0.01**	**(2.38)**
Volatility	-0.03	(-0.60)	**-0.10**	**(-2.35)**	-0.03	(-1.28)	**-0.04**	**(-3.42)**
Bond Ret	-0.01	(-0.31)	-0.03	(-1.35)	0.00	**(-1.91)**	-0.01	(-1.34)
R^2	0.01		0.003		0.01		0.01	
N	29,228		24,677		409,199		222,140	

2.4.2 Fund Size and Investment Style

We turn next to examine whether differences in the incidence of late trading exist between small and large funds. Larger funds have generally more buy and sell orders per day than smaller funds, and hence, placing orders late unnoticed might be easier, particularly when fund managers are not directly involved. The classification into small and large funds is based on the average total net assets of each fund. The results in Table 2.5 show that it is mainly the flow of larger funds which is correlated with post cutoff market movements. In the case of (large) French mutual funds the coefficients on price changes during the afternoon and 8pm and 9pm are 0.01 and 0.05 with *t*-statistics of 2.09 and 6.81, respectively. In the case of (large) German mutual funds, the coefficient estimates on $\Delta FUT^{5.30pm\text{-}6pm}$, $\Delta FUT^{8pm\text{-}9pm}$ and $\Delta FUT^{9pm\text{-}10pm}$ are all of the same (positive) magnitude and are statistically significant. Again, the coefficient estimates on lagged flow are all positive and mostly statistically significant. As before the positive estimates on lagged returns are consistent with positive feedback or return chasing trading strategies. The coefficient estimates on volatility and bond returns are negative and are significant for German funds.

Table 2.5: Large Funds versus Small Funds

This table reports regression estimates of equation (2.2). The classification into small and large funds is based on the average total net assets of the sample funds. Standard errors are clustered by fund and year. Corresponding *t*-statistics are reported in parentheses. The time period for French mutual funds is June 2008 and for German mutual funds June 2006 through July 2014.

	Large Funds				Small Funds			
	France		Germany		France		Germany	
Intercept	0.00	(0.38)	**0.00**	**(1.99)**	**0.00**	**(1.79)**	**0.00**	**(3.13)**
$\Delta FUT_{morning}$	0.00	(0.51)	0.00	(-0.23)	0.01	(1.47)	0.02	(0.82)
$\Delta FUT_{afternoon}$	**0.01**	**(2.09)**	-0.01	(-1.15)	-0.01	(-0.61)	0.01	(0.57)
$\Delta FUT_{5.30pm\ to\ 6pm}$	-0.01	(-0.44)	**0.03**	**(1.66)**	0.01	(0.56)	**0.08**	**(1.77)**
$\Delta FUT_{6pm\ to\ 7pm}$	0.00	(0.18)	0.03	(1.45)	-0.01	(-0.32)	0.03	(1.02)
$\Delta FUT_{7pm\ to\ 8pm}$	-0.01	(-1.07)	0.01	(0.20)	-0.01	(-0.30)	-0.02	(-0.46)
$\Delta FUT_{8pm\ to\ 9pm}$	**0.05**	**(6.81)**	**0.03**	**(1.73)**	-0.02	(-0.59)	0.01	(0.29)
$\Delta FUT_{9pm\ to\ 10pm}$	0.01	(1.08)	**0.03**	**(2.26)**	0.02	(1.50)	0.02	(0.82)
$Flow_{t-1}$	0.03	(1.08)	**0.08**	**(3.06)**	0.01	(1.05)	**0.03**	**(4.41)**
$Flow_{t-2}$	**0.05**	**(4.04)**	**0.03**	**(1.97)**	0.01	(1.06)	**0.03**	**(4.71)**
$Flow_{t-3}$	**0.01**	**(1.81)**	**0.03**	**(2.87)**	**0.02**	**(4.27)**	**0.02**	**(1.89)**
$Flow_{t-4}$	**0.01**	**(3.38)**	**0.02**	**(3.46)**	**0.01**	**(2.48)**	**0.03**	**(2.13)**
Ret_{t-1}	**0.99**	**(2.32)**	**0.03**	**(4.11)**	0.01	(0.01)	0.01	(0.90)
Ret_{t-2}	**0.93**	**(3.46)**	**0.02**	**(2.76)**	0.14	(0.20)	0.02	(1.37)
Ret_{t-3}	-0.22	(-0.25)	0.00	(0.37)	-1.60	(-1.26)	-0.01	(-0.69)
Ret_{t-4}	-0.39	(-1.35)	0.01	(1.13)	-0.48	(-0.62)	0.02	(1.53)
Volatility	-0.01	(-0.50)	**-0.04**	**(-3.75)**	**-0.06**	**(-1.81)**	**-0.06**	**(-2.53)**
Bond Ret	0.00	(-1.25)	**-0.01**	**(-1.81)**	-0.01	(-0.89)	-0.01	(-1.15)
R^2	0.02		0.11		0.01		0.04	
N	248,952		149,270		188,498		97,547	

Table 2.6 reports separate results for different investment styles based on Morningstar Categories. We only have a classification into large cap and small cap funds available. Small cap stocks usually react more to (market) news and hence might provide an

opportunity to maximize the benefits of late trading. In the case of French mutual funds, the flow of both fund types shows some correlation to after hour market movements. The coefficient estimate on $\Delta FUT^{8pm\text{-}9pm}$ (large cap funds) is 0.01 with a *t*-statistic of 1.68, while the coefficient on $\Delta FUT^{9pm\text{-}10pm}$ (small cap funds) is 0.05 and has a *t*-statistic of 1.99. However, in the case of German funds only net flow of large cap funds is correlated with post cutoff market movements. The coefficient estimates on $\Delta FUT^{5.30pm\text{-}6pm}$, $\Delta FUT^{8pm\text{-}9pm}$ and $\Delta FUT^{9pm\text{-}10pm}$ are 0.06, 0.04 and 0.03 with *t*-statistics of 2.39, 2.52 and 2.57, respectively. None of the coefficients for small cap funds are statistically significant. It appears that the incidence of late trading is more likely for funds investing in stocks that move closer with the market. We surmise that the additional risk from investing in small-cap stocks has been considered too onerous for most late traders, a pattern which is also consistent with the limits to late trading arbitrage, especially in view of a sample period covering two major financial crises.

Table 2.6: Large-cap Funds versus Small-cap Funds

This table reports regression estimates of equation (2.2) for large cap and small cap oriented funds by country. We take the style classification from Morningstar Categories which is based on the underlying portfolios. In case of French (German) mutual funds, $\Delta FUT^{morning}$ are log changes in futures prices between 9am and 12pm (3pm). $\Delta FUT^{afternoon}$ are log changes in future prices between 12pm (3pm) and 5.30pm. Standard errors are clustered by fund and year. Corresponding *t*-statistics are reported in parentheses. The time period for French mutual funds is June 2008 and for German mutual funds June 2006 through July 2014.

	Large-cap Funds				Small-cap Funds			
	France		Germany		France		Germany	
Intercept	0.00	(0.25)	**0.00**	**(2.34)**	**0.00**	**(2.07)**	0.00	(1.58)
$\Delta FUT^{morning}$	0.00	(0.88)	0.01	(1.43)	0.02	(1.11)	0.00	(-0.00)
$\Delta FUT^{afternoon}$	0.01	(1.30)	-0.01	(-0.61)	0.00	(-0.69)	0.00	(0.32)
$\Delta FUT_{5.30pm\ to\ 6pm}$	0.01	(0.57)	**0.06**	**(2.39)**	-0.01	(-0.36)	0.02	(0.41)
$\Delta FUT_{6pm\ to\ 7pm}$	-0.01	(-0.44)	**0.04**	**(2.52)**	0.03	(0.53)	0.03	(0.69)
$\Delta FUT_{7pm\ to\ 8pm}$	-0.01	(-0.56)	0.00	(0.13)	-0.01	(-0.24)	-0.03	(-0.55)
$\Delta FUT_{8pm\ to\ 9pm}$	0.01	(1.03)	0.04	(1.40)	**0.05**	**(1.99)**	-0.03	(-1.37)
$\Delta FUT_{9pm\ to\ 10pm}$	**0.01**	**(1.68)**	**0.03**	**(2.57)**	0.02	(1.40)	0.01	(0.18)
$Flow_{t-1}$	**0.02**	**(1.80)**	**0.05**	**(5.38)**	0.01	(0.82)	0.03	(0.45)
$Flow_{t-2}$	**0.02**	**(2.46)**	**0.03**	**(9.76)**	0.02	(1.58)	0.03	(1.63)
$Flow_{t-3}$	**0.02**	**(4.19)**	**0.03**	**(2.56)**	**0.02**	**(3.22)**	0.00	(0.56)
$Flow_{t-4}$	**0.01**	**(1.95)**	**0.03**	**(2.27)**	**0.02**	**(4.11)**	**0.02**	**(3.00)**
Ret_{t-1}	0.01	(1.15)	**0.02**	**(2.66)**	0.01	(1.12)	**0.05**	**(2.34)**
Ret_{t-2}	0.00	(0.83)	0.01	(1.61)	**0.02**	**(3.57)**	**0.04**	**(2.76)**
Ret_{t-3}	-0.01	(-0.80)	-0.01	(-1.02)	-0.01	(-0.47)	0.02	(0.84)
Ret_{t-4}	-0.01	(-1.31)	0.01	(1.13)	0.00	(0.26)	**0.02**	**(1.89)**
Volatility	-0.01	(-0.56)	**-0.05**	**(-2.60)**	**-0.08**	**(-1.98)**	**-0.03**	**(-1.76)**
Bond Ret	0.00	(-0.09)	-0.01	(-0.96)	-0.01	(-0.74)	**-0.02**	**(-4.79)**
R^2	0.02		0.06		0.02		0.04	
N	309,232		186,818		127,580		66,189	

2.5 Returns and Amount of Flow from Late Trading

In this section we first quantify the potential return from late trading using French data and compare it to a simple buy-and-hold strategy. For this purpose we assume an investor was given late trading capacity recognizing that in practice, this would be limited to the funds of specific investment companies or brokers that allow or facilitate late trading. We estimate the return from late trading as the equally-weighted return on the sample funds on day *t* if the change in futures prices after the cutoff time on day *t-1* is positive. If it is negative the investor stays out of the market and earns the risk free rate;[85] ergo

$$R_t^{Late} = \begin{cases} R_t^{EW}, & \Delta FUT_{CAC40,t-1}^{12pm-10pm} > 0 \\ R_t^{T-bill}, & \Delta FUT_{CAC40,t-1}^{12pm-10pm} \leq 0 \end{cases} \tag{2.4}$$

Table 2.7 illustrates that prior day changes in futures prices might indeed be useful for guiding the illicit trades. The correlation of changes in futures prices after the cutoff time with next day's fund returns is between 0.113 and 0.426 (see Panel A). A predictive regression shows it is the changes after market close that matter the most (see Panel B). The coefficient on price changes during the afternoon is statistically insignificant, whereas the coefficient on $\Delta FUT_{t-1}^{5.30pm-10pm}$ is 0.67 with a *t*-statistic of 6.25.

[85] We use the France three months Treasury bill rate as risk free rate.

Table 2.7: Correlation of Mutual Fund Returns with Prior Day Changes in Futures Prices and Predictive Regression

This table reports the correlation of returns on equity funds with prior day changes in futures prices. The sample consists of 351 French mutual funds equally-weighted across all funds. The table also reports a regression predicting the funds next day return using changes in futures prices after the cutoff time and market close. *t*-statistics are based on heteroskedasticity consistent standard errors and reported in parentheses. The sample period is June 2008 through July 2014.

Correlation between changes in future prices and next day mutual fund returns

	$\Delta FUT_{t-1}^{9am-5.30pm}$	$\Delta FUT_{t-1}^{9am-12pm}$	$\Delta FUT_{t-1}^{12pm-5.30pm}$	$\Delta FUT_{t-1}^{5.30pm-10pm}$	$\Delta FUT_{t-1}^{12pm-10pm}$
R_t^{EW}	**0.112**	0.033	**0.113**	**0.426**	**0.316**

Regression predicting next day mutual fund returns

	$\Delta FUT_{t-1}^{9am-12pm}$	$\Delta FUT_{t-1}^{12pm-10pm}$	$\Delta FUT_{t-1}^{12pm-5.30pm}$	$\Delta FUT_{t-1}^{5.30pm-10pm}$	Obs.	R^2
Coef.	0.06	**0.29**			1,395	0.10
(*t* -stat.)	(0.89)	**(5.19)**				
Coef.	0.06		0.05	**0.67**	1,395	0.19
(*t* -stat.)	(1.04)		(0.91)	**(6.25)**		

Significant difference from zero at the 1% level is indicated in bold.

Figure 2.1 shows that an investment of EUR 100 would have almost increased seven-fold had an investor been allowed to trade late at maximum frequency. Even during the GFC, late trading mainly earned a positive return, whereas the buy-and-hold strategy has not yet fully recovered from its losses during the GFC.[86]

[86] The buy-and-hold strategy has a cumulative return of 200% when the GFC is excluded from the sample period (March 2009 until July 2014), while late trading returns 471%.

Figure 2.1: Growth of EUR 100 invested in an EW Portfolio of Equity Mutual Funds

This graph illustrates the growth of EUR 100 invested in an equally-weighted portfolio of 351 French mutual funds that invest domestic equities. The blue lines show daily changes in the investment from late trading. The grey line shows daily changes in the investment from a buy-and-hold strategy. The sample period is June 2008 through July 2014.

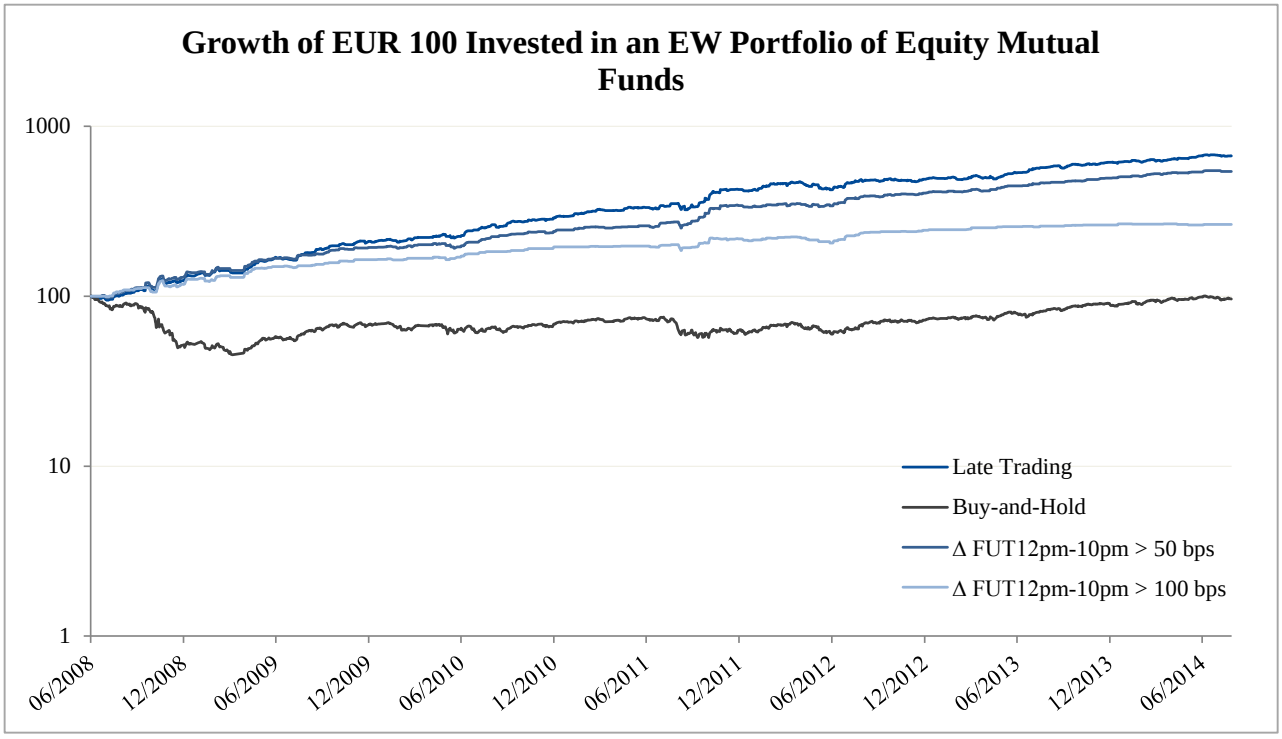


Table 2.8 shows summary statistics for both return series. Average daily return from late trading is 14 bps whereas it is 1 bps from the buy-and-hold strategy with *t*-statistics of 6.01 and 0.15, respectively.

Table 2.8 : Summary Statistics of Return Series from a Late Trading and Buy-and-Hold Strategy

This table presents summary statistics on returns from late trading compared to a buy-and-hold strategy of an equally-weighted portfolio of 351 French mutual funds. The sample period is June 2008 through July 2014.

	Daily Return in %	Standard Deviation	*t* -Statistic	Number Of Days In The Market	Number Of Returns < 0
Late Trading	0.14	0.87	6.01	766	333
Buy-and-Hold	0.01	1.25	0.15	1,395	659
Δ FUT$^{12pm\text{-}10pm}$ > 50 bps	0.12	0.74	6.28	415	205
Δ FUT$^{12pm\text{-}10pm}$ > 100 bps	0.07	0.59	4.51	217	163

Based on 250 trading days, late trading earns an uncompounded return of 35% per annum. At the same time, it has a much lower standard deviation.[87] This outperformance is mainly based on the strategy's ability to predict large positive fund returns. A late trader invests only half the time and avoids about half of the negative returns a buy-and-hold investor would experience. The table also shows statistics of returns from trading funds only when the change in futures prices is greater than 50 basis points or 100 basis points. This reduces the number of trades substantially and produces annualized returns of 31% and 18%, respectively. Considering that we ignore any possible refinements, the estimated returns in this section are rather conservative. For example, by trading only high beta or small cap funds, returns from late trading should be even higher.[88] We do not consider transaction

[87] The results are qualitatively the same when we base late trading on changes in futures prices between 5.30pm and 10pm (after market close) and virtually unchanged assuming an investor earns zero return on cash instead of the risk free rate on days she has not invested in equity funds.

[88] Our test based on the equally-weighted portfolio of funds approximates an investor trading funds late randomly.

costs in our example as it is unlikely that late traders face front-or back-end loads and the incurred costs of their trades are attributed to all investors of the funds. The potential gains from late trading are similar in magnitude to the returns reported in Goetzmann et al. (2001), Boudoukh et al. (2002) and Zitzewitz (2003). These papers study the same underlying concept of exploiting stale prices that also applies to late trading. The latter, however, is unambiguously unlawful and not a question of legal limbo. Our analysis vividly shows why this practice was so widespread and probably still is in some areas of the world.

2.6 Conclusion

We find statistical evidence consistent with the occurrence of late trading in two countries for which no major shortcomings were identified during an investigation conducted by European securities regulators in 2004. We would have expected that following the events that rocked the US funds industry in 2003 and ensuing strengthening of regulation should have made late trading more difficult to execute, but it appears to be still present. Many reasonable proposals have been considered to thwart late trading, most of which are recommendations for more effective trading procedures and internal controls, including different fee structures, strict forward pricing and fair value pricing. However, the merits from placing safer bets, the prospects of large gains and relative simplicity and appeal of this practice at least for a small number of market participants favoured by mutual fund companies are obvious. The profits from trading late, however, are matched dollar-for-dollar by the losses of long term investors. Therefore, we fully endorse the suggestion of Zitzewitz (2006) that simple statistical methods may be helpful and should be used on a regular basis as part of the assessment and monitoring of the compliance of fund companies with law and best practices. However, such tests do not indicate if fund companies

knowingly allow late trading or if late trading is mainly facilitated by intermediaries like brokerage firms, albeit they do raise a flag that may warrant further scrutiny. Nevertheless, if late trading is indeed the source behind the correlations found in this paper, it would be disheartening for investors considering an already long list of scandals beleaguering the financial services industry including the manipulation of the LIBOR and currency exchange rates and several cases of insider trading in the hedge funds industry.

Chapter 3

MUTUAL FUND FLOWS AND SEASONALITIES IN STOCK RETURNS

ABSTRACT

In this paper, we propose a flow-based explanation for a long-standing anomaly in empirical finance – the Sell in May effect. We find that aggregate mutual fund flow exhibits a similar seasonality as stock returns. Given that flow can affect contemporaneous stock returns, the Sell in May effect becomes insignificant in standard statistical tests after controlling for flow. Flow explains about 54% of the variation in excess returns over the winter months. We also find that flow helps explaining the abnormally high returns of small-cap stocks in January. Both, the Sell in May and the January effect appear to be a retail money effect. Similarly, the well-known co-movement of flow and market returns is only present in case of retail funds.

3.1 Introduction

Past research has documented various seasonal patterns in stock returns. Among the widely cited calendar month based anomalies at the aggregate stock market level are the Halloween effect dubbed as "Sell in May and go away" and the January or turn-of-the year effect. Bouman and Jacobsen (2002) document higher stock returns in 36 out of 37 countries in the November-April period than in the May-October period. Jacobsen et al. (2005), Jacobsen and Visaltanachoti (2009), Jacobsen and Zhang (2012), Zhang and Jacobsen (2013), and Andrade et al. (2013) show that this return seasonality is also present out of sample, is unrelated to other anomalies, and is more pronounced in recent years. The explanations offered in literature such as general investor behaviour, a change in risk

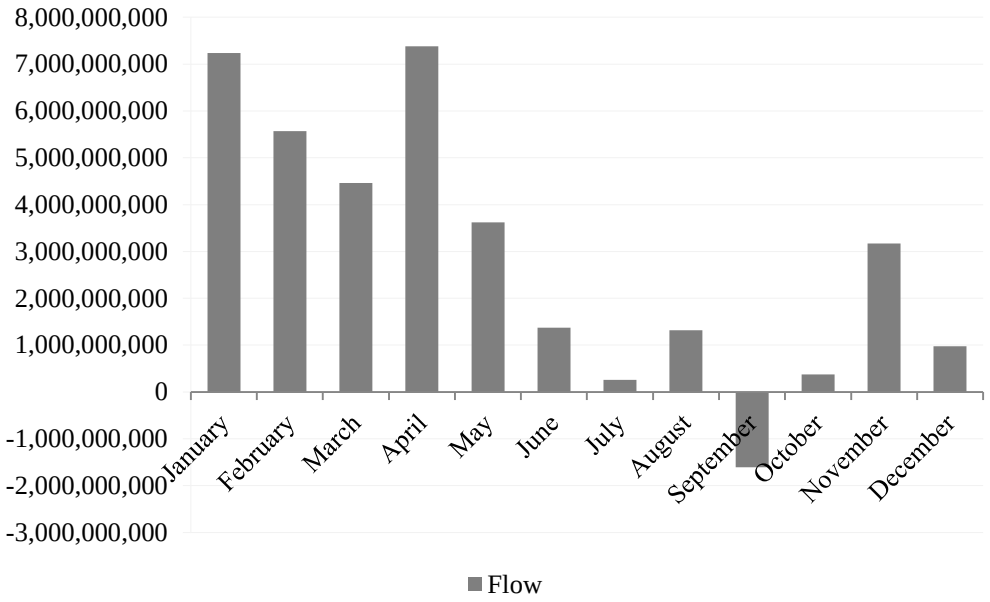
aversion due to vacations, Seasonal Affective Disorder (SAD), and investor sentiment due to temperature can at best only partially explain the puzzle (Bouman and Jacobsen, 2002; Kamstra et al., 2003, 2009; Cao and Wei, 2005; Jacobsen and Marquering, 2008, 2009; Hong and Yu, 2009). We provide a potential explanation that this empirical pattern is driven by a simple mechanism – a similar pattern in mutual fund flows.

There is a large body of literature on mutual fund flows and institutional trading documenting that stock returns are contemporaneously correlated with capital flows into funds (Chan and Lakonishok, 1993, 1995; Warther, 1995; Edelen and Warner, 2001; Rakowski and Wang, 2009), while Coval and Stafford (2007) and Lou (2012) further show strong price-pressure effects from flow-induced trading on stock returns. This is based on funds expanding (selling) their current holdings with inflow (outflow). Lou also shows that flow-induced trading can predict future stock returns. Ben-Rephael et al. (2011) provide evidence of such price-pressure effects on the market level. Actual daily cash flows of equity funds in Israel create temporary price pressure which is only partially corrected within 10 days. In addition to the claim that flows cause returns, there are other competing hypotheses to explain the co-movement such as feedback trading, sentiment, and simply information revelation. However, given that mutual fund flows can affect stock returns, we examine whether flows exhibit similar patterns based on calendar months and whether the return seasonalities are independent of those observed in flows.

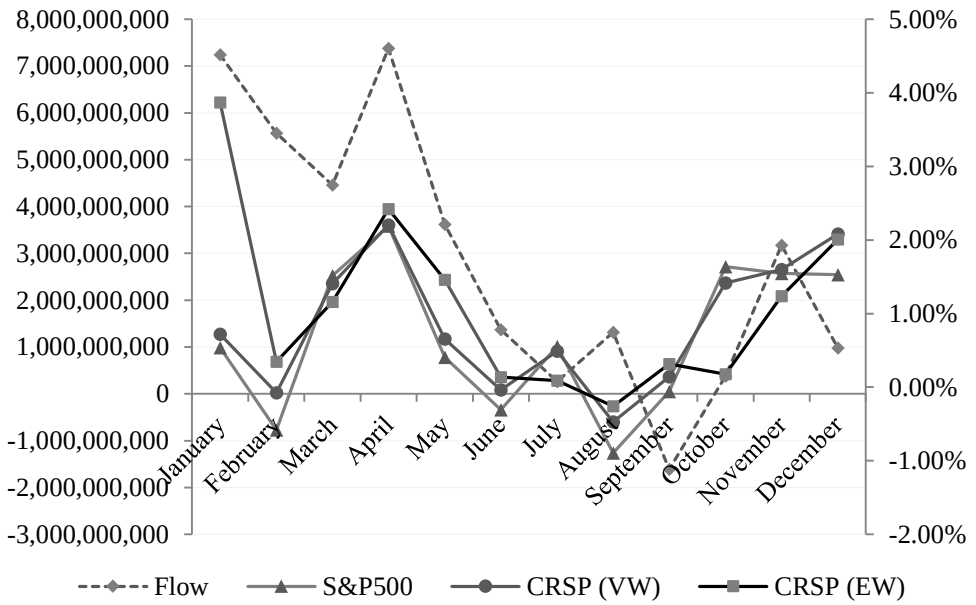
Figure 3.1: Mutual Fund Flows and Stock Returns

Panel A of this figure reports the average monthly flow of our sample funds (market-wide aggregate). Panel B plots the same flow measure together with average monthly returns on the CRSP value- and equally-weighted stock market indices (NYSE + AMEX + NASDAQ) and the S&P 500 index. Panel C reports six-month returns on the CRSP value-weighted stock market index of the period November-April in excess over May-October and the same for mutual fund flows, normalised by the value of the market (NYSE + AMEX + NASDAQ) and scaled by 1000. The sample period is January 1995 to December 2014.

Panel A – Average monthly flow



Panel B – Average monthly flow and average monthly returns



Panel C – Winter excess fund flows and market returns

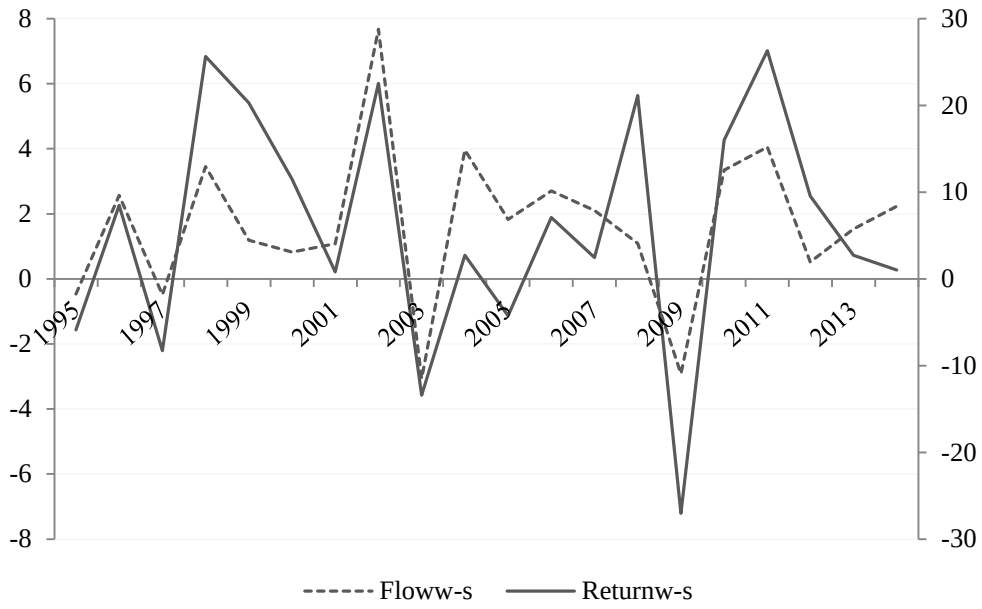


Figure 3.1 illustrates our main findings. Panel A shows that monthly average aggregate net flows into US mutual funds from November to April are substantially larger than those from May to October. Average monthly returns on broad indices clearly support the Sell in May wisdom documented in the literature and plotted in Panel B; average returns are higher during winter months than during summer months. Consistent with the January effect being predominantly found among small cap stocks, the equally-weighted market index peaks in January. During the other months of the year the market proxies are fairly close. January, together with April, is also the month with the highest flow measure. The average calendar month returns and flows when plotted together in Panel B show striking resemblance.

Panel C plots the time-series of yearly winter excess returns on the CRSP value-weighted index and winter excess fund flows over their summer counterparts. There is

some variation in the Sell in May effect consistent with Zhang and Jacobsen (2013). However, in 15 out of 20 years returns during the winter month are higher than those in the summer months. Again, a very similar pattern emerges for mutual fund flows; in most years, fund flows during winter are higher than during summer. Remarkably, when summer flows are higher than winter flows, the Sell in May effects are also negative with an only exception in 2005. The correlation between the two series is 0.73 (p-value = 0.0002).

Our test results suggest that after accounting for the effect of large fund flows during winter months, the Halloween effect is no longer statistically significant and that average net flow during the winter months in excess over the average flow during the remainder of the year explains about half of the variation of excess returns during the winter months. In addition, we find that mutual fund flow provides a stronger explanation for the January effect than other explanations discussed in previous research. Addressing the question of causality reveals that it is the unexpected component of flow which is driving the results, while expected flow lags return. Results from an unrestricted VAR model shows that flow contains information on returns and vice versa.

We also find that the calendar month pattern is present across capital flows into all investment styles. Distinguishing between flows into retail and institutional funds, however, reveals that both return seasonalities are mainly driven by retail fund flows. Institutional fund flows do not exhibit a seasonal pattern and cannot help explain the Sell in May or the January effect. Our analyses also show that the well-known co-movement of aggregate flow and market return is only present in retail fund flow.

The essay is organized as follows. Section 3.2 describes the data and methodology. Section 3.3 presents the empirical findings with robustness tests in sections 3.4 and 3.5, respectively. We conclude in section 3.6.

3.2 Data and Methodology

To estimate seasonal patterns in returns, we use CRSP value- and equal-weighted stock market index returns (NYSE + AMEX + NASDAQ), as well as total returns from the S&P 500 index. For mutual fund flows, we obtain monthly net asset values and returns of US-based mutual funds that invest in domestic equities and have more than 50 million USD in assets under management from Morningstar. Net flow is then estimated from a fund's net asset values (NAV) in the previous month, current month assets, and the monthly total return:

$$Flow_{it} = TNA_{it} - TNA_{i,\,t-1}(1+r_{it}) \tag{3.1}$$

Where TNA_{it} is fund i's total net asset in month t and r_{it} is the fund's total return in that month. In other words, we proxy net flows by simply taking the difference between current and prior month's net asset values that is not accounted for by monthly total return. The sample period is from January 1995 through December 2014.

Table 3.1: Summary Statistics of US Equity Mutual Funds

This table reports summary statistics of all US-based mutual funds that invest in domestic equities as of the end of December in each year. The only filter we apply is that they have more than 50 million dollars in assets under management based on the most recent portfolio date. The number of funds is given in share classes. We calculate percent of market value as total net assets divided by total value of the stock market (NYSE + AMEX + NASDAQ). The sample period is from 1995 to 2014.

Year	Number of Funds	Total Net Assets ($M)	% of Market Value
1994	779	501,506	10.03%
1995	908	778,391	11.47%
1996	1,071	1,058,615	12.75%
1997	1,268	1,473,680	13.65%
1998	1,425	1,842,371	13.86%
1999	1,640	2,452,570	14.41%
2000	1,938	2,375,616	15.20%
2001	2,240	2,184,445	15.78%
2002	2,414	1,634,410	14.82%
2003	2,737	2,450,488	16.81%
2004	2,989	2,953,683	17.95%
2005	3,284	3,226,563	18.57%
2006	3,505	3,745,166	19.10%
2007	3,728	4,095,311	20.28%
2008	3,998	2,447,566	20.18%
2009	4,160	3,237,890	20.49%
2010	4,325	3,751,258	20.29%
2011	4,434	3,593,521	20.09%
2012	4,498	4,013,517	19.72%
2013	4,495	5,378,888	20.47%
2014	4,364	5,739,679	19.82%

Table 3.1 reports summary statistics of the NAV's of the funds in our sample. There is a clear increasing trend visible in the number of funds and the percentage of the total market

capitalization managed by funds.[89] To the extent that price pressure from mutual funds affects stock returns, these trends might be an explanation why the anomaly has become more rather than less pronounced in recent years.

We use standard regression analysis to test for seasonalities in stock returns:

$$r_t = \mu + \beta Season_t + \beta_2 Flow_t + \gamma' Control_t + \varepsilon_t \qquad (3.2)$$

where r_t is the return on the stock index for month t, μ is a constant and ε_t is the usual error term. $Season_t$ is a seasonal dummy that assume the value of 1 for January and November to April periods respectively, and 0 otherwise, $Flow_t$ is mutual fund flow scaled by the total market capitalization, and $Control_t$ is a vector of other control variables.

3.3.1 Results

3.3.1 The Sell in May Effect

Table 3.2 reports the results of formal tests of the Halloween effect and January effect. As in previous studies we find strong calendar month seasonalities in stock returns that are statistically and economically significant. The somewhat hefty turn-of-the-year effect is only present in the equally-weighted index, and thus predominantly among small-cap stocks. With or without separating January from the rest of winter months (Column 5 and 6), the Halloween effect is statistically significant. In a nutshell, Table 3.2 confirms the

[89] Percentage of the stock market held by mutual funds is slightly overstated here because we do not consider cash holdings separately. But the figures are mainly comparable to those reported in prior research. Note that including foreign mutual funds would increase the percentage of market capitalisation held by mutual funds.

empirical regularities documented in earlier research, which we seek to explain in the following section.

Table 3.2: The Sell in May and January Effect

This table reports estimation results of the Sell in May or Halloween effect and the January effect. The first two rows are the value- and equally-weighted indices of all stocks listed on the NYSE, AMEX and NASDAQ. The S&P 500 index represents the 500 largest publicly traded corporations in the US. The January dummy is 1 for returns that fall into January and 0 otherwise. The Sell in May dummy (not) adjusted for January is 1 for the period November-April (including) excluding January and 0 otherwise. Mean and adjusted R^2 are reported from the regression including the January and the adjusted Sell in May dummy. The sample period is January 1995 to December 2014. *t*-statistics are reported in parentheses based on Newey-West corrected standard errors.

Market Index	Adj-R^2	Obs.	Mean	January Dummy	Sell in May Dummy (adjusted for January)	Sell in May Dummy (not adjusted for January)
CRSP (VW)	0.01	240	0.37	0.04	**1.22**	**1.03**
			(0.82)	(0.04)	**(2.19)**	**(1.88)**
CRSP (EW)	0.02	240	0.31	**3.30**	**1.26**	**1.60**
			(0.54)	**(2.38)**	**(1.76)**	**(2.36)**
S&P 500	0.01	240	0.24	-0.05	**1.17**	**0.96**
			(0.57)	(-0.05)	**(2.23)**	**(1.85)**

If mutual fund flows affect contemporaneous stock returns, it is natural to ask whether fund flows can help explain the seasonal patterns in stock returns given that we find similar patterns in fund flows in Figure 3.1. Table 3.3 reports the regression results with fund flows and other control variables added to the set of explanatory variables - lagged mutual fund flows, P/E ratio, and Dividend yield of the market index at the end of the previous month. Lagged fund flows are included in order to account for the possibility that fund flow may drive stock prices away from their fundamental values and lead to a reversal.

Table 3.3: Mutual Fund Flows and the Halloween Seasonality in Stock Returns

Panel A reports estimation results for different variants of equation (3.2) with *t*-statistics in parentheses based on Newey-West corrected standard errors. The dependent variable is the monthly return on the S&P 500 index. The Sell in May dummy, Hal_t, is 1 for the period November-April and 0 otherwise. PE_{t-1} and DY_{t-1} are the price-earnings ratio and the dividend yield of the market index at the end of the previous month. $Flow_t$ is the estimated monthly net flow (market-wide) of our sample funds normalised by the value of the market (NYSE + AMEX + NASDAQ) and scaled by 1000. The dependent variable in Panel B is the six-month return over the period November-April minus the six-month return May-October, a proxy for the Sell in May effect. The explanatory variable is the half-year flow over the winter months November-April minus the flow during the remainder of the year ($Flow_{w-s}$), normalised by the value of the market at the previous month and scaled by 1000. The sample period is January 1995 to December 2014.

Panel A

	(1)	(2)	(3)	(4)	(5)
Obs.	240	240	240	240	240
Adj-R^2	0.01	0.08	0.13	0.16	0.15
Intercept	0.24	0.00	0.41	**3.69**	-2.45
	(0.57)	(0.01)	(0.99)	**(2.77)**	(-1.44)
Hal	**0.96**	0.50	0.14	0.14	0.12
	(1.85)	(1.03)	(0.30)	(0.30)	(0.27)
PE_{t-1}				**-0.17**	
				(-2.71)	
DY_{t-1}					1.50
					(1.62)
Flow		**1.67**	**3.30**	**3.37**	**3.31**
		(3.71)	**(5.29)**	**(5.50)**	**(5.38)**
$Flow_{t-1}$			**-1.59**	**-1.41**	**-1.46**
			(-2.43)	**(-2.24)**	**(-2.33)**
$Flow_{t-2}$			-0.06	0.09	0.04
			(-0.07)	(0.12)	(0.06)
$Flow_{t-3}$			-0.73	-0.53	-0.58
			(-1.20)	(-0.88)	(-0.96)

Panel B

	Dependent Variable: Market $Return_{w-s}$			
	Obs.	R^2	Intercept	$Flow_{w-s}$
Coef.	20	0.54	-1.02	**4.21**
(*t* -stat.)			-0.46	**(4.89)**

With the inclusion of aggregate fund flow, the Halloween dummy is no longer significant (Column 2) indicating that after accounting for fund flow there is no winter-summer seasonality in stock returns left to be explained in a statistical sense. Contemporaneous inflow is positively and significantly related to stock returns with or without other control variables. Consistent with a reversal of the price pressure effect, lagged flow is negatively related to stock returns (*t*-statistic = -2.43 for $Flow_{t-1}$).

Panel B in Table 3.3 reports the results of a yearly regression in which the dependent variable is the six-month return over the period of November to April in excess of the six-month return from May to October. The explanatory variable is the corresponding six-month flow during the winter period in excess of the summer months. This univariate test explains 54% of the variation in the Sell in May effect. The coefficient estimate of 4.21 with a *t*-statistic of 4.89 implies that for an average excess winter flow of 1.39% of the total market capitalization, the six-month winter excess return is about 5.84%. This estimate is very close to the average difference between November-April and May-October returns reported in Jacobsen and Zhang (2012) documenting an average difference of 6.25% over the past 50 years.

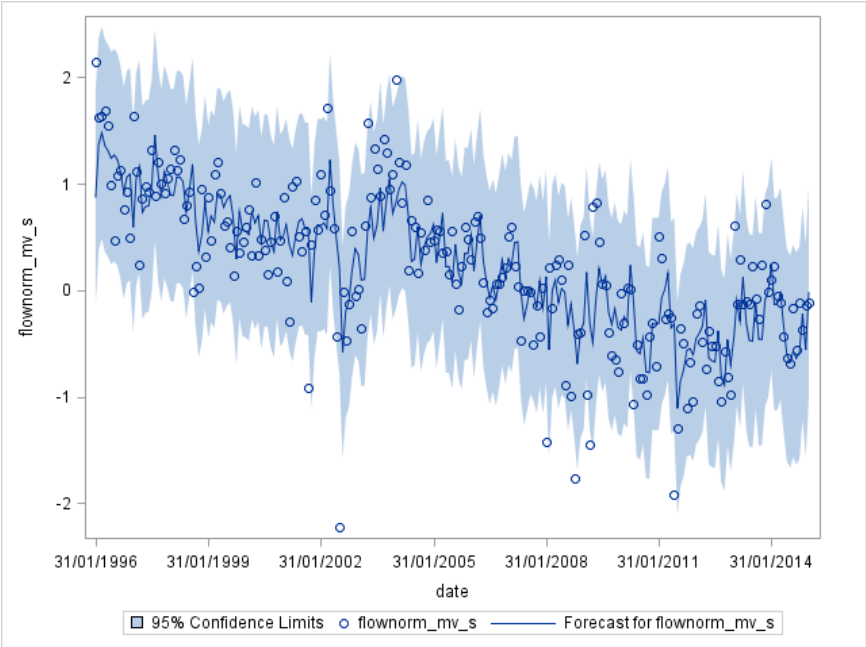
We do not include the temperature and the Onset/Recovery (SAD) variable from Kamstra et al. (2003). Both have been widely debated in literature as a potential cause for the seasonal anomaly in stock returns driven by mood changes of investors because of the variation in daylight and temperature. However, the evidence in favour for either of these two explanations is not convincing (see Jacobsen and Marquering, 2008, 2009). This is partly due to their high correlations with the Halloween indicator at 0.88 and -0.68 for

temperature and SAD, respectively, making it difficult to test their joint effects. In contrast, the correlation between flow and the Halloween indicator is only 0.18.[90]

Given that mutual fund flows are predictable, we decompose fund flows into expected and unexpected parts in order to examine whether the expected part of fund flow can forecast stock returns.

Figure 3.2: Time Series Plot of Flow and Predicted Flow

This figure shows the time series of aggregate mutual fund flow normalised by the value of the stock market (NYSE + AMEX + NASDAQ) in the previous month scaled by 1,000 and predicted flow. The blue line shows the predicted flow estimated using an ARIMA(1,0,1)(0,1,1)$_{12}$+c model. The time period is January 1996 to January 2015.



[90] The variance inflation factors are 1 or very close to 1 in all regressions that include flow.

Figure 3.2 plots the time series of normalised flow and its forecast. Besides the identified monthly seasonal, it appears that there is also a long run downward trend present.

Combining the observed patterns in Figure 3.1 and 3.2, we estimate the expected flow using a seasonal ARIMA model. Based on the ACF and PACF of the differenced flow series, we identify and fit an ARIMA(1,0,1)$(0,1,1)_{12}$ + c model. This model results in the lowest information criterion (AIC) and lowest forecast error (RMSE) compared to a large set of other competing models, including exponential smoothing, random walk and trend models as reported in Panel A of Table 3.4. The model specification is:

$$\widehat{Flow}_t = \mu + Flow_{t-12} + \phi_1(Flow_{t-1} - Flow_{t-13}) - \theta_1 e_{t-1} - \Theta_1 e_{t-12} + \theta_1 \Theta_1 e_{t-13} \quad (3.3)$$

where *Flow* is the normalised fund flow, μ is a constant, ϕ denotes an AR(1) coefficient and θ is a non-seasonal MA(1) and Θ a seasonal or SMA(1) coefficient.

Table 3.4: Expected and Unexpected Mutual Fund Flows and Stock Returns

The Panel A of this table reports statistics for different models to estimate expected and unexpected flow. The first three columns of Panel B report estimation results from regressing market returns on expected and unexpected fund flow and the Halloween indicator, *Hal*. This is based on a two-step estimation procedure where expected and unexpected flow are generated from a seasonal ARIMA (1, 0, 1)(0, 1, 1)$_{12}$+c model (model no. 1 in Panel A). Expected flow is the fitted value, while unexpected flow is the residual. In columns four and five we regress expected and unexpected flow on lagged market returns. The sample period is January 1995 to December 2014. *t*-statistics are reported in parentheses based on Newey-West corrected standard errors.

Panel A - Statistical Models for Expected and Unexpected Flow

No.	Model		AIC	RMSE
1	Seasonal ARIMA with white noise errors incl. constant	ARIMA(1,0,1)(0,1,1)$_{12}$+c	344.63	0.51
2	Equivalent to simple exponential smoothing	ARIMA(0,1,1)	354.75	0.51
3	Seasonal ARIMA with white noise errors without constant	ARIMA(1,0,1)(0,1,1)$_{12}$	355.25	0.52
4	Seasonal random trend model with MA(1) and SMA(1) terms	ARIMA(0,1,1)(0,1,1)$_{12}$	360.58	0.53
5	Equivalent to seasonal exponential smoothing	ARIMA(0,1,13)(0,1,0)$_{12}$	364.19	0.52
6	Equivalent to Winters method	ARIMA(0,1,13)(0,1,0)$_{12}$+c	365.71	0.52
7	Equivalent to double exponential smoothing	ARIMA(0,2,2)	376.06	0.53
8	Seasonal random walk model with AR(1) term	ARIMA(1,0,0)(0,1,0)$_{12}$+c	472.42	0.68
9	Seasonal random walk model	ARIMA(0,0,0)(0,1,0)$_{12}$+c	516.78	0.75
10	Seasonal random trend model	ARIMA(0,1,0)(0,1,0)$_{12}$	541.63	0.79

Panel B - Regressions of Return (Flow) on Flow (Return)

	Dependent Variable				
	Market Return			Expected Flow	Unexpected Flow
	(1)	(2)	(3)	(4)	(5)
Obs.	228	228	228	228	228
Adj-R^2	0.00	0.15	0.15	0.05	0.18
Intercept	0.15	**0.41**	0.37	**0.21**	-0.04
	(0.32)	**(1.15)**	(0.97)	**(2.84)**	(-1.52)
Hal	**0.98**	0.50	0.46		
	(1.86)	(1.11)	(1.00)		
Expected Flow	(-0.06)		(0.27)		
	(-0.10)		(0.51)		
Unexpected Flow		**3.44**	**3.47**		
		(5.66)	**(5.56)**		
Return				0.00	**0.04**
				(-0.17)	**(5.29)**
$Return_{t-1}$				**0.02**	**0.02**
				(2.87)	**(2.69)**
$Return_{t-2}$				**0.02**	0.00
				(3.46)	(-0.49)
$Return_{t-3}$				**0.01**	-0.01
				(2.36)	(-0.77)

The Sell in May dummy becomes insignificant only when we include the unexpected component of flow. The coefficient on unexpected flow is 3.47 and highly significant with a *t*-statistic of 5.56, while expected flow is not statistically significant. The results indicate that the return-flow relation is a contemporaneous one and thus the relation may stem from an unknown common factor.

Regressions four and five shed a bit more light on the relationship by regressing expected and unexpected flow on concurrent and lagged returns. These results highlight why the coefficient on the expected component of flow in the first and third column is statistically insignificant. Expected flow is affected lagged return, while concurrent return is only related to unexpected flow. Based on the findings, we can further infer that only the expected component of flow is consistent with the feedback-trader hypothesis which predicts that flows must lag returns.[91]

3.3.2 Dynamics between Flow and Market Returns and the Sell in May Effect

We turn next to investigate the joint dynamics between flow and market returns within a vector autoregressive framework that allows us to address the question of causality again using the concept of Granger (1969). This framework also provides for an alternative test without the need to be concerned about potential endogeneity issues as VAR specifications allow for both variables to affect each other. As discussed earlier, there are competing hypotheses that provide explanations for the co-movement of fund flow and market return. Coval and Stafford (2007) and Lou (2012) are recent papers that provide strong evidence for the price pressure hypothesis. But causality could go the other way in that investors buy (sell) fund shares in response to good (poor) stock market performance. Edelen and Warner (2001) find some evidence in favour of this feedback hypothesis, but their findings are also consistent with a third explanation, the information-response hypothesis which suggests that both returns and flows react to new information. Jank (2012) documents supporting evidence for the information-response hypothesis.

[91] This lag could be anything from picking up the phone or the order of months but there must be a nonzero lag between flows and returns, Warther (1995).

Using a bivariate VAR specification allows us to test the feedback hypothesis in the flow equation and the price-pressure hypothesis in the return equation. In addition we include in the VAR the Sell in May indicator and proxies for news as exogenous variables, which allows us to test for seasonality effects and for the information-response hypothesis, respectively. For the latter we follow Jank (2012) and include predictive variables as proxies for macroeconomic news. Specifically, we include changes in the dividend yield (ΔDY), default spread (ΔDefault), term spread (ΔTerm) and the three months T-bill rate (ΔT-bill). These variables have been found to be related to the current state of the economy but also to predict business activity and the equity premium (e.g. Shiller et al., 1984; Campbell, 1987; Campbell and Shiller, 1988; Fama and French, 1988, 1989; Campbell, 1991; Chen, 1991; Ferson and Harvey, 1991; Hodrick, 1992; Lettau and Ludvigson, 2005). News about the economy is reflected in changes of these variables. We also include changes in the VIX index (ΔVIX), the so-called fear index, since our sample period contains several crises. Monthly dividend yields are obtained from Thomson Reuters Datastream. Default spread is calculated as the difference between Moody's Baa and Aaa corporate bond yields and term spread is defined as the difference between ten-year and one-year maturity Treasury rates. Data on corporate bonds, Treasury rates and the VIX are obtained from the FRED database of the Federal Reserve Bank of St. Louis. Table 3.5 illustrates the correlation matrix of these variables, fund flow, and market return.

Table 3.5: Correlation between Flow, Return and News Proxies

This table reports correlation coefficients between normalised mutual fund flow, market return and predictive variables. ΔDY is the change in the dividend-price ratio of the S&P 500 index (in log terms), ΔDefault is the change in the default spread, ΔTerm is the change in the term spread, ΔT-bill is the change in the 3-months T-bill rate and ΔVIX is the change in the Chicago Board Options Exchange (CBOE) Volatility index. The sample period is January 1995 to December 2014.

	Flow	Ret	ΔDY	ΔDefault	ΔTerm	ΔT-bill	ΔVIX
Flow	1						
Ret	0.29	1					
ΔDY	-0.29	-0.96	1				
ΔDefault	-0.11	-0.14	0.15	1			
ΔTerm	0.05	0.03	-0.06	0.07	1		
ΔT-bill	0.14	0.11	-0.09	-0.06	-0.47	1	
ΔVIX	-0.17	-0.71	0.72	0.12	-0.05	-0.05	1

The co-movement of flow and returns is indicated by a correlation coefficient of 0.29. But flow is also correlated with Δ*DY*. Apart from Δ*Term*, most of the other variables are correlated with each other with coefficients above (below) 0.10 (-0.10).

A general specification of our bivariate VAR, where flow and market returns depend on different combinations of the previous *p* values of both variables, the exogenous variables mentioned above and error terms is given by:

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + B_0 x_t + \varepsilon_t \quad , \tag{3.4}$$

where, y_t is a 2x1 random vector that contains the time series of flow and market returns, A_1 through A_p are 2x2 matrices of parameters, x_t is a 5x1 vector of the exogenous variables, B_0 is a 2x5 matrix of coefficients, v is a 2x1 vector of parameters, and ε_t are the white noise

error terms. In order to carry out joint significance tests on the lags of flow and returns requires that both time series are stationary.

Table 3.6: Unit Root Test of Fund Flow and Market Returns

This table reports estimation results for the Phillips-Perron unit root test with automatic Newey-West bandwidth using Bartlett kernel. The null hypothesis is that both flow and return have a unit root. The sample period is January 1995 to December 2014.

		Flow		Return	
		Adj. *t* -stat.	Prob.*	Adj. *t* -stat.	Prob.*
Phillips-Perron test statistic		-6.49	0.000	-14.20	0.000
Test critical values:	1% level	-3.46		-3.46	
	5% level	-2.87		-2.87	
	10% level	-2.57		-2.57	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.28	18.92
HAC corrected variance (Bartlett kernel)	0.28	20.75

The Phillips-Perron tests reported in Table 3.6 reject the unit root hypotheses at the one percent level for both flow and returns.

We determine the optimal lag length based on Akaike's information criterion (AIC), which is minimised by including 9 lags out of a maximum of 12 lags. We also assess the validity of the VAR system by testing for the dynamic stability and for autocorrelation of the residuals. None of the eigenvalues lies outside the unit root and there is no serial

correlation left in the residuals. Panel A of Table 3.7 shows results from the VAR estimation.

Table 3.7: Vector Autoregression Analysis of Fund Flow and Market Returns

Panel A of this table reports estimation results from a vector autoregressive regression of normalised fund flow and market returns. *Hal* is the Sell in May dummy and is 1 for the period November-April and 0 otherwise. ΔDY is the change in the dividend yield of the S&P 500 index (logged), ΔDefault is the change in the default spread, ΔTerm is the change in the term spread, ΔT-bill is the change in the 3-months T-bill rate and ΔVIX is the change in the CBOE Volatility index. Panel B reports results of Granger Causality Wald tests. The sample period is January 1995 to December 2014.

Panel A - Vector Autoregression of Flow and Market Returns

	Flow		Return	
	Coef.	*t* -stat.	Coef.	*t* -stat.
N	231		231	
Adj. R^2	0.68		0.95	
Constant	**-0.09**	**(-2.01)**	**0.54**	**(4.75)**
$Flow_{t-1}$	**0.22**	**(3.36)**	0.14	(0.85)
$Flow_{t-2}$	**0.14**	**(2.03)**	-0.07	(-0.40)
$Flow_{t-3}$	**0.16**	**(2.38)**	**0.29**	**(1.78)**
$Flow_{t-4}$	0.10	(1.38)	-0.26	(-1.51)
$Flow_{t-5}$	**0.14**	**(2.01)**	**-0.50**	**(-2.96)**
$Flow_{t-6}$	0.07	(1.01)	0.20	(1.20)
$Flow_{t-7}$	-0.01	(-0.14)	-0.12	(-0.71)
$Flow_{t-8}$	0.04	(0.66)	-0.07	(-0.42)
$Flow_{t-9}$	0.07	(1.09)	0.02	(0.10)
$Return_{t-1}$	**0.02**	**(3.09)**	0.02	(1.26)
$Return_{t-2}$	0.00	(0.02)	**0.04**	**(1.88)**
$Return_{t-3}$	-0.01	(-1.30)	0.03	(1.42)
$Return_{t-4}$	0.01	(1.20)	**0.03**	**(1.84)**
$Return_{t-5}$	-0.01	(-1.22)	**0.06**	**(3.46)**
$Return_{t-6}$	-0.01	(-1.10)	**0.03**	**(1.85)**
$Return_{t-7}$	**-0.01**	**(-1.71)**	0.02	(1.18)
$Return_{t-8}$	-0.01	(-1.08)	**0.04**	**(2.18)**
$Return_{t-9}$	-0.01	(-1.34)	**0.04**	**(2.51)**
HAL	**0.25**	**(4.04)**	0.06	(0.42)
ΔDY	**-2.40**	**(-2.53)**	**-91.49**	**(-39.26)**
ΔDefault	0.02	(0.14)	**0.72**	**(2.06)**
ΔTerm	0.27	(1.48)	**-0.78**	**(-1.75)**
ΔT-bill	0.26	(1.39)	**-0.79**	**(-1.69)**
ΔVIX	-0.01	(-1.29)	**-0.06**	**(-2.54)**

Continued: Panel B - Granger Causality Wald Tests

Flow			Return		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
Return	22.49	0.008	Flow	23.12	0.006
All	22.49	0.008	All	23.12	0.006

Since several lags of the variables are included in each of the equations of the system, the degrees of significance and signs vary across the lag length. Both variables are described by several of their own lags but also by lags of the other variable. For example, the coefficients on r_{t-1} and r_{t-7} in the flow equation are 0.02 and -0.01 and have *t*-statistics of 3.09 and -1.71 respectively. Similarly, the coefficients on $Flow_{t-3}$ and $Flow_{t-5}$ in the return equation are 0.29 and -0.50 with *t*-statistics of 1.78 and -2.96. To overcome the difficulty of interpretation and to determine whether flow and market returns affect one another, Panel B of Table 3.7 reports results from Granger causality tests. We find strong evidence for a two-way causality. The *p*-values in both joint significance tests are below one percent. Hence, we conclude that flow contains information about market returns and vice versa. Interestingly, the coefficient on the Sell in May dummy is only significant in the flow equation but not in the return equation. After accounting for lagged values of flow and returns there is no seasonality left in stock returns, which is consistent with the results discussed in the previous section. Finally, it appears that returns react more to news about the economy than flow. All coefficients on the news proxies in the return equation are statistically significant, while only news reflected in ΔDY seems to be important in the flow equation. Overall, the results provide evidence in favour of both the price-pressure and feedback hypotheses after accounting for news proxies as exogenous variables.

3.3.3 The January Effect

Since flow spikes in January (Figure 3.1) and January falls into the winter period, we also examine whether flow helps to explain the January effect. This empirical regularity refers to abnormally high stock returns in January, first documented by Wachtel (1942). Keim (1983), Rozeff and Kinney (1976) and Reinganum (1983) find it to be mainly present among small-cap firms. Schwert (2003) shows that the effect might have become smaller since its discovery, but the effect has not disappeared. Several explanations have been proposed for this anomaly, but empirical results are mixed. For example, Rozeff and Kinney (1976), Chang and Pinegar (1988a, 1988b, 1989, 1990), Rogalski and Tinic (1986), Keamer (1994) and Sun and Tong (2010) suggest that the January effect is due to the seasonality in risk or in the compensation for risk. Tinic and West (1984) find the mean-variance trade-off is only present in January. Haugen and Lakonishok (1987) and Lakonishok et al. (1991) propose a window dressing hypothesis in which institutional investors try to make their portfolios look better by selling stocks with large losses at the end of the year. Branch (1977), Dyl (1977), Reinganum (1983), Jones et al. (1991) and Poterba and Weisenbenner (2001) attribute the effect to tax-loss selling in December and corresponding purchase activities in January. Chen and Singal (2004) also demonstrate that tax-loss selling is the main driver behind this anomaly.

To test our flow-based explanation we begin by repeating the analyses conducted earlier with a January indicator. Since we do not find a January effect in the value-weighted CRSP stock market index, all the tests below are based on the CRSP equally weighted index.

Table 3.8: Mutual Fund Flows and the January Effect

This table reports estimation results for different variants of equation (3.2). The dependent variable is the monthly return on the EW CRSP stock market index (NYSE + AMEX + NASDAQ). The January dummy, Jan_t, is 1 for returns that fall into January and 0 otherwise. $Flow_t$ is the estimated monthly net flow (market-wide) of our sample funds. Standard errors are corrected for heteroskedasticity and autocorrelation. *t*-statistics are reported in parentheses. The sample period is January 1995 to December 2014.

	(1)	(2)	(3)	(4)	(5)
Obs.	240	240	240	240	240
Adj-R^2	0.02	0.20	0.21	0.20	0.18
Intercept	**0.89**	0.74	2.86	**-1.86**	0.79
	(2.02)	(1.63)	(1.52)	**(-0.82)**	(1.56)
Jan	**2.73**	0.42	0.47	0.44	0.74
	(1.95)	(0.29)	(0.33)	(0.30)	(0.53)
Flow		**4.93**	**4.97**	**4.94**	
		(6.66)	**(6.76)**	**(6.70)**	
$Flow_{t-1}$		**-1.52**	**-1.40**	**-1.40**	
		(-1.77)	**(-1.72)**	**(-1.77)**	
$Flow_{t-2}$		-0.58	-0.49	-0.49	
		(-0.76)	(-0.63)	(-0.63)	
$Flow_{t-3}$		**-1.56**	**-1.42**	**-1.42**	
		(-2.63)	**(-2.26)**	**(-2.20)**	
PE_{t-1}			**-0.11**		
			(-1.70)		
DY_{t-1}				1.35	
				(1.08)	
Expected Flow					0.92
					(1.23)
Unexpected Flow					**4.69**
					(6.23)

The first column in Table 3.8 reports an average January effect of 2.73% with a *t*-statistic of 1.95. If we include our flow variables the January indicator is completely subsumed.[92] The coefficient on *Flow* is 4.93 with a *t*-statistic of 6.66. Again, consistent with a lagged reversal of the price pressure effect, lagged flow is negatively related to stock returns. The *t*-statistics on the first, second and third lags of flow are -1.77, -0.76 and -2.63 respectively. The estimates on flow are essentially unaffected when the price-earnings ratio and the dividend yield are included, as shown in columns three and four. Column five shows again that it is the unexpected component of flow that is driving the results with a coefficient of 4.69 and a *t*-statistic of 6.23. The coefficient on expected flow is not statistically significant due to the same reasons as discussed above. Expected flow lags returns.

Next, we test whether flow helps explaining the January regularity alongside other alternatives. For this, we first estimate abnormal return and flow in January with the following regressions:

$$r_t = \mu + \beta_1 r_{t-1} + \beta_2 Jan_{1995} + \beta_3 Jan_{1996} + \ldots + \beta_{21} Jan_{2014} + \varepsilon_t \qquad (3.5)$$

$$Flow_t = \mu + \beta_1 Flow_{t-1} + \beta_2 Jan_{1995} + \ldots + \beta_{21} Jan_{2014} + \varepsilon_t \qquad (3.6)$$

where r_t is the return on the equally-weighted CRSP stock market index in month *t*. $Flow_t$ is the aggregate net flow of our sample funds standardised by the value of the stock market (NYSE + AMEX + NASDAQ) in the previous month. Lagged returns and lagged flow are

[92] Since the January effect is size-related, we also tested our flow-based explanation using only flow of small-cap and medium-cap funds. All results reported in this section are confirmed and, if anything, the effect of flow becomes stronger. For example, the coefficients on concurrent flow in Table 3.8 are larger in magnitude and have a *t*-statistic of more than 7.3. The results can be obtained from the authors.

included to account for serial correlation. β_2 - β_{21} represent the abnormal return and flow in January estimated for each year over the sample period.

Table 3.9: Abnormal Return and Flow in January

Column two of the table reports abnormal return on the EW CRSP stock market index in January estimated with equation (3.5). Abnormal flow of the sample funds in January based on equation (3.6) is reported in column four. Standard errors are corrected for heteroskedasticity and *t*-statistics are reported in parentheses. The sample period is January 1995 to December 2014.

	January Excess Return		January Excess Flow	
	Coef.	*(t-stat.)*	Coef.	*(t-stat.)*
Obs.	240		240	
Adj-R^2	0.07		0.54	
1995	**2.41**	**5.28**	**0.59**	**19.14**
1996	**2.61**	**7.21**	**1.16**	**20.73**
1997	**5.78**	**14.40**	**1.24**	**40.56**
1998	**1.39**	**2.65**	**0.36**	**8.27**
1999	**5.41**	**15.43**	**0.61**	**18.56**
2000	**2.56**	**3.66**	**0.23**	**7.38**
2001	**21.99**	**52.10**	**0.50**	**16.09**
2002	-0.10	-0.19	**0.65**	**21.06**
2003	0.81	1.26	0.00	-0.02
2004	**5.07**	**12.78**	**1.17**	**26.23**
2005	**-4.74**	**-10.07**	**0.10**	**3.13**
2006	**6.68**	**18.88**	**-0.09**	**-2.90**
2007	**1.24**	**3.53**	**0.31**	**8.71**
2008	**-4.93**	**-11.13**	**-1.48**	**-34.51**
2009	**-3.98**	**-9.67**	**0.76**	**12.26**
2010	**-2.99**	**-6.19**	**0.48**	**5.83**
2011	-0.71	-1.23	**0.96**	**12.24**
2012	**7.95**	**19.61**	**0.47**	**4.89**
2013	**5.21**	**14.81**	**1.26**	**13.42**
2014	**-1.34**	**-3.76**	**0.08**	**1.73**

Table 3.9 shows the January effect is positive and statistically significant in 12 out of 20 years. With a few exceptions (e.g. 2002 and the GFC), we also observe that in years with strong and positive (negative) abnormal flow, the January effect is large and positive (negative).

Table 3.10: Relationship between $Flow_t$, PTS_t, Vol_t, Std_t and the January Effect

This table reports results of regressions in which the dependent variable is the January effect estimated with equation (3.5). $Flow_t$ is the abnormal flow in January estimated with equation (3.6). PTS_t is the equally weighted year's end potential tax-loss selling over all stocks listed on the NYSE, AMEX and NASDAQ. It is defined as the percentage decrease from the highest price attained during a year to December 15. If there was no trading on December 15, we take the price of the previous day. Vol_t is the natural logarithm of dollar volume in January relative to the average monthly dollar volume over the previous six months (July – December). Monthly volume is calculated from the numbers of shares traded on day *t* times closing price of day *t* of each stock listed on the NYSE, AMEX and NASDAQ. Data on prices and number of shares are obtained from CRSP via WRDS. Std_t is the natural logarithm of the standard deviation of the EW CRSP stock market index in January relative to the standard deviation of the index over the previous six months (July – December). Standard deviation is calculated from daily returns. Standard errors are corrected for heteroskedasticity and autocorrelation. *t*-statistics are reported in parentheses. The sample period is 1995 to 2014.

	Intercept	Flow	PTS	Vol	Std	R^2
Coef.	1.17	**2.87**				0.09
(t-stat.)	0.97	**(4.97)**				
Coef.	-4.39	**3.17**	-16.72	4.48	-2.35	0.20
(t-stat.)	-1.06	**(3.55)**	(-0.93)	(1.28)	(-0.63)	

Table 3.10 reports results of a regression in which the dependent variable is the January excess return estimated with equation (3.5). The only explanatory variable in the first test is the estimated abnormal flow in January. In this univariate test, flow is positively related to the January effect with a coefficient of 2.87 and a *t*-statistic = 4.97. The second model includes proxies for alternative explanations for the January effect suggested in previous

research. PTS_{t-1} is the maximum potential tax-loss selling at the end of a year. Following previous studies in the literature, we define it as the percentage decrease in stock price from the highest price during the year to mid-December, usually December 15. If there was no trading on this day, we take the price from the previous trading day.

$$PTS = \frac{\sum_{i=1}^{n}\left(\frac{price_{it,Dec.}}{price_{it,High}}\right) - 1}{n} \tag{3.7}$$

We include liquidity and volume as other potential sources for the January seasonality. Abnormally high volume usually occurs with informed trading and as such, is consistent with the information release hypothesis. However, the entry of noise traders may also affect volume. Another reason to include volume here is to avoid the possibility that flow is just volume in disguise. Standard deviation is also included to account for risk. Both of these measures are estimated in relative terms - i.e. January dollar volume and January standard deviation relative to volume and standard deviation over the previous six months.[93]

The results reported in Table 3.10 show that excess flow helps explain the January effect alongside alternative explanations discussed in literature. The coefficient of *Flow* is 3.17 with a *t*-statistic of 3.55. Consistent with previous studies, *PTS* is negatively related to the January effect with a coefficient of -16.72, but it is not significant in statistical terms.[94] The estimates on *Vol* and *Std* are also not more than two standard errors away from zero. However, if we exclude the GFC (not reported) the *t*-statistic of *PTS* is -2.29, while the signs for *Vol* and *Std* change and become more in line with the general risk-return trade-off. Yet, both variables remain insignificant while the amount of variation in the January

[93] The choice of the time period, whether it is the previous six or eleven months, does not affect the results.
[94] PTS is between -1 and 0 by construction.

effect explained increases to 30%. In any case, the coefficients on flow are consistently significant with *t*-statistics of more than 3.0. Overall, we interpret our results that flow is related to the January anomaly in stock returns.

3.4 Robustness – Retail versus Institutional Funds

In this section we distinguish between flows into retail and institutional funds as they cater to very different clienteles. Funds with a minimum investment of $100,000 or more are usually classified as institutional and generally aim at corporations, pension funds, and other large investors. On the other hand, retail funds focus on private individual investors. Prior research has shown that portfolio choice, investor behaviour and the flow-performance relation between both groups are different. For example, Del Guercio and Tkac (2002), James and Karceski (2006), and Salganik (2015) show that clients of institutional funds tend to use more sophisticated performance measures such as risk-adjusted return measures or tracking error, and do not display the same return chasing behaviour as their retail counterparts. In line with these findings, Figure 3.3 illustrates very different patterns in the flows of the two fund groups. Net flows of retail funds display a clear winter-summer seasonal, while those of institutional funds do not exhibit any pattern except for being positive throughout the year. Retail fund flows, by contrast, are mainly positive during winter months and negative, on average, during most summer months.

Figure 3.3: Retail Flow versus Institutional Flow

This figure shows the average monthly flow of retail and institutional funds separately. Funds with a minimum investment of USD 100,000 or more are categorised as institutional, all other funds are retail funds. The sample period is January 1995 to December 2014.

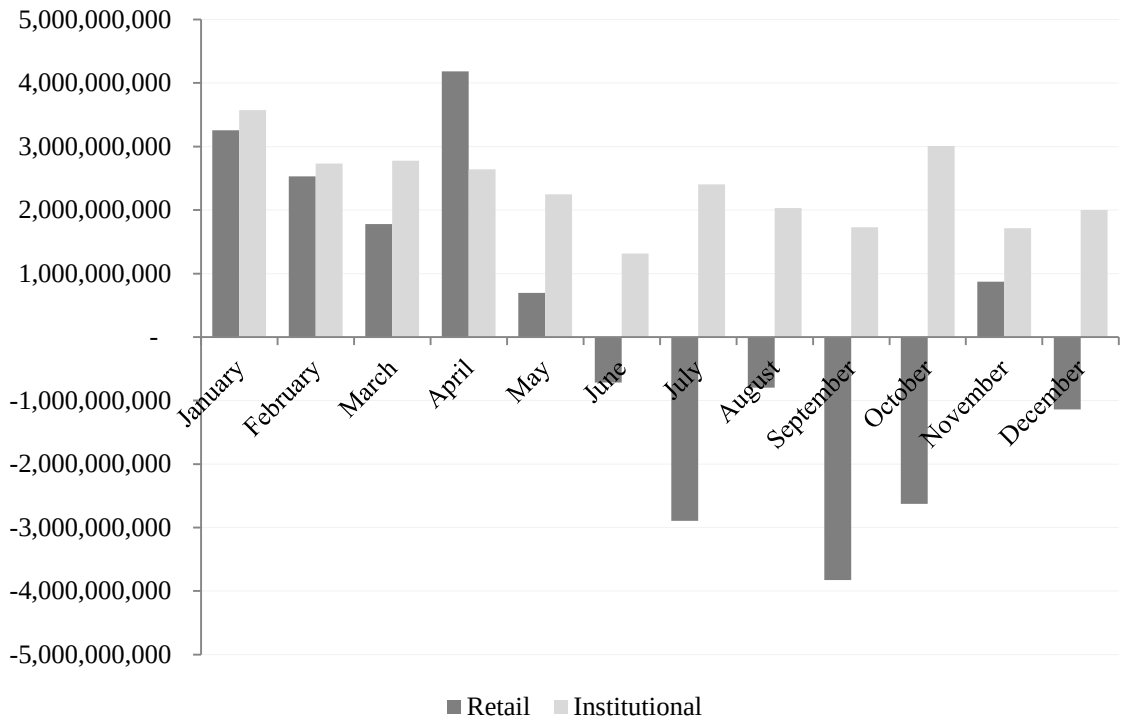


Table 3.11 reproduces the results of our previous analyses for both groups separately. Consistent with Figure 3.3, Panel A shows that the Sell in May dummy becomes insignificant only when we account for flows of retail funds. The coefficient on the seasonal dummy in column two drops to 0.11 and has a *t*-statistic of 0.24.

Table 3.11: Retail versus Institutional Funds and Seasonalities in Stock Returns

This table reports estimation results for different variants of equation (3.2). The dependent variable in Panel A is the monthly return on the S&P 500 index. The Sell in May dummy, Hal_t, is 1 for the period November-April and 0 otherwise. The dependent variable in Panel B is the monthly return on the EW CRSP stock market index (NYSE + AMEX + NASDAQ). The January dummy, Jan_t, is 1 for returns that fall into January and 0 otherwise. $Flow_t$ is the estimated monthly net flow (market-wide) of retail and institutional funds. The latter are funds with a minimum investment of USD 100,000 or more. Standard errors are corrected for heteroskedasticity and autocorrelation. *t*-statistics are reported in parentheses. The sample period is January 1995 to December 2014.

Panel A - Sell in May Effect

		Fund Types	
		Retail Funds	Institutional Funds
	(1)	(2)	(3)
N	240	240	240
Adj-R^2	0.01	0.14	0.01
Intercept	0.24	0.57	0.82
	(0.57)	(1.56)	(1.35)
Hal	**0.96**	0.11	**1.03**
	(1.85)	(0.24)	**(1.92)**
Flow		**3.60**	1.52
		(5.25)	(0.68)
$Flow_{t-1}$		**-1.70**	-3.38
		(-2.30)	(-1.41)
$Flow_{t-2}$		0.01	-1.85
		(0.01)	(-1.10)
$Flow_{t-3}$		-1.02	-0.16
		(-1.50)	(-0.07)

Continued: Panel B - January Effect

		Fund Types	
		Retail Funds	Institutional Funds
	(1)	(2)	(3)
N	240	240	240
Adj-R^2	0.01	0.20	0.01
Intercept	**0.89**	**0.94**	**1.31**
	(2.08)	**(2.44)**	**(1.68)**
Jan	**2.73**	0.73	2.35
	(1.99)	(0.53)	(1.64)
Flow		**5.30**	3.40
		(6.17)	(1.11)
$Flow_{t-1}$		**-1.68**	-1.32
		(-1.67)	(-0.40)
$Flow_{t-2}$		-0.54	-2.27
		(-0.59)	(-1.04)
$Flow_{t-3}$		**-1.90**	-2.31
		(-2.90)	(-0.74)

However, the Sell in May effect remains at about 1% when we account for institutional fund flows with a *t*-statistic of 1.92. This is largely due to the lack of a clear flow-performance relation in institutional funds, which is in line with James and Karceski (2006). They find that institutional fund flow is less sensitive to performance than retail fund flow, explained by the more sophisticated performance measures that this investor group implement. Accordingly, the coefficients on flow and lagged flow in column three are all less than two standard errors away from zero. Hence, we can further conclude that the well-known positive relation between aggregate fund flow and concurrent market return seems to stem mainly from retail flows. The coefficient on *Flow* in column one is 3.60 with a *t*-

statistic of 5.25. The estimate on lagged flow is again negative, -1.70 with a *t*-statistic of -2.30.

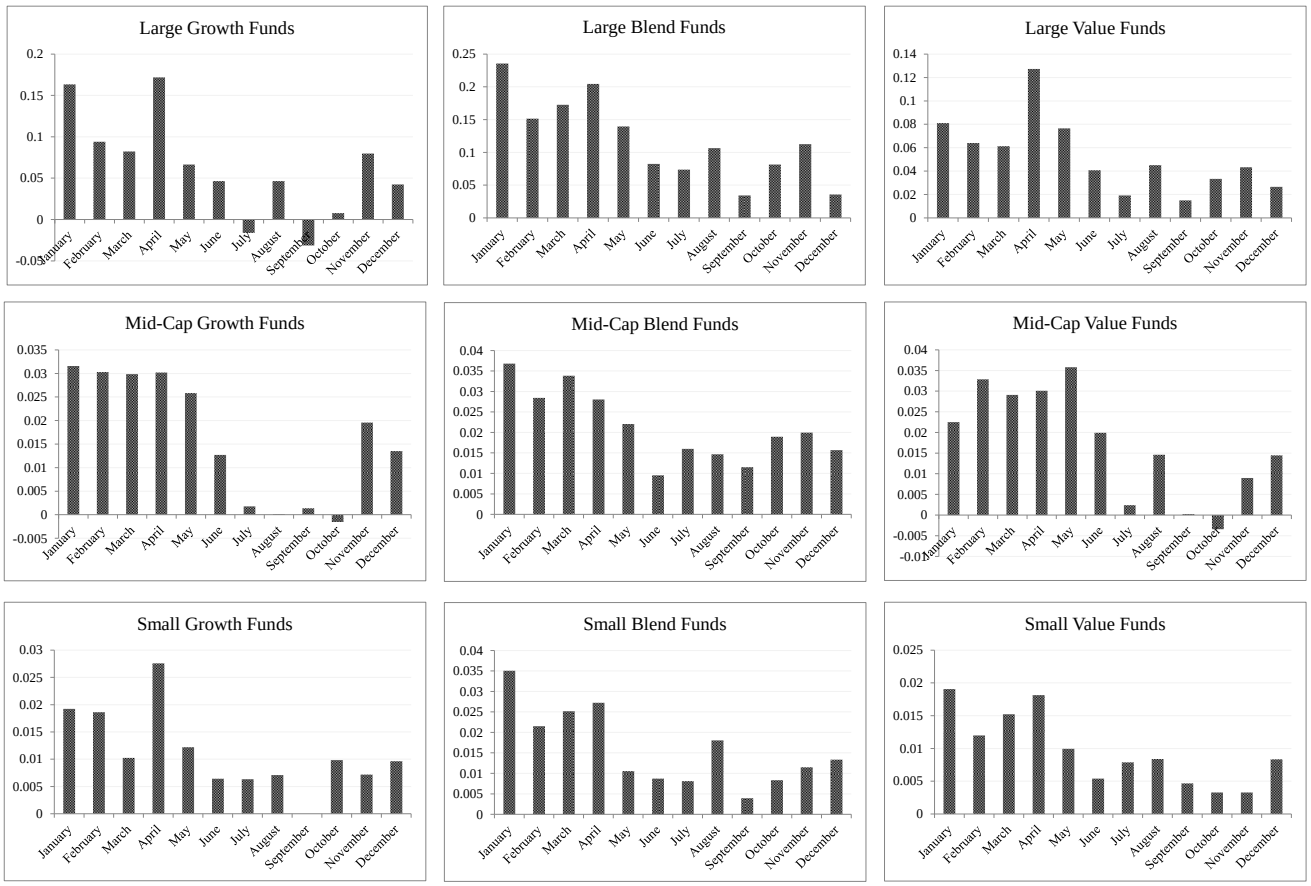
Panel B shows essentially the same results for the January effect. After accounting for retail investor flow, the estimated excess return drops from 2.73% to 0.73% with an insignificant *t*-statistic of 0.53. The coefficients on lagged flow are -1.68 and -1.90 with *t*-statistics of -1.67 and -2.90 respectively. After accounting for institutional fund flow, the coefficient on the seasonal dummy is with 2.35% not much different compared to column one but insignificant with a *t*-statistic of 1.64. Again, none of the flow variables are related to market returns.

3.5 Seasonality in Fund Flow by Fund Style

To shed more light on the seasonality of fund flows, we calculate average monthly flows by fund style in order to examine if the documented patterns in fund flow are largely driven by investor's appetite for certain stocks that varies over the seasons. We group all the funds in our sample using the nine Morningstar categories which are assigned based on the underlying securities in each portfolio. The categories are built along two dimensions - market capitalisation (large, mid-cap and small) and valuation ratios (growth, blend and value). Figure 3.4 shows that essentially all investment styles exhibit a similar winter-summer seasonal as the overall market.

Figure 3.4: Fund Flow and Investment Style

This figure shows the average monthly fund flow of all funds categorised by investment style. The categories are taken from Morningstar which are assigned based on the underlying securities in each fund portfolio. The nine categories are large growth, large blend, large value, mid-cap growth, mid-cap blend, mid-cap value, small growth, small blend and small value. The time period is January 1995 to December 2014.



Flow during the winter months is on average larger than during the summer months. This pattern is particularly pronounced in funds that predominantly invest in large and mid-cap growth stocks, with very low or even net outflow in most of the summer months. However, value funds also exhibit a similarly strong winter-summer seasonal. There is not

much difference in the pattern between large-cap and small-cap oriented funds, or between those that predominantly invest in stocks for which neither growth nor value characteristics are dominating (blend stocks). Overall, we cannot identify a clear preference for a certain style characteristic during the winter months. Instead, the pattern appears to be strikingly robust across all categories.

3.6 Conclusion

Consistent with prior research we find a statistically and economically significant difference between returns during the winter and the summer months. We provide a flow-based explanation for this long-standing anomaly that challenges basic financial theory. Specifically, we first document a strong winter-summer seasonality in mutual fund flows which is present across all investment styles. We then show that the Sell in May effect is positive (negative) in years when fund flows during the winter months are higher (lower) than those during the summer months. After controlling for mutual fund flows the Sell in May effect becomes insignificant. Excess fund flow in winter months explains almost half of the variation in the Sell in May effect. We also find that fund flow helps to explain the January effect. Both of these calendar month effects are mainly driven by flows of retail funds. Similarly, the well-known contemporaneous relation between fund flow and market returns is only exhibited in retail fund flow. Results from an unrestricted VAR model shows that flows contain information on return and vice versa. Our findings are therefore consistent with both the price pressure and the positive feedback trading hypothesis.

If flow provides an explanation for seasonalities in stock returns an interesting question remains, what drives seasonalities in fund flows? Maybe the marginal propensity to save of individual investors is simply lower during the summer months compared to the winter

months when end-of-year bonuses are paid. For most people summer is the time to spend on leisure activities such as travelling. Not at least because of the long school vacation in the US from the end of July until mid-September. While this is just speculation, it is consistent with an increase in the number of US outbound travels during the summer months available from the Office of Travel and Tourism Industries. It is also consistent with the oldest explanation for the Sell in May effect, that investors take holidays during the summer months away from the stock market and hence do not trade as much. Finding an explanation for the seasonality in fund flows provides an interesting area of future research.

PART III

CONCLUSION

In the introduction I motivate the focus of my first essay on emerging market funds by the lack of attention this sector has received, the ongoing debate about the performance of mutual funds and the theoretical appeal of the efficient market hypothesis. Market or informational efficiency refers to the proposition that security prices fully reflect all available information that is known at time *t*. By implication, investors are not able to consistently achieve above average returns by spending time and resources to detect mispriced securities or timing the market, since all investments are presumably fairly priced. However, markets where information is not evenly disseminated and hence not immediately or correctly priced might provide more opportunities for active investing to add value. And indeed, funds that predominantly invest in emerging market equities have higher reward-to-risk ratios compared to a set of market indices. However, in terms of benchmark-adjusted returns emerging market funds only outperform before costs. After expenses the usual alpha measures are indistinguishable from zero. On the country level, performance varies greatly with China funds on top, significantly outperforming the market net of expenses, whereas Latin America funds (Brazil and Chile) substantially underperform on average. Similarly, security selection skills may be biased downwards in models not accounting for rather poor market timing skills on average. Distinguishing between funds that are located within (local investors) and those outside their geographical investment focus (foreign investors) reveals that local funds tend to perform better than foreign investors. I show that foreign funds invest less in small cap and growth stocks, which might be an explanation for the different performance. My analysis on style portfolios indicates that small beats large and growth value investing. Overall, I follow a rather traditional approach in chapter 1 which allows making meaningful comparisons to the greater part of the existing performance literature on mutual funds. Future research

should consider recent developments and some of the novel statistical methods in this area, as discussed in the introduction.

The second essay provides evidence of late trading in mutual fund shares in European markets. Late trading is a form of backward pricing and prohibited by law. According to the SEC, it refers to the practice of permitting buy and sell orders received after the cutoff time but for the price calculated at cutoff. Late trading appears to be mainly present in large funds, where it might be easier to hide the illicit trades among the large number of orders and the higher amount of flow compared to smaller funds. Given the outcome of an investigation by European regulators which concluded that late trading is not a concern in the member states my results are surprising and unexpected. I find that late trading accounts for up to 10% of daily flow and investors who are allowed to trade late can earn up to 35% annually. Finding evidence of this practice in statistical models highlights the potential benefit of using such tests for general investor protection. However, despite my best efforts model errors cannot be excluded with certainty. The initial suspicion of late trading is therefore subject to an open investigation until confirmed or refuted. Another limitation is that even if the tests are correct, no information regarding the parties involved is provided.

The main contribution of my third essay is a flow-based explanation for the Sell in May and January effects. According to financial theory these anomalies should not exist, yet both are rather pervasive and prior research has not come up with a convincing story for these empirical regularities. Mood changes and temperature as possible explanations for the Sell in May effect have been challenged in literature, while tax-loss selling suggested for the January effect is reasonable but leaves much unexplained. Just as market returns tend to be higher during winter months compared to summer months, I document that in most years fund flow is also higher during winter months than during summer months. In

all years where this is not the case, summer returns are higher than winter returns, i.e. the Sell in May effect is negative. Furthermore, after controlling for aggregate mutual fund flow, there are no seasonalities left to be explained in market returns. Both appear to be a retail money effect. Distinguishing between retail and institutional funds also shows that the contemporaneous relation of aggregate flow and market returns, known since Warther (1995), is only present in the case of retail funds. Addressing the question of causality reveals that it is the unexpected component of flow which is driving the results, while expected flow lags return. Based on an unrestricted VAR model, I find that flow Granger-causes return and vice versa. The distinct winter-summer pattern found in flow is present across all investment styles. Understanding why flow is higher during winter months is an interesting area for future research.

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