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# The Impact of Equity Mutual Fund Flows on the Stock Market

Evidence from International Data

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# Problem description

Is the variation in association between equity mutual fund flows and stock prices across national borders due to variation in investor responsiveness to changes in macroeconomic factors? What is the universal impact of equity mutual fund flows on the stock market?

# Preface

This master's thesis is written in the final semester of the master's programme Industrial Economics and Technology Management at the Norwegian University of Science and Technology (NTNU). The thesis is written in the form of an article with the purpose of being published in a scientific journal, and it explores the relationship between aggregate equity mutual fund flows and stock market returns.

We would like to extend our appreciation to our supervisor, Peter Molnár, for all his input. His insight and experience has been of great value to us.

# Abstract

The impact of equity mutual fund flows on the stock market has been studied extensively, but always on individual countries, and the literature remains inconclusive. We therefore utilise a decade's worth of data from 13 countries to investigate the impact of equity mutual fund flows on stock market returns and vice versa. Through panel data analysis, we find no evidence of a link between equity mutual fund flows and stock market returns that is common across countries. This result holds both in periods of market tranquility and market turmoil. When analysing each country separately, we fail to uncover a significant relationship in most countries. Furthermore, the statistically significant relationships we find differ across countries both in sign and in direction of causality. This suggests that the relationship between equity mutual fund flows and stock movements is much weaker than one would infer from past studies.

Keywords: equity mutual funds; net fund flows; excess index returns; information-response hypothesis

# Sammendrag

Virkningen nettoinnskudd i aksjefond har på aksjemarkedet har blitt studert grundig, men alltid på enkeltland, og mange av disse studiene trekker motstridende konklusjoner. Derfor har vi benyttet oss av data fra 13 land. Når vi behandler dataene som paneldata i vår analyse av samspillet mellom nettoinnskudd i aksjefond og avkastning i aksjemarkedet, finner vi ingen sammenheng som er felles for landene, og vi har studert både oppgangstider og en periode med børskrakk. Når vi analyserer samspillet i hvert enkelte land, finner vi signifikante sammenhenger i bare noen av landene. For disse markedene, varierer både retningen på kausaliteten og fortegnet på disse sammenhengene. Dette antyder at sammmenhengen mellom innskudd i aksjefond og avkastningen i aksjemarkedet er mye svakere enn man skulle anta ut ifra tidligere studier.

# 1 Introduction

Over the course of the 1990's, equity mutual funds soared in popularity in the US, showing compounded growth in total net assets of 36.9 % annually from 1990 to 1999 (Reid, 2000). The immense growth of the US equity mutual fund industry during the 1990's is illustrated in figure 1. In the wake of this, people began questioning whether mutual funds potentially have market moving impact (Edwards and Zhang, 1998), and in the late 90's, a fair amount of research was conducted on the US mutual fund market. The burst of the dotcom bubble provided further indication that the large investments in equity mutual funds had elevated stock prices from their true values, and post 2003, studies of the market impact of mutual funds have been carried out in numerous countries around the world.

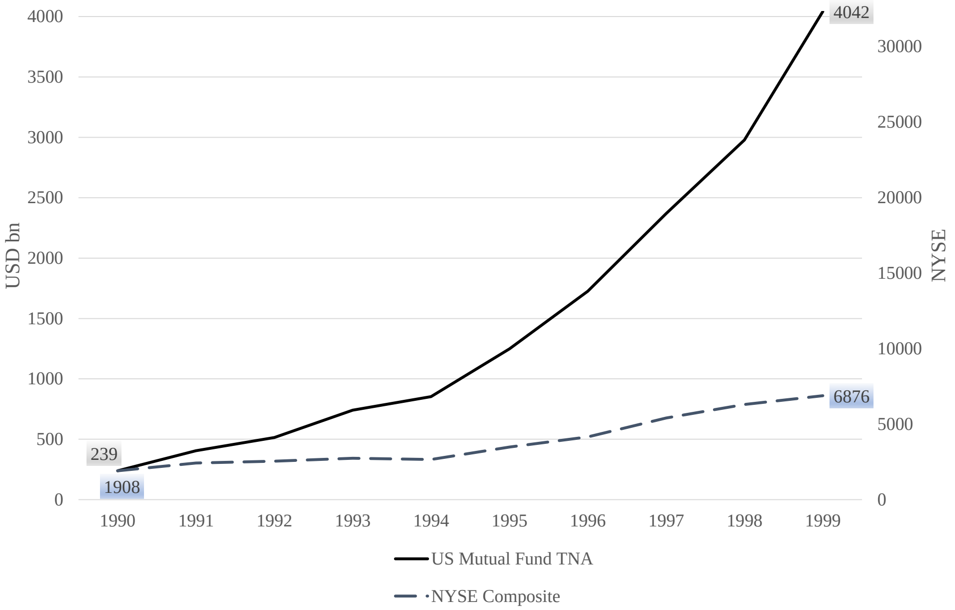



**Figure 1:** Development of US equity mutual funds (left) and the NYSE Composite index (right) over the period Dec 1990 – Dec 1999. Sources: ICI, Yahoo! Finance

Prior research, all of which has been conducted country-by-country, indicates large differences in the relationship between equity mutual fund flows and stock market returns between countries without reasoning why it is the case. One possible explanation is that previously studied data sets contained too few observations for accurate conclusions to be drawn. By studying panel data from 13 countries, we seek to produce a more precise result and discover the country-independent effect of domestic equity mutual fund flows on the stock market in that same country. Another possible explanation is that there exist differences between countries unaccounted for in previous studies. By controlling for numerous factors known to explain or predict stock market returns or equity mutual fund flows, this study aims to discover whether the variation in the relationship between equity mutual fund flows and stock price changes across national markets can be explained by variation in market sensitivity to macroeconomic and financial factors. To uncover the nature of the relationship between equity mutual fund net flows and stock market returns, both temporal and causal links are investigated, and we control for macroeconomic factors in both cases.

We find no common relationship between monthly domestic equity mutual fund net flows and monthly excess stock market returns across countries. A relationship between the two is absent both in periods of rising stock markets and during a market crash. For individual countries, we uncover differing relationships even when macroeconomic and financial variables are controlled for, revealing that the variation in the relationship between equity mutual fund flows and stock price changes across national markets cannot be explained by variation in market sensitivity to macroeconomic and financial factors. This implies that equity mutual fund investors behave differently in different countries.

The rest of this article is structured as follows. First we provide an overview of previous literature on this topic, after which the data and all transformations applied to it are presented. The methodology section describes the statistical techniques and regression models used in our analyses. Results are given and compared to previous findings in section 5, before section 6 concludes.

## 2 Literature Review

**First findings give birth to many hypotheses**

Warther (1995) was the first to study a potential association between aggregate mutual fund flows and market returns. He partitions mutual fund flows into expected and unexpected components and finds a strong contemporaneous relationship between unexpected flows and index returns in monthly data. He suggests three possible reasons for this: (a) information revelation - mutual fund investors are better informed than the wider market, and as the market responds to this new information, asset prices will move in the same direction as the fund flows; (b) price pressure - fund flows put price pressure on the assets they invest in; (c) investor sentiment - mutual fund investors are among those least informed in the market and their investment decisions are not entirely rational.

A positive association between equity mutual fund flows and stock returns is well-documented (Fortune, 1997; Edwards and Zhang, 1998; Edelen and Warner, 2001). This begs the question: are mutual fund investors responding to stock market developments, or do stock returns follow mutual fund flows? Knowing the direction of causality goes a long way in uncovering the process at work that explains this concurrent relationship.

**Four hypotheses and causal relationships – explaining the links**

The time it takes for equity mutual fund flows to respond to stock market returns and vice versa is not known. Neither is the duration of such a reaction. We classify responses detected in monthly or lower frequency data as long-term responses, and responses detected in weekly or higher frequency data as short-term responses. The inferences we make from short- and long-term responses differ, and they relate to how quickly inflows to equity mutual funds are invested in the stock market. Portfolio manager Odd Rune Heggheim at KLP and investment director Gunnar J. Torgersen at Holberg Fondene both said that net inflows to their equity funds are invested almost immediately, whereas head of equities at Alfred Berg Kapitalforvaltning, Leif Eriksrød, stated that funds are normally invested within a few days when we asked by email. Based on these responses, it is fair to assume that fund managers invest the majority of new capital inflows within the next trading day and all of it within a few days. We now put forth what the different possible responses (i.e. causal relationships) as well as findings of a contemporaneous relationship imply. An overview is given in table 1.

Market returns responding to aggregate net flows would provide support for the information revelation hypothesis (a) in both the short and long term. It is not obvious how long the broader market would take to respond to the information contained in the mutual fund flows. Likely, it would vary, but we consider some reaction in both the short and long term possible.

Returns following flows in the short-term would also provide support for the price pressure hypothesis (b). This is because much of the capital inflows to a fund are invested the following trading day or days.

A negative long-term response in returns to flows in addition to a positive concurrent relationship would be indicative of temporary price pressure (b). The vast majority of net capital inflows to equity funds will be invested in the stock market in the same month as the flows came in. If this elevates stock prices beyond their true values, smart investors will trade its value down again. Although the efficient market hypothesis has repeatedly come under scrutiny (Malkiel, 2003), it may be the case that such trading opportunities are almost always noticed so quickly that a negative relationship between flows and subsequent returns would not be found at the monthly level. Even if the market reacts within a week on average, though, the negative relationship will be observable in monthly data, and we therefore deem it plausible. Higher net flows following higher market returns would indicate that fund investors follow a momentum trading strategy, whereas higher net flows lagging lower market returns would indicate a contrarian strategy (c).

Net flows responding positively to market returns would indicate that fund investors follow a momentum trading strategy, whereas a negative response would indicate a contrarian strategy (c). This is true both in the short and long term. Should there be bidirectional positive causality, positive feedback trading would be at work (Remolona et al., 1997).

**Table 1:** Overview of which relationships between net flow to equity mutual funds and stock market returns are indicative of the different hypotheses. The first column in each panel shows net flows impacting market returns, the second market returns impacting net flows, and the third the contemporaneous relationship. A '+' represents a positive relationship; a '-' represents a negative relationship; parentheses indicate that the connection between the relationship and the corresponding hypothesis is less likely.
*If prices revert to "true" values quickly enough e.g. within a matter of days, there will be no long-term response.

| | **Short-Term** | | | **Long-Term** | | |
|---|---|---|---|---|---|---|
| | NF → Ret | Ret → NF | Cont | NF → Ret | Ret → NF | Cont |
| **Information Revelation (a)** | + | | | (+) | | + |
| **Price Pressure (b)** | + | | + | -* | | +* |
| **Momentum (c)** | | (+) | | | + | (+) |
| **Contrarian (c)** | | (-) | | | - | (-) |

**Further studies in various countries draw contradictory findings**

The causal relationship between equity mutual fund flows and stock market returns has been studied in the USA by numerous authors drawing different conclusions. E.g., Warther (1995) and Fant (1999) find that net flows are lower in months following high returns, whereas Fortune (1998) and Edwards and Zhang (1998) find that they are higher. More recently, also various other countries have been the subject of mutual fund flow study. The positive concurrent relationship between equity mutual fund flows and stock returns has been found in Korea by Oh and Parwada (2007), in India by Thenmozhi and Kumar (2009), and in both Hong Kong and Singapore by Yangbo et al. (2010). The degree to which the stock market increases with higher fund flows varies across markets, however, as is evident from Yangbo et al. (2010)'s comparative analysis of Hong Kong and Singapore. The causal relationships also seem to vary from country to country; Lee et al. (2015) studied both directions of causality within five Western and five Asian markets, finding significant differences.

Although previous papers concur that there exists a positive association between equity mutual fund flows and stock market returns, as mentioned, there is division in the literature about the nature of the causal relationship(s) between the two. This disaccord is highlighted in table 2, which provides an overview of previous findings. Applying the framework in table 1 to the findings of each paper featured in table 2 individually, one can deduce which hypotheses each paper supports. Such an overview is given in table 3.

**Table 2:** Overview of the relationships found in various research papers between net flows to equity mutual funds and stock market returns, significant at the 5 % level. The articles, including the market and data frequency studied, are listed in the leftmost column. The following three columns show net flows impacting returns, returns impacting net flows, and the contemporaneous relationship, respectively. A '+' represents a positive relationship; a '-' represents a negative relationship; a blank space indicates that no relationship was found; a '?' indicates that a relationship was found, but that the sign is unknown; an 'X' indicates that the relationship was not studied.

| | **Short-Term** | | |
|---|---|---|---|
| **Paper** | NF → Ret | Ret → NF | Cont |
| Warther (1995); weekly | + | | X |
| Edelen and Warner (2001); daily, semi-weekly | | + | + |
| Goetzmann and Massa (2003); daily | + | | + |
| Caporale et al. (2004); daily | - | + | |
| Alexakis et al. (2005); daily | - | + | |
| Oh and Parwada (2007); daily | | - | + |
| Thenmozhi and Kumar (2009); daily | | - | + |
| Aydogan et al. (2014); daily | + | + | ? |
| | **Long-Term** | | |
| | NF → Ret | Ret → NF | Cont |
| Warther (1995); monthly | | - | + |
| Fortune (1997, 1998); monthly | | + | + |
| Edwards and Zhang (1998); monthly | | + | + |
| Fant (1999); monthly | + | - | X |
| Yangbo et al. (2010); quarterly | + | + | + |
| Yangbo et al. (2010); quarterly | | | + |
| Watson and Wickramanayake (2012); monthly | | ? | + |
| Lee et al. (2015); monthly | | + | X |
| Lee et al. (2015); monthly | | | X |

Table 3 reveals that much support exists for (c), with an overweight toward the hypothesis that mutual fund investors chase returns. However, support also exists for (a) and (b). Khan et al. (2012) found that for "stocks exposed to buying pressure from mutual funds experiencing large capital inflows, but not subject to widespread buying pressure from other mutual funds", "the probability of an SEO, insider sales, and the probability of a stock-based acquisition increase significantly in the four quarters following the mutual fund buying pressure" (Khan et al., 2012), and thus concluded that funds experiencing very high net inflows have significant pricing impact. It is alarming that so many research papers present contradictory findings, and one plausible reason is that different papers have researched different markets.

**Table 3:** Past evidence of Warther (1995)'s hypotheses. Here, the framework in table 1 has been applied to the findings of causal and temporal relationships between equity mutual fund flows and stock market returns in individual papers.

| **Information Revelation (a)** | **Price Pressure (b)** |
|---|---|
| Warther (1995) | Warther (1995) |
| (Fant (1999) ) | Goetzmann and Massa (2003) |
| Goetzmann and Massa (2003) | Aydogan et al. (2014) |
| (Yangbo et al. (2010) ) | |
| **Momentum (c)** | **Contrarian (c)** |
| Fortune (1997, 1998) | Warther (1995) |
| Edwards and Zhang (1998) | Fant (1999) |
| (Edelen and Warner (2001) ) | (Oh and Parwada (2007) ) |
| (Caporale et al. (2004) ) | (Thenmozhi and Kumar (2009) ) |
| (Alexakis et al. (2005) ) | |
| (Aydogan et al. (2014) ) | |
| Yangbo et al. (2010) | |
| Lee et al. (2015) | |

**"Information-response", a new hypothesis**

The information revelation hypothesis has received limited attention. Warther's exact words were: *"If mutual fund investors possess information, or if they merely trade in the same direction as another group of investors who possess information, then their trades will reveal or be associated with new information. As the market responds to this information revelation, prices will move in the same direction as the fund flows"*. In our view, the notion that mutual fund investors are better informed than the wider market is not credible, but we elect not to discard the hypothesis for the sake of completeness. However, we prefer the interpretation taken by Edelen and Warner (1999), Jank (2012) and Babalos et al. (2016), that investors of mutual funds and those investing directly in the underlying assets are responding similarly to the same new information flow. While certain investor groups are likely to react quicker than others, this interpretation does not assume any chronology, and must therefore be tested by other means than causality tests. Jank (2012) found support for this hypothesis and uses the term “the information-response effect”, while Babalos et al. (2016) found no such support. To distinguish between the two interpretations of (a), henceforth, we attribute the interpretation presented first to the term “information revelation” and this second one to “information-response”.

**Significance of the time period studied**

Another plausible reason for differing findings in this field is that of the time period studied. Narayan et al. (2014) created a “spillover index” that they used to show causality between fund flows and stock market returns in India. They found that before the financial crisis, this “spillover effect” was non-existent, but during the financial crisis, cross-variance terms explained around 10 % of the forecast error variance in both stock market returns and aggregate net equity mutual fund flows. In 2010 and 2011, between 5 % and 7.5 % of the forecast error variance could be explained, when forecasting from one to 30 days ahead. Babalos et al. (2016) also found the financial crisis to have had effect on the behaviour of mutual fund investors, in particular noticing a decline in volatility of net flows and lower net flows post September 2008. Further evidence that the relationship between equity mutual fund flows and stock returns may be time-variant is the work by Edwards and Zhang (1998), where a period of 35 years was studied. Their Granger causality test on data from Jan 1961 to Feb 1996 shows no evidence that fund flows affect stock market returns. Only over the course of the period Jan 1971 – Dec 1981, a time frame selection most suspicious, do they find statistical significance, and then only at the 10 % level.

**Does a relationship really exist?**

As a last note, it can be observed from table 2 that contradictory results also within the same national market, namely the US market, have been found over a relatively short time frame (Warther, 1995; Fortune, 1998; Edwards and Zhang, 1998; Fant, 1999). This most unsettling fact casts doubt over whether any true relationship between equity fund flows and stock market returns exists, something this article also seeks to uncover. This field of research may have fallen victim to publication bias since, even with ten years of monthly data, there is a reasonable chance of finding false positives when only studying the relations between two time series.

# 3 Data

We made use of various data sources in this study. This section first describes the fund flow data and the process of retrieving it before explaining the transformation applied to the fund data. Next, the macroeconomic and financial data used is presented. An overview of all data utilised, including where it was gathered from, can be found in table 7, at the end of this section.

## 3.1 Fund Flow Data

Domestic equity mutual fund data was collected from Thomson Reuters EIKON (Lipper) and various investment associations native to the countries of study. We wanted to study all countries featured in past papers on this topic. Moreover, no study on the relationship between aggregate domestic equity mutual fund flows and stock market returns in Norway, Portugal, Spain or Switzerland has previously been conducted, and hence our studies of these countries represent new additions to the literature.

### 3.1.1 Fund Association Data

There exist international fund associations that publish reports on mutual fund flows and total assets under management regularly. Data is supplied to them by member national fund associations. The European Fund and Asset Management Association (EFAMA) publishes monthly statistics of the European mutual fund industry as a whole as well as a thorough annual report. The International Investment Funds Association (IIFA) publishes quarterly industry statistics by country. As we wanted to study monthly data series of individual countries, we needed to look elsewhere for data. Also, it is unclear from the IIFA reports whether the countrywise flows correspond to net flows to funds domiciled in that country or funds invested in that country's market. For our study, the most important thing is that the net flows are to funds that invest primarily in equities listed in that country; flows to funds that invest in foreign equities will not directly affect returns in the domestic stock market. We successfully retrieved fund flow data from national associations for Norway, Spain, Switzerland, Sweden, and Taiwan.

Norwegian data was sent to us by the Norwegian Fund and Asset Management Association (VFF) upon request. It contains exact values of monthly inflows, outflows and total net assets of individual funds domiciled in Norway. We made use of data on the domestic equity funds.

Spanish inflow and outflow data to/from equity mutual funds was gathered from the Association of Collective Investment Institutions and Pension Funds (INVERCO), which stores monthly reports of subscriptions and reimbursements of funds, i.e., in- and outflows. To make the data as comparable as possible to data collected from other sources, where we focused on funds domiciled in the country in question, we exclusively made use of the domestic equity mutual fund data classified as "national" (*Renta Variable Nacional Euro*).

Swiss figures of assets under management and estimated net sales by fund category beginning March 2011 was retrieved from Swiss Fund Data's website. The data resides in pdf documents and must therefore be hand-collected.

We also made use of domestic equity fund flow data made freely downloadable from the Swedish Investment Fund Association's website. Aggregate monthly data for various mutual fund categories is available as far back as Jan 2010, and annual data stretches as far back as 1994. Quarterly data, segmented also by investor category is available as far back as Q1 2008.

Lastly, Taiwanese monthly fund subscription (inflow), fund redemption (outflow) and fund size data was retrieved from Securities Investment Trust and Consulting Association of the R.O.C. (SITCA)'s website, where we selected funds under fund type *AA1. Domestic Equity Fund.*

### 3.1.2 Lipper Data

For many of the countries we wanted to study, we were unable to find a national association with publicly available domestic fund data at monthly frequencies. Therefore we consulted the Thomson Reuters EIKON database. We also used this source for all domestic bond mutual fund data. Using the search parameters given in table 4, we obtained fund data for a total of 13936 different equity mutual funds and 19573 different bond mutual funds. Figure 2 shows the number of funds for which data was retrieved for each country.

**Table 4:** Search parameters for equity mutual fund data retrieved from Thomson Reuters EIKON (Lipper).

| **Selection Criteria** | **Value** | |
|---|---|---|
| Fund Type | Open-end funds | |
| Fund Category | **Equity funds**: | Equity, Equity S&M, Equity Income, Equity Diversified |
| | **Bond funds**: | all bond funds |
| Domicile | [country in question] | |
| Country registered for sale | [country in question] | |
| Currency | [local currency] | |
| Exchange | USA – NASDAQ Stock Exchange Capital Market<br>Others – Lipper | |

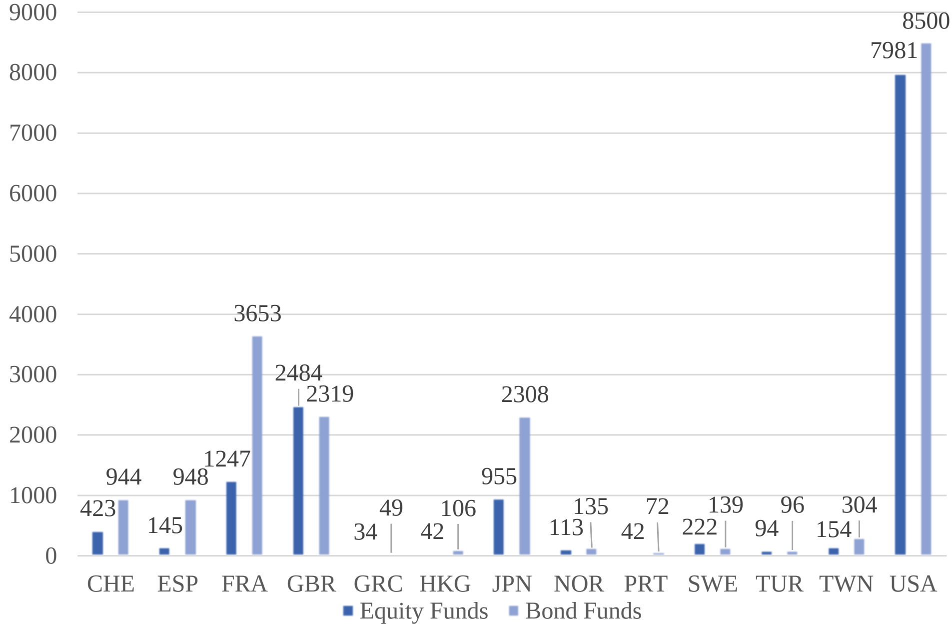



**Figure 2:** Total number of mutual funds in sample by country and fund category retrieved from Thomson Reuters EIKON (Lipper).

### 3.1.3 Data Selection

For the five countries where we obtained monthly aggregate fund flow data from two sources, we have compared the data sets. One was selected for use in the later analyses for each country. Statistics of fund data for the remaining countries of study are also presented in table 5 for completeness.

**Table 5:** Descriptive statistics of fund data from Lipper (panel A) and national fund associations (panel B). Column 3 shows the average number of active funds, column 4 the average combined market value of equity mutual fund holdings, and column 6 the standard deviation of real aggregate net flow to equity mutual funds over the period. The average combined value of holdings and standard deviation of net flows is also given in USD in columns 5 and 7. (1 bn = $10^9$)

| Country | Period | Mean Active Funds | Mean TNA | Mean TNA (USD) | Stdev(*NETFLOW*) | Stdev (USD) |
|---|---|---|---|---|---|---|
| **Panel A – Lipper Data** | | | | | | |
| France* | Feb 2006 – Dec 2016 | 541 | €66.7bn | $87.8bn | €705m | $875m |
| Greece* | Feb 2006 – Dec 2016 | 24 | €1.36bn | $1.82bn | €37.4m | $48.7m |
| Hong Kong* | May 2007 – Dec 2016 | 11 | HKD 24.1bn | $3.11bn | HKD 397m | $58.1m |
| Japan* | Feb 2006 – Dec 2016 | 520 | ¥4849bn | $46.8bn | ¥116bn | $1.05bn |
| **Norway** | Feb 2006 – Dec 2016 | 90 | NOK 110bn | $17.2bn | NOK 7.08bn | $1.13bn |
| Portugal* | Feb 2006 – Dec 2016 | 16 | €0.47bn | $0.63bn | €23.5m | $33.1m |
| **Spain** | Feb 2006 – Dec 2016 | 85 | €4.33bn | $5.59bn | €182m | $250m |
| **Sweden*** | Jan 2006 – Dec 2016 | 111 | SEK 341bn | $47.3bn | SEK 3.53bn | $494bn |
| **Switzerland*** | Feb 2006 – Dec 2016 | 186 | CHF 37.8bn | $37.7bn | CHF 374m | $381m |
| **Taiwan** | Jan 2006 – Dec 2016 | 125 | TWD 225bn | $7.20bn | TWD 8.51bn | $266m |
| Turkey* | Apr 2009 – Dec 2016 | 66 | TRL 2.36bn | $1.09bn | TRL 77.8m | $35.9m |
| UK* | Feb 2006 – Dec 2016 | 577 | £131bn | $215bn | £2.55bn | $4.02bn |
| USA* | Jan 2006 – Dec 2016 | 4650 | $2586bn | $2586bn | $25.1bn | $25.1bn |
| **Panel B – Fund Association Data** | | | | | | |
| **Norway*** | Jan 2006 – Dec 2016 | 77 | NOK 74.1bn | $11.7bn | NOK 825m | $128m |
| **Spain*** | Jan 2006 – Dec 2016 | 198 | €14.5bn** | $18.3bn** | €169m | $236m |
| **Sweden** | Jan 2010 – Dec 2016 | 120 | SEK 383 | $52.4bn | SEK 3.65bn | $511m |
| **Switzerland** | Mar 2011 – Dec 2016 | -*** | CHF 291bn | $310bn | CHF 1.62bn | $1.74bn |
| **Taiwan*** | Jan 2007 – Dec 2016 | 170 | TWD 291bn | $9.35bn | TWD 11.2bn | $347m |

*Note:*
*Selected for further analyses
**TNA only available from Feb 2011.
***Undisclosed by fund association

We selected data from the Norwegian Fund and Asset Management Association (VFF) on account of the lower standard deviation of net flow to mean total net assets (TNA) ratio. Why we appreciate a low standard deviation of net flows is explained in section 3.2. Data from the Association of Collective Investment Institutions and Pension Funds (INVERCO) was chosen for Spain due to the larger mean TNA and number of active funds. Lipper data was selected for Sweden and Switzerland due to the longer time period for which data was available from this database. Data from the Securities Investment Trust and Consulting Association of the R.O.C. (SITCA) was selected for Taiwan due to the larger mean values of TNA and number of active funds held by this database. For the remaining countries, the equity mutual fund data used comes from Thomson Reuters EIKON (Lipper). The equity mutual fund data presented in table 7 is the data selected here.

## 3.2 Derivation of Net Flows

For most countries, we were unable to directly retrieve exact equity mutual fund flows and had to calculate them. Thomson Reuters EIKON (Lipper) does not contain time series of fund flows, but rather "Total net assets" (net value of assets under management) and "NAV" (net value of assets per share in the fund) of individual funds. Lee et al. (2015) derive net flow for country $i$ from total net assets using the formula:

$$NETFLOW_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t}) \quad (1)$$

where $r_{\mathrm{i,t}}$ represents the return on the market index and $TNA_{\mathrm{i,t}}$ the total net assets of all funds in country $i$ in time period $t$. The implied assumption here is that the fund market obtains the same return as the broader stock market in every period. We circumvent such an assumption by deriving net flow of each individual fund in the fashion of Del Guercio and Tkac (2002) and Watson and Wickramanayake (2012) and only afterwards summing them. Per period returns of each fund are obtained from time series data of fund net asset value, which is analogous to the price of a stock. We therefore have:

$$NETFLOW_{i,t} = \sum_{n=1}^{N_{i,t}} (tna_{n,t} - tna_{n,t-1} \frac{nav_{n,t}}{nav_{n,t-1}}) \quad (2)$$

where $tna_{\mathrm{n,t}}$ is the total net assets and $nav_{\mathrm{n,t}}$ the net asset value of fund $n$ in month $t$. $N_{\mathrm{i,t}}$ is the total number of funds in country $i$ active both in months $t$ and *t-1*. Domestic bond mutual fund flows were derived in the same manner.

By now we realise that superficially large fluctuations in total net asset (TNA) values would result in a higher variance net flow series. TNA data from the Lipper database was quarterly rather than monthly for several funds, which is why we appreciated a low standard deviation of net flows in the data selection. The problem was so severe for Australia, Canada and South Korea that we had to excluded these countries from our study.

An added benefit to using equation (2) is that it makes possible the study of fund flows even using fund databases with a survivorship bias – where the aggregate fund returns are high in relation to the market return. The approach presented in equation (3) would yield very imprecise net flow estimates under such circumstances. Table 6 reveals that the total fund markets in some countries have obtained returns significantly different from that of the broader stock market during the decade we study. Although we do not detect a survivorship bias inn our data, assuming that the fund market obtains the market return would have lead to imprecise net flow estimates.

**Table 6:** Total fund market return, implied from Lipper funds' NAV and TNA values, compared to total index return. Individual fund returns have been weighted by their previous month TNA values in computation of the fund market return.

| Country | Period | Fund market return total | Index return total |
|---|---|---|---|
| CHE | Jan 2006 – Dec 2016 | -22.2 % | 5.2 % |
| ESP | Jan 2006 – Dec 2016 | 23.08 % | -15.8 % |
| FRA | Jan 2006 – Dec 2016 | -2.3 % | -1.7 % |
| GBR | Jan 2006 – Dec 2016 | 55.8 % | 24.0 % |
| GRC | Jan 2006 – Dec 2016 | -79.6 % | -92.0 % |
| HKG | Apr 2007 – Dec 2016 | 27.1 % | 8.3 % |
| JPN | Jan 2006 – Dec 2016 | -22.3 % | 14.8 % |
| NOR | Jan 2006 – Dec 2016 | 78.0 % | 104.3 % |
| PRT | Jan 2006 – Dec 2016 | -23.9 % | -46.6 % |
| SWE | Jan 2006 – Dec 2016 | -26.7 % | 57.7 % |
| TUR | Mar 2009 – Dec 2016 | 216.7% | 203.3% |
| TWN | Jan 2006 – Dec 2016 | 20.9 % | 40.6 % |
| USA | Jan 2006 – Dec 2016 | 35.2 % | 93.7 % |

## 3.3 Normalisation of Net Flows

The literature acknowledges numerous ways of normalising fund flows. One is to divide by total net assets (TNA) at the end of the previous period such as Edelen and Warner (2001); Caporale et al. (2004); Rakowski and Wang (2009). Another option is to divide by the market capitalisation (MCap) of the stock market, proxied by an index, averaged over the past 90 days (Goetzmann and Massa, 2003; Oh and Parwada, 2007). A third is to divide by the MCap of a stock market index at the end of the previous period (Warther, 1995; Fant, 1999; Jank, 2012). We propose that the impact of mutual fund flows on stock prices relates to the size of the stock market, and therefore choose to normalise by MCap. Finding the third option most meaningful, we choose this approach and express net flows as a percentage. I.e.:

$$NetFlow_{i,t} = \frac{NETFLOW_{i,t}}{MCap_{i,t-1}} \times 100 \tag{3}$$

where $MCap_{\text{i,t}}$ is the market capitalisation of the stock index used for country $i$ at the end of month $t$. For all countries in our study except Hong Kong, the correlation between the fund flows normalised by division by $MCap_{\text{i,t-1}}$ and $TNA_{\text{i,t-1}}$ was >93 %, and the two methods will therefore in most cases yield very similar results.

In this paper, we attempt to predict net flows to equity mutual funds using past values of net flows to bond mutual funds. We hypothesize that high recent net inflows to bond mutual funds imply that investors have less spare cash to invest and that equity mutual fund net flows will therefore be lower. To keep the two variables comparable, we also normalise bond mutual fund net flows by dividing by the market capitalisation of the stock market at the end of the previous period.

## 3.4 Macroeconomic & Financial Variables

Both market returns and net flows to equity mutual funds are potentially affected by a multitude of macroeconomic and financial variables. For this reason, in our regressions, we control for variables that previous research has found to be explanatory or predictive of stock market returns or equity mutual fund net flows. The variables are described below, with variable names in parentheses.

- Bond net flow – domestic aggregate net flow to bond mutual funds.
- Inflation – monthly and annual changes in the level of consumer prices (CPI) relative to a set date (where index=100).
  $MoMInflation_{\text{i,t}} = ln(\frac{CPI_{\text{i,t}}}{CPI_{\text{i,t-1}}})$, $YoYInflation_{\text{i,t}} = ln(\frac{CPI_{\text{i,t}}}{CPI_{\text{i,t-12}}})$
- Foreign exchange rate (FOREX) – exchange rate against the US dollar. In the case of the US, it is the exchange rate against the Euro.
- Three-month interbank offered rate (IBOR) – three-month lending rate offer between banks in the same country. In the case of Turkey, it is the middle rate, i.e. the average of the bid and offer rates.

- Industrial production index (IPI) – measures the level of industrial production relative to a set date (where index=100).
- Term premium (TermPrem) – difference between long- and short-term interest rate levels, defined here as the yield on 10-year treasury bills minus the 3M IBOR.
- Unemployment (Unempl) – rate of unemployment. Whenever possible, we have used harmonised unemployment rates for them to be as comparable as possible across countries.
- Oil price (BrentSpot) – Brent Crude spot price, the global benchmark for the spot price of oil.
- Baltic Dry Index (BDI) – index of dry bulk freight rates.
- Industrial metals (IndMetals) – S&P Goldman Sachs Commodity Index Industrial Metals, subindex of the S&P Goldman Sachs Commodity Index (S&P GSCI). The S&P GSCI Industrial Metals is composed of copper, aluminium, nickel, lead and zinc. It is weighted by the production levels of each commodity, a weighting method most appropriate when assessing the impact of commodities on the stock market.
- VIX – next 30-day market volatility expectation. Derived from option prices, the volatility expectation provided by the VIX is generally higher than the volatility observed in the following month (Blair et al., 2010), but when the VIX is higher, the observed volatility in the following 30 days is generally higher.

Due to difficulty of finding monthly data for some of the above mentioned variables, India was excluded from this study. Summary statistics can be found in the appendix.

## 3.5 Deseasonalisation of Macro Data

Consumer prices, unemployment rates and levels of industrial production can vary substantially over the course of a year due to seasonality. Therefore, although we wish to capture how short-term economic changes impact stock returns and fund flows, we must account for seasonal differences and utilise seasonally adjusted data.

Because we were unable to collect seasonally adjusted data series in some cases, we have deseasonalised these ourselves. Deseasonalisation has been performed in *R* using methods decompose() and seasdj() from the package 'forecast'. When possible, we have made use of data further back than Jan 2006 to identify the seasonal effects in order to perform better adjustments even though we do not study fund flows prior to this period. The data series gathered in need of deseasonalisation were data of consumer prices and industrial production. These are reported as indices, and relative changes were calculated prior to deseasonalisation.

Calendar adjusted data – where the number of holidays are adjusted for when determining e.g. industrial production levels – has been used where possible, but we have not taken steps to perform calendar adjustments ourselves on the data series that were not already calendar adjusted.

**Table 7:** Data overview.

| **Variable** | **Description** | **Source** |
|---|---|---|
| **France (FRA)** | | |
| Fund Data | Total net assets, NAV | TR EIKON |
| Index | CAC 40 – most valuable and liquid stocks on Euronext Paris | TR Datastream |
| CPI | Total all items, unadjusted | FRED[1] (OECD) |
| FOREX | USD/EUR | Investing.com |
| 3M IBOR | EURIBOR | FRED |
| IPI | Volume index of production, incl. mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply (seasonally and calendar adjusted) | Compustat |
| 10Y Yield | Government bond yield | FRED |
| Unemployment | "Harmonised, all persons" (seasonally adjusted) | FRED |
| **Greece (GRC)** | | |
| Fund Data | Total net assets | TR EIKON |
| Index | ATHEX 20 | TR Datastream |
| CPI | Total all items, unadjusted | FRED (OECD) |
| FOREX | USD/EUR | Investing.com |
| 3M IBOR | EURIBOR | FRED |
| IPI | Volume index of production, incl. mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply (seasonally and calendar adjusted) | Compustat |
| 10Y Yield | Government bond yield | FRED |
| Unemployment | "Harmonised, all persons" (seasonally adjusted) | FRED |
| **Hong Kong (HKG)** | | |
| Fund Data | Total net assets, NAV | TR EIKON |
| Index | HSI – 50 of the most valuable stocks on the Hong Kong Stock Exchange | TR Datastream |
| CPI | | C&SD[2] |
| FOREX | USD/HKD | |

| | | |
|---|---|---|
| 3M IBOR | HIBOR | TR Datastream |
| IPI | Unadjusted | TR Datastream |
| 10Y Yield | Government bond yield | Investing.com |
| Unemployment | Seasonally adjusted | TR Datastream |
| **Japan (JPN)** | | |
| Fund Data | Total net assets, NAV | TR EIKON |
| Index | NI225 – price-weighted index representative of the Japanese economy | TR Datastream |
| CPI | Total all items, unadjusted | FRED (OECD) |
| FOREX | USD/JPY | Investing.com |
| 3M IBOR | TIBOR | FRED |
| IPI | Production of total industry (seasonally adjusted) | FRED |
| 10Y Yield | Government bond yield | FRED |
| Unemployment | "Harmonised, all persons" (seasonally adjusted) | FRED |
| **Norway (NOR)** | | |
| Equity Fund Data | Inflow, Outflow, Total net assets | VFF[3] |
| Bond Fund Data | Total net assets, NAV | TR EIKON |
| Index | OSEBX – stocks on the Oslo Stock Exchange. Inclusion criteria are free float, liquidity and sector representation | TR Datastream |
| CPI | Seasonally and calendar adjusted | Statistics Norway |
| FOREX | USD/NOK | Investing.com |
| 3M IBOR | NIBOR | Statistics Norway |
| IPI | Volume index of production, incl. mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply (seasonally and calendar adjusted) | Compustat |
| 10Y Yield | Government bond yield | FRED |
| Unemployment | Registered unemployed aged 15-74 (seasonally adjusted) | Statistics Norway |
| **Portugal (PRT)** | | |
| Fund Data | Total net assets, NAV | TR EIKON |
| Index | PSI-20 – highest MCap & most liquid stocks on Euronext Lisbon | TR Datastream |
| CPI | Total all items, unadjusted | FRED (OECD) |
| FOREX | USD/EUR | Investing.com |
| 3M IBOR | EURIBOR | FRED |
| IPI | Volume index of production, incl. mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply (seasonally and calendar adjusted) | Compustat |

| | | |
|---|---|---|
| 10Y Yield | Government bond yield | FRED |
| Unemployment | Seasonally adjusted | FRED |
| **Spain (ESP)** | | |
| Equity Fund Data | Inflow, Outflow, Total net assets | INVERCO[4] |
| Bond Fund Data | Total net assets, NAV | TR EIKON |
| Index | IBEX 35 – most liquid stocks on the Madrid Stock Exchange | TR Datastream |
| CPI | Total all items, unadjusted | FRED (OECD) |
| FOREX | USD/EUR | Investing.com |
| 3M IBOR | EURIBOR | FRED |
| IPI | Volume index of production, incl. mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply (seasonally and calendar adjusted) | Compustat |
| 10Y Yield | Government bond yield | FRED |
| Unemployment | Seasonally adjusted | FRED |
| **Sweden (SWE)** | | |
| Equity Fund Data | Inflow, Outflow, Total net assets | Swedish Investment Fund Association |
| Bond Fund Data | Total net assets, NAV | TR EIKON |
| Index | OMX Stockholm 30 – most liquid stocks on the Stockholm Stock Exchange | TR Datastream |
| CPI | Total all items, unadjusted | FRED (OECD) |
| FOREX | USD/SEK | Investing.com |
| 3M IBOR | STIBOR | FRED |
| IPI | Volume index of production, incl. mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply (seasonally and calendar adjusted) | Compustat |
| 10Y Yield | Government bond yield | FRED |
| Unemployment | Seasonally adjusted | FRED |
| **Switzerland (CHE)** | | |
| Fund Data | Total net assets, NAV | TR EIKON |
| Index | SMI 20 – highest MCap & liquid stocks on the SIX Swiss Exchange | TR Datastream |
| CPI | Total all items, unadjusted | FRED (OECD) |
| FOREX | USD/CHF | Investing.com |
| 3M IBOR | 3-Month LIBOR based on Swiss Franc | FRED |
| IPI | Unadjusted | TR Datastream |
| 10Y Yield | Government bond yield | FRED |
| Unemployment | Seasonally adjusted | FRED |

| | | |
|---|---|---|
| **Taiwan (TWN)** | | |
| Equity Fund Data | Inflow, Outflow, Total net assets | SITCA[5] |
| Bond Fund Data | Total net assets, NAV | TR EIKON |
| Index | TSEC 50 – highest MCap & most liquid stocks on the Taiwan Stock Exchange | TR Datastream |
| CPI | Unadjusted | National Statistics[6] |
| FOREX | USD/TWD | Investing.com |
| 3M IBOR | TAIBOR | FRED |
| IPI | Unadjusted | CEIC |
| 10Y Yield | Government bond yield | Investing.com |
| Unemployment | Seasonally adjusted | FRED |
| **Turkey (TUR)** | | |
| Fund Data | Total net assets, NAV | TR EIKON |
| Index | BIST 100 – highest MCap & most liquid stocks on Borsa Istanbul | TR Datastream |
| CPI | Unadjusted | FRED (OECD) |
| FOREX | USD/TRY | Investing.com |
| 3M IBOR | TRLIBMR (middle rate) | TR Datastream |
| IPI | Seasonally & calendar adjusted | TurkStat |
| 10Y Yield | Government bond yield | Investing.com |
| Unemployment | Seasonally adjusted | FRED |
| **United Kingdom (GBR)** | | |
| Fund Data | Total net assets, NAV | TR EIKON |
| Index | FTSE100 – highest MCap & most liquid stocks on the London Stock Exchange | TR Datastream |
| CPI | Total all items, unadjusted | FRED (OECD) |
| FOREX | USD/GBP | Investing.com |
| 3M IBOR | LIBOR | FRED |
| IPI | Volume index of production, incl. mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply (seasonally and calendar adjusted) | Compustat |
| 10Y Yield | Government bond yield | FRED |
| Unemployment | Seasonally adjusted | FRED |
| **USA (USA)** | | |
| Fund Data | Total net assets, NAV | TR EIKON |
| Index | S&P500, NASDAQ100 – highest MCap & most liquid stocks on the NYSE and NASDAQ Stock exchange | TR Datastream |

| | | |
|---|---|---|
| CPI | Total all items, seasonally adjusted | FRED (OECD) |
| FOREX | EUR/USD | Investing.com |
| 3M IBOR | Effective Federal Funds Rate-3-Month Treasury Bill: Secondary Market Rate | FRED |
| IPI | Production of total industry (seasonally adjusted) | FRED |
| 10Y Yield | Government bond yield | FRED |
| Unemployment | Seasonally adjusted | FRED |
| **Global** | | |
| BDI | Baltic Dry Index – Index of dry bulk freight rates | Investing.com |
| BrentSpot | Brent Crude spot price | Investing.com |
| S&P GSCI Industrial Metals | Production-weighted index with constituents: aluminium, copper, lead, nickel, zinc | TR Datastream |
| VIX | Implied market volatility | Yahoo! Finance |
| *Notes:* | 1: Federal Reserve Bank of St. Louis<br>2: Census and Statistics Department<br>3: Norwegian Fund and Asset Management Association<br>4: Association of Collective Investment Institutions and Pension Funds<br>5: Securities Investment Trust & Consulting Association of the Republic of China<br>6: National Statistics Republic of China (Taiwan) | |

# 4 Methodology

This section presents statistical techniques and regression models used in our analyses. We reason for the inclusion of each variable in each model.

## 4.1 Expected & Unexpected Flows

Warther (1995) shows equity mutual fund flows to have a strongly autoregressive nature. Because of their predictability, he argues that only deviations from the values of net flows that can be expected should impact stock market returns. We separate aggregate net flow to equity mutual funds in the same manner as Warther (1995).

The decision concerning which lags to include in the autoregressive (AR) model of net flows was made separately for each country, where the first four lags were considered. The Bayesian Information Criterion (BIC) was used to decide which lags to include in the AR-model, conditional on at least one lag displaying significance at the 5 % level in the resulting model. For the USA, no lags displayed significant coefficients, and US net flows were not decomposed as a result. An overview of the lags included in the model of expected flows as well as their coefficients is given in table 8. The regressions were first performed with the constant term, but whenever the constant term was found insignificant, it was removed from the final regression. This was the case for all countries, and hence constant terms do not appear in table 8.

As an example, the expected net flow for France is:

**Table 8:** *NetFlow*$_{\text{i,t}}$ regressed on its own lags over the period Feb 2006 – Dec 2016. Only regressors with coefficients found significant are included. The USA net flow series displayed no autocorrelation.

| | *Dependent variable: NetFlow$_{i,t}$* | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| i: | CHE | ESP | FRA | GBR | GRC | HKG | JPN | NOR | PRT | SWE | TWN | TUR |
| $\text{NetFlow}_{\text{i,t-1}}$ | 0.265* | 0.313** | | 0.414** | | 0.246** | 0.568** | | -0.349** | 0.195* | 0.626** | 0.410** |
| | (0.083) | (0.074) | | (0.084) | | ( 0.089) | (0.071) | | (0.083) | (0.083) | (0.066) | (0.093) |
| $\text{NetFlow}_{\text{i,t-2}}$ | | | 0.255** | 0.209** | 0.246** | | | -0.460** | | | | |
| | | | (0.081) | (0.084) | (0.083) | | | (0.083) | | | | |
| $\text{NetFlow}_{\text{i,t-3}}$ | | | 0.244** | | | | | | | | | |
| | | | (0.081) | | | | | | | | | |
| $\text{NetFlow}_{\text{i,t-4}}$ | | 0.275** | | | | | | -0.222** | | | | |
| | | (0.073) | | | | | | (0.082) | | | | |
| Observations | 128 | 128 | 128 | 119 | 128 | 128 | 128 | 128 | 128 | 128 | 128 | 96 |
| $R^2$ | 0.141 | 0.061 | 0.070 | 0.060 | 0.320 | 0.190 | 0.100 | 0.257 | 0.039 | 0.393 | 0.306 | 0.168 |
| Adjusted $R^2$ | 0.128 | 0.054 | 0.063 | 0.052 | 0.316 | 0.178 | 0.093 | 0.257 | 0.032 | 0.388 | 0.296 | 0.159 |
| *S*ignificance levels: | | | | | | | | | | | | *p<0.05; **p<0.01 |

$ExpectedFlow_{FRA,t} = 0.255Flow_{FRA,t-2} + 0.244Flow_{FRA,t-3}$. The unexpected flow is simply the difference between the actual and expected flows.

## 4.2 Excess Index Returns

In our analyses, we regard the excess stock market return, proxied by and index, over the three-month interbank rate (see equation (4)). Excess returns are more comparable across countries, particularly when inflation levels differ. This is important to us because we perform panel regressions.

$$ExcessReturn_{i,t} = IndexReturn_{i,t} - \frac{ln(1 + IBOR_{i,t})}{12} \tag{4}$$

## 4.3 Granger Causality

Testing for Granger causality is a popular way to study the causal relationship between fund flows and returns (Edwards and Zhang, 1998; Fant, 1999; Oh and Parwada, 2007), and we also make use of this technique. Use of Granger causality tests has not gone uncriticised, however. Mosebach and Najand (1999) and Caporale et al. (2004) critique that the asymptotic properties of the Granger causality tests when the series contain unit roots are sometimes not accounted for. We circumvent such a problem by regarding relative returns (logarithmic changes in stock indices) and normalised net flows. The augmented Dickey-Fuller test (ADF) was performed on these data series, and the null hypothesis that the series contains a unit root was rejected in each case.

## 4.4 Regression Models

For the purpose of investigating the information-response hypothesis, we include a number of variables reflecting short-term changes in the economy and financial markets as control variables. It may be the case that the observed association between equity mutual fund flows and stock price movements can be attributed to a subset of these variables. Some are country-specific, whereas other variables are included in regression models of every country. In the following subsections, we reason for our selection of control variables, firstly in the contemporaneous model, and afterwards in the predictive models.

### 4.4.1 Contemporaneous Model of Returns

*IPI, TermPrem* – Expected stock market returns are partially explained by industrial production (Chen et al., 1986), changes in the credit risk premium (Chen et al., 1986; Fama and French, 1989), and changes in the term structure premium (Chen et al., 1986; Fama and French, 1989). Adequate data for the credit risk premium was difficult to find for every country, and rather than reducing the number of countries studied, we omitted this variable. Changes in each country's industrial production level and term premium are controlled for, however, where the term premium is defined as the excess yield on 10-year treasury bills over the three-month interbank rate.

*IBOR, Unempl, MoMInflation* – Remolona et al. (1997) determined the effect of returns on net flows in the US using the Federal Reserve's target federal funds rate, the consumer price index and domestic employment as instruments. Inspired by this, we also include monthly changes in the three-month interbank offered rate, unemployment and consumer prices as control variables in our contemporaneous model of returns.

*FOREX* – Because economic downturns can be cushioned (substantially, measured in the country's local currency) by easing of monetary policy, we wish to control for changing FOREX rates. For this rason, we include the local currency's exchange rate against the US dollar. In the case of the USA, we include the exchange rate against the Euro.

*BrentSpot* – Sadorsky (1999) used impulse responses to show that the US stock market reacts negatively to increases in oil prices, and that this effect persists for around three months. Kilian and Park (2009) found that "demand and supply shocks driving the global crude oil market jointly account for 22% of the long-run variation in U.S. real stock returns". Therefore, we include per period changes in the Brent Crude spot price in our contemporaneous regression model of excess market returns.

*IndMetals* – Jacobsen et al. (2018) showed that monthly changes in the S&P GSCI Industrial Metals index are predictive of next-month stock market returns in the USA. We suspect the market to react to same-period changes as well, and for simplicity just include same-period changes in the contemporaneous return model.

*BDI* – Shipping is an important industry to a number of countries we study, including Greece and Norway. Therefore freight rates may affect the stock market in these countries. Beyond that, shipping rates can be viewed as a measure of development in global trade and the health of the global economy as a whole, and therefore could affect stock markets worldwide. For these reasons, we include the changes in the Baltic Dry Index (BDI), an index for dry bulk freight rates, in the contemporaneous regression model for excess returns.

*VIX* – It is well-documented in the literature that an increase in volatility is associated with negative returns, known as the leverage effect (Bouchaud et al., 2001). Moreover, Giot (2005) shows that a negative relationship exists between concurrent changes in the VIX and the S&P100 and NASDAQ100 indices. For these reasons, the relative change in the VIX is included in our contemporaneous regression model. Since higher expected future volatility is associated with higher returns, the level of the VIX at the start of the month is also included.

*YoYInflation, TermPrem* – Additionally, expected inflation, the term premium, and lagged stock returns have all been found to predict stock market returns (Chen, 1991). Without data of inflation expectations, we instead use actual year-over-year inflation. An explanation for why lags of excess index returns are omitted is given in section 4.5. Our model is therefore specified as follows:

$$\begin{aligned} ExcessReturn_{i,t} = & Flow_{i,t} + \delta FOREX_{i,t} + \Delta IBOR_{i,t} + \delta IPI_{i,t} \\ & + MoMInflation_{i,t} + TermPrem_{i,t-1} + \Delta TermPrem_{i,t} \\ & + \Delta Unempl_{i,t} + YoYInflation_{i,t-1} + \delta BDI_t + \delta BrentSpot_t \\ & + \delta IndMetals_t + \delta VIX_t + VIX_{t-1} \end{aligned} \tag{5}$$

First differences are prefixed with a $\Delta$, and relative changes are prefixed with a $\delta$.

### 4.4.2 Predictive Model of Returns

When assessing the predictive power of net flow to equity mutual funds on stock market returns, we use a lagged net flow variable. Recall that the term premium and expected inflation have been found to predict stock market returns (Chen, 1991). The same goes for monthly changes in the price of industrial metals (Jacobsen et al., 2018). Furthermore, the excess return an investor can expect is dependent on the level of market risk. For these reasons, we control for previous-month values of the term premium, yearly inflation, the change in industrial metal prices and the VIX. The predictive return model becomes:

$$\begin{aligned} ExcessReturn_{i,t} = & Flow_{i,t-1} + TermPrem_{i,t-1} + YoYInflation_{i,t-1} \\ & + \delta IndMetals_{t-1} + VIX_{t-1} \end{aligned} \tag{6}$$

$Flow_{\mathrm{i,t}}$ takes the values of net flows or unexpected net flows. Alternatively, the mean of the first three lags of either of these is used, defined as:

$$ThreeLagsFlow_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} Flow_{i,t-m}.$$

### 4.4.3 Predictive Model of Net Flows

*FOREX, VIX, TermPrem* – To study the potential causal relationship from returns to flows, we control for a third set of variables. In a study of annual and quarterly data, Ferson and Kim (2012) find that equity fund flows can be predicted by macroeconomic and financial variables, including exchange rates, market volatility and the term spread. The first lag of the exchange rate towards the US dollar, the VIX and the term premium are selected as control variables for this reason.

*IBOR, YoYInflation, BondNetFlow, Unempl* – In a study of quarterly Swedish equity mutual fund flows, based largely on the work by Jank (2012), Kopsch et al. (2015) constructed an explanatory model of net flows to equity mutual funds with a large number of regressors, including: the VIX, short-term interest rates, the term premium, household inflation expectations, and outflow from bond mutual funds. Inspired by this, we also use the first lag of the IBOR and yearly inflation as control variables when predicting flows with returns. One might expect high inflation and low interest rates to be associated with high net flows to equity mutual funds because individuals feel that saving their money in bank accounts is a poor alternative. Using Lipper data, we were only able to estimate net flow to bond mutual funds, and therefore use this measure rather than outflows from bond mutual funds to predict net flow to equity mutual funds. Bond funds are substitute investment products, and if investors have recently poured large sums in to these funds, they may have less to invest in equity funds. Additionally, we include the unemployment rate at the end of the previous period because whether or not someone is employed is likely to affect their ability to put savings into equity funds. Our predictive model of net flows is therefore:

$$\begin{aligned} NetFlow_{i,t} = & \sum_{m=1}^{4} (Z_{i,m} \times NetFlow_{i,t-m}) + \sum_{m=1}^{3} BondNetFlow_{i,t-m} \\ & + ExcessReturn_{i,t-1} + FOREX_{i,t-1} + IBOR_{i,t-1} \\ & + TermPrem_{i,t-1} + Unempl_{i,t-1} + YoYInflation_{i,t-1} + VIX_{t-1} \end{aligned} \tag{7}$$

In model (7), $Z_{\mathrm{i,m}}$=1 if the mth lag of net flow for country $i$ is to be included in the model, and 0 otherwise. We only wish to include significant lags to control for autocorrelation, and an overview of these is given in table 8. The variable *ExcessReturn*$_{\mathrm{i,t}}$ is sometimes interchanged with the mean of the first three lags of excess return, defines as:

$$ThreeLagsEReturn_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} ExcessReturn_{i,t-m}.$$

## 4.5 Accounting for Past Returns

In search of a good way of controlling for historical market returns, we first regressed excess stock market returns on its first twelve lags for every country in our sample over the period Jan 2007 – Dec 2016. Only a few lags in total displayed significance, and which lags were significant varied between countries. We regressed excess market returns on the average of its past twelve lags as well, but this variable displayed no significance for any of the 13 countries. These results indicate that monthly market returns are not dependent on recent market returns, consistent with hypotheses of market efficiency, and lagged returns are therefore excluded from our explanatory and predictive models of excess stock market returns.

## 4.6 Panel Regressions

The fixed-effects model was selected for the panel regressions because we wished to account for possible countrywise differences that equity mutual fund net flows do not capture and analyse the impact of variables that vary over time. We are not concerned with why excess index returns vary across countries. For that research question, a random-effects model would be preferred. The simple contemporaneous model becomes:

$$ExcessReturn_{i,t} = \beta Flow_{i,t} + \alpha_i + \epsilon_{i,t} \tag{8}$$

where $\alpha_i$ is the time-invariant individual fixed-effect, and $\epsilon_{i,t}$ is the error term.

# 5 Results

In this section, we present the results of our study on the relationship between equity mutual fund flows and excess stock market returns across all the countries, firstly for the whole studied period, and then for subsamples in time. Afterwards, countrywise analyses are presented, where differences between national markets are highlighted. Results are discussed in light of the existing literature.

We adjust for heteroscedasticity in all regressions. The adjustments have been done using the HC3 version of the heteroscedasticity-consistent covariance matrix (HCCM), following the recommendation of Long and Ervin (2000) since our sample sizes are smaller than 250 (months).

## 5.1 Panel Data Analyses – Searching for Common Effects

We investigate the relationships between stock market returns and equity mutual fund flows across national markets using panel regression. We assume that the strength of a relationship between fund flows and market returns is dependent on the size of the flows in relation to the size of the stock market. Since $NetFlow_{\mathrm{i}}$ is normalised by MCap, it is therefore fair for countries with high *NetFlow* values to be assigned greater importance in the panel regressions. The standard deviations of $NetFlow_{\mathrm{i}}$, shown in table 9, are therefore indicative of the general importance assigned to each country in the panel regressions.

**Table 9:** Standard deviation of *NetFlow* for each country.

| **Country** | **Stdev(*NetFlow*)** |
|---|---|
| France | 0.0586 % |
| Greece | 0.0561 % |
| Hong Kong | 0.0031 % |
| Japan | 0.0389 % |
| Norway | 0.0541 % |
| Portugal | 0.0382 % |
| Spain | 0.0300 % |
| Sweden | 0.0952 % |
| Switzerland | 0.0396 % |
| Taiwan | 0.0781 % |
| Turkey | 0.0175 % |
| UK | 0.1472 % |
| USA | 0.1220 % |

### 5.1.1 Contemporaneous Analysis

To investigate the contemporaneous relationship between equity mutual fund flows and market returns, we regress excess market returns on net flows to equity mutual funds in fixed-effects model (8) from section 4.6.

**Table 10:** Unbalanced fixed-effects panel regressions of excess index returns on net flow and unexpected net flow to equity mutual funds [Feb 2006 – Dec 2016]. Base model: $ExcessReturn_{i,t} = \beta Flow^{*}_{i,t} + \alpha_i + \epsilon_{i,t}$.
$^{*}Flow_{i,t}$ equals $NetFlow_{i,t}$ in model (1) and $UnexpectedNetFlow_{i,t}$ in model (2).

| | *Dependent variable:* $ExcessReturn_{i,t}$ | |
|---|---|---|
| | (1) | (2) |
| $\mathrm{NetFlow_{i,t}}$ | 0.063* | |
| | (0.032) | |
| $\mathrm{UnexpectedNetFlow_{i,t}}$ | | 0.059 |
| | | (0.034) |
| Observations | 1,619 | 1,595 |
| $R^2$ | 0.006 | 0.004 |
| Adjusted $R^2$ | −0.002 | −0.004 |
| *Significance levels:* | | *p<0.05; **p<0.01 |

Table 10 shows the results of the simple contemporaneous panel regressions, where $NetFlow_{\mathrm{i,t}}$ and $UnexpectedNetFlow_{\mathrm{i,t}}$ in turn have been used as independent variable. While the coefficient of $NetFlow_{\mathrm{i,t}}$ is significant at the 5 % level, the negative adjusted $R^2$ of regression (1) reveals that the variable provides no real explanatory power. The results therefore do not indicate that a significant contemporaneous relationship exists between equity mutual fund flows and stock market returns at monthly frequencies that is common across countries. This result comes as a surprise, for in all articles we have come across where a contemporaneous analysis has been conducted, a more significant positive association was found. Table 11 shows the results of the regressions after control variables from model (5) have been added. Still, there remains no evidence of a temporal link between net flows and excess returns.

Interpretation of the significant coefficients in table 11 is given in table 12. Increases in short-term interest rates, the term premium, and the VIX are all associated with lower excess market returns. So are higher inflation and VIX values. Increases in the prices of oil and industrial metals, on the other hand, are associated with higher market returns.

**Table 11:** Unbalanced fixed-effects panel regressions of excess index returns on net flow and unexpected net flow to equity mutual funds and macro variables [Apr 2006 – Dec 2016]. Base model:

$$ExcessReturn_{i,t} = \beta_1 Flow^{*}_{i,t} + \sum_{j=2}^{14} \beta_j Var^{**}_{j,i,t} + \alpha_i + \epsilon_{i,t}.$$

*$Flow_{i,t}$ equals $NetFlow_{i,t}$ in model (1) and $UnexpectedNetFlow_{i,t}$ in model (2).
**Variables $\mathrm{Var_j}$ are listed in the leftmost column.

| | *Dependent variable: $ExcessReturn_{i,t}$* | |
|---|---|---|
| | (1) | (2) |
| $\mathrm{NetFlow_{i,t}}$ | 0.032 | |
| | (0.018) | |
| $\mathrm{UnexpectedNetFlow_{i,t}}$ | | 0.031 |
| | | (0.019) |
| $\delta\mathrm{FOREX_{i,t}}$ | −0.038 | −0.050 |
| | (0.135) | (0.136) |
| $\Delta\mathrm{IBOR_{i,t}}$ | $-0.027^{**}$ | $-0.027^{**}$ |
| | (0.009) | (0.009) |
| $\delta\mathrm{IPI_{i,t}}$ | −0.011 | −0.015 |
| | (0.037) | (0.037) |
| $\mathrm{MoMInflation_{i,t}}$ | 0.190 | 0.197 |
| | (0.283) | (0.290) |
| $\mathrm{TermPrem_{i,t\text{-}1}}$ | −0.0003 | −0.0004 |
| | (0.001) | (0.001) |
| $\Delta\mathrm{TermPrem_{i,t}}$ | $-0.008^{**}$ | $-0.007^{**}$ |
| | (0.002) | (0.002) |
| $\Delta\mathrm{Unempl_{i,t}}$ | −0.006 | −0.006 |
| | (0.011) | (0.010) |
| $\mathrm{YoYInflation_{i,t\text{-}1}}$ | $-0.404^{**}$ | $-0.395^{**}$ |
| | (0.122) | (0.122) |
| $\delta\mathrm{BDI_t}$ | 0.001 | 0.001 |
| | (0.005) | (0.005) |
| $\delta\mathrm{BrentSpot_t}$ | $0.093^{**}$ | $0.088^{**}$ |
| | (0.014) | (0.014) |
| $\delta\mathrm{IndMetals_t}$ | $0.143^{**}$ | $0.158^{**}$ |
| | (0.022) | (0.022) |
| $\mathrm{VIX_{t\text{-}1}}$ | $-0.001^{**}$ | $-0.001^{**}$ |
| | (0.0001) | (0.0001) |
| $\delta\mathrm{VIX_t}$ | $-0.120^{**}$ | $-0.118^{**}$ |
| | (0.009) | (0.009) |
| Observations | 1,606 | 1,588 |
| $\mathrm{R}^2$ | 0.355 | 0.357 |
| Adjusted $\mathrm{R}^2$ | 0.344 | 0.346 |
| *Significance levels:* | | $^{*}$p<0.05; $^{**}$p<0.01 |

**Table 12:** Interpretation of significant coefficients in table 11. The left column shows the magnitude of change in the independent variable; the middle column shows the impact on the dependent variable $ExcessReturn_{i,t}$.

| Variable Change | Effect | Interpretation |
|---|---|---|
| $\Delta \mathrm{IBOR}_{i,t} \uparrow$ 100 bp | $\mathrm{ExcessReturn}_{i,t} \downarrow$ 270 bp | An increase in the three-month interbank rate is associated with negative market returns. |
| $\Delta \mathrm{TermPrem}_{i,t} \uparrow$ 100 bp | $\mathrm{ExcessReturn}_{i,t} \downarrow$ 75 bp | An increase in the term premium is associated with negative market returns. |
| $\mathrm{YoYInflation}_{i,t\text{-}1} \uparrow$ 100bp | $\mathrm{ExcessReturn}_{i,t} \downarrow$ 40 bp | In periods with high inflation, excess market returns tend to be lower. |
| $\delta \mathrm{BrentSpot}_{t} \uparrow$ 1 % | $\mathrm{ExcessReturn}_{i,t} \uparrow$ 9 bp | An increase in the spot price of Brent Crude is associated with higher market returns. This finding is different from that of Sadorsky (1999) who finds that the US stock market reacts negatively to oil price increases. |
| $\delta \mathrm{IndMetals}_{t} \uparrow$ 1 % | $\mathrm{ExcessReturn}_{i,t} \uparrow$ 15 bp | An increase in the price of industry metals is associated with higher stock market returns. |
| $\mathrm{VIX}_{t\text{-}1} \uparrow 1$ | $\mathrm{ExcessReturn}_{i,t} \downarrow$ 10 bp | In months where volatility is expected to be higher, market returns are slightly lower. |
| $\delta \mathrm{VIX}_{t} \uparrow$ 1 % | $\mathrm{ExcessReturn}_{i,t} \downarrow$ 12 bp | An increase in market volatility is associated with negative market returns, known as the leverage effect (Bouchaud et al., 2001). |

*Note:* bp = basis points

### 5.1.2 Predicting Stock Market Returns

Next, we analyse the worldwide predictive power of domestic net flows to equity mutual funds on the stock market. Table 13 shows the results of a fixed-effects panel regression where excess market returns have been regressed on the first lag and the mean of the first three lags of (unexpected) net flows. Although the coefficients of the mean of the first three lags of both net flows ($ThreeLagsNetFlow_{i,t\text{-}1}$) and unexpected net flows ($ThreeLagsUnFlow_{i,t\text{-}1}$) seem significant at the 5 % level, the variables do not provide any noticeable predictive power. The reader may also note that none of the flow variable coefficients displayed statistical significance when robust standard errors were not used.

The flow variable coefficients may change, however, once other predictive variables of excess market returns are controlled for. Table 14 shows that when macroeconomic and financial variables are controlled for, the flow variables coefficients are not statistically significant. We therefore cannot conclude that net flows are predictive of excess stock market returns. Our result is consistent with most of the literature. Furthermore, we find that the term premium and expected volatility do not predict stock market returns, and the low $R^2$ values of the regressions indicate that excess stock market returns are hard to predict, as the theory of efficient markets tells us. An interpretation of the significant coefficients is given in table 15.

**Table 13:** Unbalanced fixed-effects panel regressions of excess index returns on lags of net flow and unexpected net flow to equity mutual funds [Apr 2006 – Dec 2016]. Base model: $ExcessReturn_{i,t} = Flow^{*}_{i,t-1} + \alpha_i + \epsilon_{i,t}$.
$^{*}Flow_{i,t-1}$ equals $NetFlow_{i,t-1}$ in model (1), $ThreeLagsNetFlow_{i,t-1}$ in model (2), $UnexpectedNetFlow_{i,t-1}$ in model (3) and $ThreeLagsUnFlow_{i,t-1}$ in model (4), where
$ThreeLagsNetFlow_{i,t-1} = \frac{1}{3} \times \sum_{m=0}^{2} NetFlow_{i,t-m}$,
$ThreeLagsUnFlow_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} UnexpectedNetFlow_{i,t-m}$.

| | *Dependent variable: $ExcessReturn_{i,t}$* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\mathrm{NetFlow_{i,t\text{-}1}}$ | 0.003 | | | |
| | (0.018) | | | |
| $\mathrm{ThreeLagsNetFlow_{i,t\text{-}1}}$ | | 0.041* | | |
| | | (0.020) | | |
| $\mathrm{UnexpectedNetFlow_{i,t\text{-}1}}$ | | | −0.006 | |
| | | | (0.018) | |
| $\mathrm{ThreeLagsUnFlow_{i,t\text{-}1}}$ | | | | 0.072* |
| | | | | (0.036) |
| Observations | 1,616 | 1,602 | 1,584 | 1,560 |
| $R^2$ | 0.00001 | 0.001 | 0.00004 | 0.002 |
| Adjusted $R^2$ | −0.008 | −0.007 | −0.008 | −0.006 |
| *Significance levels:* | | | | $^{*}p<0.05$; $^{**}p<0.01$ |

**Table 14:** Unbalanced fixed-effects panel regressions of excess index returns on lags of net flow and unexpected net flow to equity mutual funds and macro variables [Apr 2006 – Dec 2016]. Base model:
$ExcessReturn_{i,t} = \beta_1 Flow^{*}_{i,t-1} + \beta_2 TermPrem_{i,t-1} + \beta_3 YoYInflation_{i,t-1}$
$+ \beta_4 \delta IndMetals_{t-1} + \beta_5 VIX_{t-1} + \alpha_i + \epsilon_{i,t}$.
*$Flow_{i,t-1}$ equals $NetFlow_{i,t-1}$ in model (1), $ThreeLagsNetFlow_{i,t-1}$ in model (2), $UnexpectedNetFlow_{i,t-1}$ in model (3) and $ThreeLagsUnFlow_{i,t-1}$ in model (4), where
$ThreeLagsNetFlow_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} NetFlow_{i,t-m}$,
$ThreeLagsUnFlow_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} UnexpectedNetFlow_{i,t-m}$.

| | *Dependent variable: ExcessReturn$_{i,t}$* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $NetFlow_{i,t-1}$ | −0.010 | | | |
| | (0.016) | | | |
| $ThreeLagsNetFlow_{i,t-1}$ | | 0.014 | | |
| | | (0.019) | | |
| $UnexpectedNetFlow_{i,t-1}$ | | | −0.021 | |
| | | | (0.013) | |
| $ThreeLagsUnFlow_{i,t-1}$ | | | | 0.027 |
| | | | | (0.030) |
| $TermPrem_{i,t-1}$ | 0.0003 | 0.0003 | 0.0003 | 0.0003 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| $YoYInflation_{i,t-1}$ | $-0.596^{**}$ | $-0.577^{**}$ | $-0.580^{**}$ | $-0.577^{**}$ |
| | (0.134) | (0.135) | (0.134) | (0.137) |
| $\delta IndMetals_{t-1}$ | $0.152^{**}$ | $0.153^{**}$ | $0.172^{**}$ | $0.172^{**}$ |
| | (0.021) | (0.021) | (0.021) | (0.021) |
| $VIX_{t-1}$ | 0.0002 | 0.0002 | 0.0002 | $0.0002^{*}$ |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Observations | 1,605 | 1,593 | 1,579 | 1,557 |
| $R^2$ | 0.045 | 0.045 | 0.052 | 0.053 |
| Adjusted $R^2$ | 0.035 | 0.035 | 0.041 | 0.042 |
| *Significance levels:* | | | $^{*}$p<0.05; $^{**}$p<0.01 | |

**Table 15:** Interpretation of significant coefficients in table 14. The left column shows the magnitude of change in the independent variable; the middle column shows the impact on the dependent variable $ExcessReturn_{i,t}$.

| Variable Change | Effect | Interpretation |
|---|---|---|
| $YoYInflation_{i,t-1}$ ↑ 100bp | Excess $Return_{i,t}$ ↓ 58 bp | Higher inflation is associated with lower excess market returns. |
| $\delta IndMetals_{t-1}$ ↑ 1 % | $ExcessReturn_{i,t}$ ↑ 16bp | A previous-month increase in the price of industrial metals is associated with higher stock market returns. |
| *Note:* | | bp = basis points |

### 5.1.3 Predicting Net Fund Flows

We proceeded to assess the predictive power of stock market returns on equity mutual fund net flows. We regressed $NetFlow_i$ on its own lags in a fixed-effects panel regression and found the first two lags significant. These are therefore included in the regression models.

**Table 16:** Unbalanced fixed-effects predictive panel regression of net flows [Apr 2006 – Dec 2016]. Base model: $NetFlow_{i,t} = \beta_1 Return^*_{i,t-1} + \sum_{m=1}^{2}(\beta_m NetFlow_{i,t-m}) + \alpha_i + \epsilon_{i,t}$. *$Return_{i,t-1}$ equals $ExcessReturn_{i,t-1}$ in model (1) and $ThreeLagsEReturn_{i,t-1}$ in model (2), where $ThreeLagsEReturn_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} ExcessReturn_{i,t-m}$.

| | *Dependent variable: $NetFlow_{i,t}$* | |
|---|---|---|
| | (1) | (2) |
| $ExcessReturn_{i,t-1}$ | 0.009 | |
| | (0.034) | |
| $ThreeLagsEReturn_{i,t-1}$ | | 0.027 |
| | | (0.036) |
| $NetFlow_{i,t-1}$ | 0.246** | 0.246** |
| | (0.089) | (0.088) |
| $NetFlow_{i,t-2}$ | 0.151** | 0.150** |
| | (0.038) | (0.039) |
| Observations | 1,613 | 1,613 |
| $R^2$ | 0.105 | 0.105 |
| Adjusted $R^2$ | 0.097 | 0.097 |
| *Significance levels:* | | *p<0.05; **p<0.01 |

Table 16 gives no indication that net flows to equity mutual funds are influenced by returns from the recent past. Lags of excess market returns do not seem to predict net flows, even when macroeconomic and financial variables are controlled for, as is visible from table 17, displaying the results of fixed-effects panel regressions applied to model (7), given in section 4.4.3. Table 17 reveals further that net flows to equity mutual funds can be partially predicted by its own lags and that they are largely unaffected by recent macroeconomic information. Neither past lags of net flow to bond mutual funds, exchange rates, interest rates, inflation, the unemployment level, nor expected stock market volatility seems to predict net flows to equity mutual funds.

**Table 17:** Unbalanced fixed-effects predictive panel regression of net flows with macroeconomic variables [Apr 2006 – Dec 2016]. Base model:
$NetFlow_{i,t} = \beta_1 Return^{*}_{i,t-1} \sum_{j=2}^{12} \beta_j Var^{**}_{j,i,t} + \alpha_i + \epsilon_{i,t}$.
*$Return_{i,t-1}$ equals $ExcessReturn_{i,t-1}$ in model (1) and $ThreeLagsEReturn_{i,t-1}$ in model (2), where $ThreeLagsEReturn_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} ExcessReturn_{i,t-m}$.
**Variables $\mathrm{Var_j}$ are listed in the leftmost column.

| | *Dependent variable: $NetFlow_{i,t}$* | |
|---|---|---|
| | (1) | (2) |
| $\mathrm{ExcessReturn_{i,t-1}}$ | 0.017 | |
| | (0.036) | |
| $\mathrm{ThreeLagsEReturn_{i,t-1}}$ | | 0.067 |
| | | (0.043) |
| $\mathrm{NetFlow_{i,t-1}}$ | 0.244** | 0.243** |
| | (0.087) | (0.087) |
| $\mathrm{NetFlow_{i,t-2}}$ | 0.144** | 0.143** |
| | (0.036) | (0.038) |
| $\mathrm{BondNetFlow_{i,t-1}}$ | −0.007 | −0.007 |
| | (0.014) | (0.014) |
| $\mathrm{BondNetFlow_{i,t-2}}$ | 0.014 | 0.013 |
| | (0.013) | (0.013) |
| $\mathrm{BondNetFlow_{i,t-3}}$ | −0.008 | −0.008 |
| | (0.005) | (0.005) |
| $\mathrm{FOREX_{i,t-1}}$ | 0.048 | 0.053 |
| | (0.031) | (0.030) |
| $\mathrm{IBOR_{i,t-1}}$ | −0.001 | −0.001 |
| | (0.001) | (0.001) |
| $\mathrm{TermPrem_{i,t-1}}$ | 0.001 | 0.001 |
| | (0.001) | (0.001) |
| $\mathrm{Unempl_{i,t-1}}$ | −0.001 | −0.001 |
| | (0.001) | (0.001) |
| $\mathrm{YoYInflation_{i,t-1}}$ | −0.255 | −0.229 |
| | (0.218) | (0.228) |
| $\mathrm{VIX_{t-1}}$ | 0.0004 | 0.0004 |
| | (0.0003) | (0.0003) |
| Observations | 1,592 | 1,592 |
| $R^2$ | 0.114 | 0.115 |
| Adjusted $R^2$ | 0.101 | 0.101 |
| *Significance levels:* | | $^{*}$p<0.05; $^{**}$p<0.01 |

Where we have used lags of the dependent variable as regressors, the panel is dynamic. This implies that the fixed-effects model can produce biased estimates (Baltagi, 2008), and the so-called "Nickell bias" is worse for shorter time series. This issue can be circumvented using a Generalized Method of Moments (GMM) estimator of the dynamic panel (Arellano and Bond, 1991). We therefore ran dynamic panel regressions on the predictive model of net flows as a robustness check, still without finding that excess market returns predict net flow to equity mutual funds.

## 5.2 Sub-Period Analyses

Our studied time period includes the financial crisis, which allows us to explore whether different states of the world economy can influence the relationship between equity mutual fund net flows and market returns. We divide our studied time period into three: pre-crisis (Apr 2006 – Dec 2007); crisis (Jan 2008 – Oct 2009); post-crisis (Nov 2009 – Dec 2016) and investigate whether the relationships we find between fund flows and stock returns differ across these periods. An added motivational factor for doing this is that Narayan et al. (2014) found a structural break in the relationship between equity mutual fund flows and stock market returns occurring around the time of the financial crisis. Exactly when the financial crisis began and ended is not well-defined, and it had longer lasting effects in some countries than others. We have defined the crisis period as we have because financial markets began a period of recession at the start of 2008, and the level of the VIX receded to a fairly normal level in November 2009.

### 5.2.1 Contemporaneous Analysis

In this section, we investigate the contemporaneous relationship between equity mutual fund flows and stock market returns over three different time periods, following the same approach as in section 5.1.1. Table 18 shows the results of the simple contemporaneous panel regressions, where $NetFlow_{\mathrm{i,t}}$ and $UnexpectedNetFlow_{\mathrm{i,t}}$ in turn have been used as independent variable. The coefficients of both $NetFlow_{\mathrm{i,t}}$ and $UnexpectedNetFlow_{\mathrm{i,t}}$ are significant at the 1 % level in Panel B, indicating that a concurrent relationship existed during the financial crisis. However, the flow variables yield hardly any explanatory power, as can be seen from the adjusted $\mathrm{R}^2$ values of the regressions.

As before, we now add macroeconomic and financial control variables to the regressions, the results of which are shown in table 19. The flow coefficients are no longer significant for the crisis period. Only in the pre-crisis period does it appear that *NetFlow* can explain concurrent excess market returns in conjunction with macro variables, and its coefficient is significant only at the 5 % level. The pre-crisis $NetFlow_{\mathrm{i,t}}$ coefficient tells us that net flows to equity mutual funds higher by 0.1 % of the market capitalisation of the main stock index are associated with 0.96 % higher excess returns on the main stock index during this period.

**Table 18:** Unbalanced fixed-effects contemporaneous panel regression of excess returns for each sub period. Panel A: pre-crisis [Apr 2006 – Dec 2007], Panel B: crisis [Jan 2008 – Oct 2009], Panel C: post-crisis [Nov 2009 – Dec 2016]. Base model:
$ExcessReturn_{i,t} = \beta Flow^{*}_{i,t} + \alpha_i + \epsilon_{i,t}$.
*$Flow_{i,t}$ equals $NetFlow_{i,t}$ in model (1) and $UnexpectedNetFlow_{i,t}$ in model (2).

| | *Dependent variable: $ExcessReturn_{i,t}$* | | | | | |
|---|---|---|---|---|---|---|
| | A: Pre-crisis | | B: Crisis | | C: Post-crisis | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathrm{NetFlow_{i,t}}$ | 0.081 | | 0.371** | | 0.029 | |
| | (0.065) | | (0.072) | | (0.033) | |
| $\mathrm{UnexpectedNetFlow_{i,t}}$ | | 0.063 | | 0.334** | | 0.027 |
| | | (0.063) | | (0.061) | | (0.039) |
| Observations | 230 | 212 | 271 | 265 | 1,118 | 1,118 |
| $R^2$ | 0.029 | 0.018 | 0.053 | 0.041 | 0.001 | 0.001 |
| Adjusted $R^2$ | −0.024 | −0.041 | 0.005 | −0.008 | −0.010 | −0.011 |
| *Significance levels:* | | | | | | *p<0.05; **p<0.01 |

**Table 19:** Unbalanced fixed-effects contemporaneous panel regression of excess returns for each sub period with macro variables. Panel A: pre-crisis [Apr 2006 – Dec 2007], Panel B: crisis [Jan 2008 – Oct 2009], Panel C: post-crisis [Nov 2009 – Dec 2016]. Base model: $ExcessReturn_{i,t} = \beta_1 Flow^{*}_{i,t} + \sum_{j=2}^{14} \beta_j Var^{**}_{j,i,t} + \alpha_i + \epsilon_{i,t}$.
$^{*}Flow_{i,t}$ equals $NetFlow_{i,t}$ in model (1) and $UnexpectedNetFlow_{i,t}$ in model (2).

| | *Dependent variable: $ExcessReturn_{i,t}$* | | | | | |
|---|---|---|---|---|---|---|
| | A: Pre-crisis | | B: Crisis | | C: Post-crisis | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $NetFlow_{i,t}$ | 0.096* | | 0.059 | | 0.004 | |
| | (0.042) | | (0.058) | | (0.015) | |
| $UnexpectedNetFlow_{i,t}$ | | 0.070 | | 0.055 | | 0.005 |
| | | (0.040) | | (0.053) | | (0.021) |
| $FOREX_{i,t}$ | 0.344 | 0.195 | 0.239** | 0.239** | −0.076 | −0.076 |
| | (0.191) | (0.183) | (0.088) | (0.087) | (0.179) | (0.179) |
| $\Delta IBOR_{i,t}$ | −0.016 | −0.008 | 0.012 | 0.012 | −0.035** | −0.035** |
| | (0.019) | (0.015) | (0.020) | (0.020) | (0.005) | (0.005) |
| $\delta IPI_{i,t}$ | 0.119 | 0.178 | −0.147 | −0.142 | −0.029 | −0.029 |
| | (0.132) | (0.132) | (0.100) | (0.099) | (0.028) | (0.028) |
| $MoMInflation_{i,t}$ | 0.079 | 0.354 | −0.495 | −0.509 | 0.036 | 0.036 |
| | (0.768) | (0.811) | (1.014) | (1.021) | (0.257) | (0.258) |
| $TermPrem_{i,t-1}$ | −0.019** | −0.004 | 0.011** | 0.012** | 0.001 | 0.001 |
| | (0.007) | (0.005) | (0.003) | (0.003) | (0.0004) | (0.0004) |
| $\Delta TermPrem_{i,t}$ | 0.002 | 0.014 | 0.017 | 0.017 | −0.008* | −0.008* |
| | (0.010) | (0.009) | (0.021) | (0.021) | (0.004) | (0.004) |
| $\Delta Unempl_{i,t}$ | 0.025 | 0.016 | 0.003 | 0.003 | −0.015 | −0.015 |
| | (0.017) | (0.018) | (0.018) | (0.018) | (0.011) | (0.011) |
| $YoYInflation_{i,t-1}$ | −0.373 | −0.831** | −1.081** | −1.062** | −0.099 | −0.099 |
| | (0.284) | (0.281) | (0.209) | (0.206) | (0.182) | (0.181) |
| $\delta BDI_t$ | 0.082** | 0.027 | −0.031 | −0.031 | −0.021** | −0.021** |
| | (0.028) | (0.032) | (0.018) | (0.018) | (0.006) | (0.006) |
| $\delta BrentSpot_t$ | 0.093* | 0.065 | 0.136* | 0.137* | 0.072** | 0.072** |
| | (0.045) | (0.048) | (0.066) | (0.066) | (0.009) | (0.009) |
| $\delta IndMetals_t$ | 0.033 | 0.085* | 0.161** | 0.160** | 0.116** | 0.116** |
| | (0.032) | (0.034) | (0.041) | (0.041) | (0.041) | (0.041) |
| $VIX_{t-1}$ | −0.005** | −0.004** | −0.0003 | −0.0003 | −0.001** | −0.001** |
| | (0.001) | (0.001) | (0.0005) | (0.0005) | (0.0003) | (0.0003) |
| $\delta VIX_t$ | −0.102** | −0.088** | −0.227** | −0.227** | −0.109** | −0.109** |
| | (0.012) | (0.015) | (0.010) | (0.010) | (0.012) | (0.012) |
| Observations | 230 | 212 | 264 | 264 | 1,112 | 1,112 |
| $R^2$ | 0.425 | 0.420 | 0.622 | 0.622 | 0.314 | 0.314 |
| Adjusted $R^2$ | 0.354 | 0.342 | 0.583 | 0.583 | 0.298 | 0.298 |
| *Significance levels:* | | | | | | *p<0.05; **p<0.01 |

### 5.2.2 Predicting Excess Returns

Next, we analyse the predictive power of equity mutual fund net flows on the stock market during different time periods using the same approach as in section 5.1.2. Table 20 gives no indication that any of our flow configurations can predict excess index returns in any of the time periods: none of the coefficients are significant, and the adjusted $R^2$ of every regression is negative. Table 21 reveals that the flow variable coefficients remain insignificant with the inclusion of control variables in the regressions. I.e., the flow variables appear incapable of predicting excess index returns also in conjunction with macroeconomic and financial variables found predictive of returns in previous papers.

The results in table 21 also indicate that excess stock market returns were fairly predictable during the financial crisis. However, monthly stock returns were generally negative in this period, and so independent variables that were generally either positive or negative are very likely to appear to have been good predictors of monthly stock market returns over this period.

**Table 20:** Unbalanced fixed-effects predictive panel regression of excess returns for each sub period. Panel A: pre-crisis [Apr 2006 – Dec 2007], Panel B: crisis [Jan 2008 – Oct 2009], Panel C: post-crisis [Nov 2009 – Dec 2016]. Base model:
$ExcessReturn_{i,t} = \beta Flow^{*}_{i,t-1} + \epsilon_{i,t}$.
$^{*}Flow_{i,t-1}$ equals $NetFlow_{i,t-1}$ in model (1), $ThreeLagsNetFlow_{i,t-1}$ in model (2), $UnexpectedNetFlow_{i,t-1}$ in model (3) and $ThreeLagsUnFlow_{i,t-1}$ in model (4), where

$$ThreeLagsNetFlow_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} NetFlow_{i,t-m},$$

$$ThreeLagsUnFlow_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} UnexpectedNetFlow_{i,t-m}.$$

| | *Dependent variable: $ExcessReturn_{i,t}$* | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | A: Pre-crisis | | | | B: Crisis | | | | C: Post-crisis | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $NetFlow_{i,t-1}$ | 0.016 | | | | 0.072 | | | | −0.005 | | | |
| | (0.018) | | | | (0.116) | | | | (0.014) | | | |
| $ThreeLagsNetFlow_{i,t-1}$ | | 0.001 | | | | 0.361 | | | | 0.018 | | |
| | | (0.037) | | | | (0.196) | | | | (0.017) | | |
| $UnexpectedNetFlow_{i,t-1}$ | | | 0.049 | | | | 0.025 | | | | −0.012 | |
| | | | (0.036) | | | | (0.090) | | | | (0.012) | |
| $ThreeLagsUnFlow_{i,t-1}$ | | | | 0.109 | | | | 0.392 | | | | 0.028 |
| | | | | (0.070) | | | | (0.248) | | | | (0.019) |
| Observations | 228 | 216 | 202 | 180 | 270 | 268 | 264 | 264 | 1,118 | 1,118 | 1,118 | 1,116 |
| $R^2$ | 0.001 | 0.000 | 0.007 | 0.012 | 0.003 | 0.029 | 0.0004 | 0.026 | 0.00003 | 0.0003 | 0.0002 | 0.0004 |
| Adjusted $R^2$ | −0.055 | −0.059 | −0.056 | −0.059 | −0.047 | −0.021 | −0.047 | −0.021 | −0.012 | −0.011 | −0.012 | −0.011 |

*Significance levels:* $^{*}p<0.05$; $^{**}p<0.01$

**Table 21:** Unbalanced fixed-effects predictive panel regression of excess returns for each sub period with macro variables. Panel A: pre-crisis [Apr 2006 – Dec 2007], Panel B: crisis [Jan 2008 – Oct 2009], Panel C: post-crisis [Nov 2009 – Dec 2016]. Base model: $ExcessReturn_{i,t} = \beta_1 Flow^*_{i,t-1} + \beta_2 TermPrem_{i,t-1} + \beta_3 YoYInflation_{i,t-1} + \beta_4 \delta IndMetals_{t-1} + \beta_5 VIX_{t-1} + \alpha_i + \epsilon_{i,t}$.
*$Flow_{i,t-1}$ equals $NetFlow_{i,t-1}$ in model (1), $ThreeLagsNetFlow_{i,t-1}$ in model (2), $UnexpectedNetFlow_{i,t-1}$ in model (3) and $ThreeLagsUnFlow_{i,t-1}$ in model (4), where

$ThreeLagsNetFlow_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} NetFlow_{i,t-m}$,

$ThreeLagsUnFlow_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} UnexpectedNetFlow_{i,t-m}$.

| | *Dependent variable: ExcessReturn$_{i,t}$* | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | A: Pre-crisis | | | | B: Crisis | | | | C: Post-crisis | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $NetFlow_{i,t-1}$ | −0.007 | | | | −0.013 | | | | −0.005 | | | |
| | (0.023) | | | | (0.034) | | | | (0.014) | | | |
| $ThreeLagsNetFlow_{i,t-1}$ | | −0.013 | | | | −0.049 | | | | 0.017 | | |
| | | (0.047) | | | | (0.043) | | | | (0.018) | | |
| $UnexpectedNetFlow_{i,t-1}$ | | | 0.004 | | | | −0.026 | | | | −0.012 | |
| | | | (0.055) | | | | (0.041) | | | | (0.012) | |
| $ThreeLagsUnFlow_{i,t-1}$ | | | | −0.011 | | | | −0.007 | | | | 0.027 |
| | | | | (0.060) | | | | (0.065) | | | | (0.020) |
| $TermPrem_{i,t-1}$ | −0.007 | −0.007 | 0.006 | 0.004 | 0.011** | 0.012** | 0.011** | 0.011** | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| | (0.006) | (0.006) | (0.006) | (0.009) | (0.003) | (0.003) | (0.003) | (0.003) | (0.001) | (0.001) | (0.001) | (0.001) |
| $YoYInflation_{i,t-1}$ | −0.867 | −0.914* | −1.222** | −1.406** | −1.076** | −1.063** | −1.077** | −1.080** | −0.254 | −0.244 | −0.255 | −0.243 |
| | (0.440) | (0.439) | (0.407) | (0.502) | (0.203) | (0.211) | (0.204) | (0.206) | (0.267) | (0.269) | (0.268) | (0.269) |
| $\delta IndMetals_{t-1}$ | −0.039 | −0.035 | 0.116* | 0.123* | 0.393** | 0.394** | 0.393** | 0.394** | 0.009 | 0.008 | 0.009 | 0.008 |
| | (0.023) | (0.024) | (0.045) | (0.051) | (0.039) | (0.038) | (0.038) | (0.038) | (0.018) | (0.018) | (0.017) | (0.018) |
| $VIX_{t-1}$ | −0.002** | −0.002** | −0.002* | −0.002* | 0.002** | 0.002** | 0.002** | 0.002** | 0.0003 | 0.0003 | 0.0003 | 0.0003 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Observations | 228 | 216 | 202 | 180 | 264 | 264 | 264 | 264 | 1,113 | 1,113 | 1,113 | 1,113 |
| $R^2$ | 0.070 | 0.070 | 0.162 | 0.171 | 0.368 | 0.368 | 0.368 | 0.368 | 0.003 | 0.003 | 0.003 | 0.003 |
| Adjusted $R^2$ | −0.001 | −0.004 | 0.089 | 0.089 | 0.327 | 0.327 | 0.327 | 0.327 | −0.012 | −0.012 | −0.012 | −0.012 |

*Significance levels:* *p<0.05; **p<0.01

### 5.2.3 Predicting Net Flows

We proceeded to assess the predictive power of stock market returns on equity mutual fund net flows during different time periods, taking the same approach as in section 5.1.3.

**Table 22:** Unbalanced fixed-effects predictive panel regression of net flows for each sub period. Panel A: pre-crisis [Apr 2006 – Dec 2007], Panel B: crisis [Jan 2008 – Oct 2009], Panel C: post-crisis [Nov 2009 – Dec 2016]. Base model:
$NetFlow_{i,t} = \beta_1 Return^*_{i,t-1} + \sum_{m=1}^{2} (\beta_m NetFlow_{i,t-m}) + \alpha_i + \epsilon_{i,t}$.
$^*Return_{i,t-1}$ equals $ExcessReturn_{i,t-1}$ in model (1) and $ThreeLagsEReturn_{i,t-1}$ in model (2), where $ThreeLagsEReturn_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} ExcessReturn_{i,t-m}$.

| | *Dependent variable: $NetFlow_{i,t}$* | | | | | |
|---|---|---|---|---|---|---|
| | A: Pre-crisis | | B: Crisis | | C: Post-crisis | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\text{ExcessReturn}_{\text{i,t-1}}$ | −0.057 | | 0.069 | | 0.008 | |
| | (0.119) | | (0.061) | | (0.034) | |
| $\text{ThreeLagsEReturn}_{\text{i,t-1}}$ | | 0.047 | | 0.030 | | 0.109* |
| | | (0.192) | | (0.053) | | (0.051) |
| $\text{NetFlow}_{\text{i,t-1}}$ | 0.294 | 0.282 | −0.015 | −0.002 | 0.259** | 0.256** |
| | (0.166) | (0.173) | (0.086) | (0.087) | (0.098) | (0.099) |
| $\text{NetFlow}_{\text{i,t-2}}$ | −0.168** | −0.168** | 0.115 | 0.117 | 0.161** | 0.160** |
| | (0.045) | (0.048) | (0.121) | (0.127) | (0.046) | (0.048) |
| Observations | 226 | 226 | 269 | 269 | 1,118 | 1,118 |
| $R^2$ | 0.064 | 0.063 | 0.035 | 0.025 | 0.116 | 0.118 |
| Adjusted $R^2$ | 0.002 | 0.001 | −0.022 | −0.033 | 0.104 | 0.106 |
| *Significance levels:* | | | | | | *p<0.05; **p<0.01 |

The results in table 22 indicate that net flow to equity mutual funds are not strongly influenced by past returns in any of the time periods we study. We find a statistically significant link only in the post-crisis period between net flows and the average of the past three lags of excess market returns. Interestingly, none of the lagged *NetFlow* variables are significant in crisis periods. This indicates that in times of economic turmoil, net flows to equity mutual funds are not autocorrelated. The same result can be seen in table 23, where the regressions are run with the inclusion of macroeconomic and financial control variables. The low adjusted $R^2$ values for regressions 1 and 2 in table 22 reveal that net flows displayed little autocorrelation also in the run-up up to the financial crisis.

Table 23 shows that when macroeconomic and financial control variables are included in the regressions, the coefficient of *ThreeLagsEReturn*$_{\text{i,t-1}}$ in the post-crisis period remains the only significant flow variable coefficient. When we compare the adjusted $R^2$ of regressions (6) and (7), we see that by including this variable, one only explains approximately 0.2 % additional variance of net flows. Therefore, although the coefficient is significant at the 1 % level, only a very weak connection between lagged returns and net flows is indicated. The coefficient tells us that when the average excess return on the market index over the past three months is one percentage point higher, net flow to equity mutual funds is generally higher by 0.149 % of the market capitalisation of the market index. 0.149 % is around 2.5 times the average standard deviation of net flows over the whole time period across all countries.

**Table 23:** Unbalanced fixed-effects predictive panel regression of net flows for each sub period with macro variables. Panel A: pre-crisis [Apr 2006 – Dec 2007], Panel B: crisis [Jan 2008 – Oct 2009], Panel C: post-crisis [Nov 2009 – Dec 2016]. Base model:
$NetFlow_{i,t} = \beta_1 Return^{*}_{i,t-1} \sum_{j=2}^{12} \beta_j Var^{**}_{j,i,t} + \alpha_i + \epsilon_{i,t}$.
*$Return_{i,t-1}$ equals $ExcessReturn_{i,t-1}$ in model (1) and $ThreeLagsEReturn_{i,t-1}$ in model (2), where $ThreeLagsEReturn_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} ExcessReturn_{i,t-m}$.
**Variables $\mathrm{Var_j}$ are listed in the leftmost column.

| | *Dependent variable: $NetFlow_{i,t}$* | | | | | | |
|---|---|---|---|---|---|---|---|
| | A: Pre-crisis | | B: Crisis | | C: Post-crisis | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $\mathrm{ExcessReturn_{i,t\text{-}1}}$ | −0.031 | | 0.093 | | 0.007 | | |
| | (0.189) | | (0.066) | | (0.028) | | |
| $\mathrm{ThreeLagsEReturn_{i,t\text{-}1}}$ | | 0.058 | | 0.052 | | 0.149** | |
| | | (0.244) | | (0.091) | | (0.048) | |
| $\mathrm{NetFlow_{i,t\text{-}1}}$ | 0.341* | 0.335* | −0.042 | | 0.248** | 0.246* | 0.249** |
| | (0.144) | (0.146) | (0.054) | (0.057) | (0.095) | (0.096) | (0.095) |
| $\mathrm{NetFlow_{i,t\text{-}2}}$ | −0.157* | −0.158* | −0.042 | −0.033 | 0.152** | 0.152** | 0.152** |
| | (0.064) | (0.066) | (0.054) | (0.057) | (0.044) | (0.046) | (0.045) |
| $\mathrm{BondNetFlow_{i,t\text{-}1}}$ | 0.056* | 0.056* | −0.079 | −0.075 | 0.003 | 0.003 | 0.003 |
| | (0.023) | (0.024) | (0.044) | (0.046) | (0.012) | (0.014) | (0.012) |
| $\mathrm{BondNetFlow_{i,t\text{-}2}}$ | 0.007 | 0.006 | 0.092 | 0.088 | 0.004 | 0.003 | 0.004 |
| | (0.023) | (0.023) | (0.054) | (0.057) | (0.007) | (0.008) | (0.007) |
| $\mathrm{BondNetFlow_{i,t\text{-}3}}$ | 0.032* | 0.030 | 0.013 | 0.007 | −0.006 | −0.005 | −0.006 |
| | (0.013) | (0.016) | (0.023) | (0.022) | (0.007) | (0.007) | (0.007) |
| $\mathrm{FOREX_{i,t\text{-}1}}$ | −0.552 | −0.528 | −0.386 | −0.376 | 0.057 | 0.069 | 0.056 |
| | (0.461) | (0.378) | (0.206) | (0.215) | (0.036) | (0.036) | (0.036) |
| $\mathrm{IBOR_{i,t\text{-}1}}$ | −0.065 | −0.065 | −0.016 | −0.019 | 0.0001 | 0.001 | 0.001 |
| | (0.035) | (0.037) | (0.010) | (0.011) | (0.002) | (0.002) | (0.002) |
| $\mathrm{TermPrem_{i,t\text{-}1}}$ | −0.020 | −0.020 | −0.003 | −0.005 | 0.001 | 0.001 | 0.001 |
| | (0.028) | (0.030) | (0.010) | (0.010) | (0.001) | (0.001) | (0.001) |
| $\mathrm{Unempl_{i,t\text{-}1}}$ | −0.024 | −0.024 | 0.001 | 0.001 | −0.002 | −0.003 | −0.002* |
| | (0.017) | (0.016) | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) |
| $\mathrm{YoYInflation_{i,t\text{-}1}}$ | −1.514 | −1.505 | 0.532 | 0.504 | −0.467 | −0.456 | −0.468 |
| | (1.281) | (1.294) | (0.334) | (0.310) | (0.276) | (0.274) | (0.276) |
| $\mathrm{VIX_{t\text{-}1}}$ | 0.001 | 0.001 | 0.002* | 0.002 | −0.0002 | 0.0001 | −0.0002 |
| | (0.002) | (0.001) | (0.001) | (0.001) | (0.0003) | (0.0003) | (0.0004) |
| Observations | 215 | 215 | 264 | 264 | 1,113 | 1,113 | 1,113 |
| $R^2$ | 0.146 | 0.146 | 0.234 | 0.222 | 0.125 | 0.128 | 0.125 |
| Adjusted $R^2$ | 0.044 | 0.044 | 0.160 | 0.147 | 0.106 | 0.109 | 0.107 |
| *Significance levels:* | | | | | | | *p<0.05; **p<0.01 |

In summary, although the predictability of both excess market returns and equity mutual fund net flows seems to have varied over our studied time period, we find limited evidence of a link between equity mutual fund net flows and market returns in our analysis of subperiods. We find a significant positive association between concurrent flows and returns in the run-up to the financial crisis and that higher net flows lead to higher returns in the post-crisis sample, but these findings are weak. A last small indication that the financial crisis affected the behaviour of equity mutual fund investors is that only after the crisis do the net flows display autocorrelation. One possible explanation is that the crisis dented the confidence of mutual fund investors, and that many of these are no longer trying to time the market, but rather have set up monthly savings plans. Still, the main results of section 5.1 are fairly robust across periods of both market crisis and tranquility.

## 5.3 Country-Level Analyses

While the panel regressions in section 5.1 give no indication that a relationship between equity mutual fund flows and stock market returns exists, there may be a connection in some of the countries. If fact, there may still be statistically significant relationships in all countries, merely with differing signs.

### 5.3.1 Contemporaneous Analyses

We now investigate whether a contemporaneous relationship exists between aggregate net flow to equity mutual funds and excess stock market returns in each individual country. The results of these regressions are given in table 24.

**Table 24:** Excess returns regressed on net flows (Panel A) and unexpected net flows (Panel B) in each country [Feb 2006 – Dec 2016]. Because the USA series of net flows displayed no autocorrelation, the USA net flows are entirely unexpected.

| | *Dependent variable: $ExcessReturn_{i,t}$* | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| i: | CHE | ESP | FRA | GBR | GRC | HKG | JPN | NOR | PRT | SWE | TUR | TWN | USA |
| **Panel A** | | | | | | | | | | | | | |
| $\mathrm{NetFlow}_{i,t}$ | −0.077 | 0.323 | 0.131 | 0.029* | 0.122 | −3.604 | −0.410** | 0.273* | −0.030 | 0.223** | −1.388** | 0.043 | 0.016 |
| | (0.095) | (0.195) | (0.076) | (0.014) | (0.106) | (3.736) | (0.148) | (0.118) | (0.024) | (0.040) | (0.301) | (0.081) | (0.028) |
| Constant | 0.0002 | −0.0004 | 0.002 | −0.001 | −0.020* | 0.006 | −0.001 | 0.001 | −0.006 | −0.001 | 0.013* | 0.001 | 0.003 |
| | (0.003) | (0.005) | (0.005) | (0.004) | (0.010) | (0.010) | (0.005) | (0.005) | (0.005) | (0.004) | (0.007) | (0.005) | (0.005) |
| Observations | 131 | 132 | 131 | 131 | 131 | 116 | 131 | 132 | 131 | 131 | 93 | 120 | 131 |
| $R^2$ | 0.007 | 0.026 | 0.024 | 0.011 | 0.004 | 0.027 | 0.071 | 0.064 | 0.013 | 0.187 | 0.128 | 0.004 | 0.002 |
| Adjusted $R^2$ | −0.001 | 0.019 | 0.017 | 0.003 | −0.004 | 0.018 | 0.064 | 0.057 | 0.005 | 0.181 | 0.118 | −0.005 | −0.006 |
| **Panel B** | | | | | | | | | | | | | |
| $\mathrm{UnexpectedNetFlow}_{i,t}$ | −0.102 | −0.038 | 0.118 | 0.015 | 0.169 | −2.905 | −0.204 | 0.253 | 0.086 | 0.216** | −1.540** | 0.057 | 0.016 |
| | (0.100) | (0.263) | (0.077) | (0.018) | (0.122) | (3.387) | (0.147) | (0.131) | (0.123) | (0.044) | (0.325) | (0.120) | (0.028) |
| Constant | 0.0005 | −0.004 | 0.0001 | 0.00002 | −0.020* | 0.003 | 0.002 | 0.003 | −0.006 | −0.0002 | 0.003 | 0.001 | 0.003 |
| | (0.003) | (0.005) | (0.005) | (0.004) | (0.010) | (0.008) | (0.005) | (0.005) | (0.005) | (0.004) | (0.006) | (0.005) | (0.005) |
| Observations | 127 | 127 | 127 | 127 | 127 | 115 | 127 | 131 | 131 | 127 | 87 | 119 | 131 |
| $R^2$ | 0.011 | 0.0003 | 0.018 | 0.002 | 0.006 | 0.018 | 0.021 | 0.049 | 0.007 | 0.167 | 0.169 | 0.004 | 0.002 |
| Adjusted $R^2$ | 0.003 | −0.008 | 0.010 | −0.006 | −0.002 | 0.010 | 0.013 | 0.041 | 0.001 | 0.161 | 0.159 | −0.005 | −0.006 |

*Significance levels:* *p<0.05; **p<0.01

**Table 25:** Interpretation of significant coefficients in table 24. The left column shows the magnitude of change in the independent variable; the middle column shows the impact on the dependent variable $ExcessReturn_{i,t}$.

| Variable Change | Effect | Interpretation |
|---|---|---|
| $NetFlow_{i,t} \uparrow 0.1$ % of MCap | $ExcessReturn_{GBR,t} \uparrow 0.29$ %<br>$ExcessReturn_{JPN,t} \downarrow 4.10$ %<br>$ExcessReturn_{NOR,t} \uparrow 2.73$ %<br>$ExcessReturn_{SWE,t} \uparrow 2.23$ %<br>$ExcessReturn_{TUR,t} \downarrow 13.88$ % | Higher net flows are associated with higher stock market returns in the UK, Norway and Sweden, and lower excess market returns in Japan and Turkey. |
| $UnexpectedNetFlow_{i,t} \uparrow 0.1$ % of MCap | $ExcessReturn_{SWE,t} \uparrow 2.16$ %<br>$ExcessReturn_{TUR,t} \downarrow 15.40$ % | Higher net flows are associated with higher stock market returns in Sweden and lower returns in Turkey. |

*Note:* bp = basis points

From table 24, panel A, we observe that aggregate net flows only appear to explain index returns in five of the 13 studied countries. For unexpected flows, there appears to be a statistically significant relationship in just two of the countries, as is visible from panel B. Interpretations of significant coefficients are given in table 25. Previous research agrees that there exists a positive contemporaneous relationship between stock index returns and (unexpected) net flow to equity mutual funds (Warther, 1995; Edelen and Warner, 2001; Goetzmann and Massa, 2003; Oh and Parwada, 2007), and in light of this, the absence of a significant relationship in most of the studied countries is surprising. It is equally surprising that the relationships we find for Japan and Turkey are negative. Taking into account the revelations of sections 5.1 and 5.2, however, these results do not surprise at all.

Comparing panels A and B in table 24, we observe the same coefficient signs for both flow variables apart from in Japan – where the coefficient of $UnexpectedNetFlow_t$ is insignificant – and in Spain – where neither variable coefficient is found significant. Although the explanatory power of $UnexpectedNetFlow_{TUR,t}$ is somewhat higher than $NetFlow_{TUR,t}$, for every other country, unexpected net flows explain less return variance. For this reason and the sake of simplicity, we disregard unexpected net flows in the remainder of our analyses, concentrating solely on net flows.

To evaluate whether information-response is the reason for the countrywise differences and the observed association in some of the countries, a set of macroeconomic and financial control variables have been included in the following regressions for all countries. The model used is model (5), given in section 4.4.1, and the results are presented in table 26.

**Table 26:** Regressions by country of excess index returns on net flows and macroeconomic and financial variables [Feb 2006 – Dec 2016].

Model: $ExcessReturn_{i,t} = \beta_1 NetFlow_{i,t} + \sum_{j=2}^{14} \beta_j Var^*_{j,i,t} + \alpha_i + \epsilon_{i,t}$.

*Variables $\mathrm{Var_j}$ are listed in the leftmost column.

| | *Dependent variable: Excess Return$_{i,t}$* | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| i: | CHE | ESP | FRA | GBR | GRC | HKG | JPN | NOR | PRT | SWE | TUR | TWN | USA |
| $\mathrm{NetFlow_{i,t}}$ | −0.015 | 0.067 | −0.001 | 0.015 | 0.100 | −1.803 | −0.223 | 0.210* | 0.080 | 0.122* | −1.291** | 0.102 | 0.014 |
| | (0.086) | (0.266) | (0.100) | (0.018) | (0.132) | (2.347) | (0.127) | (0.084) | (0.110) | (0.047) | (0.402) | (0.051) | (0.015) |
| $\delta\mathrm{FOREX_{i,t}}$ | 0.344** | −0.536** | −0.080 | 0.016 | −0.760 | −8.071 | 0.961** | −0.393** | −0.353 | 0.026 | −0.845** | −1.195** | 0.284* |
| | (0.091) | (0.182) | (0.154) | (0.140) | (0.416) | (4.456) | (0.243) | (0.129) | (0.225) | (0.129) | (0.420) | (0.284) | (0.114) |
| $\Delta\mathrm{IBOR_{i,t}}$ | 0.014 | 0.003 | 0.076* | −0.005 | 0.009 | 0.002 | −0.020 | 0.040 | 0.031 | 0.024 | −0.016 | 0.035 | 0.038 |
| | (0.021) | (0.034) | (0.038) | (0.025) | (0.086) | (0.201) | (0.238) | (0.037) | (0.050) | (0.041) | (0.015) | (0.122) | (0.030) |
| $\delta\mathrm{IPI_{i,t}}$ | −0.202 | 0.528 | 0.279 | 0.164 | −0.004 | 0.098 | −0.001 | −0.167 | 0.054 | 0.085 | −0.118 | −0.075 | 0.002 |
| | (0.435) | (0.394) | (0.214) | (0.360) | (0.320) | (0.162) | (0.210) | (0.121) | (0.219) | (0.161) | (0.319) | (0.086) | (0.761) |
| $\mathrm{MoMInflation_{i,t}}$ | 0.337 | 0.481 | −1.120 | 1.288 | 1.806 | 1.177 | −0.327 | −1.175 | 0.807 | 0.884 | −1.203 | −1.15 | 0.340 |
| | (1.243) | (0.878) | (1.267) | (1.011) | (1.560) | (0.821) | (1.098) | (2.519) | (1.106) | (1.139) | (1.239) | (0.059) | (1.300) |
| $\mathrm{TermPrem_{i,t\text{-}1}}$ | 0.011 | −0.002 | 0.008 | 0.003 | −0.0001 | 0.004 | −0.003 | 0.008 | −0.001 | 0.007 | 0.008 | −0.014 | 0.003 |
| | (0.007) | (0.003) | (0.004) | (0.003) | (0.002) | (0.007) | (0.013) | (0.006) | (0.002) | (0.007) | (0.004) | (0.014) | (0.004) |
| $\Delta\mathrm{TermPrem_{i,t}}$ | 0.022 | −0.014 | 0.063** | 0.013 | −0.006 | −0.003 | 0.041 | 0.047* | −0.005 | 0.022 | 0.018 | 0.109* | 0.013 |
| | (0.019) | (0.023) | (0.024) | (0.016) | (0.011) | (0.028) | (0.055) | (0.023) | (0.011) | (0.023) | (0.020) | (0.039) | (0.014) |
| $\Delta\mathrm{Unempl_{i,t}}$ | 0.032 | −0.013 | −0.001 | −0.016 | −0.035 | −0.016 | −0.001 | 0.017 | 0.016 | 0.020 | −0.022 | −0.047 | −0.016 |
| | (0.049) | (0.030) | (0.048) | (0.027) | (0.040) | (0.049) | (0.042) | (0.035) | (0.025) | (0.016) | (0.032) | (0.040) | (0.019) |
| $\mathrm{YoYInflation_{i,t\text{-}1}}$ | −0.342 | 0.510 | −0.070 | 0.466 | −0.375 | −0.467 | −0.481 | −0.658 | −0.313 | −0.125 | −0.256 | −0.687 | −0.579 |
| | (0.304) | (0.640) | (1.115) | (0.513) | (0.620) | (0.388) | (0.561) | (0.393) | (0.594) | (0.349) | (0.433) | (0.265) | (0.940) |
| $\delta\mathrm{BDI_t}$ | −0.009 | −0.020 | −0.022 | 0.002 | −0.037 | 0.038 | 0.016 | 0.034* | 0.015 | 0.023 | −0.015 | 0.004 | −0.004 |
| | (0.015) | (0.020) | (0.012) | (0.013) | (0.050) | (0.022) | (0.023) | (0.017) | (0.024) | (0.019) | (0.021) | (0.013) | (0.012) |
| $\delta\mathrm{BrentSpot_t}$ | 0.013 | 0.036 | −0.071 | −0.070 | 0.023 | −0.097 | −0.079 | −0.021 | −0.053 | −0.098* | −0.133* | −0.076 | 0.003 |
| | (0.029) | (0.063) | (0.049) | (0.037) | (0.108) | (0.061) | (0.050) | (0.054) | (0.064) | (0.048) | (0.056) | (0.042) | (0.033) |
| $\delta\mathrm{IndMetals_t}$ | 0.091 | 0.036 | 0.115 | 0.190** | 0.209 | 0.378** | 0.159 | 0.107 | 0.022 | 0.095 | −0.141 | 0.212* | 0.141* |
| | (0.048) | (0.082) | (0.067) | (0.052) | (0.175) | (0.107) | (0.082) | (0.093) | (0.092) | (0.073) | (0.173) | (0.065) | (0.055) |
| $\mathrm{VIX_{t\text{-}1}}$ | −0.001* | −0.0004 | −0.001* | −0.001 | −0.001 | −0.0005 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.0002 | −0.001 |
| | (0.001) | (0.003) | (0.001) | (0.0005) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\delta\mathrm{VIX_t}$ | −0.105** | −0.116** | −0.139** | −0.099** | −0.199** | −0.103** | −0.091** | −0.095** | −0.108** | −0.104** | −0.064 | −0.049* | −0.114** |
| | (0.013) | (0.022) | (0.015) | (0.013) | (0.051) | (0.027) | (0.028) | (0.017) | (0.023) | (0.021) | (0.039) | (0.021) | (0.015) |
| Constant | 0.020* | 0.0004 | 0.014 | 0.0005 | 0.014 | 0.023 | 0.024 | 0.037* | 0.019 | 0.009 | 0.058 | 0.022 | 0.028 |
| | (0.009) | (0.026) | (0.016) | (0.011) | (0.034) | (0.022) | (0.021) | (0.015) | (0.017) | (0.012) | (0.037) | (0.014) | (0.026) |
| Observations | 130 | 130 | 130 | 130 | 128 | 116 | 130 | 130 | 130 | 130 | 82 | 120 | 130 |
| $R^2$ | 0.486 | 0.431 | 0.548 | 0.547 | 0.394 | 0.514 | 0.586 | 0.614 | 0.303 | 0.531 | 0.605 | 0.586 | 0.672 |
| Adjusted $R^2$ | 0.424 | 0.362 | 0.492 | 0.491 | 0.319 | 0.447 | 0.536 | 0.567 | 0.218 | 0.474 | 0.522 | 0.531 | 0.632 |

*Significance levels:* *p<0.05; **p<0.01

**Table 27:** Interpretation of significant coefficients in table 26. The left column shows the magnitude of change in the independent variable; the middle column shows the impact on the dependent variable $ExcessReturn_{i,t}$.

| Variable Change | Effect | Interpretation |
|---|---|---|
| $NetFlow_{i,t} \uparrow$ 0.1 % of MCap | $ExcessReturn_{NOR,t} \uparrow$ 2.1 %<br>$ExcessReturn_{SWE,t} \uparrow$ 1.2 %<br>$ExcessReturn_{TUR,t} \downarrow$ 12.9 % | Higher net flows to equity mutual funds are associated with higher market returns in Norway and Sweden, and lower market returns in Turkey. |
| $\delta FOREX_{i,t} \uparrow$ 1 % | $ExcessReturn_{CHE,t} \uparrow$ 34 bp<br>$ExcessReturn_{ESP,t} \downarrow$ 54 bp<br>$ExcessReturn_{JPN,t} \uparrow$ 96 bp<br>$ExcessReturn_{NOR,t} \downarrow$ 39 bp<br>$ExcessReturn_{TUR,t} \downarrow$ 85 bp<br>$ExcessReturn_{TWN,t} \downarrow$ 119 bp<br>$ExcessReturn_{USA,t} \downarrow$ 28 bp | An increase in the exchange rate against the US dollar for the local currency in (i.e. a depreciation of local currency toward USD) is associ ated with higher market returns in Switzerland and Japan, and lower market returns in Spain, Norway, Turkey and Taiwan. A depreciation of the USD versus the Euro is associated with lower returns in the USA. |
| $\Delta TermPrem_{i,t} \uparrow$ 100 bp | $ExcessReturn_{FRA,t} \uparrow$ 6 bp<br>Excess $Return_{NOR,t} \uparrow$ 5 bp | An increase in the term premium is associated with higher market returns in France and Norway. |
| $\delta BrentSpot_{t} \uparrow$ 1 % | $ExcessReturn_{SWE,t} \downarrow$ 10 bp<br>$ExcessReturn_{TUR,t} \downarrow$ 13 bp | An increase in the spot price of Brent is associated with lower market returns in Sweden and Turkey. |
| $\delta IndMetals_{t} \uparrow$ 1 % | $ExcessReturn_{GBR,t} \uparrow$ 19 bp<br>$ExcessReturn_{HKG,t} \uparrow$ 38 bp<br>$ExcessReturn_{TWN,t} \uparrow$ 22 bp<br>$ExcessReturn_{USA,t} \uparrow$ 14 bp | An increase in the price of metals used in industrial production is associated with higher market returns in the UK, Hong Kong, Taiwan and the USA. |
| $\delta VIX_{t} \uparrow$ 1 % | $ExcessReturn_{i,t} \downarrow$ 5-14 bp | An increase in market volatility is associated with lower market returns. |

*Note:* bp = basis points

When comparing the results in table 24 and 26, one observes that the coefficients of $NetFlow_{i,t}$ are less significant for all countries $i$ when macro variables are controlled for. Still, the results remain similar, with the main exception being the coefficient of $NetFlow_{JPN,t}$, which is no longer significant. However, the coefficient of $NetFlow_{JPN,t}$ in the initial regression was negative, and so these results are strongly refutative of the information-response hypothesis. Interpretations of the significant coefficients in table 26 are given in table 27. For Norway and Sweden, net flows are positively associated with excess returns, while Turkey displays a negative association. Most notably, when net flows are higher by 0.1% of the market capitalisation of the main stock index in Turkey, the BIST 100, the monthly return on that index tends to be as much as 12.9 % lower. These results should be viewed in light of the standard deviation of net flows reported for each country in table 9, however. 0.1 % of the market capitalisation of the BIST 100 represents close to six standard deviations of Turkish net flows!

## 5.4 Predicting Stock Market Returns

This section investigates the predictive power of fund flows on excess index returns in each of the 13 countries. We begin by testing whether net flows to equity mutual funds Granger-cause excess stock index returns. Because only one predicting variable is used in each Granger test, Granger causality is determined simply by whether the significance level of the predicting net flow variable is below 5 %. The results are shown in table 28.

**Table 28:** Countrywise tests for whether equity mutual fund net flows Granger-cause excess index returns. Panel A: $ExcessReturn$ regressed on the first lag of $NetFlow$. Panel B: $ExcessReturn$ regressed on the mean of the first three lags of $NetFlow$. Lagged returns are not included for reasons given in section 4.5.
Model A: $ExcessReturn_{i,t} = \beta NetFlow_{i,t-1} + \alpha_i + \epsilon_{i,t}$.
Model B: $ExcessReturn_{i,t} = \beta ThreeLagsNetFlow_{i,t-1} + \alpha_i + \epsilon_{i,t}$, where
$ThreeLagsNetFlow_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} NetFlow_{i,t-m}$.

| | *Dependent variable: ExcessReturn$_{i,t}$* | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| i: | CHE | ESP | FRA | GBR | GRC | HKG | JPN | NOR | PRT | SWE | TWN | TUR | USA |
| **Panel A** | | | | | | | | | | | | | |
| $NetFlow_{i,t-1}$ | 0.044 | 0.088 | −0.003 | 0.023 | −0.010 | −2.510 | −0.070 | 0.135 | 0.037 | 0.019 | 0.018 | −0.302 | −0.062* |
| | (0.079) | (0.118) | (0.100) | (0.017) | (0.132) | (1.597) | (0.119) | (0.080) | (0.231) | (0.051) | (0.066) | (0.326) | (0.029) |
| Constant | −0.0003 | −0.004 | −0.002 | −0.001 | −0.021* | 0.004 | 0.0004 | 0.001 | −0.007 | 0.001 | 0.004 | 0.001 | 0.007 |
| | (0.003) | (0.005) | (0.005) | (0.004) | (0.010) | (0.007) | (0.005) | (0.005) | (0.005) | (0.004) | (0.007) | (0.005) | (0.004) |
| Observations | 129 | 129 | 129 | 129 | 129 | 115 | 129 | 129 | 129 | 129 | 119 | 92 | 129 |
| **Panel B** | | | | | | | | | | | | | |
| $ThreeLagsNetFlow_{i,t-1}$ | −0.251 | 0.425* | 0.209 | 0.023 | 0.067 | −10.728* | −0.323 | 0.141 | 0.682 | 0.283** | 0.049 | −1.350** | −0.015 |
| | (0.148) | (0.183) | (0.140) | (0.021) | (0.195) | (4.302) | (0.120) | (0.148) | (0.459) | (0.062) | (0.087) | (0.362) | (0.059) |
| Constant | −0.0002 | −0.004 | 0.002 | −0.001 | −0.018 | −0.004 | 0.0004 | 0.00002 | −0.005 | 0.002 | 0.0003 | 0.001 | 0.003 |
| | (0.003) | (0.005) | (0.005) | (0.004) | (0.010) | (0.008) | (0.005) | (0.006) | (0.005) | (0.005) | (0.006) | (0.008) | (0.005) |
| Observations | 129 | 129 | 129 | 129 | 129 | 114 | 129 | 129 | 129 | 129 | 118 | 91 | 129 |

*Significance levels:* *p<0.05; **p<0.01

Panel A shows that net flows have very limited predictive power of excess index returns. Only in the USA is $NetFlow_{\mathrm{i,t\text{-}1}}$ significant at the 5 % level. This coefficient is negative, indicating that higher monthly net flows are associated with lower next-month excess market returns. Were it also the case that a positive association existed at the monthly level for the USA, these two results combined would be indicative of net flows applying temporary price pressure on the stock market. Because we find no contemporaneous relationship between US flows and returns, this result is difficult to interpret economically. When conducting regressions on 13 countries and using a 5 % significance level, one is fairly likely to get a false positive, and it is likely the case here.

Panel B shows the results of regressions with an average of the first three lags of $NetFlow_{\mathrm{i}}$ as independent variable. This configuration seems to predict returns better than $NetFlow_{\mathrm{i,t\text{-}1}}$ overall, as it seems to have predictive power in four countries: Spain, Hong Kong, Sweden, and Turkey. The sign of this relationship is inconsistent across countries, however, as there appears to be positive causality in Spain and Sweden and negative causality in Hong Kong and Turkey. Overall, the results in table 28 are in accord with the literature since stock index returns are not shown to respond to equity mutual fund net flows in the long term in the majority of the studied countries.

Regression model (6), given in section 4.4.2, with macroeconomic control variables is now run on the countries for which net flows to equity mutual funds seemed to predict excess market returns. The results are given in table 29.

**Table 29:** Regressions by country of excess index returns on lagged net flow to equity mutual funds and predictive control variables [Apr 2006 – Dec 2016]. Model:
$ExcessReturn_{i,t} = \beta_1 ThreeLagsNetFlow_{i,t-1} + \beta_2 TermPrem_{i,t-1} + \beta_3 YoYInflation_{i,t-1} + \beta_4 \delta IndMetals_{t-1} + \beta_5 VIX_{t-1} + \alpha_i + \epsilon_{i,t}$, where $ThreeLagsNetFlow_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} NetFlow_{i,t-m}$.

| | *Dependent variable: ExcessReturn*$_{i,t}$ | | | |
|---|---|---|---|---|
| i: | ESP | HKG | SWE | TUR |
| $\mathrm{ThreeLagsNetFlow_{i,t\text{-}1}}$ | $0.635^{*}$ | $-10.267^{*}$ | $0.246^{**}$ | $-1.493^{**}$ |
| | (0.311) | (4.098) | (0.080) | (0.421) |
| $\mathrm{TermPrem_{i,t\text{-}1}}$ | −0.001 | −0.006 | 0.009 | 0.002 |
| | (0.006) | (0.007) | (0.007) | (0.006) |
| $\mathrm{YoYInflation_{i,t\text{-}1}}$ | 0.646 | −0.677 | 0.119 | −0.155 |
| | (0.646) | (0.413) | (0.390) | (0.540) |
| $\delta\mathrm{IndMetals_{t\text{-}1}}$ | $0.194^{*}$ | 0.108 | 0.031 | 0.082 |
| | (0.088) | (0.113) | (0.077) | (0.141) |
| $\mathrm{VIX_{t\text{-}1}}$ | 0.001 | 0.0003 | −0.0001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| Constant | −0.021 | 0.039 | −0.011 | 0.003 |
| | (0.017) | (0.029) | (0.016) | (0.048) |
| Observations | 128 | 114 | 128 | 81 |
| $R^2$ | 0.077 | 0.127 | 0.156 | 0.097 |
| Adjusted $R^2$ | 0.040 | 0.087 | 0.122 | 0.036 |
| *Significance levels:* | | | $^{*}$p<0.05; $^{**}$p<0.01 | |

**Table 30:** Interpretation of significant coefficients in table 29. The left column shows the magnitude of change in the independent variable; the middle column shows the impact on *ExcessReturn*$_{\mathrm{i,t}}$.

| Variable Change | Effect | Interpretation |
|---|---|---|
| $\mathrm{ThreeLagsNetFlow_{i,t\text{-}1}} \uparrow$ 0.1 % of MCap | $\mathrm{ExcessReturn_{ESP,t}} \uparrow$ 6.35 %<br>$\mathrm{ExcessReturn_{HKG,t}} \downarrow$ 102.67 %<br>$\mathrm{ExcessReturn_{SWE,t}} \uparrow$ 2.46 %<br>$\mathrm{ExcessReturn_{TUR,t}} \downarrow$ 14.93 % | Higher net flows in the past three months is associated with higher stock market returns in Spain and Sweden and lower returns in Hong Kong and Turkey. |
| $\delta\mathrm{IndMetals_{t\text{-}1}} \uparrow$ 1 % of MCap | $\mathrm{ExcessReturn_{ESP,t}} \uparrow$ 19 bp | An increase in the price of industrial metals is associated with higher next-month stock returns in Spain. |
| *Note:* | | bp = basis points |

From tables 28 and 29, one can observe that the coefficients of the fund flow variable remain much the same when macro variables are controlled for and that they retain their significance. We are surprised to find that higher net flows in the previous three months predict lower excess market returns in Hong Kong since Yangbo et al. (2010) document a positive long-term response in market returns to equity mutual fund net flows in their study of Hong Kong. It is also interesting to note that $YoYInflation_{\text{i,t-1}}$ cannot predict excess market returns for these four countries, considering that the predictive panel regression results from section 5.1.2 indicated that it could.

Interpretations of the significant coefficients in table 29 are given in table 30. Most protruding here is that an average net flow over the past three months higher by 0.1 % of the market capitalisation of the main stock index in Hong Kong is associated with 102.67 % lower returns (which isn't even possible for most mutual funds since managers generally lack the mandate to gear investments). However, one must recall that the domestic mutual fund market in Hong Kong is very small compared to the Hang Seng Index. 0.1 % of the market capitalisation of the Hang Seng Index represents over 30 standard deviations of Hong Kong net flows (see table 9)!

### 5.4.1 Predicting Net Fund Flows

We proceed to study whether market returns can predict net flows to equity mutual funds. Taking the same steps as before, we test for Granger causality, this time from excess index returns to equity mutual fund net flows, and afterwards include macroeconomic control variables. We also use the mean of the past three lags of excess returns to predict net flows for each country. This seeks to account for the possibility that equity mutual fund investors look at the performance of the stock market over a longer time period when contemplating investment.

**Table 31:** Countrywise tests for whether excess index returns Granger-cause equity mutual fund net flows. In panel A, *NetFlow* is regressed on its significant lags and the first lag of *ExcessReturn*. In Panel B, *NetFlow* is regressed on its significant lags and the mean of the first three lags of *ExcessReturn*. For both models, the binary variable $Z_{i,m}$=1 if the mth lag of $NetFlow_i$ was found predictive of $NetFlow_i$, and 0 otherwise.

Model A: $NetFlow_{i,t} = \beta_1 ExcessReturn_{i,t-1} + \sum_{m=1}^{4}(Z_{i,m} \times \beta_{m+1} NetFlow_{i,t-m}) + \alpha_i + \epsilon_{i,t}$.

Model B: $NetFlow_{i,t} = \beta_1 ThreeLagsEReturn_{i,t-1} + \sum_{m=1}^{4}(Z_{i,m} \times \beta_{m+1} NetFlow_{i,t-m}) + \alpha_i + \epsilon_{i,t}$, where

$ThreeLagsEReturn_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} ExcessReturn_{i,t-m}$.

| | *Dependent variable: $NetFlow_{i,t}$* | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| i: | CHE | ESP | FRA | GBR | GRC | HKG | JPN | NOR | PRT | SWE | TUR | TWN | USA |
| Panel A | | | | | | | | | | | | | |
| $ExcessReturn_{i,t-1}$ | −0.313** | 0.071* | 0.186* | −0.220 | −0.007 | −0.010** | 0.025 | −0.170 | 0.071 | 0.386* | 0.022 | 0.024 | 0.228 |
| | (0.067) | (0.029) | (0.083) | (0.166) | (0.031) | (0.004) | (0.054) | (0.111) | (0.043) | (0.153) | (0.158) | (0.023) | (0.222) |
| $NetFlow_{i,t-1}$ | 0.226** | 0.362** | | 0.409 | | −0.010 | 0.567** | | −0.354 | 0.108 | 0.653** | 0.364** | |
| | (0.082) | (0.133) | | (0.38) | | (0.084) | (0.150) | | (0.361) | (0.087) | (0.187) | (0.117) | |
| $NetFlow_{i,t-2}$ | | | 0.219* | 0.200 | 0.226** | | | 0.345** | | | | | |
| | | | (0.086) | (0.185) | (0.082) | | | (0.082) | | | | | |
| $NetFlow_{i,t-3}$ | | | 0.200** | | | | | | | | | | |
| | | | (0.068) | | | | | | | | | | |
| $NetFlow_{i,t-4}$ | | 0.349* | | | | | | 0.345** | | | | | |
| | | (0.144) | | | | | | (0.099) | | | | | |
| Constant | 0.000 | −0.000 | −0.000 | 0.000 | −0.000 | 0.00002* | −0.000 | 0.000 | −0.000 | 0.000 | −0.000 | 0.000 | 0.0004* |
| | (0.001) | (0.001) | (0.002) | (0.003) | (0.001) | (0.000) | (0.001) | (0.002) | (0.001) | (0.004) | (0.000) | (0.002) | (0.005) |
| Observations | 129 | 129 | 128 | 129 | 129 | 116 | 129 | 129 | 129 | 128 | 119 | 93 | 129 |
| Panel B | | | | | | | | | | | | | |
| $ThreeLagsEReturn_{i,t-1}$ | −0.283* | 0.108 | 0.342* | 0.001 | 0.221 | −0.007 | −0.124 | 0.051 | 0.132 | 1.102** | 0.105 | −0.110* | −0.116 |
| | (0.126) | (0.057) | (0.153) | (0.184) | (0.166) | (0.004) | (0.085) | (0.179) | (0.115) | (0.393) | (0.226) | (0.043) | (0.487) |
| $NetFlow_{i,t-1}$ | 0.244** | 0.370** | | 0.402 | | 0.023 | 0.513** | | -0.364** | 0.104 | 0.652** | 0.279* | |
| | (0.088) | (0.129) | | (0.261) | | (0.074) | (0.146) | | (0.190) | (0.086) | (0.188) | (0.113) | |
| $NetFlow_{i,t-2}$ | | | 0.219* | 0.200 | 0.226** | | | 0.345** | | | | | |
| | | | (0.086) | (0.185) | (0.082) | | | (0.082) | | | | | |
| $NetFlow_{i,t-3}$ | | | 0.233** | | | | | | | | | | |
| | | | (0.069) | | | | | | | | | | |
| $NetFlow_{i,t-4}$ | | 0.336* | | | | | | 0.028 | | | | | |
| | | (0.146) | | | | | | (0.136) | | | | | |
| Constant | 0.000 | −0.000 | −0.000 | 0.000 | −0.000 | 0.00002* | −0.000 | 0.000 | −0.000 | 0.000 | −0.000 | 0.000 | 0.0004* |
| | (0.001) | (0.001) | (0.002) | (0.003) | (0.001) | (0.000) | (0.001) | (0.002) | (0.001) | (0.004) | (0.000) | (0.002) | (0.005) |
| Observations | 127 | 128 | 127 | 127 | 127 | 112 | 127 | 128 | 127 | 127 | 116 | 89 | 127 |

*Significance levels:* *p<0.05; **p<0.01

Table 31 shows the results of tests for Granger causality from excess returns to net flows. Lags of *NetFlow* found significant predictors of *NetFlow* for a given country have been included in that country's regression model. We find a positive causal relationship from *ExcessReturn* to *NetFlow* in Spain, France and Sweden, and negative causality in Switzerland and Hong Kong (see panel A). Panel B shows the results of the regressions with the average of the three first lags of excess returns as a predictive variable. Using this specification, excess market returns are found to have positive impact on net flows in France and Sweden, and negatively impact net flows in Switzerland and Taiwan.

For countries with a statistically significant relationship between equity mutual fund net flows and lagged excess market returns, we now rerun the regressions, controlling for macroeconomic and financial variables as per model (7) in section 4.4.3. Results are shown in table 32.

**Table 32:** Net flow to equity mutual funds regressed on lagged returns and predictive control variables by country [May 2006 – Dec 2016]. Base model:

$$NetFlow_{i,t} = \beta_1 Return^{*}_{i,t-1} + \sum_{m=1}^{4} (Z^{**}_{i,m} \times \beta_{m+1} NetFlow_{i,t-m}) + \sum_{j=6}^{14} \beta_j Var^{***}_{j,i,t} + \alpha_i + \epsilon_{i,t}$$

*$Return_{i,t-1}$ equals $ExcessReturn_{i,t-1}$ in panel A and $ThreeLagsEReturn_{i,t-1}$ in panel B, where $ThreeLagsEReturn_{i,t} = \frac{1}{3} \times \sum_{m=0}^{2} ExcessReturn_{i,t-m}$.

**The binary variable $Z_{i,m}$=1 if the mth lag of $NetFlow_i$ was found predictive of $NetFlow_i$, and 0 otherwise.

***Variables $\mathrm{Var_j}$ are listed in the leftmost column.

| | *Dependent variable: $NetFlow_{i,t}$* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | *Panel A* | | | | | *Panel B* | | | |
| i: | CHE | ESP | FRA | HKG | SWE | CHE | FRA | SWE | TWN |
| $\mathrm{ExcessReturn_{i,t\text{-}1}}$ | $-0.267^{**}$ | 0.070 | $0.271^{*}$ | $-0.008$ | $0.622^{**}$ | | | | |
| | (0.092) | (0.037) | (0.109) | (0.004) | (0.165) | | | | |
| $\mathrm{ThreeLagsEReturn_{i,t\text{-}1}}$ | | | | | | $-0.159$ | $0.370^{*}$ | $1.159^{**}$ | 0.224 |
| | | | | | | (0.190) | (0.167) | (0.409) | (0.265) |
| $\mathrm{NetFlow_{i,t\text{-}1}}$ | $0.216^{*}$ | 0.157 | | $-0.075$ | $-0.114$ | $0.214^{*}$ | | $-0.048$ | $0.553^{**}$ |
| | (0.095) | (0.133) | | (0.130) | (0.088) | (0.107) | | (0.102) | (0.198) |
| $\mathrm{NetFlow_{i,t\text{-}2}}$ | | | | $0.218^{*}$ | | | 0.174 | | |
| | | | | (0.100) | | | (0.090) | | |
| $\mathrm{NetFlow_{i,t\text{-}3}}$ | | | | $0.181^{*}$ | | | $0.215^{**}$ | | |
| | | | | (0.076) | | | (0.078) | | |
| $\mathrm{NetFlow_{i,t\text{-}4}}$ | | | 0.181 | | | | | | |
| | | | (0.083) | | | | | | |
| $\mathrm{BondNetFlow_{i,t\text{-}1}}$ | $-0.037$ | 0.026 | $-0.032$ | $-0.083$ | 0.028 | $-0.080$ | $-0.034$ | $-0.126$ | 0.017 |
| | (0.052) | (0.022) | (0.025) | (0.100) | (0.121) | (0.021) | (0.028) | (0.119) | (0.108) |
| $\mathrm{BondNetFlow_{i,t\text{-}2}}$ | $-0.001$ | $-0.015$ | 0.051 | 0.132 | $-0.092$ | $-0.015$ | 0.035 | $-0.094$ | 0.108 |
| | (0.039) | (0.024) | (0.016) | (0.133) | (0.147) | (0.024) | (0.027) | (0.141) | (0.151) |
| $\mathrm{BondNetFlow_{i,t\text{-}3}}$ | $-0.054$ | 0.028 | $-0.007$ | 0.093 | $-0.173$ | 0.029 | 0.001 | $-0.182$ | $-0.029^{*}$ |
| | (0.053) | (0.021) | (0.023) | (0.108) | (0.098) | (0.023) | (0.122) | (0.084) | (0.009) |
| $\mathrm{FOREX_{i,t\text{-}1}}$ | 0.030 | $-0.023$ | 0.025 | 0.046 | $-0.036$ | $-0.012$ | 0.076 | $-0.041^{*}$ | $-0.005$ |
| | (0.047) | (0.049) | (0.131) | (0.030) | (0.018) | (0.043) | (0.104) | (0.017) | (0.005) |
| $\mathrm{IBOR_{i,t\text{-}1}}$ | $-0.005$ | $-0.002$ | 0.022 | $-0.001$ | $-0.025^{*}$ | $-0.001$ | 0.016 | $-0.021$ | $0.044^{*}$ |
| | (0.006) | (0.004) | (0.016) | (0.001) | (0.012) | (0.004) | (0.014) | (0.012) | (0.019) |
| $\mathrm{TermPrem_{i,t\text{-}1}}$ | $-0.007$ | $-0.002$ | 0.002 | $-0.001$ | 0.002 | 0.003 | 0.006 | $-0.003$ | 0.032 |
| | (0.008) | (0.004) | (0.011) | (0.001) | (0.011) | (0.003) | (0.010) | (0.011) | (0.023) |
| $\mathrm{Unempl_{i,t\text{-}1}}$ | 0.003 | 0.001 | 0.037 | $-0.000$ | $-0.041^{*}$ | 0.001 | 0.015 | $-0.038^{*}$ | $-0.029^{*}$ |
| | (0.016) | (0.001) | (0.028) | (0.001) | (0.017) | (0.001) | (0.022) | (0.018) | (0.013) |
| $\mathrm{YoYInflation_{i,t\text{-}1}}$ | 0.049 | 0.101 | $-1.227$ | $-0.004$ | $-3.561^{**}$ | 0.048 | $-3.354$ | $-3.291^{**}$ | $-1.195$ |
| | (0.537) | (0.454) | (2.942) | (0.024) | (1.124) | (0.361) | (2.590) | (1.093) | (0.652) |
| $\mathrm{VIX_{t\text{-}1}}$ | 0.00 | 0.000 | $0.001^{*}$ | 0.000 | $0.004^{**}$ | 0.000 | 0.001 | $0.003^{**}$ | 0.001 |
| | (0.001) | (0.000) | (0.001) | (0.000) | (0.001) | (0.000) | (0.001) | (0.001) | (0.001) |
| Constant | $-0.029$ | $-0.010$ | $-0.427$ | $-0.354$ | $0.568^{*}$ | $-0.019$ | $-0.217$ | $0.591^{**}$ | 0.222 |
| | (0.047) | (0.051) | (0.265) | (0.235) | (0.223) | (0.039) | (0.232) | (0.224) | (0.160) |
| Observations | 128 | 127 | 128 | 113 | 128 | 128 | 127 | 127 | 118 |
| $R^2$ | 0.182 | 0.141 | 0.165 | 0.100 | 0.279 | 0.489 | 0.194 | 0.326 | 0.505 |
| Adjusted $R^2$ | 0.105 | 0.059 | 0.078 | 0.002 | 0.211 | 0.110 | 0.436 | 0.261 | 0.454 |
| *Significance levels:* | | | | | | | | | $^{*}$p<0.05; $^{**}$p<0.01 |

As is visible from tables 31 and 32, the lagged return coefficients remain much the same after the inclusion of macroeconomic variables in the regressions. The exceptions are Switzerland and Taiwan, where the coefficients of $ThreeLagsEReturn_{\text{t-1}}$ have become insignificant. The coefficients of $ExcessReturn_{\text{ESP,t}}$ and $ExcessReturn_{\text{HKG,t}}$ too have lost their significance. We also observe that for every country, most of the macroeconomic variables are poor predictors of next-month net flow.

The positive excess return coefficients in table 32 for France and Sweden indicate that equity mutual fund investors in these countries follow a momentum trading strategy. In Switzerland, however, it appears that equity mutual fund investors follow a contrarian strategy.

Our results differ from previous findings on numerous accounts. Firstly, previous research has found significant causal relationships from stock market returns to equity mutual fund net flows in the USA (Warther, 1995; Fortune, 1998; Edwards and Zhang, 1998; Fant, 1999; Lee et al., 2015), albeit with differing signs, whereas we do not. Secondly, unlike Yangbo et al. (2010), we find no relationship in Hong Kong. Thirdly, our results suggest that stock market returns predict equity mutual fund net flows in France and Spain, contrary to Lee et al. (2015)'s findings.

Which variable coefficients that display significance in table 32 varies greatly from country to country. Interpretations of the significant coefficients are given in table 33. None of the independent variables appear to have a particularly large impact on net flows.

**Table 33:** Interpretation of significant coefficients in table 32. The left column shows the magnitude of change in the independent variable; the middle column shows the impact on the dependent variable $NetFlow_{\text{i,t}}$.

| **Variable Change** | **Effect** | **Interpretation** |
|---|---|---|
| $\text{ExcessReturn}_{\text{i,t-1}} \uparrow 1\ \%$ | $\text{NetFlow}_{\text{CHE,t}} \downarrow 0.003\ \%$ of MCap<br>$\text{NetFlow}_{\text{FRA,t}} \uparrow 0.003\ \%$ of MCap<br>$\text{NetFlow}_{\text{SWE,t}} \uparrow 0.006\ \%$ of MCap | A higher excess market return in the previous month is associated with lower net flows in Switzerland and higher net flows in France and Sweden. |
| $\text{ThreeLagsEReturn}_{\text{i,t-1}} \uparrow 1\ \%$ | $\text{NetFlow}_{\text{FRA,t}} \uparrow 0.004\ \%$ of MCap<br>$\text{NetFlow}_{\text{SWE,t}} \uparrow 0.012\ \%$ of MCap | Higher excess market returns over the past three months are associated with higher net flows in France and Sweden. |
| $\text{FOREX}_{\text{i,t-1}} \uparrow 1$ | $\text{NetFlow}_{\text{SWE,t}} \downarrow 0.0004\ \%$ of MCap | Higher USD/SEK in the previous month is associated with slightly lower net flows in Sweden. |
| $\text{IBOR}_{\text{i,t-1}} \uparrow 100$ bp | $\text{NetFlow}_{\text{SWE,t}} \downarrow 0.025\%$ of MCap<br>$\text{NetFlow}_{\text{TWN,t}} \uparrow 0.044\%$ of MCap | Higher short-term interest rates in one month are associated with lower next-month net flows in Sweden and higher net flows in Taiwan. |
| $\text{Unempl}_{\text{i,t-1}} \uparrow 1\ \%$ | $\text{NetFlow}_{\text{SWE,t}} \downarrow 0.04\ \%$ of MCap<br>$\text{NetFlow}_{\text{TWN,t}} \downarrow 0.029\ \%$ of MCap | A higher unemployment rate is associated with lower next-month net flows in Sweden and Taiwan. |
| $\text{YoYInflation}_{\text{i,t-1}} \uparrow 100$ bp | $\text{NetFlow}_{\text{SWE,t}} \downarrow 0.034\ \%$ of MCap | A higher level of inflation at the start of the month is associated with lower net flows in Sweden. |
| $\text{VIX}_{\text{t-1}} \uparrow 1$ | $\text{NetFlow}_{\text{FRA,t}} \uparrow 0.001\%$ of MCap<br>$\text{NetFlow}_{\text{SWE,t}} \uparrow 0.004\%$ of MCap | In months where the market expects higher volatility, net flows are higher in France and Sweden. |

*Note:* bp = basis points

### 5.4.2 Summary

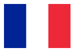
Here, we apply the framework from section 2 to our own countrywise findings to give a concise overview. The discovered relationships between equity mutual fund net flows and excess stock market returns are shown in table 34, and which hypotheses are supported by these findings are displayed in table 35. As previously stated, our results are refutative of information-response. The results for Turkey do not rhyme with any hypothesis.

The main takeaway from this subsection is that support for the different hypotheses can quite easily be found in data from one single country. For many countries, though, we find no connection between monthly equity mutual fund flows and monthly excess stock market returns.

**Table 34:** Overview of the relationships found for each country, significant at the 5 % level. The countries are listed in the leftmost column. The following three columns show net flows impacting returns, returns impacting net flows, and the contemporaneous relationship, respectively. A '+' indicates a positive relationship; a '-' indicates a negative relationship; a blank space indicates that no relationship was found.

| | **Long-Term** | | |
|---|---|---|---|
| **Country** | NF → Ret | Ret → NF | Cont |
| France | | + | |
| Greece | | | |
| Hong Kong | - | | |
| Japan | | | |
| Norway | | | + |
| Portugal | | | |
| Spain | + | | |
| Switzerland | | - | |
| Sweden | + | + | + |
| Taiwan | | | |
| Turkey | - | | - |
| UK | | | |
| USA | | | |

**Table 35:** Overview of which hypotheses are supported by data from the individual countries. The positive bidirectional causal relationship documented for Sweden indicates positive feedback trading, not shown in the figure.

| Information Revelation | Price Pressure | Momentum Trading | Contrarian Trading |
|---|---|---|---|
|  | |  |  |
|  | |  |  |

# 6 Conclusion

Studies of equity mutual fund flows and stock market returns have traditionally been conducted on just a single financial market, and those few studies conducted on multiple markets only studied the impact of fund flows on returns and vice versa within each market. Furthermore, the findings made and conclusions drawn in previously published articles on this topic vary greatly, and the literature does not provide any satisfactory reasoning for why the link between equity mutual fund flows and stock market returns should vary across countries. The main purpose of this article was therefore twofold: (1) evaluate the common effects of equity mutual fund net flows on stock market returns and vice versa across countries; (2) investigate whether the observed association between equity mutual fund net flows and stock market returns in certain countries is a result of investors reacting similarly to new information flow.

Most importantly, we find evidence of neither a contemporaneous nor causal relationship between domestic monthly equity mutual fund net flows and stock market returns at a global scale. We do not find a connection common across markets over the whole time period [Feb 2006 – Dec 2016], nor any strong relationship during bull runs or in a period of market crisis. This suggests that the link between equity mutual fund flows and stock movements is much weaker than one would infer from past studies.

When net flows and excess returns were regressed upon one another country-by-country, their coefficient values and significance levels were largely unchanged by the inclusion of macroeconomic control variables. This indicates that whatever connection there may be between the two is not primarily a result of investors responding similarly to new macroeconomic information. In short, the countrywise results indicate great differences in mutual fund investor behaviour across countries.

We find support for the information revelation hypothesis in Spain and Sweden, i.e. that equity mutual fund investors are better informed than the wider market. Further, we find evidence in support of the investment sentiment hypothesis in four countries, where it appears that equity mutual fund investors chase returns in France and Sweden and take a contrarian trading strategy in Switzerland and Hong Kong. The bidirectional positive causality found in Sweden indicates that a positive feedback process is at work in this market.

Perhaps the most surprising of our results is that we do not find evidence of a contemporaneous relationship at a global scale, and a significant positive association in just two countries, namely Norway and Sweden. This result comes as a surprise because there is strong consensus in the literature that a positive temporal link exists between equity mutual fund flows and stock market returns. One plausible reason why we observe no common relationship, even though previous studies have shown there to be a positive association in numerous countries, is that advances in computer technology in finance have made it possible to respond quicker to pricing anomalies. Financial markets have developed substantially over the past decades, and the way trading was conducted during the time period we study is very different from how trading was done in the 80's and 90's.

An additional finding is that net flows explain stock market returns just as well as unexpected net flows. Lastly, we find that equity mutual fund net flows are difficult to predict.

# Appendix

**Table 36:** Summary statistics for all variables over the period Feb 2006 – Dec 2016.

| | **Mean** | **Stdev** | **Min** | **Max** |
|---|---|---|---|---|
| **France (FRA)** | | | | |
| NetFlow | −0.023% | 0.059% | −0.304% | 0.280% |
| BondNetFlow | −0.026% | 0.226% | −0.982% | 0.581% |
| ExcessReturn | −0.10% | 5.00% | −14.90% | 11.70% |
| USD/EUR | 0.772 | 0.076 | 0.634 | 0.951 |
| $\delta$USD/EUR | 0.10% | 3.10% | −9.60% | 10.40% |
| IBOR | 1.45% | 1.69% | −0.33% | 5.11% |
| $\Delta$IBOR | −22bp | 17bp | −95bp | 32bp |
| $\delta$IPI | −0.10% | 1.50% | −5.20% | 3.40% |
| MoMInflation | 0.10% | 0.28% | −0.87% | 0.67% |
| TermPrem | 1.28% | 0.97% | −0.93% | 2.84% |
| $\Delta$TermPrem | 0bp | 21bp | −51bp | 89bp |
| Unemployment | 9.3% | 1.0% | 7.2% | 10.6% |
| $\Delta$Unemployment | 0bp | 9bp | −20bp | 30bp |
| YoYInflation | 1.1% | 0.4% | 0.2% | 1.8% |
| | **Mean** | **Stdev** | **Min** | **Max** |
| **Greece (GRC)** | | | | |
| NetFlow | −0.008% | 0.056% | −0.250% | 0.354% |
| BondNetFlow | −0.053% | 0.227% | −2.876% | 0.702% |
| ExcessReturn | −2.00% | 10.90% | −35.00% | 24.40% |
| USD/EUR | 0.772 | 0.076 | 0.634 | 0.951 |
| $\delta$USD/EUR | 0.10% | 3.10% | −9.60% | 10.40% |

| | | | | |
|---|---|---|---|---|
| IBOR | 1.45% | 1.69% | −0.33% | 5.11% |
| ΔIBOR | −22bp | 17bp | −95bp | 32% |
| δIPI | −0.20% | 3.20% | −8.60% | 8.40% |
| MoMInflation | 0.11% | 0.52% | −1.22% | 1.36% |
| TermPrem | 7.74% | 6.53% | −0.32% | 28.19% |
| ΔTermPrem | 6bp | 151bp | −999bp | 548bp |
| Unemployment | 17.6% | 7.8% | 7.3% | 27.9% |
| ΔUnemployment | 10bp | 30bp | −60bp | 110bp |
| YoYInflation | 0.9% | 2.0% | −3.7% | 4.2% |

| | **Mean** | **Stdev** | **Min** | **Max** |
|---|---|---|---|---|
| **Hong Kong (HKG)** | | | | |
| NetFlow | 0.002% | 0.003% | −0.015% | 0.013% |
| BondNetFlow | 0.002% | 0.003% | −0.006% | 0.011% |
| ExcessReturn | 0.20% | 6.40% | −25.60% | 15.60% |
| USD/HKD | 7.767 | 0.019 | 7.750 | 7.827 |
| δUSD/HKD | 0.00% | 0.10% | −0.50% | 0.5% |
| IBOR | 1.15% | 0.54% | 0.55% | 2.27% |
| ΔIBOR | −1bp | 4bp | −10bp | 10bp |
| δIPI | −0.1% | 3.60% | −16.70% | 17.70% |
| MoMInflation | 0.26% | 0.75% | −02.04% | 2.71% |
| TermPrem | 1.25% | 0.87% | −0.51% | 3.26% |
| ΔTermPrem | −1bp | 27bp | −81bp | 76.40bp |
| Unemployment | 3.8% | 0.7% | 3.1% | 5.5% |
| ΔUnemployment | −1bp | 12bp | −30bp | 50bp |
| YoYInflation | 3.1% | 1.6% | −1.6% | 7.6% |

| | Mean | Stdev | Min | Max |
|---|---|---|---|---|
| **Japan (JPN)** | | | | |
| NetFlow | −0.005% | 0.039% | −0.142% | 0.147% |
| BondNetFlow | 0.042% | 0.080% | −0.109% | 0.286% |
| ExcessReturn | 0.10% | 6.00% | −27.30% | 12.10% |
| USD/JPY | 101.031 | 14.649 | 76.230 | 124.140 |
| $\delta$USD/JPY | −0.01% | 2.90% | −7.40% | 8.80% |
| IBOR | 0.24% | 0.24% | 0.01% | 0.79% |
| $\Delta$IBOR | −0.bp | 3bp | −14bp | 15bp |
| $\delta$IPI | −0.10% | 2.60% | −17.20% | 6.40% |
| MoMInflation | 0.02% | 0.35% | −0.74% | 1.49% |
| TermPrem | 0.73% | 0.43% | −0.24% | 1.90% |
| $\Delta$TermPrem | −1bp | 10bp | −30bp | 40bp |
| Unemployment | 4.1% | 0.6% | 3.0% | 5.5% |
| $\Delta$Unemployment | −1bp | 12bp | −30bp | 40bp |
| YoYInflation | 0.0% | 0.9% | −1.5% | 2.5% |

| | Mean | Stdev | Min | Max |
|---|---|---|---|---|
| **Norway (NOR)** | | | | |
| NetFlow | 0.008% | 0.054% | −0.146% | 0.232% |
| BondNetFlow | 0.113% | 0.218% | −0.499% | 0.968% |
| ExcessReturn | 0.31% | 5.90% | −27.90% | 13.83% |
| USD/NOK | 6.394 | 0.992 | 5.085 | 8.842 |
| $\delta$USD/NOK | 0.2% | 3.50% | −7.90% | 13.60% |
| IBOR | 2.73% | 1.55% | 0.98% | 6.92% |
| $\Delta$IBOR | −1bp | 21bp | −154bp | 33bp |
| $\delta$IPI | −0.10% | 3.00% | −7.10% | 12.10% |
| MoMInflation | 0.08% | 0.20% | −0.52% | 0.71% |
| TermPrem | 0.35% | 0.96% | −2.75% | 2.29% |

| | | | | |
|---|---|---|---|---|
| ΔTermPrem | −0bp | 26bp | −80bp | 113bp |
| Unemployment | 3.4% | 0.7% | 2.3% | 4.9% |
| ΔUnemployment | 0bp | 12bp | −30bp | 30bp |
| YoYInflation | 2.1% | 1.1% | −0.4% | 5.3% |

| | **Mean** | **Stdev** | **Min** | **Max** |
|---|---|---|---|---|
| **Portugal (PRT)** | | | | |
| NetFlow | −0.007% | 0.038% | −0.244% | 0.248% |
| BondNetFlow | −0.088% | 0.212% | −0.646% | 0.395% |
| Excess Return | −0.60% | 5.90% | −23.70% | 10.10% |
| USD/EUR | 0.772 | 0.076 | 0.634 | 0.951 |
| $\delta$USD/EUR | 0.1% | 3.10% | −9.60% | 10.4% |
| IBOR | 1.45% | 1.69% | −0.33% | 5.11% |
| ΔIBOR | −22bp | 17bp | −95bp | 32% |
| $\delta$IPI | −0.10% | 2.40% | −7.00% | 6.00% |
| MoMInflation | 0.10% | 0.49% | −1.53% | 1.44% |
| TermPrem | 3.91% | 3.27% | −0.55% | 12.63% |
| ΔTermPrem | 3bp | 47bp | −119bp | 125bp |
| Unemployment | 12.057% | 2.594% | 8.500% | 17.500% |
| ΔUnemployment | 1bp | 22bp | -70bp | 50bp |
| YoYInflation | 1.4% | 1.0% | −0.5% | 4.0% |

| | **Mean** | **Stdev** | **Min** | **Max** |
|---|---|---|---|---|
| **Spain (ESP)** | | | | |
| NetFlow | −0.006% | 0.030% | −0.170% | 0.061% |
| BondNetFlow | 0.011% | 0.174% | −0.498% | 0.507% |
| ExcessReturn | −0.40% | 6.00% | −19.10% | 15.10% |
| USD/EUR | 0.772 | 0.076 | 0.634 | 0.951 |
| $\delta$USD/EUR | 0.10% | 3.10% | −9.60% | 10.4% |
| IBOR | 1.45% | 1.69% | −0.33% | 5-11% |

| | | | | |
|---|---|---|---|---|
| ΔIBOR | −22bp | 17bp | −95bp | 32% |
| δIPI | −0.20% | 1.50% | −5.30% | 2.90% |
| MoMInflation | 0.13% | 0.52% | −1.79% | 1.10% |
| TermPrem | 0.62% | 1.28% | −1.63% | 3.46% |
| ΔTermPrem | 1bp | 31bp | −68bp | 175bp |
| Unemployment | 18.6% | 6.2% | 7.9% | 26.3% |
| ΔUnemployment | 7bp | 28bp | −40bp | 110bp |
| YoYInflation | 1.2% | 0.9% | −0.3% | 2.8% |

| | **Mean** | **Stdev** | **Min** | **Max** |
|---|---|---|---|---|
| **Sweden (SWE)** | | | | |
| NetFlow | 0.015% | 0.095% | −0.411% | 0.237% |
| BondNetFlow | 0.026% | 0.074% | −0.152% | 0.287% |
| ExcessReturn | 0.20% | 4.90% | −18.70% | 15.60% |
| USD/SEK | 7.195 | 0.822 | 5.945 | 9.226 |
| δUSD/SEK | 0.10% | 3.50% | −9.10% | 11.80% |
| IBOR | 1.25% | 1.46% | −0.79% | 4.49% |
| ΔIBOR | −2bp | 19bp | −138bp | 30bp |
| δIPI | −0.1% | 2.30% | −6.50% | 7.50% |
| MoMInflation | 0.09% | 0.39% | −1.23% | 0.86% |
| TermPrem | 1.20% | 0.87% | −0.59% | 3.29% |
| ΔTermPrem | −0bp | 21bp | −49bp | 71bp |
| Unemployment | 7.5% | 0.9% | 5.6% | 9.3% |
| ΔUnemployment | 0bp | 30bp | −60bp | 110bp |
| YoYInflation | 1.0% | 1.2% | −1.8% | 4.1% |

| | **Mean** | **Stdev** | **Min** | **Max** |
|---|---|---|---|---|
| **Switzerland (CHE)** | | | | |
| NetFlow | 0.003% | 0.040% | −0.125% | 0.196% |
| BondNetFlow | 0.031% | 0.081% | −0.245% | 0.320% |
| ExcessReturn | −0.003% | 3.80% | −12.10% | 9.60% |

| | | | | |
|---|---|---|---|---|
| USD/CHF | 1.023 | 0.120 | 0.786 | 1.312 |
| $\delta$USD/CHF | −0.20% | 3.20% | −12.90% | 11.90% |
| IBOR | 0.52% | 1.14% | −0.85% | 2.96% |
| ΔIBOR | −1bp | 17bp | −146bp | 23bp |
| $\delta$IPI | 0.20% | 0.70% | −1.40% | 2.00% |
| MoMInflation | 0.01% | 0.33% | −0.86% | 1.09% |
| TermPrem | 0.87% | 0.53% | −0.29% | 2.14% |
| ΔTermPrem | −0bp | 17bp | −48bp | 92bp |
| Unemployment | 3.12% | 0.36% | 2.50% | 4.10% |
| ΔUnemployment | 0bp | 7bp | −30bp | 20bp |
| YoYInflation | 0.2% | 1.0% | −1.5% | 3.2% |

| | **Mean** | **Stdev** | **Min** | **Max** |
|---|---|---|---|---|
| **Taiwan (TWN)** | | | | |
| NetFlow | −0.006% | 0.078% | −0.201% | 0.544% |
| BondNetFlow | −0.014% | 0.057% | −0.385% | 0.174% |
| ExcessReturn | 0.20% | 5.40% | −18.10% | 13.20% |
| USD/TWD | 31.301 | 1.439 | 28.645 | 34.995 |
| $\delta$USD/TWD | −0.01% | 1.50% | −4.40% | 5.00% |
| IBOR | 1.15% | 0.54% | 0.55% | 2.27% |
| ΔIBOR | −1bp | 4bp | −10bp | 10bp |
| $\delta$IPI | 0.20% | 4.50% | −17.80% | 20.10% |
| MoMInflation | 0.10% | 0.64% | −1.68% | 2.16% |
| TermPrem | 0.44% | 0.31% | −0.57% | 1.01% |
| ΔTermPrem | 0bp | 11bp | −41bp | 37bp |
| Unemployment | 4.3% | 0.6% | 3.6% | 6.1% |
| ΔUnemployment | 0bp | 11bp | −28bp | 44bp |
| YoYInflation | 1.1% | 1.4% | −2.4% | 5.6% |

| | Mean | Stdev | Min | Max |
|---|---|---|---|---|
| **Turkey (TUR)** | | | | |
| NetFlow | 0.006% | 0.017% | −0.050% | 0.064% |
| BondNetFlow | 0.022% | 0.040% | −0.130% | 0.121% |
| ExcessReturn | −0.40% | 7.80% | −27.50% | 19.70% |
| USD/TRY | 1.863 | 0.565 | 1.162 | 3.528 |
| $\delta$USD/TRY | 0.70% | 4.00% | −7.40% | 18.90% |
| IBOR | 11.17% | 4.25% | 5.13% | 20.72% |
| $\Delta$IBOR | −8bp | 83bp | −324bp | 274bp |
| $\delta$IPI | 0.30% | 2.20% | −7.50% | 8.60% |
| MoMInflation | 0.68% | 0.58% | −0.51% | 2.45% |
| TermPrem | 0.19% | 1.49% | −2.12% | 3.69% |
| $\Delta$TermPrem | −3bp | 58bp | −228bp | 100bp |
| Unemployment | 9.77% | 1.34% | 7.80% | 13.30% |
| $\Delta$Unemployment | 2bp | 25bp | −50bp | 90bp |
| YoYInflation | 7.3% | 1.6% | 3.6% | 10.2% |

| | Mean | Stdev | Min | Max |
|---|---|---|---|---|
| **United Kingdom (GBR)** | | | | |
| NetFlow | 0.032% | 0.147% | −0.324% | 0.840% |
| BondNetFlow | 0.014% | 0.048% | −0.154% | 0.202% |
| ExcessReturn | 0.01% | 4.00% | −14.50% | 8.00% |
| USD/GBP | 0.606 | 0.057 | 0.480 | 0.702 |
| $\delta$USD/GBP | 0.001 | 0.025 | −0.091 | 0.104 |
| IBOR | 1.96% | 2.15% | 0.35% | 6.58% |
| $\Delta$IBOR | −3bp | 23bp | −178bp | 36bp |
| $\delta$IPI | −0.05% | 0.95% | −3.53% | 2.6% |
| MoMInflation | 0.20% | 0.30% | −0.68% | 1.01% |
| TermPrem | 1.16% | 1.36% | −1.66% | 3.50% |

| | | | | |
|---|---|---|---|---|
| ΔTermPrem | 1bp | 26bp | −62bp | 1456bp |
| Unemployment | 6.5% | 1.3% | 4.6% | 8.4% |
| ΔUnemployment | 0bp | 12bp | −30bp | 40bp |
| YoYInflation | 1.9% | 0.7% | 0.8% | 3.6% |

| | **Mean** | **Stdev** | **Min** | **Max** |
|---|---|---|---|---|
| **USA (USA)** | | | | |
| NetFlow | 0.044% | 0.122% | −0.103% | 0.724% |
| BondNetFlow | 0.074% | 0.087% | −0.214% | 0.346% |
| ExcessReturn | 0.40% | 4.50% | −18.80% | 10.30% |
| EUR/USD | 1.307 | 0.124 | 1.052 | 1.577 |
| $\delta$EUR/USD | −0.10% | 3.10% | −10.40% | 9.60% |
| IBOR | 1.00% | 1.71% | 0.01% | 5.03% |
| ΔIBOR | −3bp | 16bp | −86bp | 44bp |
| $\delta$IPI | 0.02% | 0.70% | −4.40% | 1.50% |
| MoMInflation | 0.15% | 0.32% | −1.78% | 1.05% |
| TermPrem | 1.99% | 1.04% | −0.38% | 3.69% |
| ΔTermPrem | 1bp | 23bp | −95bp | 63bp |
| Unemployment | 6.8% | 1.9% | 4.4% | 10.0% |
| ΔUnemployment | 0bp | 18bp | −50bp | 50bp |
| YoYInflation | 1.9% | 0.5% | 0.6% | 2.9% |

| | **Mean** | **Stdev** | **Min** | **Max** |
|---|---|---|---|---|
| **Macroeconomic variables** | | | | |
| $\delta$BrentSpot | −0.0 % | 9.2 % | -40.7 % | 25.5 % |
| $\delta$IndMetals | 0.1 % | 7.0 % | -29.6 % | 17.8 % |
| $\delta$BDI | −0.59 % | 27.6 % | -132.9 % | 81.2 % |
| VIX | 19.03 | 9.338 | 10.27 | 56.73 |
| $\delta$VIX | 0.0 % | 22.0 % | −50.7 % | 81.2 % |

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