

PhD Thesis

**Chasing stock market returns.**

**Mutual funds extrapolative flow, performance and asset pricing implications**

Keywords: mutual funds, extrapolation, market-timing

**Alberto Cagnazzo**

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Department of Economics and Finance

LUISS Guido Carli

Supervisor: Prof. Nicola Borri

Roma, May 2017

Committee:

Prof. Nicola Borri, LUISS Guido Carli

Prof. Bruno S. Sergi, Harvard University

Prof. Domenico Curcio, LUISS Guido Carli

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# Abstract

Survey evidence shows that investor expectations on future market realizations are highly correlated with inflows into mutual funds and tend to extrapolate information from past returns. This work investigates cyclical determinants of net aggregate fund flows in Emerging Markets, it measures the profitability of market-timing strategies of Italian investors in equity mutual funds and provides first insights about the effects of these strategies on asset prices.

Chapter 2 investigates how cyclical variables drive net aggregate fund flows towards Emerging Markets (EMs). Through the aggregation of net flows of all open-end dedicated funds, the analysis finds that flows in equity and fixed income are driven by recent past performance in both developed and emerging economies. Further analysis confirms that much of the evidence comes from US and EU larger mutual funds. A structural VAR shows that flows become more responsive through time to market uncertainty and rates. In particular, after the Great Recession flows exhibit a lower reaction to the S&P index, becoming more responsive to market volatility and to US interest rates. Furthermore the US consumer sentiment index has a key role in the explanation of fund flows and it increased through time with an effect that is more sluggish and persistent with respect to other cyclical determinants.

Chapter 3 shows that simple buy-and-hold strategies beat the market-timing strategies effectively used by Italian investors in equity mutual funds. Therefore, investors should reconsider their investment behavior and choose cheaper, in terms of fees, and simpler, passive strategies. The analysis estimates returns from market-timing strategies using aggregate data on a large sample of equity mutual funds' net flows and considers funds investing either in Europe and the Euro Area, or the US, or Emerging Markets. In all cases, buy-and-hold wins with extra returns that go from 0.24% per quarter (Europe and Euro Area) to 0.87% per quarter (US market). Differences in the performance of the two strategies are not explained by differences in risk and risk exposure.

Chapter 4 presents future research developing a discrete asset pricing model with het-

erogeneous agents. Some of them, called chasers, develop their demand of the risky asset relying on extrapolative subjective beliefs, in equilibrium this has effects on the asset price.

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# 1 Introduction & Literature review

## 1.1 Introduction

Survey evidence shows that investor expectations on future market realizations are highly correlated with inflows into mutual funds and tend to extrapolate information from past returns. This work investigates cyclical determinants of net aggregate fund flows in Emerging Markets, it measures the profitability of market-timing strategies of Italian investors in equity mutual funds and provides first insights about the effects of these strategies on asset prices.

The topic of return predictability, with implications on agents' expectations, has been widely developed in literature, and its relevance for market efficiency is being for years on the frontier of research in international finance and asset pricing. Returns are completely unpredictable if, after a rise in the price of an asset yesterday, there is no clear tendency for that to decline or to rise today, and therefore no arbitrage opportunity can be exploited through momentum or mean-reversion strategy. This early intuition has been for long considered as one of the main theoretical bulwarks for market efficiency. However, almost 30 years after his seminal work, [Fama \(1999\)](#) points out that “the predictability of stock returns from dividend yields is not in itself evidence for or against market efficiency”. In fact, forecasting future performance through the dividend yield can be possible, at least in the long-run, by the fact that prices are low with respect to dividends when discount rates are high, as shown by [Cochrane \(2011\)](#).

This research provides contributions to the topic, investigating whether mutual fund flows towards Emerging Markets are driven by past performance and evaluating the profitability of market-timing strategies effectively used by Italian investors. Moreover, if investment flows are uninformative, mutual fund managers should scale up or down their existing positions accordingly and therefore short-term investor decisions brings flow-induced price pressure. The intuition that agents' expectations on future prices, extrapolated from past performance, may have effects on observed prices has been developed in several works. [Shiller \(2005\)](#)



points out that “investors, their confidence and expectations buoyed by past price increases, bid up speculative prices further, thereby enticing more investors to do the same, so that the cycle repeats again and again”. Although the main variable of interest of this work is the net aggregate flow in the mutual fund market, the analysis is strictly linked to agents’ expectations. In fact, [Greenwood and Shleifer \(2014\)](#) point out that investor expectations on future market realizations, are highly correlated with net inflows into mutual funds and tend to be extrapolative. Nowadays mutual funds represent the most relevant vehicle for managed savings account. These instruments are relatively new since they began to appear in the European market at the beginning of 80s growing almost steadily in the last decades both in terms of asset under management and number of funds. It is mainly due to the fact that before the recent European Sovereign Crisis, Government bonds couldn’t guarantee comparable returns with equity markets and a large part of investors didn’t want, or didn’t have sufficient funds to get directly involved with stocks.

Chapter 2 investigates how cyclical variables drive net aggregate fund flows towards Emerging Markets (EMs). Through the aggregation of net flows of all open-end dedicated funds, the analysis finds that flows in equity and fixed income are driven by recent past performance in both developed and emerging economies. Further analysis confirms that much of the evidence comes from US and EU larger mutual funds. A structural VAR shows that flows become more responsive through time to market uncertainty and rates. In particular, after the Great Recession flows exhibit a lower reaction to the S&P index, becoming more responsive to market volatility and to US interest rates. Furthermore the US consumer sentiment index has a key role in the explanation of fund flows and it increased through time with an effect that is more sluggish and persistent with respect to other cyclical determinants.

Chapter 3 measures the profitability of investors’ return chasing strategies, relying on a publicly available database, of good quality, that covers all funds available to Italian

investors<sup>1</sup> in three different markets: Europe and Euro Area, US and Emerging Markets. The analysis finds that in all markets, a simple buy-and-hold strategy outperforms a chasing strategy with extra returns that go from 0.24% per quarter (Europe and Euro Area) to 0.87% per quarter (US market). Differences in the performance of the two strategies are not explained by differences in risk and risk exposure. Since findings clearly show that chasing strategies are not profitable, results make it hard to interpret all agents as rational forecasters. Investigating behavioral, and sometimes psychological, reasons behind agent beliefs is beyond the scope of this work, however the possibility that mutual funds aggregate flows (and thus investors' expectations) are partially driven by a form of irrationality should be properly taken into account. In fact, although the standard disclaimer in the prospectus of any mutual fund reminds investors that "past performance is not necessarily indicative of future results", many investors (and managers) tend to prefer funds or categories of funds that realized higher returns in the previous months. With a continuously growing number of agents that are becoming active in financial markets and with a wide market participation promoted by new financial services, the issue of financial knowledge in the latest years is gaining a key relevance for market functioning and a growing branch of literature has been studying topics related to financial literacy<sup>2</sup>. For instance [Van Rooij et al. \(2011\)](#) interviewed more than 1,500 US investors and find that almost one third of the total don't know if sentences like "mutual funds pay a guaranteed rate of return which depends on their past performance" are true or not<sup>3</sup>. Efficient Market Hypothesis further prescribes that, if there are irrational investors, rational agents should immediately exploit any arbitrage opportunities (if they create any), while this work provides clear evidence on the persistence of extrapolative (i.e. chasing) strategies. Therefore it is reasonable to expect these behaviors

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<sup>1</sup>In terms of financial volumes Italy is an area of particular relevance due to the large stock of wealth of Italian households that is approximately equal to seven times the net national income. See [Banca d'Italia \(2015\)](#)

<sup>2</sup>Although the line of literature that covers behavioral finance and related issues is gaining relevance in the last years, its early developments started with the nontechnical work of [Kindleberger \(1978\)](#).

<sup>3</sup>Their sample covers 1,508 households respondent. The 11.2% incorrectly replied to advanced questions on mutual funds while the 21.7% admitted of not knowing the answer.

to have significant effects on equilibrium prices, through aggregate demand, even in such a wide market as the one of mutual funds.

Chapter 4 presents future research developing a discrete asset pricing model with heterogeneous agents. Some of them, called chasers, develop their demand of the risky asset relying on extrapolative subjective beliefs, in equilibrium this has effects on the asset price.

The remainder of the work is organized as follows: Chapter 2 shows that net aggregate fund flows in EM equity and fixed income are driven by recent past performance in both developed and emerging economies. Chapter 3 shows that simple buy-and-hold strategies beat the market-timing strategies effectively used by Italian investors in equity mutual funds that invest in three different markets. Chapter 4 presents future research developing an extrapolative discrete asset pricing model with heterogeneous agents.

## 1.2 Literature review

Chapter 2 refers to two main branches of literature: the first one concerns the identification of drivers of capital flows in Emerging Markets while the other is focused on the link between investor expectations and short-term past performance. The first strand of analysis has been widely developed and a complete literature review on determinants of capital flows in Emerging Markets, that covers main data, methodologies and results is made by [Koepke \(2015\)](#). Many papers rely on a VAR analysis in order to evaluate the effects of those determinants on investment flows, for example [Bekaert et al. \(2002\)](#) study the interactions between flows, returns and interest rates in Emerging Markets<sup>4</sup>. [Bruno and Shin \(2015\)](#) identify the impact of the risk-taking channel of monetary policy into the transmission of global liquidity conditions showing how it drives capital flows. The channel of risk aversion has been followed also by [Ghosh et al. \(2014\)](#) that shed light on the role of contagion on capital flows and by [Broner et al. \(2013\)](#) that investigate how volatile gross capital flows and

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<sup>4</sup>Similarly, [De Vita and Kyaw \(2008\)](#) investigate the determinants of capital flows to Emerging Markets across different time horizons finding that shocks to real variables are the most important drivers of capital flows to Emerging Markets.

find how crises affect domestic and foreign agents asymmetrically. [European Central Bank \(2016\)](#) evaluates at aggregate level potential drivers of capital inflows to Emerging Markets confirming the main role of global risk aversion. Interestingly their results do not find a significant impact of advanced economy rate differentials on net inflows to Emerging Markets. As far as the second line of literature, [Greenwood and Shleifer \(2014\)](#) argue that investor expectations, highly correlated with mutual fund flows, in the period 1963-2011 follow past stock returns rather than model-implied expectations. [Ferreira et al. \(2012\)](#) evaluate how mutual fund flows depend on past performance across 28 countries, while [Lou \(2012\)](#) proposes an investment-flow based explanation for return predictability. Some interesting works as [Frazzini and Lamont \(2008\)](#) and [Ben-Rephael et al. \(2012\)](#) look at mutual fund flows as a measure of individual investor sentiment for different stocks, finding that high sentiment predicts low future returns. Other works show that fund investment flows significantly respond not only to past performance but also to fund specific factors<sup>5</sup>.

Chapter 3 mainly follows the wide branch of literature that discusses the empirical finding that investors chase returns, obtaining performances that are smaller than those of a simply buy-and-hold strategy. [Yagan \(2014\)](#) looks at the possibility that investors “ride the bubble”, buying in a boom and selling early in a burst, but finds evidence indicating buy-and-hold strategies. [Friesen and Sapp \(2007\)](#) measure the timing ability of mutual funds investors through cash flow data. They find that investors on average underperform by about 0.13% per month or 1.56% annually, relative to buy-and-hold strategy<sup>6</sup>. [Chien \(2014\)](#) looks at the correlation of net current flows into US equity mutual funds with past stock market performance and finds that they are all positive and approaching 0.4 with respect to returns in the previous quarter. Interestingly, he also finds that the correlation of current net flows with respect to future equity returns are negative, even though small in magnitude: on

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<sup>5</sup>For example [Del Guercio and Tkac \(2002, 2008\)](#) point out that there are additional characteristics to be considered, as the nature of the fund or the effect of Morningstar ratings. Similarly, [Ivkovic and Weisbenner \(2009\)](#) study the relation between individual mutual fund flows and fund characteristics.

<sup>6</sup>[Berk and Green \(2002\)](#) develop a simple rational model of active portfolio management in order to evaluate observed relationship between fund flows and returns while [Cashman et al. \(2012\)](#) find that outflows and inflows into mutual funds respond asymmetrically to past performance.

the basis of this evidence he argues that a return-chasing investment strategy that goes long (short) equity following good (poor) realized past stock returns might be costly for investors. [Venanzi \(2016\)](#), working on Italian data, discusses the differences among metrics. She finds that the spreads between time-weighted and money-weighted returns are significant at level of individual funds in the simulated scenario while differentials are not significant for aggregate data. The connection between agent expectations and past prices (returns) can be justified by recent developments in empirical finance showing that excess returns are somewhat predictable, at least in the medium to long-run, therefore market-timing strategies are not necessarily doomed to fail. In fact, according to the theory, if returns are somewhat predictable as showed by [Cochrane \(2011\)](#), investors might be able to achieve higher Sharpe ratios by timing the market. [Chabot et al. \(2014\)](#) show that momentum strategies that invest in recent past winners outperform the aggregate return on the market<sup>7</sup>. Therefore, *a priori*, it is not possible to say if investors could do better than simply holding the market.

Chapter 4 refers to a very interesting line of literature on extrapolation started by [De Long et al. \(1990\)](#). They build a model with noise traders that extrapolate past prices and through this channel influence asset prices. Years later [Brock and Hommes \(1998\)](#) investigate the dynamics of an asset pricing model with heterogeneous agents, some of which form their expectations from past realized profits. Price fluctuations are thus driven by an evolutionary dynamics between different expectation schemes<sup>8</sup>. Recently this area of research is gaining new relevance and recent papers show that agents' extrapolative behaviors help in the explanation of empirical puzzles. For example [Barberis et al. \(2015\)](#) write down a more *modern* model of price extrapolation, through which they capture many features of actual prices and returns (as price predictability, excess volatility or negative autocorrelations in price changes)<sup>9</sup>, while [Adam et al. \(2016\)](#) build a consumption-based asset pricing model

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<sup>7</sup>See also: [Gallant et al. \(1990\)](#), [Jegadeesh and Titman \(1993\)](#), [Brandt \(1999\)](#) and [Campbell and Viceira \(2002\)](#).

<sup>8</sup>[Chiarella and He \(2003\)](#) add to this scenario the presence of a market maker (as a market-clearing mechanism) showing how it affects the dynamics.

<sup>9</sup>The feature of extrapolation can also be used in order to explain other market empirical regularities as the formation of bubbles. [Barberis et al. \(2016\)](#) present a discrete extrapolative model predicting that good

in which agents learn about price behavior from past price observations with a constant updating learning rule.

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news about fundamentals can trigger large price bubbles.

## 2 The determinants of aggregate fund flows to Emerging Markets. A push-pull analysis<sup>10</sup>

### 2.1 Introduction

This chapter investigates how cyclical variables drive net aggregate fund flows towards Emerging Markets (EMs). Through the aggregation net flows of all open-end dedicated funds, the analysis finds that flows in equity and fixed income are driven by recent past performance in both developed and emerging economies. Further analysis confirms that much of the evidence comes from US and EU larger mutual funds.

After the burst of the Great Recession, capital flows to EMs significantly increased, while in the latest years, since 2010, main capital flows (i.e. FDI, banking flows, other portfolio equity and debt investments) have been showing a common retrenchment<sup>11</sup>. Conversely funds in the last years have been growing with net aggregate inflows overcoming the pre-crisis levels and with an overall TNA that reaches its historical peak in August 2014 of 667 billion US\$. The relevance of aggregate fund flows towards developing economies is under debate for years. A wide literature investigates the relevance of these investments for financial stability of EMs evaluating their role for global financial integration<sup>12</sup>. [Gelos \(2011\)](#) provides a survey on international mutual fund behaviors with relative implications for capital flows, while [Raddatz and Schmukler \(2012\)](#) find that mutual funds tend to amplify the procyclicality of investments to developing economies. [Puy \(2016\)](#) investigates the dynamics of international mutual funds located in advanced markets, identifying geographical patterns in both equity

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<sup>11</sup>See for example [Milesi-Ferretti and Tille \(2011\)](#), [International Monetary Fund \(2016\)](#) and [European Central Bank \(2016\)](#).

<sup>12</sup>[Koepke \(2015\)](#) reviews the main literature on drivers of capital flows to EMs with respect to different investments (by type of capital, residency of investors, currency, maturity etc.) taking into account both cyclical and structural determinants.

and bond flows and suggesting that push effects from advanced market investors significantly affect developing countries. Under this perspective the analysis on determinants for managed investments is considerable both for the magnitude and for the role of these instruments among portfolio investments towards developing economies.

Although these flows could be simply thought as a part of Balance of Payments (BoP) transactions<sup>13</sup>, there are some reasons for which fund flows in a country (or area) deserve a separate analysis with respect to that made on net incurrence of liabilities of portfolio investments from financial account for the same country (or area). A first issue concerns the fact that portfolio investments from the BoP financial account cover in principle a larger amount of transactions including stocks and bonds directly traded by non-residents or earning reinvestments. Moreover there is a conceptual difference in the measurement of international transactions: in fact the BoP relies on total non-resident portfolio inflows, while funds flows measure transactions in and out of financial instruments. The latter implies that the analysis of fund flows allows to trace transactions that otherwise would not emerge in the BoP and that are more subject to instrument-specific issues<sup>14</sup>. Last but not least data on investment funds are available at a higher frequency with respect to those on BoP that are quarterly released by the IMF. Therefore an analysis on cyclical determinants on BoP data should be made at a lower frequency. Nowadays investment funds represent the most relevant channel for managed savings account and it is due to their popularity among general investors that do not want to get directly involved with portfolio decisions and at the same time are more exposed to behavioral biases in investing or withdrawing capital<sup>15</sup>.

In order to identify key determinants of net aggregate flows, I adopt the ‘push-pull’ approach, first introduced in the seminal works by [Calvo et al. \(1993, 1996\)](#) and [Fernández-](#)

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<sup>13</sup>[Miao and Pant \(2012\)](#) find that any rise in the Emerging Portfolio Fund Research (EPFR) coverage of gross bond and equity flows is positively and significantly associated with transactions reported in the BoP portfolio flows.

<sup>14</sup>An interesting branch of literature studies MF individual flows identifying common determinants as: prior performance, fund size, level of fees or area of availability. See for example: [Sirri and Tufano \(1998\)](#), [Ferreira et al. \(2012\)](#), [Lou \(2012\)](#).

<sup>15</sup>For example [Greenwood and Shleifer \(2014\)](#) find that investor expectations, highly correlated with mutual fund flows, in the period 1963-2011 follow past stock returns rather than model-implied expectations.



[Arias \(1996\)](#). This methodology prescribes to divide drivers by the direction to (from) which they push (pull) capitals, allowing to link the empirical evidence on investment flows to the propagation mechanism of any relevant shock. Since this strategy implicitly asks to evaluate each of the two sides separately, sometimes the use of differentials between comparable push and pull drivers could be preferable. However keeping variables separate better allows to assess how much any change in capital net flows can be attributable to a developed economy cyclical change rather than to recent performance of emerging assets. This approach presents of course some limitations, for example it does not easily allow to classify indirect and contagion effects, however it is at the same time a useful and a straightforward strategy to investigate key effects of determinants.

Findings show that aggregate flows for both objects of investment significantly respond to both push and pull selected determinants. As far as push factors, data show clear inflows immediately after a positive performance of mature economy index, by object, or after any increase in the oil price, while global risk aversion and mature economy interest rate are negative and significant explanatory variables for new investments. An increase in each of the latter two variables would make agents more afraid on less attractive investments. [Frazzini and Lamont \(2008\)](#) and [Ben-Rephael et al. \(2012\)](#) look at mutual fund flows as a good measure of current sentiment. I therefore include among push factors the [US Consumer Sentiment index](#) provided by Michigan University<sup>16</sup>. The empirical analysis shows that immediately after a period of negative (positive) feelings for US consumers, there is a substantial inflow (outflow) in EM funds. On the other hand pull determinants are recent EM index performance, by object, and dividend yields. Coefficients for the first variable are positive and highly significant, suggesting that investors are pulled into EMs by recent positive performance. Signs for dividend yield are also positive but coefficients become significant after 4-6 months, in line with [Cochrane \(2011\)](#)'s findings that past dividend yields

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<sup>16</sup>Although consumers polled for the [US Consumer Sentiment index](#) are not asked directly for their views on asset prices, [Qiu and Welch \(2004\)](#) find that changes in that consumer confidence index is highly correlated with changes in the UBS/Gallup index of investor optimism.

are good explanatory variables for long-run expected returns. Further analysis, in [Appendix 2](#), explores key dimensions of the dataset, aggregating funds by type of instrument, area of domicile and size. Findings from subsamples show that much of the evidence comes North American and Central European larger mutual funds. A structural VAR evaluates the likely response of net aggregate flows towards EM equity to push determinants. IRs show that net aggregate flows become more responsive through time to market uncertainty and rates. In particular, after the Great Recession flows exhibit a lower reaction to the S&P index, becoming more responsive to market volatility and to US interest rates. The US sentiment index has a key role in the explanation of fund flows and its relevance increased through time with an effect that is more sluggish and persistent with respect to other cyclical variables.

The remainder of the chapter is organized as follows: section [2.2](#) presents flow-level data and facts while section [2.3](#) presents the methodology of aggregation and further discusses the comparison with the BoP. Section [2.4](#) reports results on determinants, section [2.5](#) presents impulse responses, section [2.6](#) reports robustness checks and section [2.7](#) concludes.

## 2.2 Individual data and facts

I collect individual data on all open-end funds in US\$ that invest in EM equity (E) and fixed income (FI) from Bloomberg. The resulting dataset, that contains different instruments, is mainly covered by mutual funds, Sociétés d’Investissement à Capital Variable (SICAV) and Unit Trusts (UT)<sup>17</sup>. The dataset contains 917 equity funds and 573 fixed income funds ([Appendix 3](#) reports the two lists in alphabetical order), data cover a 15-year period, from Jan. 2001 to Dec. 2015 at monthly frequency and for each fund I collect Total Net Asset (TNA) and Total Return (TR)<sup>18</sup>. For both objects of investment (i.e.  $obj = E, FI$ ), I compute net individual return for fund  $i$  at time  $t$  ( $R_{i,t}^{obj}$ ) as:

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<sup>17</sup>Other instruments in the samples are Fonds Commun de Placement (FCP), Open-Ended Investment Companies (OEIC), Undertakings for Collective Investment in Transferable Securities (UCIT), Separately Managed Accounts (SMA), open-end pensions, variable annuities and funds of funds.

<sup>18</sup>Individual flows that account for dividend reinvestments can be correctly computed since, for the funds in the sample TRs are different to Net Asset Values (NAVs).

$$R_{i,t}^{obj} = \frac{TR_{i,t}^{obj}}{TR_{i,t-1}^{obj}} - 1. \quad (1)$$

Therefore I compute individual flows in levels ( $Flow_{i,t}^{obj}$ ) under the hypothesis that flows are dated at the end of each month and that dividends are reinvested in the fund. Thus, the monthly net cash flow for fund  $i$  in month  $t$  is:

$$Flow_{i,t}^{obj} = TNA_{i,t}^{obj} - TNA_{i,t-1}^{obj}(1 + R_{i,t}^{obj}). \quad (2)$$

Table 1 reports descriptive statistics for the two samples. The TNA for average equity fund is slightly higher than 600 million \$, while the TNA for the average fixed income fund is lower and almost 400 millions. The flow levels are very similar in magnitude and respectively equal to 3.76 million \$ for equity and 3.51 for fixed income, with standard deviations of 9.10 and 11.23. Yearly turnovers, computed as the minimum of purchase or sale of each fund during each year divided by the TNA of the fund during the same period, are similar between the two categories and around 15% in both cases (respectively 14.32% and 17.10%). It means that the average fund substitutes around one sixth of its total capital per year, suggesting that during the 15-year time interval, there has been a quite high market activity on these instruments<sup>19</sup>.

Figure 1 compares the monthly return of the average fund that invests in equity or fixed income and the monthly return of a market index with the same object of investment. In doing that I refer to the MSCI Emerging Markets TR index<sup>20</sup> as a representative index that

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<sup>19</sup>I compute average turnovers on sub-components of the two samples (by type of instrument, area of domicile and size) finding that it is substantially equal across funds.

<sup>20</sup>The MSCI Emerging Markets index covers large and mid caps across 23 EMs. The index has 836 constituents and it covers approximately 85% of the free float-adjusted market capitalization in each country. The list of Countries is: Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, Qatar, South Africa, Taiwan, Thailand, Turkey and United Arab Emirates.

Table 1: Sample statistics

	Mean	Median	25th	75th	Std
<hr/>					
TNA (million \$)					
Equity	616.62	738.15	352.05	852.02	299.65
Fixed income	392.18	410.59	179.30	578.19	230.23
<hr/>					
Flows (million \$)					
Equity	3.76	3.35	-0.37	7.71	9.10
Fixed income	3.51	2.03	-1.65	10.76	11.23
<hr/>					
Turnover (%/year)					
Equity	14.32	14.40	12.32	15.64	3.09
Fixed income	17.10	14.21	12.61	17.78	8.97

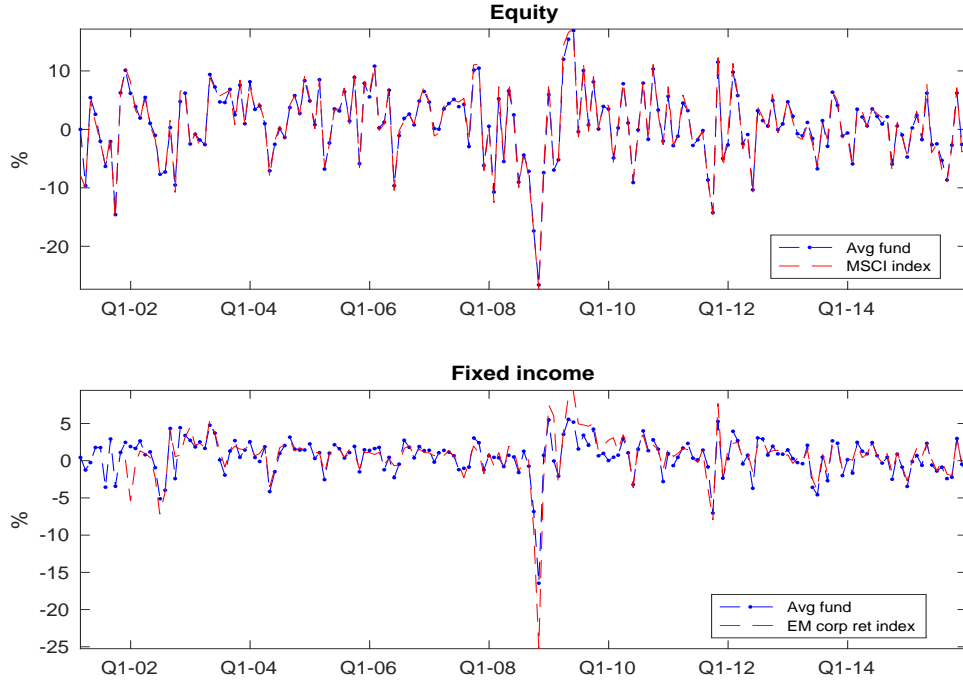
This table reports TNAs, net flows, and turnovers for funds that invest in EM equity and fixed income. Yearly individual turnovers are computed as the minimum of purchase or sale of each fund during each year, divided by the TNA of the fund during the same period. Flows and TNAs are in US\$ and expressed in millions, while turnovers are in %. Statistics for each item are computed from the series of monthly cross-sectional averages for TNAs and flows and yearly cross-sectional averages for turnovers. Data are monthly from Bloomberg for the sample Jan. 2001 - Dec. 2015.

invests in EM equity and to the Morningstar EM corporate bond index<sup>21</sup> for fixed income. Figure 1 shows that the average fund tracks the index in both cases during the whole period, suggesting that on average, funds in the samples carry out simple passive strategies. In fact, the correlation between the average fund on EM equity and the MSCI EM TR index is 0.99 while the correlation between the return of the fixed income average fund and the Morningstar EM corporate bond index, although relatively lower, is also high and equal to 0.87. Relying on these findings, I include past recent performance of the two indexes among pull determinants. In sections 2.3 I refer to the list of countries in which the MSCI index declares to invest, in order to identify comparable portfolio flows towards EMs from the BoP financial account.

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<sup>21</sup>The Morningstar Emerging Markets Corporate Bond Index includes the most liquid corporate bonds issued in US\$ by corporations domiciled in the Emerging Markets.

Figure 1: Returns



This figure plots the returns for the average funds that invest in EM equity and fixed income against the returns of a representative index with the same object of investment (i.e. the MSCI EM TR index and Morningstar EM corporate bond index). Data are monthly from Bloomberg for the sample Jan. 2001 - Dec. 2015.

## 2.3 Aggregation of data

In this section I aggregate funds by object of investment (i.e. equity and fixed income) discussing reasons, methodology of aggregation and comparing the obtained flows with the BoP transactions. [Appendix 1](#) reports a further analysis on the dataset through fund subsamples by type of instrument, area of domicile and size.

The choice of an aggregate measure is convenient at least for two reasons: the first one is linked to the characteristics of the dataset while the second refers to the aim of the analysis. In terms of the dataset, even if it is possible to identify individual flows, the comparison between monthly flow of fund  $i$ ,  $Flow_{i,t}^{obj}$ , with its past monthly return,  $R_{i,t-k}^{obj}$ , for  $k = 1, \dots, K$  and  $obj = E, FI$  remains unlikely. This is due to the fact that the dataset is highly fragmented, since Bloomberg for some funds provides data for TR but not for TNA at same dates, or viceversa (i.e. for those dates the value of the flow is considered missing).

Moreover the panel is strongly unbalanced, because funds are different in lifetime. In order to check the robustness of the aggregate analysis I correct the dataset for aforementioned discrepancies, keeping only funds that have existing values for flows at any time in a sub-period starting in Jan. 2010 to the end of the sample (i.e. Dec. 2015), at monthly frequency. Table 5 reports results from a panel fixed effect analysis. Findings are fully in line with those of the aggregate exercises, showing that individual flows are significantly driven by past returns and by developed economy market rates, after controlling for area and time fixed effects. However, in this way the remaining samples definitely lose relevance and significance in terms of both the fund coverage and the magnitude of the phenomenon. In fact, after selecting only entities with all existing values from Jan. 2010 to Dec. 2015, the remaining funds are 157 for equity and 72 for fixed income. Furthermore, the use of an aggregate measure allows to consider fund flows as a macroeconomic variable, with policy implications relevant for both investors and financial regulators. In terms of methodology, I define aggregate values for TNAs and net flows as the sum of all individual values in the sample, period by period<sup>22</sup>.

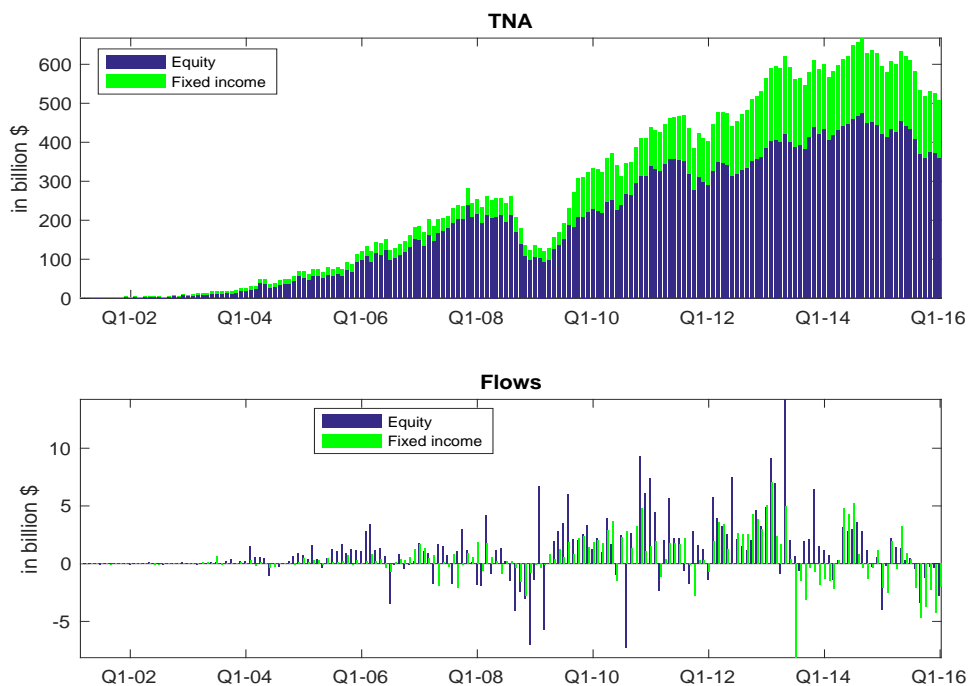
Figure 2 shows the series of aggregate TNAs and net flows for all funds that invest in EM equity and fixed income. At first glance both variables clearly show that the relevance of this market has been growing in the last twelve years, at least nominally<sup>23</sup>, despite a major slowdown between 2008 and 2009. EM funds start to collect significant amounts of capital on the market from the beginning of 2000s reaching a first peak in October 2007 when the sum of the two components equates 282 billion \$. Starting from the last part of 2008, in line with the main trend shown by global markets, these funds exhibit a major decrease falling to an aggregate TNA of 119 billion \$ in February 2009. After that, EM begin to recover their aggregate capitalization, collecting significant amounts of capitals on the markets and becoming again one of the largest vehicles for investments to emerging economies. Almost

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<sup>22</sup>The methodology of aggregation is consistent with that chosen by [Investment Company Institute](#) that periodically provides statistics on aggregate flows. Note that this computation does not correct for short-selling.

<sup>23</sup>Since all funds are in US\$, even after correcting for inflation, aggregate values do not significantly change.

Figure 2: Aggregate variables



This figure plots aggregate TNAs and net aggregate flows for funds that invest in EM equity and fixed income. Variables are denominated in US\$ and expressed in billions. Data are monthly from Bloomberg for the sample Jan. 2001 - Dec. 2015.

5 years after the burst of the Great Recession these instruments reach the historic peak of both aggregate series with a total TNA of 667 billion \$ in August 2014. More recently, in the last year of the sample, the trends for the TNA, both aggregated and disentangled by component, exhibit an interesting decline until an overall capitalization of 509 billion \$ in December 2015.

Leaving aside this most recent dynamic shown in the last month of the series, that can be a signal of a new slowdown in this market and that should be further investigated, the impressive rise shown in the last five years of the sample shed light on the macro relevance of the this market. It can be attributed to higher reinvested returns, higher inflows and to a higher number of funds. In terms of the composition of the aggregate TNA, both series exhibit a similar dynamic through time but the relevance of equity component remains higher for the whole period with respect to that for fixed income. Net flows confirm that the

magnitude for both series grows after the Great Recession with significant outflows for equity funds in November 2008 (-7 billion \$), in February 2009 (-5.7 billion \$), in July 2010 (-7.3 billion\$) and high inflows in January 2009 (+6.67 billion \$), in October 2010 (+9.3 billion \$) and in April 2013 (+14.2 billion \$). Fixed income funds track the dynamic of equity funds, although smaller in magnitude, with some discrepancies as such as a major outflow in July 2013 of 8.14 billion \$.

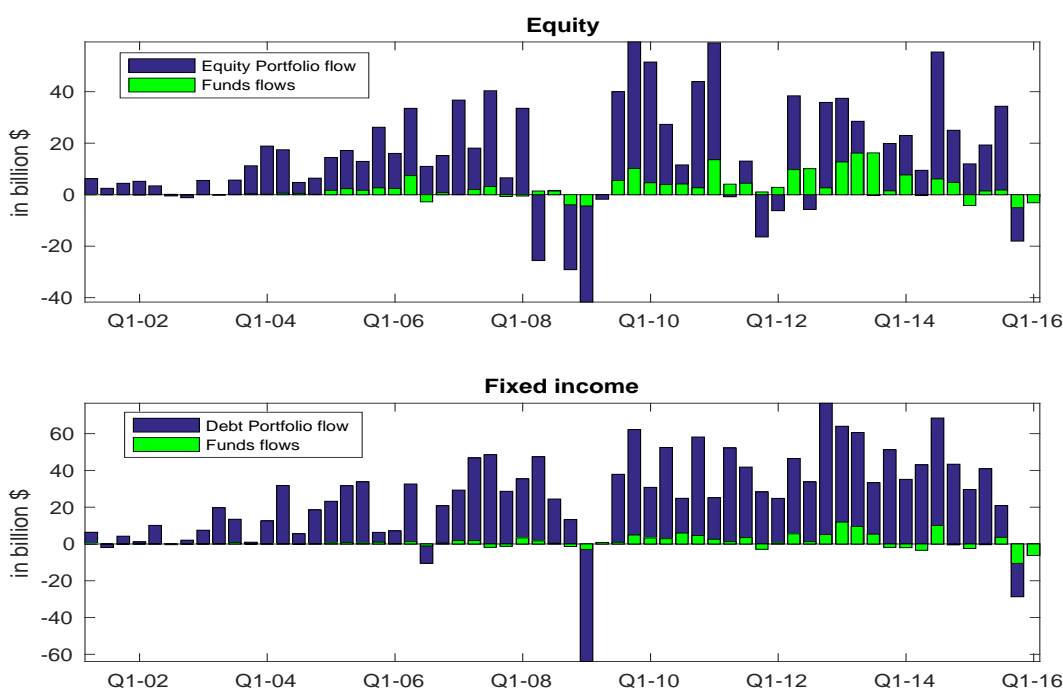
In order to further evaluate the characteristics of the dataset, [Appendix 1](#) reports descriptive statistics on fund subsamples and TNAs by type of instrument, area of domicile and size at December 2015. Descriptive statistics shows that the majority of funds in the dataset for both objects of investment is made by mutual funds and SICAV. Equity mutual funds are 588 with an aggregate TNA of almost 277 million \$ while fixed income mutual funds are 290 with a TNA of 60 millions, SICAV that invest in EM equity are 266 with a capitalization of 77 millions and those that invest in fixed income are 194 with assets for 75 millions. The residual parts of the samples, made by UTs and other instruments, are made by 63 equity funds and 89 for fixed income. In terms of location, the majority of funds have domicile in North America, 334 for equity and 135 for fixed income, and Central Europe, respectively 496 and 349 funds. Interestingly, although the number of North American funds is lower for both objects, the aggregate TNA for equity funds is higher with respect to that of Central European funds, suggesting that on average North American equity funds have a higher capitalization. Funds from other areas represent a smaller aggregate share with 87 funds for equity and 89 for fixed income. As far as fund size, many of the funds in both samples have a TNA between 5 and 500 million \$, respectively 573 for equity and 373 for fixed income, even if funds are distributed quite homogeneously among sizes.

In order to better evaluate the macroeconomic relevance of these flows, I compare net flows into equity and fixed income funds with portfolio equity and debt investment in EMs, from the financial accounts of the BoP (net incurrence of liabilities). Data are available from IMF at quarterly frequency and expressed in US\$, while I define the perimeter of emerging



countries referring to the investment sample of the MSCI EM index<sup>24</sup>. Therefore I compute the EM portfolio investment aggregating the net positions for all emerging countries in the investment sample of the MSCI index, with the exceptions of Taiwan and United Arab Emirates whose data are not available from IMF. Figure 3 compares portfolio investment in emerging countries available from financial account with quarterlized flows of mutual funds that invest in EMs, by object of investment<sup>25</sup>. Although the two series clearly exhibit

Figure 3: BoP portfolio flow vs. fund flows



This figure plots net aggregate fund flows in EM equity and fixed income against portfolio investment in EM equity and EM debt (net incurrence of liabilities) from financial accounts. The sample for EM includes the 23 Countries covered by the MSCI Emerging Market index, with exceptions of Taiwan and United Arab Emirates whose data are not available from IMF. The aggregate position for EMs has been computed as the unweighted sum of net positions for all Countries in each quarter. Data are denominated in US\$ and expressed in billions. Data are quarterly from IMF and quarterlized from Bloomberg for the sample 2001Q1 - 2015Q4.

a common dynamic for both objects, figure 3 shows that the signs for the two series are sometimes different. Firstly, this is due to the fact that portfolio investments from the BoP

<sup>24</sup>This assumption appears reasonable on the basis of findings from Section 2.2 that shows that the average equity fund tracks the index.

<sup>25</sup>A fund transaction is included in the BoP of a country (or area) from the IMF statistics, if it has domicile outside that country (area). Therefore, I check the domicile of each fund in the sample, finding that less than 5% of the total have domicile in one of the EMs.

financial account cover a larger amount of transactions since it includes stocks and bonds directly traded by non-residents or earning reinvestments. Moreover since the two measures of international transactions present conceptual discrepancies<sup>26</sup>, the analysis of fund flows should not be considered only as an empirical investigation on a sub-component of the corresponding BoP. In fact it allows to trace transactions that otherwise would not emerge from financial account, that are more subject to issues specific for such kind of instruments and an analysis on proper determinants of these flows deserves to be considered separately.

## 2.4 Determinants

This section investigates cyclical determinants of net aggregate flows of funds that invest in EM equity and fixed income and hereafter presents results for the analysis on the two aggregate variables. In order to further investigate which sub-components mainly explain aggregate findings, [Appendix 2](#) presents detailed results for main fund subsamples by type of instrument, area of domicile and size.

I assume that both categories of funds respond to similar kinds of shocks by object of investment and [table 2](#) summarizes the main expected drivers of aggregate fund flows with the expected sign for each of them. Since the analysis aims to focus on cyclical determinants, [table 2](#) does not report any real variables and no emerging country-related variable is included since the analysis does not disentangle EMs by country. This is mainly due to the fact that, even if for some funds the updated portfolio, in terms of the country(ies) of investment is available, it is not true for all funds in the sample. Moreover since the portfolio of each fund could change through time, particularly for actively managed funds, it would be difficult to collect the time series of portfolios by country of investment for all funds in the sample. Following the seminal works by [Calvo et al. \(1993, 1996\)](#) and [Fernández-Arias \(1996\)](#), I adopt the ‘push-pull’ approach dividing factors by the direction to (from) which they push (pull)

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<sup>26</sup>For example, if an EM fund located in the US experiences an outflow that forces managers to sell a Chinese bond, the counterpart to this transaction is not necessarily a Chinese resident and in this case the transaction is not recorded in Chinese BoP. See: [Koepke and Mohammed \(2014\)](#).

and I select determinants relying on [Fratzscher \(2012\)](#) and [Koepke \(2015\)](#).

Table 2: Flows - main drivers

Driver	Expected sign
<b>Push</b>	
Global risk aversion	-
Mature economy interest rate	-
Mature economy index performance (by object)	+
Mature economy consumer sentiment	-
Key commodity price	+
<b>Pull</b>	
Emerging market index performance (by object)	+
Emerging market dividend yield	+

This table reports main drivers of net aggregate flow of funds that invest in EM equity and fixed income. The first column report the list of driver by type (push vs. pull), while the second column reports the expected sign for each of them.

Both global risk aversion and interest rates in developed economies are expected to have a negative effect on aggregate fund flows: an increase in each of the two variables would make agents more afraid on less attractive investments. Conversely the developed economy index, by object, is expected to have a positive impact on flows because any positive recent performance of current investments generates further inflows also in other markets (wealth effect). On the other hand the US Consumer Sentiment index is expected to have a negative sign because immediately after a period of positive feelings on US economy investors are expected to withdraw capitals from EMs and move them to developed countries (substitution effect). Last but not least the price of a global commodity that is key for low-income countries growth, as the crude oil price, is expected to have a positive sign due to its direct and indirect effects on emerging economies<sup>27</sup>. As far as pull determinants, table 2 reports the EM index performance, by object, and the dividend yield. In fact investors should be pulled into EM investments by recent positive performance and a similar effect should be played by

<sup>27</sup>In principle this variable could be included among pull determinants, but since main oil benchmarks are mainly traded in developed stock markets and the analysis is focused on cyclical oscillations of prices and returns, here it is included among push determinants.

past dividend yield. The latter relies on findings of [Cochrane \(2011\)](#), that shows that past dividend yield is a good explanatory variable for future expected returns.

I run OLS regressions including recent past realizations of determinants as explanatory variables in different specifications of the following model:

$$Flows_t^{obj} = b_0 + b_1 Z_{1,t-k} + \dots + b_j Z_{j,t-k} + u_t, \quad (3)$$

for  $k = 1, \dots, K$  and  $obj = E, FI$ .  $Flows_t$  is the aggregate fund net flows that invest in EM equity or fixed income and  $Z_{j,t-1}$  denotes the  $j$ -th lagged determinant.

Since aggregate fund net flows for both objects are stationary, after testing for ADF unit root test, flows are kept in level (expressed in billions US\$) and for all regressions HAC standard errors with Newey-West fixed bandwidth are used to correct for heteroskedasticity. In order to include variables that can empirically match push determinants summarized in [table 2](#) the VIX index is used as a proxy for global risk aversion<sup>28</sup> and the 3-month Tbills, the 3-month Euribor and the US term spread are considered as alternative measures of mature economy interest rates. The S&P TR index (risk premium) and the Bloomberg Barclays US corporate high yield bond TR index (risk premium) are chosen as benchmark developed economy asset returns respectively for equity and fixed income. In order to get an indicator of sentiment I choose the [US Consumer Sentiment index](#) provided by Michigan University<sup>29</sup> and the Brent price is identified as a key commodity. A dummy for US recession, starting in Sept 2008, is included in order to control for possible structural breaks in the series.

As far as pull determinants I include recent past realization of both the corresponding average fund (risk premium) and the return of the MSCI EM TR index (risk premium) and its past dividend yield while for fixed income I substitute the stock index with the Morningstar EM corporate bond TR index (risk premium), as a benchmark. Monthly risk premia are built

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<sup>28</sup>Many papers use a volatility index to identify global risk aversion. For instance see [Milesi-Ferretti and Tille \(2011\)](#), [Broner et al. \(2013\)](#) and [Ghosh et al. \(2014\)](#).

<sup>29</sup>The index is normalized to have a value of 100 in December 1964. Each month at least 500 telephone interviews are conducted of a continental United States sample (Alaska and Hawaii are excluded). Fifty core questions are asked.

with respect to the 1-month Euribor rate as risk-free rate. All explanatory variables, with exception of interest rates and the oil price, are stationary after testing for ADF unit root test, therefore in order to get rid of any spurious regression issue I use the 3-month Tbills, the 3-month Euribor and the oil price in percentage change. With exception of the sentiment index, all variables are from Bloomberg. Index returns, interest rates and oil price change are expressed in %. In order to evaluate the contemporaneous cross-significance between aggregate flows aggregated by object of investment, I eventually include fixed income flows as explanatory variable for equity and viceversa.

Table 3 reports 10 different linear specifications of the push model for fund aggregate flows that invest in EM equity and fixed income. As far as EM equity aggregate flows, specification (1) the coefficient for the risk premium on the S&P index is positive (0.22), while the lagged 3-month Tbills exhibits a negative coefficient (-0.01). Both variables are significant at 1%, signs are in line with our expectations and adjusted  $R^2$  is 0.193. Results remain stable substituting the 3-month Euribor. Specification (3) adds the lagged US Consumer Sentiment index to the S&P return and in line with expectations the Sentiment index coefficient is negative, equal to -0.03 and significant at 5%. In (4) the VIX index and the US Consumer Sentiment index are jointly added to the S&P, the Sentiment coefficient is still negative (-0.06) and significant at 5% while the VIX coefficient (-0.06) is significant at 10%. (5) includes all variables together, with the 3-month Tbills, signs and significances are confirmed while the goodness of fit improves up to 0.220. While specification (4) and (5) control for the state of the economy through the US Sentiment, the VIX index and interest rates, specification (6) controls for any structural break with a US recession dummy. The sign of the variable is positive (0.91) and significant at 5% supporting again the intuition that in a bad period for the US, capital flows to EMs increase. Specification (7) and (8) include the role of oil (3.60) and significant at 10% and that of the US term spread (-0.01). Finally the last two specifications consider the contemporaneous effect of fixed income flows, found positive and highly significant. Anyway it is necessarily to point out that for this variable there is a risk

of endogeneity due to the fact that the two aggregate flows partially respond to the same determinants. In fact, as far as EM fixed income aggregate flows, table 3 in specifications (1) and (2) shows that fixed income flows respond to both US corporate index and to the S&P, respectively equal to 0.14 (significant at 1%) and 0.06% (significant at 5%). In both cases the 3-month Tbills is negative, equal to -0.01 and significant at 1%. Signs for US Sentiment, and VIX are similar in sign, magnitude and significance with respect to those for equity flows, while coefficients for US recession, oil price and term spread are not significant in this case. Finally coefficients for equity flows, added to 3-month Tbills and to US sentiment are positive and significant.

Table 4 reports 10 different linear specifications of the pull model for fund aggregate flows that invest in EM equity and fixed income. While push specifications can include different variables together, pull drivers' effects have to be evaluated separately in order to avoid any multicollinearity risk due to the fact that pull determinants essentially represent alternative measures of EM past and expected asset performance. Therefore drivers' effects are evaluated at different lags. Concerning equity funds, table 4 in specifications (1) and (2) reports a positive coefficient for recent average fund return (respectively 0.16 and 0.09) and significant at 1% while the goodness of fit is lower with larger lag (adjusted  $R^2$  are respectively 0.154 and 0.047). Specifications (3)-(5) confirm the tendency for the MSCI EM index, that remains positive and significant until three-month lags with a decreasing goodness of fit. Relying on [Cochrane \(2011\)](#)'s findings that past dividend yield is an explanatory variable for long-run expected returns, (6) to (8) include past dividend yield at different lags. Results clearly show that, considering older realizations of dividends, coefficients become more significant as the goodness of the fit, in fact the 6-month lagged dividend yield is positive (1.67) and significant at 1%. Finally equity flows respond to past realization of fixed income funds with results that are positive and significant at 1%. As far as fixed income, table 4 once again shows that fixed income flows mostly respond to the same determinants, with some exceptions. In details the first (5) specifications show that all coefficients are positive and significant at 1%,

despite lower  $R^2$ . As far as the dividend yield, the dynamic is similar to that of equity flows, but results are less significant since only in specification (8) its coefficient with 6 month lagged is significant at 5%. As for the table 4 past realization of the average fund of the other category are significant, although lower in  $R^2$ .

Table 3: Push determinants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<b>Equity</b>										
SP $\text{ret}_{t-1}-\text{rf}_{t-1}$	0.22*** (5.24)	0.17*** (3.78)	0.22*** (4.62)	0.17*** (3.47)	0.18*** (3.65)	0.20*** (3.93)	0.18*** (3.86)	0.19*** (4.10)	0.19*** (4.97)	0.17*** (3.97)
3m Tbills % $\text{ch}_{t-1}$	-0.01*** (-4.85)				-0.01*** (-4.67)	-0.01*** (-4.60)	-0.01*** (-3.80)		-0.01*** (-2.25)	-0.01** (-2.44)
3m Euribor % $\text{ch}_{t-1}$		-0.27* (-1.74)								
US $\text{Sent}_{t-1}$			-0.03** (-1.99)	-0.06** (-2.36)	-0.05** (2.32)					
VIX $_{t-1}$				-0.06* (-1.97)	-0.06** (-1.98)					
Oil % $\text{ch}_{t-1}$							3.60* (1.69)			
US term spread $_{t-1}$								-0.01** (-2.32)		
Fi flows $_t$									0.60*** (4.61)	0.58*** (4.54)
US recession						0.91** (2.25)	1.07*** (2.76)	1.03** (2.50)		0.58* (1.67)
Constant	1.39*** (6.11)	1.82*** (4.11)	4.12*** (2.75)	7.28*** (2.80)	7.14*** (2.79)	0.77*** (3.98)	0.77*** (3.98)	1.45*** (4.03)	1.05*** (5.64)	0.75*** (4.18)
R <sup>2</sup>	0.202	0.187	0.189	0.207	0.238	0.230	0.242	0.205	0.365	0.376
Adj. R <sup>2</sup>	0.193	0.178	0.180	0.194	0.220	0.216	0.225	0.191	0.354	0.361
<b>Fixed income</b>										
US $\text{corp}_{t-1}-\text{rf}_{t-1}$	0.14*** (3.94)		0.12*** (3.44)	0.13*** (3.78)	0.10*** (3.08)	0.11*** (4.22)	0.13*** (3.64)	0.13*** (3.56)		
SP $\text{ret}_{t-1}-\text{rf}_{t-1}$		0.06** (2.33)								
3m Tbills % $\text{ch}_{t-1}$	-0.01*** (-5.39)	-0.01*** (-5.95)		-0.01*** (-5.04)	-0.01*** (-5.23)	-0.01*** (-5.18)	-0.01*** (-5.21)		-0.01*** (-5.02)	-0.01*** (-4.84)
US $\text{Sent}_{t-1}$			-0.03** (-2.42)	-0.03** (-2.50)	-0.04*** (-2.68)					-0.02** (2.11)
VIX $_{t-1}$					-0.03* (-1.71)					
Oil % $\text{ch}_{t-1}$							0.29 (0.24)			
US term spread $_{t-1}$								-0.01 (-0.77)		
Eq flows $_t$									0.33*** (4.89)	0.32*** (4.82)
US recession						0.43 (1.22)				
Constant	0.65*** (3.25)	0.58*** (2.80)	3.14*** (2.88)	2.99*** (3.00)	4.84*** (2.83)	0.42*** (4.22)	0.65*** (3.10)	0.77** (2.38)	0.13 (0.85)	1.85*** (2.17)
R <sup>2</sup>	0.123	0.085	0.093	0.150	0.167	0.131	0.123	0.060	0.271	0.286
Adj. R <sup>2</sup>	0.113	0.074	0.083	0.137	0.148	0.119	0.108	0.050	0.267	0.274

The table reports the coefficients for different specifications of the following regression:  $Flows_t^{obj} = a + b_1 Z_{1,t-k} + \dots + b_j Z_{j,t-k} + u_t$ , for  $k = 1, \dots, K$  and  $obj = E, FI$ .  $Flows_t$  is the aggregate fund net flows that invest in EM equity or fixed income and  $Z_{j,t-k}$  denotes the  $j$ -th lagged push determinant. Specifications include total returns on market indexes (risk premia), alternative measures of developed economy rates, the [US Consumer Sentiment index](#) from Michigan University, the VIX index, the Brent price. Specifications for equity funds include contemporaneous aggregate fixed income fund flows and viceversa. A dummy for US recession, starting in Sept 2008, is included. Monthly risk premia are built with respect to the 1-month Euribor rate as the risk-free rate. Index returns, interest rates and oil price change are expressed in % while flows are in billion \$. The t-statistics are reported below the coefficients in parentheses. The standard errors are corrected for heteroskedasticity using HAC standard errors & covariance with Newey-West fixed bandwidth (3 lags). Data are monthly from Bloomberg and from Michigan University for the sample Jan. 2001-Dec. 2015. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .



Table 4: Pull determinants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<b>Equity</b>										
Avg. eq fund $ret_{t-1}-rf_{t-1}$	0.16*** (5.05)									
Avg. eq fund $ret_{t-2}-rf_{t-2}$		0.09*** (2.75)								
MSCI EM $ret_{t-1}-rf_{t-1}$			0.15*** (4.92)							
MSCI EM $ret_{t-2}-rf_{t-2}$				0.08** (2.52)						
MSCI EM $ret_{t-3}-rf_{t-3}$					0.08** (2.35)					
MSCI EM DP $_{t-4}$						0.97* (1.76)				
MSCI EM DP $_{t-5}$							1.33** (2.24)			
MSCI EM DP $_{t-6}$								1.67*** (3.61)		
Avg. fi fund $ret_{t-1}-rf_{t-1}$									0.35*** (6.67)	
Avg. fi fund $ret_{t-2}-rf_{t-2}$										0.24*** (3.52)
Constant	1.21*** (5.55)	1.14*** (5.01)	1.18*** (5.49)	1.11*** (4.90)	1.11*** (4.65)	-1.43 (-1.06)	-2.31 (-1.61)	-3.17*** (-2.84)	1.52*** (6.22)	1.37*** (5.41)
R <sup>2</sup>	0.159	0.052	0.157	0.045	0.042	0.029	0.053	0.086	0.172	0.082
Adj. R <sup>2</sup>	0.154	0.047	0.152	0.039	0.032	0.023	0.048	0.081	0.168	0.076
<b>Fixed income</b>										
Avg. fi fund $ret_{t-1}-rf_{t-1}$	0.19*** (3.88)									
Avg. fi fund $ret_{t-2}-rf_{t-2}$		0.13*** (2.79)								
EM corp $ret_{t-1}-rf_{t-1}$			0.13*** (3.45)							
EM corp $ret_{t-2}-rf_{t-2}$				0.10*** (2.64)						
EM corp $ret_{t-3}-rf_{t-3}$					0.12*** (2.76)					
MSCI EM DP $_{t-4}$						0.26 (0.82)				
MSCI EM DP $_{t-5}$							0.47 (1.54)			
MSCI EM DP $_{t-6}$								0.63** (2.06)		
Avg. eq fund $ret_{t-1}-rf_{t-1}$									0.07*** (3.82)	
Avg. eq fund $ret_{t-2}-rf_{t-2}$										0.04*** (2.88)
Constant	0.70*** (3.23)	0.62*** (2.74)	0.61*** (2.87)	0.57*** (2.65)	0.60*** (2.77)	-0.22 (-0.31)	-0.77 (-1.08)	-1.15 (-1.65)	0.51*** (2.69)	0.49** (2.53)
R <sup>2</sup>	0.099	0.047	0.068	0.038	0.057	0.004	0.014	0.025	0.060	0.023
Adj. R <sup>2</sup>	0.094	0.042	0.063	0.032	0.051	0.001	0.090	0.019	0.054	0.018

The table reports the coefficients for different specifications of the following regression:  $Flows_t^{obj} = a + b_j Z_{j,t-k} + u_t$ , for  $k = 1, \dots, K$  and  $obj = E, FI$ .  $Flows_t$  is the aggregate fund net flows that invest in EM equity or fixed income and  $Z_{j,t-1}$  denotes the  $j$ -th lagged pull determinant. Specifications include returns of average fund (risk premia), total returns (risk premia) and dividend yields on market indexes. Specifications for equity funds include returns (risk premia) of average fixed income fund and viceversa. Monthly risk premia are built with respect to the 1-month Euribor rate as the risk-free rate. Returns are expressed in % while flows are in billion \$. The t-statistics are reported below the coefficients in parentheses. The standard errors are corrected for heteroskedasticity using HAC standard errors & covariance with Newey-West fixed bandwidth (3 lags). Data are monthly from Bloomberg for the sample Jan. 2001-Dec. 2015. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

In order to further investigate which sub-components mainly explain aggregate findings, [Appendix 2](#) presents detailed results for main fund subsamples by type of instrument, area of domicile and fund size. Regressions confirm previous findings particularly for larger mutual funds located in developed economies. In details, concerning the type of instrument, [table 10](#) shows that both mutual funds and SICAV, that are the most relevant both in terms of the number of funds and in terms of the aggregate TNA, have the most significant coefficients. In terms of the area of domicile, [table 11](#) shows that funds with domicile in North America and Central Europe, that are the two areas that collect more funds both in terms of numbers and aggregate TNA, respond with high levels of significance to push and pull determinants. It supports the intuition that funds located in developed countries look at cyclical key variables of the US economy and to recent realization of pull determinants to take short-term investment decisions. Last but not least, in term of the size of the funds, [table 12](#) shows that larger funds (i.e. those with a TNA between 100 and 500 million \$ or higher) well respond to selected determinants and this provide support to the idea that larger mutual funds are better tailored for general investors whose investment behaviors are more affected by short-term biases<sup>30</sup>.

## 2.5 VAR analysis on equity flows

This section evaluates how fund net aggregate flows in EM equity respond to push variables shock. Hereafter the analysis is focused on equity funds, relying on findings from [table 2.4](#) that shows that equity net aggregate flows have a better goodness of fit with respect to push determinants. Identification methodology relies on orthogonalized shocks to 4 exogenous variables: VIX index, 3-month Tbills, S&P TR index (risk premium) and US Consumer Sentiment index. Isolating the effects on fund net aggregate flows is not straightforward,

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<sup>30</sup>[Chen et al. \(2004\)](#) show that individual fund returns, both before and after fees and expenses, decline with lagged fund size, supporting the idea that less specialized investors buy these instruments and that investors in large funds are less discriminating about returns than investors in small funds

even because each of these variables respond to the state of the global economy and some of them could be influenced by the others. I deal with the issue through Cholesky identification, considering the following model:

$$Y_t = B_0 + B_1 Y_{t-1} + \dots + B_k Y_{t-k} + u_t \quad (4)$$

with  $t = 1, \dots, T$ .  $Y_t$  is an  $n \times 1$  vector of observed endogenous variables,  $B_0$  is the  $n \times 1$  vector of coefficients that represent the constant term,  $B_i$  are  $n \times n$  matrices of coefficients,  $u_t$  are the observable error terms with variance covariance matrix  $\Omega$ . Consider the triangular reduction of  $\Omega$ :

$$\Omega = A^{-1} \Sigma \Sigma' A^{-1'} \quad (5)$$

or equivalently:

$$A \Omega A' = \Sigma \Sigma' \quad (6)$$

where  $A$  is the lower triangular matrix:

$$A = \begin{bmatrix} 1 & 0 & \dots & 0 \\ \alpha_{21} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n1} & \dots & \alpha_{nn-1} & 1 \end{bmatrix} \quad (7)$$

and  $\Sigma$  is the diagonal matrix with  $\sigma_i$  on the diagonal, with  $i = 1, \dots, n$ . It follows that:

$$Y_t = C + B_1 Y_{t-1} + \dots + B_k Y_{t-k} + A^{-1} \Sigma \epsilon_t \quad (8)$$

$\epsilon$  is the underlying white noise shock, not observable with variance-covariance matrix equal to the identity matrix. Model selection criteria (namely, the Akaike, Schwarz, and Hannan-Quinn information criteria) are used to determine the appropriate number of lags for the

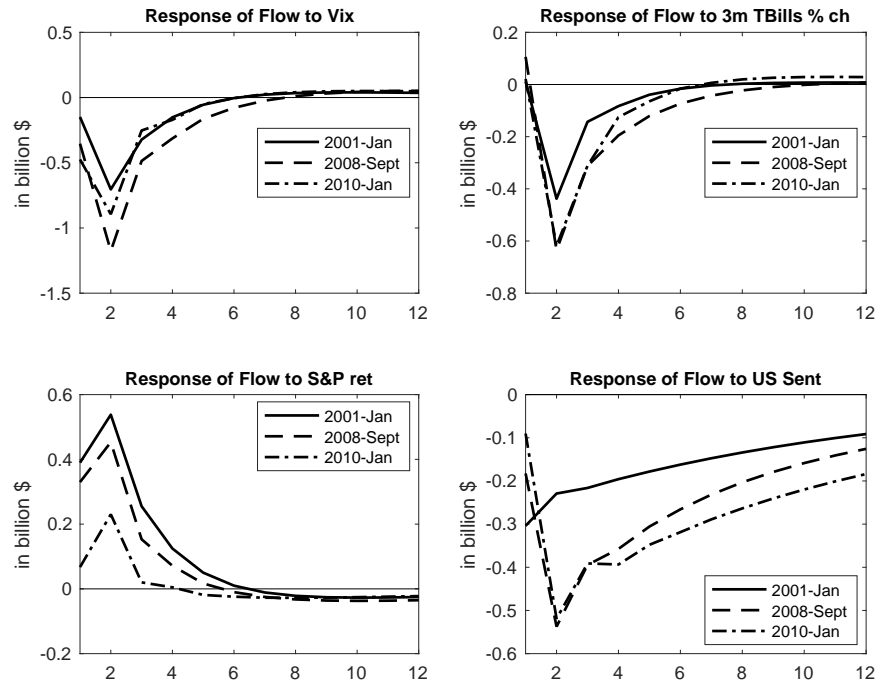
estimated model and the lag chosen for the VAR is 1 (i.e.  $k = 1$ ), eigenvalues lie inside the unit circle confirming that the VAR is stable. The order is set to be  $VIX_t$ ,  $3m\ Tbills_t$  % change,  $S\&P\ ret_t$  (risk premium),  $US\ Sent_t$  and  $Flows_t$ . Monthly risk premia are built with respect to the 1-month Euribor rate as the risk-free rate. I assume that the market volatility, and therefore the global risk aversion, is the most exogenous variable, followed by monetary policy decisions on rates. Then, I assume that the stock market responds and, finally the consumer sentiment is considered as a results of the overall picture. In order to evaluate how flow responses change during the 15-year interval, impulse responses are computed for 3 subsamples. First I consider the whole period from Jan. 2001 to Dec. 2015, then the interval from the burst of the Great Recession, dated in September 2008 to the end of 2015<sup>31</sup> and finally the last 5 years of the samples, from Jan. 2010 to Dec. 2015 in which fund aggregate TNAs exhibit the impressive rise shown by figure 2. Figure 4 shows flow responses, over a 12-month horizon to a one-standard-deviation shock of other variables.

Figure 4 shows that the response of flows to one-standard deviation shock of VIX is negative and during the sample period the effect lasts from 6 to 8 months. In details, a shock in VIX brings a net outflow of about 600 million \$ one month after the shock in 2001. The effect is widened in 2008, probably due to a higher perception of market uncertainty and a higher risk aversion, overcoming 1 billion \$ with a slight decrease in the last part of the sample when market gets back to lower values of volatility. The behavior of flows to a 3m Tbills % change shock is similar in shape although relatively smaller in magnitude. One month after the shock, flows response shows a negative outflow in all sub-periods that increase through time equating 600 millions in both 2008 and 2010. This can be partially explained by the decline in interest rates in the second part of the sample that make investment flows more reactive to shocks. As far as the response of net flows to S&P index (risk premium), it is positive and interestingly is declining through time. In fact, while in the 15-year interval

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<sup>31</sup>This choice is supported by the significance of US recession dummy in (6), (7), (8) and (10) in table 3.

Figure 4: Effects of shocks on equity flows - push determinants



This figure plots the estimated response functions of net aggregate fund flows in EM equity to impulses of push factors. The order is set to be: *VIX*, *3m Tbills % change*, *S&P ret* (risk premium) and *US Sent*. *US Sent* refers to the [US Consumer Sentiment index](#) from Michigan University. Monthly risk premia are built with respect to the 1-month Euribor rate as the risk-free rate. The figure reports responses for 3 different samples, starting in: January 2001, September 2008 and January 2010. All samples end at December 2015. The size of each shock is one standard deviation and it materializes at time 1.

the response of flows to a one-standard deviation shock to the S&P is slightly higher than 0.5 billions, in the second part of the sample the effect decreases to around 0.2 billions. Last but not least, the response to a US Sentiment shock is negative and increased through time, from 300 million \$ in 2001 to almost 500 millions in 2008 and 2010. Interestingly while flows immediately react to sentiment shock in 2001, the response is shifted of one period in the last part of the sample and in both cases IRs are still affected by the shock after 1 year. It suggests that the consumer sentiment has a higher persistence on fund flows that invest in EM equity.

## 2.6 Robustness

This section presents robustness checks on the two main assumptions of the work. The first one concerns the choice of an aggregate measure of flows, while the second refers to the lag set for determinants. The main reasons underlying the choice of an aggregate measure for fund flows have been raised and discussed in section 2.3.

Table 5 presents results of a panel analysis made on a sub-interval, from Jan. 2010 to Dec. 2015. For this period I select funds for which flows are available for all dates and the resulting sample is made by 157 equity funds and 59 fixed income funds. In line with the rest of the analysis, panel results are presented separately by object of investment. The fixed effect (within) estimator is chosen, after testing for the Hausman test and time fixed effects is included.

Table 5: Methodology - robustness

	Equity			Fixed income		
	(1)	(2)	(3)	(1)	(2)	(3)
$R_{i,t-1}^E$	0.47** (2.25)	0.43** (2.19)	0.68** (2.37)			
$R_{i,t-1}^{FI}$				5.21*** (9.72)	5.17*** (9.67)	5.06*** (4.22)
3m Tbills % $ch_{t-1}$		-0.01** (-2.20)	-0.14** (-2.05)		-0.82*** (-4.07)	-5.07*** (-3.58)
R <sup>2</sup>	0.001	0.001	0.010	0.022	0.026	0.095
Adj. R <sup>2</sup>	0.001	0.001	0.001	0.008	0.012	0.067
Time fixed effect	No	No	Yes	No	No	Yes
Number of funds	157	157	157	59	59	59
Number of obs.	11,147	11,147	11,147	4,189	4,189	4,189
Wald test (p-value)	0.026	0.063	0.000	0.000	0.000	0.000

The table reports robustness specifications of the following regression:  $Flow_{i,t}^{obj} = b_1 R_{i,t-1}^{obj} + b_2 Z_{t-1} + u_t$ , with  $obj = E, FI$ .  $Flow_{i,t}$  is the individual flow of the fund  $i$  that invests in EM equity or fixed income and  $Z_{t-1}$  denotes the 1-month lagged 3mTbills % change. Returns and rates are expressed in % while flows are in million \$. Robust t-statistics clustered by fund are reported in parentheses. Data are monthly from Bloomberg for the sample Jan. 2010 - Dec. 2015. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

Table 5 shows that lagged individual return is a significant explanatory variable for

flows. As far as equity funds, specifications (1) to (3) show that its coefficient is positive and significant at 5% in all cases. I add the 3m Tbills percentage change as a market control variable in (2) and (3) finding that its coefficient is negative, and significant at 5%. Fixed income funds show very similar results, with higher levels of significance, in fact the two variables are significant at 1% in all specifications. Results on coefficient signs and levels of significance for both object of investment confirm the main findings of the aggregate analysis on two key explanatory variables, as such as past returns and lagged developed economy interest rates. However, all specifications in table 5 show a very low goodness of fit and this issue should be briefly discussed. It is mainly due to the fact that the analysis is controlling only for two independent variables. In fact, in order to raise the  $R^2$  the panel analysis should further control for specific characteristics of each fund as the level of fees, the age of the fund or FF factors. However this is beyond the scope of this robustness check. Anyway  $R^2$ s of this magnitude should not discourage the reader since low levels of fit are quite common in the literature on mutual funds. For example [Sirri and Tufano \(1998\)](#), investigating the effects of relative performance on mutual fund individual flows, report all adjusted  $R^2$ s lower than 0.143 for US funds, while [Ferreira et al. \(2012\)](#), examining the aggregate flow-performance relationship with funds pooled across 28 countries, report all adjusted  $R^2$ s lower than 0.095. Both studies control for more than 10 explanatory variables. As far as the second assumption, the analysis relies on monthly data and determinants are often taken with a lag of one month.

Table 6 reports 8 linear specifications of both push and pull variables taken at quarterly frequency. Results show that key push and pull determinants remain significant for both equity and fixed income net aggregate flows and the goodness of fit remains stable for all specifications, ruling out hypothesis of spurious regression and of contemporaneous effect between aggregate flows and the cyclical determinants.

Table 6: Lag of determinants - robustness

	Equity				Fixed income			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
SP $ret_{t-1}-rf_{t-1}$	0.49*** (5.39)		0.46*** (4.31)	0.31*** (4.45)				
MSCI EM $ret_{t-1}-rf_{t-1}$		0.27*** (4.24)						
Us $corp_{t-1}-rf_{t-1}$					0.38*** (0.11)		0.34*** (3.39)	
EM $corp_{t-1}-rf_{t-1}$						0.36*** (3.73)		
US $Sent_{t-1}$			-0.11*** (-2.07)				-0.07* (-1.72)	
Eq $flows_t$								0.53*** (5.66)
Fi $flows_t$				0.78*** (5.30)				
Constant	3.54*** (4.63)	2.93*** (3.92)	12.59*** (2.70)	2.41*** (5.22)	1.64*** (2.73)	1.54** (2.65)	7.30** (2.15)	-0.35 (-0.90)
R <sup>2</sup>	0.269	0.191	0.333	0.587	0.155	0.134	0.197	0.486
Adj. R <sup>2</sup>	0.256	0.177	0.307	0.572	0.140	0.118	0.169	0.477

The table reports the coefficients for different specifications of the following regression:  $Flows_t^{obj} = a + b_1 Z_{1,t-k} + \dots + b_j Z_{j,t-k} + u_t$ , for  $k = 1, \dots, K$  and  $obj = E, FI$ .  $Flows_t$  is the net aggregate fund flows that invest in EM equity or fixed income and  $Z_{j,t-1}$  denotes the  $j$ -th lagged push determinant. Specifications include total returns on market indexes (risk premia) and the [US Consumer Sentiment index](#) from Michigan University. Specifications for equity funds include contemporaneous aggregate fixed income fund flows and viceversa. Quarterly risk premia are built with respect to the 1-month Euribor rate as the risk-free rate. Index returns are expressed in % while flows are in billion \$. The t-statistics are reported below the coefficients in parentheses. The standard errors are corrected for heteroskedasticity using HAC standard errors & covariance with Newey-West fixed bandwidth (3 lags). Data are quarterized from Bloomberg and from Michigan University for the sample Jan. 2001-Dec. 2015. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

## 2.7 Conclusions

This chapter investigates how cyclical variables drive net aggregate fund flows towards Emerging Markets (EMs). Using unique measures of aggregate fund net flows that cover all dedicated open-end funds and are collected at high frequency, the analysis finds that flows in EM equity and fixed income are driven by recent past performance in both developed and emerging economies. Further analysis confirms that much of the evidence comes from US and EU larger mutual funds.



A structural VAR shows that flows become more responsive through time to market uncertainty and rates. In particular, after the Great Recession flows exhibit a lower reaction to the S&P index, becoming more responsive to market volatility and to US interest rates. Furthermore the US consumer sentiment index has a key role in the explanation of fund flows and it increased through time with an effect that is more sluggish and persistent with respect to other cyclical variables.

The literature on international capital flows is divided into three main categories. The first concerns the identification of drivers, the second investigates macroeconomic and financial effects of investments on a certain country (or area), while the third evaluates policy implications. This chapter is focused on the first step, it provides clear evidence on the relevance of EM mutual fund and identifies how fund flows are driven by cyclical push and pull variables. The effects of these transactions on financial integration of developing economies should be further evaluated and at the same time empirical findings have significant policy implications<sup>32</sup>. Policymakers should carefully look at potential risks to EM financial stability deriving from a sudden mutual fund aggregate outflow from the area and the empirical analysis of this work helps to identify cyclical variables driving investor short-term decisions.

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<sup>32</sup>For instance the link between short-term interest rates and net aggregate inflows to emerging economies should be better investigated. [Banegas et al. \(2016\)](#) working with long-term mutual funds domiciled in the US find that positive unexpected shocks to monetary policy path are associated with persistent outflows from bond funds.

## 2.8 Appendix 1

In order to further investigate the dataset characteristics, this Appendix presents fund subsamples by type of instrument, area of domicile and size. Table 7 reports the number of funds and aggregate TNAs for instruments that invest on EM equity and fixed income at December 2015. Funds are aggregated with respect to the type of the instrument.

Table 7: Funds by instrument

	Equity		Fixed income	
	Funds	TNA (billion \$)	Funds	TNA (billion \$)
Mutual funds	588	276.68	290	59.81
Sicav	266	76.14	194	74.63
Unit trust	12	3.13	14	1.47
Others	51	5.10	75	12.35
Total	917	361.05	573	148.27

This table reports the number of funds and aggregate TNAs for instruments that invest on EM equity and fixed income at December 2015. Funds are aggregated with respect to the type of the instrument. Data are from Bloomberg.

Mutual funds and SICAV are the most relevant typologies both in terms of numbers and TNAs for the two objects of investment. Mutual funds are respectively 588 for equity and 290 for fixed income, with aggregated TNA respectively equal to 267 and 60 billions, while SICAV are 266 and 194 with TNAs equal to 76 and 75 billion \$. Finally, Unit Trusts are respectively 12 and 14 while other instruments are relatively less and their aggregate numbers are equal to 51 and 75.

Table 8 reports the number of funds and aggregate TNAs for instruments that invest on EM equity and fixed income at December 2015. Funds are aggregated with respect to the area of domicile. The majority of funds have domicile in North America and in Central Europe: american equity funds are 334 with a TNA of 238 billion \$ and fixed income funds are 135 with a TNA of 43 billions. European equity funds are more (496) with a lower TNA (121 billions), suggesting that european equity funds have on average lower capitalization.

European funds that invest on fixed income are 349 with a TNA of 103 billion \$. Funds with domicile in other areas (Asia, Africa and middle east<sup>33</sup>, Latin America and Western Europe) are less (respectively 87 for equity and 89 for fixed income) and less capitalized, in both cases the aggregate capitalization remains below 2 billion \$.

Table 8: Funds by area of domicile

	Equity		Fixed income	
	Funds	TNA (billion \$)	Funds	TNA (billion \$)
North America	334	238.49	135	42.96
Central Europe	496	121.43	349	103.65
Asia	44	0.66	8	0.57
Africa and middle-east	30	0.46	72	1.02
Latin America	5	0.01	8	0.07
Western Europe	8	0.01	1	0.01
Total	917	361.05	573	148.27

This table reports the number of funds and aggregate TNAs for instruments that invest on EM equity and fixed income at December 2015. Funds are aggregated with respect to the area of domicile at Dec. 2015. Data are from Bloomberg.

Table 9 reports the number of funds and aggregate TNAs for instruments that invest on EM equity and fixed income at December 2015. Funds are aggregated with respect to their size.

Smaller funds, with  $TNA \leq 5$  mln\$ are 202 for equity and 130 for fixed income, funds with TNA between 5 and 100 million \$ are respectively 367 and 22. Larger funds, with TNA between 100 and 500 million \$ are 206 and 151 while the largest, with  $TNA > 500$  mln\$, are 142 and 70.

## 2.9 Appendix 2

In order to further investigate which are fund subsamples that mainly respond to determinants identified in table 2 by main types of instrument, domiciles and sizes, this Appendix

<sup>33</sup>Antilles, Bahamas, Bermuda, Cayman, Jersey Island, Marianne, Mauritius, Saint Lucia are included in the area Africa and middle east.

Table 9: Funds by size

	Equity		Fixed income	
	Funds	TNA (billion \$)	Funds	TNA (billion \$)
TNA > 500 mln\$	142	309.35	70	109.80
100 < TNA ≤ 500 mln\$	206	43.20	151	32.41
5 < TNA ≤ 100 mln\$	367	8.33	222	6.06
TNA ≤ 5 mln\$	202	0.17	130	0.01
Total	917	361.05	573	148.27

This table reports the number of funds and aggregate TNAs for instruments that invest on EM equity and fixed income at December 2015. Funds are aggregated with respect to size at Dec. 2015. Data are from Bloomberg.

reports determinants of mutual fund flows that invest in EM equity and fixed income.

Table 10 reports 10 linear specifications per each, both of the push and the pull models for mutual fund and SICAV net aggregate flows that respectively invest in EM equity and fixed income. Table 11 reports 10 linear specifications per each, both of the push and the pull models for fund aggregate flows that respectively invest in EM equity and fixed income and are respectively located in North America and Central Europe. Finally table 12 reports 10 linear specifications per each, both of the push and the pull models for larger fund aggregate flows that respectively invest in EM equity and fixed income.

Table 10: Determinants by main instruments

	Equity					Fixed income				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Mutual funds										
SP $\text{ret}_{t-1}-\text{rf}_{t-1}$	0.18*** (4.55)		0.19*** (4.20)	0.13*** (3.26)	0.15*** (4.01)					
US corp $\text{ret}_{t-1}-\text{rf}_{t-1}$						0.03** (2.48)		0.03** (2.48)	0.02 (1.59)	0.02** (2.56)
MSCI $_{t-1}-\text{rf}_{t-1}$		0.11*** (3.60)								
EM corp $\text{ret}_{t-1}-\text{rf}_{t-1}$							0.03** (2.16)			
3m Tbills % $\text{ch}_{t-1}$	-0.01*** (-3.40)		-0.01*** (-3.06)	-0.01*** (-3.30)	-0.01*** (-3.45)	-0.01*** (-4.73)		-0.01*** (-4.47)	-0.01*** (-4.71)	-0.01*** (-4.63)
US Sent $_{t-1}$			-0.02 (-1.64)	-0.05** (-2.43)				-0.01** (-2.55)	-0.01*** (-2.76)	
VIX $_{t-1}$				-0.06** (-2.41)					-0.01* (-1.90)	
US recession					1.00*** (2.85)					0.15 (1.42)
Constant	1.27*** (6.68)	1.08*** (6.02)	3.21** (2.55)	6.41*** (3.04)	0.73*** (4.01)	0.14** (2.38)	0.13** (2.16)	0.82*** (2.84)	1.48*** (2.77)	0.06** (2.46)
R <sup>2</sup>	0.179	0.113	0.193	0.0219	0.224	0.051	0.027	0.077	0.097	0.065
Adj. R <sup>2</sup>	0.170	0.108	0.173	0.200	0.211	0.040	0.021	0.061	0.076	0.048
Sicav										
SP $\text{ret}_{t-1}-\text{rf}_{t-1}$	0.03** (2.17)		0.03** (2.17)	0.04*** (2.64)	0.03** (2.21)					
US corp $\text{ret}_{t-1}-\text{rf}_{t-1}$						0.10*** (3.84)		0.10*** (3.65)	0.08*** (3.16)	0.08*** (3.37)
MSCI $_{t-1}-\text{rf}_{t-1}$		0.04*** (5.09)								
EM corp $\text{ret}_{t-1}-\text{rf}_{t-1}$							0.42*** (2.90)			
3m Tbills % $\text{ch}_{t-1}$	-0.01*** (-7.47)		-0.01*** (-6.39)	-0.01*** (-6.27)	-0.01*** (-6.75)	-0.01*** (-5.14)		-0.01*** (-4.79)	-0.01*** (-4.93)	-0.01*** (-4.94)
US Sent $_{t-1}$			-0.01 (-1.62)	-0.01 (-0.71)				-0.02* (-1.90)	-0.02** (-2.14)	
VIX $_{t-1}$				0.01 (1.34)					-0.02 (-1.35)	
US recession					-0.10 (0.53)					0.29 (1.14)
Constant	0.16 (1.59)	0.14 (1.63)	1.13* (1.75)	0.04 (0.47)	0.11* (1.81)	0.45*** (3.29)	0.42*** (2.90)	1.77** (2.42)	2.78** (2.36)	0.30*** (3.29)
R <sup>2</sup>	0.047	0.069	0.064	0.070	0.049	0.122	0.071	0.141	0.149	0.132
Adj. R <sup>2</sup>	0.036	0.064	0.048	0.048	0.032	0.112	0.065	0.126	0.130	0.117

The table reports the coefficients for different specifications of the following regression:  $Flows_t^{obj,I} = a + b_1 Z_{1,t-k} + \dots + b_j Z_{j,t-k} + u_t$ , for  $k = 1, \dots, K$ ,  $obj = E, FI$  and  $I = MF, SICAV$ .  $Flows_t$  is the aggregate fund net flows that invest in EM equity or fixed income and  $Z_{j,t-1}$  denotes the  $j$ -th lagged push determinant. Specifications include total returns on market indexes (risk premia), alternative measures of developed economy rates, the [US Consumer Sentiment index](#) from Michigan University, the VIX index. A dummy for US recession, starting in Sept 2008, is included. Monthly risk premia are built with respect to the 1-month Euribor rate as the risk-free rate. Index returns, interest rates are expressed in % while flows are in billion \$. The t-statistics are reported below the coefficients in parentheses. The standard errors are corrected for heteroskedasticity using HAC standard errors & covariance with Newey-West fixed bandwidth (3 lags). Data are monthly from Bloomberg and from Michigan University for the sample Jan. 2001-Dec. 2015. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

Table 11: Determinants by main areas

	Equity					Fixed income				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
North America										
SP $ret_{t-1}-rf_{t-1}$	0.16*** (4.15)		0.16*** (3.90)	0.13*** (3.07)	0.14*** (2.90)					
US corp $ret_{t-1}-rf_{t-1}$						0.01* (1.86)		0.01* (1.74)	0.01 (0.82)	0.01 (1.44)
MSCI $ret_{t-1}-rf_{t-1}$		0.10*** (3.40)								
EM corp $ret_{t-1}-rf_{t-1}$							0.01* (1.79)			
3m Tbills % $ch_{t-1}$	-0.01*** (-2.77)		-0.01** (-2.57)	-0.01** (-2.71)	-0.01*** (-2.85)	-0.01*** (-3.21)		-0.01*** (-3.07)	-0.01*** (-3.23)	-0.01*** (-3.29)
US Sent $_{t-1}$			-0.02 (-1.32)	-0.04** (-2.14)				-0.01** (-2.02)	-0.01*** (-2.62)	
VIX $_{t-1}$				-0.05** (-2.20)					-0.01*** (-2.45)	
US recession					0.83** (2.51)					0.09* (1.84)
Constant	1.09*** (6.20)	0.93*** (5.50)	2.61** (2.17)	5.41** (2.76)	0.64*** (2.68)	0.07** (2.16)	0.06* (1.85)	0.38** (2.26)	0.84*** (2.78)	0.02 (1.04)
R <sup>2</sup>	0.164	0.104	0.173	0.194	0.198	0.047	0.016	0.063	0.092	0.064
Adj. R <sup>2</sup>	0.154	0.099	0.158	0.175	0.184	0.036	0.010	0.047	0.071	0.048
Central Europe										
SP $ret_{t-1}-rf_{t-1}$	0.05*** (3.19)		0.05*** (3.25)	0.04** (2.58)	0.05*** (2.76)					
US corp $ret_{t-1}-rf_{t-1}$						0.12*** (4.01)		0.12*** (3.77)	0.10*** (3.14)	0.10*** (3.70)
MSCI $ret_{t-1}-rf_{t-1}$		0.05*** (5.37)								
EM corp $ret_{t-1}-rf_{t-1}$							0.12*** (3.65)			
3m Tbills % $ch_{t-1}$	-0.01*** (-7.15)		-0.01*** (-6.15)	-0.01*** (-6.22)	-0.01*** (-6.38)	-0.01*** (-5.83)		-0.01*** (-5.44)	-0.01*** (-5.63)	-0.01*** (-5.52)
US Sent $_{t-1}$			-0.01 (1.57)	-0.02 (-1.51)				-0.02** (-2.27)	-0.03** (-2.44)	
VIX $_{t-1}$				-0.01 (-0.58)					-0.03 (-1.53)	
US recession					0.13 (-0.54)					0.32 (1.03)
Constant	0.29** (2.40)	0.24** (2.19)	1.37* (1.84)	1.89* (1.56)	0.22*** (2.81)	0.57*** (3.29)	0.53*** (2.92)	2.45*** (2.81)	3.89*** (2.61)	0.40*** (3.97)
R <sup>2</sup>	0.056	0.061	0.068	0.070	0.058	0.117	0.068	0.142	0.153	0.126
Adj. R <sup>2</sup>	0.045	0.056	0.052	0.049	0.042	0.107	0.063	0.127	0.133	0.111

The table reports the coefficients for different specifications of the following regression:  $Flows_t^{obj,A} = a + b_1 Z_{1,t-k} + \dots + b_j Z_{j,t-k} + u_t$ , for  $k = 1, \dots, K$ ,  $obj = E, FI$  and  $A = NA, CE$ .  $Flows_t$  is the aggregate fund net flows that invest in EM equity or fixed income and  $Z_{j,t-k}$  denotes the  $j$ -th lagged push determinant. Specifications include total returns on market indexes (risk premia), alternative measures of developed economy rates, the [US Consumer Sentiment index](#) from Michigan University, the VIX index. A dummy for US recession, starting in Sept 2008, is included. Monthly risk premia are built with respect to the 1-month Euribor rate as the risk-free rate. Index returns, interest rates are expressed in % while flows are in billion \$. The t-statistics are reported below the coefficients in parentheses. The standard errors are corrected for heteroskedasticity using HAC standard errors & covariance with Newey-West fixed bandwidth (3 lags). Data are monthly from Bloomberg and from Michigan University for the sample Jan. 2001-Dec. 2015. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

Table 12: Determinants by main sizes

	Equity					Fixed income				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
<b>TNA &gt; 500 mln\$</b>										
SP $ret_{t-1}-rf_{t-1}$	0.20*** (4.82)		0.20*** (4.45)	0.16*** (3.35)	0.18*** (3.92)					
US corp $ret_{t-1}-rf_{t-1}$						0.10*** (3.59)		0.10*** (3.54)	0.08*** (2.93)	0.08*** (3.59)
MSCI $ret_{t-1}-rf_{t-1}$		0.13*** (4.64)								
EM corp $ret_{t-1}-rf_{t-1}$							0.10*** (3.11)			
3m Tbills % $ch_{t-1}$	-0.01*** (-3.89)		-0.01*** (-3.57)	-0.01*** (-3.73)	-0.01*** (-3.80)	-0.01*** (-4.65)		-0.01*** (-4.26)	-0.01*** (-4.39)	-0.01*** (-4.50)
US Sent $_{t-1}$			-0.03** (-2.05)	-0.05** (-2.44)				-0.03*** (-3.01)	-0.04*** (-2.93)	
VIX $_{t-1}$				-0.05* (-1.92)					-0.02 (-1.35)	
US recession					0.65* (1.80)					0.35 (1.28)
Constant	1.18*** (5.59)	0.98*** (5.03)	3.71*** (2.80)	6.53*** (2.86)	0.83*** (4.52)	0.51*** (3.19)	0.47*** (2.87)	2.75*** (3.44)	3.87*** (2.95)	0.31*** (3.72)
R <sup>2</sup>	0.186	0.138	0.205	0.221	0.202	0.104	0.061	0.149	0.157	0.117
Adj. R <sup>2</sup>	0.176	0.133	0.191	0.203	0.188	0.094	0.055	0.134	0.138	0.102
<b>100 &lt; TNA ≤ 500 mln\$</b>										
SP $ret_{t-1}-rf_{t-1}$	0.02*** (2.73)		0.02*** (2.65)	0.01 (1.46)	0.01 (1.32)					
US corp $ret_{t-1}-rf_{t-1}$						0.03*** (4.01)		0.03*** (3.94)	0.02*** (3.37)	0.03*** (3.87)
MSCI $ret_{t-1}-rf_{t-1}$		0.01*** (2.82)								
EM corp $ret_{t-1}-rf_{t-1}$							0.03*** (3.77)			
3m Tbills % $ch_{t-1}$	-0.01*** (-2.88)		-0.01*** (-2.66)	-0.01*** (-2.63)	-0.01*** (-3.37)	-0.01*** (-6.76)		-0.01*** (-6.73)	-0.01*** (-6.95)	-0.01*** (-6.55)
US Sent $_{t-1}$			-0.01 (-0.65)	-0.01 (-0.97)				-0.01 (-0.29)	-0.01 (-1.38)	-0.01
VIX $_{t-1}$				-0.01 (-1.08)						-0.01* (-1.93)
US recession					0.21* (1.96)					0.05 (0.63)
Constant	0.17*** (3.26)	0.16*** (3.19)	0.34 (1.18)	0.74 (1.25)	0.06 (1.63)	0.13*** (2.73)	0.12** (2.28)	0.19 (0.93)	0.76 (1.83)	0.10*** (4.11)
R <sup>2</sup>	0.019	0.019	0.020	0.025	0.043	0.127	0.063	0.128	0.151	0.130
Adj. R <sup>2</sup>	0.008	0.013	0.003	0.003	0.026	0.117	0.057	0.113	0.131	0.115

The table reports the coefficients for different specifications of the following regression:  $Flows_t^{obj,S} = a + b_1 Z_{1,t-k} + \dots + b_j Z_{j,t-k} + u_t$ , for  $k = 1, \dots, K$ ,  $obj = E, FI$  and  $S = M, L$ .  $Flows_t$  is the aggregate fund net flows that invest in EM equity or fixed income and  $Z_{j,t-k}$  denotes the  $j$ -th lagged push determinant. Specifications include total returns on market indexes (risk premia), alternative measures of developed economy rates, the [US Consumer Sentiment index](#) from Michigan University, the VIX index. A dummy for US recession, starting in Sept 2008, is included. Monthly risk premia are built with respect to the 1-month Euribor rate as the risk-free rate. Index returns, interest rates are expressed in % while flows are in billion \$. The t-statistics are reported below the coefficients in parentheses. The standard errors are corrected for heteroskedasticity using HAC standard errors & covariance with Newey-West fixed bandwidth (3 lags). Data are monthly from Bloomberg and from Michigan University for the sample Jan. 2001-Dec. 2015. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

## 2.10 Appendix 3

This appendix reports the lists of funds that invest in EM equity and fixed income. The sample has been defined selecting only funds in US\$, excluding closed-end funds and exchange traded products for a 15-year period, from Jan. 2001 to Dec. 2015. The whole dataset contains 917 equity funds and 573 fixed income funds. Tables 13 and 14 list equity funds in alphabetical order. Tables 15 and 16 list equity funds in alphabetical order.









Table 16: List of fixed income funds (2/2)

SCHRODER EM MK DB RELATV ST	STONE HARBOR EM DBT BLND-INS	THE STANDARD S/T BOND FD-A	UBS-EMERG MKT BD 2016-PAC
SCHRODER EMG MKTS DEBT FUND	STONE HARBOR EM DEBT ALLOC-I	THREADNEEDLE EMRG MKT BOND F	ULT AVULL-JNL/GS EMMK
SCHRODER ISF EM DBT A R-A AC	STONE HARBOR EM MKT CORP-INS	THREADNEEDLE-EM MKT DBT-AU	UNIQA EMERGING MARKETS DEBT
SCHRODER ISF-EM COR BD-AUSDA	STONE HARBOR EM MKT DEBT-INS	THREADNEEDLE-EMMKT CP BD-AUP	UNIVERSAL EMER MKTS DEBT-I
SCHRODER SEL NEW MKT EM BD-A	STONE HARBOR GL-EM MK DB-M&A	THREADNEEDLE-GL E MKT ST-AU	VALARTIS GLOB EMERG MKTS-A
SCHRODER-CHINA FX INC-IUSDA	STONE HARBOR GL-EMLC DT-M&A	TIAA-CREF EM MRKT DEBT-INST	VALLEY FUND-FIXED INCOME AGG
SCUDDER EMRG MRKTS DEBT-IN	STONE HARBOR-EM MK DBT-MUSDA	TOWER FUND-LOC CUR EMRG MKTS	VAM-INT SPECIAL OPPORT
SCUDDER GLB OP-EM MKT BND-A1	STONE-INV GR EMMK DEBT-IUSDA	TRANSAM EMER MKTS DBT-A	VAN ECK UNCONST EMERG BND-A
SEB SICAV 1-EMK CRP BD-CUSD	STRATEGIC-GLB EMG MKTS FI	TRG EMERGING MKT LOCAL DEBT	VAN ECK-UNCONST EMR MK B-II
SECURITY LOC EM MKT DBT-A	SUL AMERICA FUND-LEXUS CLASS	TROWE GLOBAL INV GR CRP BD-A	VAN KAMPEN EMERG MARK INC-A
SEI INST INTL EMG MKT DEBT-F	SUMMIT EMERGING MKTS BOND FD	TROWE PRICE-EMKTS CORP B-A	VANGUARD EM MKT GOV BND-ADM
SEI INST INV EMG MKT DEBT-A	SUMMIT EMERGING MKTS BOND FD	UBAM EMERG MKT CP BD USD-AC	VANGUARD EMERG MKTS BND-INV
SEI MASTER-EM MK DBT-USDIS A	SWISS LF LX-BD EMKTS CP-IC	UBAM FCP-E INV G CRP B-ICUSD	VIRTUS EMERGING MKTS DEBT-A
SGAM FUND-BONDS EMG COUN-A	SWISSCANTO LU B EM A HUSD-AT	UBAM-EM IG CRP BD-ASCAP	VONTOBEL FD-EM MKT LC BD-B
SH-EM MKTS CORP DEBT-MUSDACC	SYDINVEST ENGR EM MKT LO CU\$	UBAM-EMERGING MK BD USD-AC	VONTOBEL-EM MK BD-X
SH-EM MKTS DEBT BLD #2-IUSDA	SYMBIOTICS EMER IMP BD-A/C	UBAM-LOC CURR EMMKT BD-AC	VONTOBEL-EM MKT DBT-B
SH-EMR MKTS DEBT BLEND-IUSDA	T ROWE PR EMERG CORP BND-INV	UBP OPP-EM HIGH YLD SD CB-AC	VOYA DIV EMERG MKTS DEBT-A
SILK-AFRICAN BOND-R	T ROWE PR EMERG MKTS BND	UBS EMERGING MARKETS DEBT-A	VOYA EM MRKT HRD CUR DBT-P
SINOPAC SHORT TERM USD FI FD	T ROWE PR INST EM MRKT BND	UBS EMKTS BDS 2018 USD-K1ACC	VOYA EMER MKTS CORP DEBT-P
SISF-EM MKT BND-A1 USD ACC	T ROWE PR-EMER MK BD-I	UBS EMKTS CORP HI YLD USD-F	WA EMERG MK BOND-\$ ACC
SISF-EM MKT LCL CUR-A EUR AC	T. ROWE PRICE-GL HI BD-A	UBS EMKTS CORP INV GR USD-F	WELL EMG MKTS DBT T USD AC
SOVEREIGN H/Y HARD CURR FD-A	TCW EMERG MKTS INCOME-I	UBS EMKTS SOV HI YLD USD-F	WELL OP EM DBT-S USD AC
SOVEREIGN HIGH YIELD LOCAL-A	TCW EMG MKTS FXD INC TOT RET	UBS EMKTS SOV INV GR USD-F	WESTERN ASSET EM MKT DEBT-A
SSGA-MUL-FAC PR EMK B-SUSD	TCW FUNDS-EMER MKT INC-AU	UBS EMR ECO-G BD USD-USDP AC	WF GUOTAI JUNAN EM TR-B1 USD
STANDARD LIFE EMERG MK DT-AA	TEMPLETON EMERG MKTS BND-A	UBS GS-HIGH YLD EMMA BDS-FD	WORLD EXPRESS II-GL E M-AU\$
STANDARD MAST-EMMKT DEBT-A1\$	TERREUS HIGH INCOME FUND-FAF	UBS LUX EXPOS-EM MRK BND-GD	WWIDE INV PORT-EMERG FIXED-A
STANDARD-EMR MKT ST BD-A	THE ARAB INCOME FUND LTD	UBS LX INST EM MKTS BD-BA	
STANDISH MELL EMG MKT DBT	THE EMERGING MARKETS DEBT FD	UBS-EM BD 2017 USD - P ACC	
STNDRD LIFE-EMMK CRP BD-D	THE STANDARD LATIN DAILY-A	UBS-EMERG ECON CRP USD-UX-IX	

# 3 The performance of market-timing strategies of Italian mutual fund investors<sup>34</sup>

## 3.1 Introduction

In this chapter, we show that simple buy-and-hold strategies beat the market-timing strategies effectively used by Italian investors in equity mutual funds. Therefore, investors should re-consider their investment behavior and choose cheaper, in terms of fees, and simpler, passive strategies. We estimate returns from market-timing strategies using aggregate data on a large sample of equity mutual funds' net flows and consider funds investing either in Europe and the Euro Area, or the US, or Emerging Markets. In all cases, buy-and-hold wins with extra returns that go from 0.24% per quarter (Europe and Euro Area) to 0.87% per quarter (US market). We also show that the differences in returns, between the two strategies, are not explained by differences in risk and risk exposure.

A large body of literature has analyzed the empirical finding that investors tend to chase returns. For example, [Greenwood and Shleifer \(2014\)](#) argue that investors expectations of future stock market returns in the period 1963-2011 are correlated with past stock returns and with the level of the stock market and not with model-implied expectations. [Remolona et al. \(1997\)](#) investigate the possible causation link that goes from unexpected (rather than realized) recent past stock returns to mutual fund flows and did not find a strong relationship in the short-run, but only in the longer run. [Yagan \(2014\)](#) looks at the possibility that investors “ride the bubble”, buying in a boom and selling early in a bust. [Chien \(2014\)](#) looks at the correlation of net current flows into US equity mutual funds with past stock market performance and finds that they are all positive and approaching 0.4 with respect to returns in the previous quarter. Interestingly, [Chien \(2014\)](#) also finds that the correlation of current

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<sup>34</sup>This Chapter is co-authored with Nicola Borri, LUISS Guido Carli. It is a substantial revision of a paper previously titled “Chasing Stock Market Returns”, LUISS CASMEF WP Series 2015 No. 3. A revised version of this work is forthcoming on Economic Notes. We thank Federico Nucera for valuable suggestions and seminar participants at the 7th annual meeting of the Academy of Behavioral Finance & Economics, Drexel University, Philadelphia.

net flows with respect to *future* equity returns are negative, even though small in magnitude: on the basis of this evidence, [Chien \(2014\)](#) argues that a return-chasing investment strategy that goes long (short) equity following good (poor) realized past stock returns might be costly for the investor. Note that market-timing strategies are not necessarily doomed to fail. In fact, according to the theory, if returns are somewhat predictable ([Cochrane \(2011\)](#)), then investors may be able to achieve higher Sharpe ratios by timing the market (see, for example, [Gallant et al. \(1990\)](#), [Brandt \(1999\)](#) and [Campbell and Viceira \(2002\)](#)). Therefore, *a priori*, we cannot say if investors could do better than simply holding the market.

In this chapter, we provide more substantial evidence on the cost of market-timing strategies using data covering a large number of funds available to Italian investors. Prior works either considered the US experience, or small samples of funds from different countries. First, relying on data on Italian investors is convenient as it is publicly available, of good quality, and covering all funds available to the investors. Second, the Italian market is of particular relevance given the large stock of wealth of Italian households that is approximately equal to seven times the net national income ([Banca d'Italia \(2015\)](#)).

The remainder of the chapter is organized as follows: in section [3.2](#), we present the data on equity mutual fund flows; in section [3.3](#), we compare the performance of buy-and-hold and market-timing investment strategies; in section [3.4](#), we present robustness results; finally, in section [3.5](#), we conclude.

## 3.2 Data

We collect aggregate data on equity mutual funds' net flows from [Assogestioni Cubo Database](#). Assogestioni is the Italian association of the investment management industry and it is a member of European Fund and Asset Management Association (EFAMA). It represents the vast majority of asset management companies operating in Italy, in addition to banks and insurance companies managing both discretionary and mutual funds<sup>35</sup>. Therefore, our ini-

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<sup>35</sup>At the end of 2015, the gross stock of assets under management in Italy, including all mutual funds, is approximately 1000 billions Euros, and the total number of investors is approximately 8 millions.

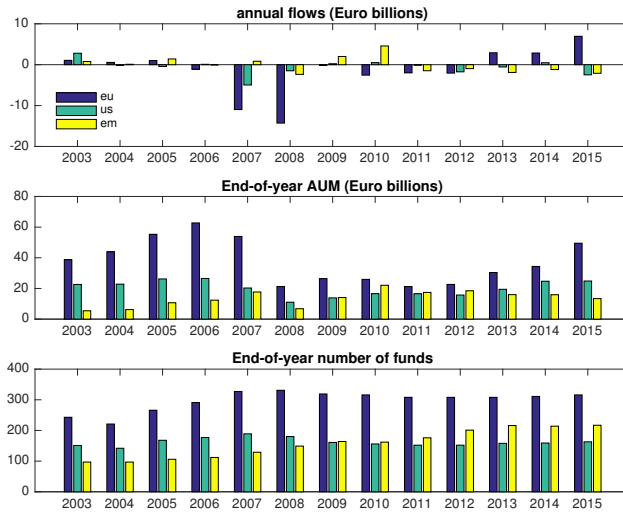
tial sample contains, roughly, most of the equity mutual funds available to Italian investors. Although the dataset starts on 12/31/1984 with annual frequency data, we select a shorter sample, at quarterly frequency, from 2003:Q3 to 2015:Q4. For this sample, we could retrieve net flows, asset under management (AUM), and total number of funds, disaggregated according to the “explicitly declared” market of investment. In particular, we select all equity mutual funds with the following, mutually exclusive, markets of investment: Europe and the Euro Area, the US market, and Emerging Markets. Our sub-sample of all the equity mutual funds contains, at the end of 2015, about 700 funds, out of approximately 1600 equity mutual funds, and corresponds to AUM of about 88 billions Euro, out of a total of 190 billions Euro for all equity mutual funds. Figure 5 summarizes, at annual frequency, our mutual fund data. The top panel reports annual net flows and shows, clearly, the large outflow, from all funds, with the exception of funds investing in Emerging Markets, during the Great Recession, and then the inflows into Euro Area fund starting in 2013 and the continuing outflows from funds investing in the US and Emerging Markets up until the end of the sample. Overall, the bar-plot shows the activism of Italian investors who entry and exit mutual funds, and change their portfolio allocation within the market for equity mutual funds<sup>36</sup>. The middle panel of the figure reports the end-of-year asset under management. Not surprisingly, AUM declined significantly during the Great Recession both because of the large outflows and the sharp drop in asset prices, and then recovered a bit starting in 2009. The bottom panel shows that the total number of funds has been roughly stable in our sample period. The largest number of funds is for the category “Europe and Euro Area”, while a similar, smaller, number of funds declare to invest in the US and Emerging Markets.

We also collect, from Bloomberg, time series for the total return indices of three broad markets corresponding to the areas of investment of the funds in our sample. In particular, the MSCI Europe, the S&P 500 and the MSCI Emerging Markets indices. We start with monthly frequency data, and build quarterly excess returns using the 1-month Euribor rate,

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<sup>36</sup>In this chapter, we completely abstract from all the other assets that are part of the typical households’ wealth, like real estate, or, for example, fixed-income and money market mutual funds.

Figure 5: Mutual funds net flows



Notes: The top panel of this figure plots the net flows into equity mutual funds available to Italian investors (in billions of Euros) for the three areas of investments: Europe and Euro Area, the US and Emerging Markets. The middle panel plots the aggregate stock of assets under management (in billions of Euros). The bottom panel plots the total number of funds. Data are annual from [Assogestioni Cubo Database](#). The sample is 2003-2015.

also from Bloomberg, as the risk-free rate. Note that all return indices are total return, and thus account for reinvestment of dividends.

### 3.3 Buy-and-hold and market timing strategies

In this section, we investigate whether market-timing strategies effectively used by Italian investors, measured by the observed flows into and out of equity mutual funds, beat a simple buy-and-hold strategy. We find that the performance gap, or the spread between returns of a return-chasing and buy-and-hold investment strategies, goes from -0.87% per quarter, for investment in mutual funds investing in the US equity market, to -0.24% per quarter, for investments in funds with a focus on the Euro Area market. These results are robust to changing the investment horizon, controlling for risk and different measures to compute the returns from market timing strategies.

A large body of literature shows that agents time their investments into, and out of,



equity mutual funds on the base of recent past returns<sup>37</sup>. In particular, investors tend to invest more into equity funds after quarters of relatively high returns, and viceversa tend to withdraw resources from equity mutual funds after quarters of low returns. In addition, if returns are somewhat predictable, market timing strategies can lead to higher Sharpe ratios (for example, [Brandt \(1999\)](#), [Gallant et al. \(1990\)](#) and [Campbell and Viceira \(2002\)](#)). We use observed equity mutual funds' net flows to measure the effective market-timing of Italian investors.

Since our data on net flows are at the aggregate, rather than fund level, we need to make some working assumptions. In particular, we assume that funds' returns track broad market indices corresponding to their geographical markets of investment (i.e., Europe and Euro Area, the US, and Emerging Markets). Therefore, we assume away any heterogeneity in performance, at the fund level, and, thus, the possibility that some funds are, for example, better than others at stock picking, or time the market. While this assumption might sound heroic, we find that in fact it is quite reasonable in our sample of funds available to Italian investors. In particular, we collect, from Bloomberg, a large data set of individual mutual funds available to the Italian investors, and retrieve their net-asset values (NAVs). We were able to collect data on 101 funds investing in the Euro Area market, 169 funds investing in the US market, and 201 funds investing in Emerging Markets<sup>38</sup>. The sample is at monthly frequency, from 12/1999 to 12/2015. We then estimate the equally weighted mean NAV returns and compared it to the mean returns from large equity indices. Maybe a bit surprisingly, we found that mutual funds track the returns from broad equity indices very closely: the mean sample correlation between funds and market indices' returns is 0.97 for funds investing in Europe and the Euro Area, 0.96 in the US market, and 0.98 in

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<sup>37</sup>For example: [Warther \(1995\)](#), [Edelen \(1999\)](#), [Fant \(1999\)](#), [Edelen and Warner \(2001\)](#), [Friesen and Sapp \(2007\)](#), [Frazzini and Lamont \(2008\)](#), [Lou \(2012\)](#), [Ben-Rephael et al. \(2012\)](#) and [Ferreira et al. \(2012\)](#).

<sup>38</sup>We exclude from the sample closed-end funds and exchange traded products. Note that our sample, even though is not necessarily the same as the one covered by the Cubo Database, covers a very similar number of funds. For example, according to Cubo Database, the number of funds who explicitly declare to invest in the Euro Area are 217; in the US market 163; and in Emerging Markets 217. All NAV returns are in Euros.

Emerging Markets. Therefore, even though the funds in our sample are not officially following passive strategies, they, *de facto*, track their benchmarks very closely. Note that previous literature (for example, [Chevalier and Ellison \(1997\)](#), [Sirri and Tufano \(1998\)](#), [Friesen and Sapp \(2007\)](#)) exploited the difference between funds' NAV prices and dividend payments to their shareholders to estimate the net flows at the fund level. However, in Bloomberg we could find this information for just a small subset of funds so that we could not follow the same empirical strategy.

A buy-and-hold investment strategy invests €1 at the beginning of period  $t$  in the market portfolio and holds the investment for  $h$  quarters reinvesting any accrued dividends. In the baseline simulations we fix the investment horizon to  $h = 12$ , so that the holding period corresponds to 12 quarters and in [section 3.4](#) we show that results are robust to different values for  $h$ . We denote with  $\bar{r}_{t,t+h}^{BH,m}$  the time-weighted net geometric excess return of an investment started in quarter  $t$  with an horizon of  $h$  quarters in market  $m$ :

$$\bar{r}_{t,t+h}^{BH,m} = \left[ \prod_{i=1}^h R_{t+i}^m \right]^{1/h} - 1, \quad (9)$$

where  $m$  stands for Europe and the Euro Area, the US, and Emerging Markets, and  $R_t^m$  is the quarterly gross excess return on market  $m$  between period  $t - 1$  to  $t$ . Excess returns are constructed by subtracting the quarterly 1-month Euribor rate to  $R_t^m$ .

If buy-and-hold is a simple passive investment strategy, return-chasing is instead an active market-timing strategy that invests every quarter, and with a holding period of 12 quarters, an amount of resources equal to the net flows into mutual funds. Outflows from mutual funds are considered as dividend distributions, and inflows as additional investment. Note that since return-chasing requires buying and selling stocks (or, similarly, buying into a fund and/or redeeming the fund shares), investors will typically have to pay transaction costs (i.e., bid/ask spreads and mutual fund entry/exit fees if the investment is channeled through an intermediary). For simplicity, we abstract from these transaction costs that are likely

to reduce the profitability of a return-chasing strategy. Therefore, we estimate an upper boundary for the returns of return-chasing strategies. Following the existing literature, we estimate the performance of the return-chasing strategy using the concept of internal rate of return (IRR). In particular, we compute the net rate of return, for each area of investment, ( $\bar{r}^m$ ), that solves the following equation:

$$AUM_t = - \sum_{i=1}^h \frac{Flows_{t+i}}{(1 + \bar{r}_t^m)^i} + \frac{AUM_{t+h}}{(1 + \bar{r}_t^m)^i}, \quad (10)$$

where  $AUM_t$ , i.e., the value for the asset under management at time  $t$ , is the initial size of the investment,  $FLOW_{t+i}$ , with  $i = 1, \dots, h$ , are the net flows in and out equity mutual funds<sup>39</sup>, and  $AUM_{t+h}$  is the final value of the investment. The net excess return on the return-chasing strategy,  $\bar{r}_{t,t+h}^{RC,m}$ , is obtained by subtracting from  $\bar{r}^m$  the mean quarterly 1-month Euribor rate over the investing period. Note that, since flows take both positive and negative values, the IRR is not necessarily unique, or real valued. Therefore, we follow standard assumptions and, when more than one strictly positive internal rate of return is found, we select the minimum; when no strictly positive internal rate of return is found, but one or multiple negative rates are found, we select the maximum.

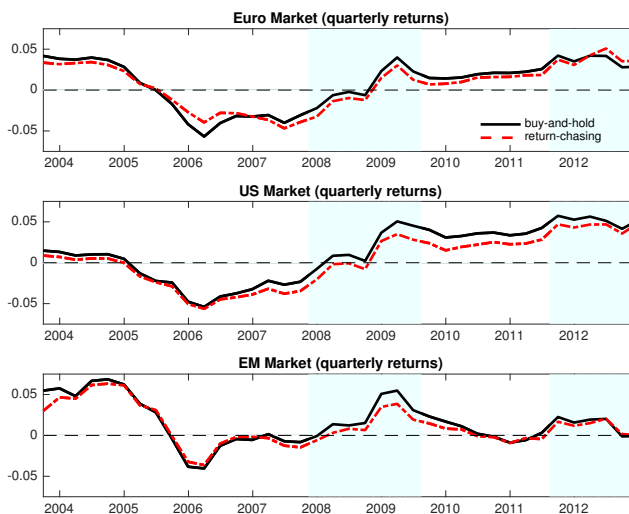
Figure 6 reports the quarterly returns for buy-and-hold (black solid line) and return-chasing (dashed red line) strategies with a holding period of 12 quarters. Note that, as we need to compute returns with a holding period of 12 quarters and our sample ends 2015:Q4, the figure reports returns up to 2012:Q4. The top panel corresponds to investment in the Euro Area; the middle panel in the US market; and the bottom panel in Emerging Markets. The returns from the two strategies are clearly highly correlated. However, casual inspection of figure 6 reveals that return-chasing underperforms buy-and-hold in most quarters, and especially in bad times, which in the figure are denoted by the colored bands corresponding to official US and Euro Area recessions. This is even more clear by inspection of figure 7 that

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<sup>39</sup>Note that inflows into mutual funds have a positive sign. Therefore, in the formula (10) for the IRR we need to multiply flows by  $-1$ .

plots the performance gap, or the difference between the returns from return-chasing and buy-and-hold, for investments in the three different markets. For funds investing in the US and in Emerging Markets, the performance gap is almost always negative, while for funds investing in Europe and the Euro Area is mostly negative, with the exception of the period that preceded the Great Recession (i.e., 2006-07) and the end part of the sample.

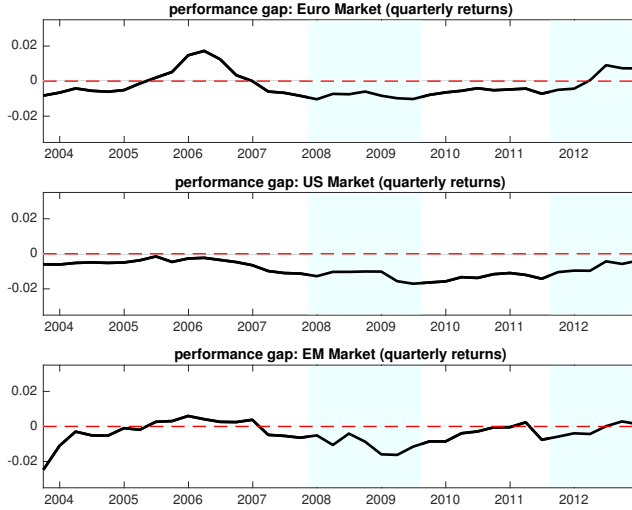
Figure 6: Buy-and-hold vs. Return-chasing



*Notes:* This figure plots returns from buy-and-hold (black solid line) and return-chasing (red dotted line) strategies with a holding period of 12 quarters. The top panel consider funds investing in the Euro Area; the middle panel in the US market; the bottom panel in Emerging Markets. Shaded areas represent US and Euro Area official recessions. Returns are at quarterly frequency. Data are from Bloomberg and Assogestioni for the period 2003:Q3-2015:Q4.

In table 17 we report summary statistics for the returns of the two strategies for the different areas of investment. On average, returns from return-chasing are always below buy-and-hold so that the average performance gap is always negative. The standard deviations of quarterly returns are quite large and not very informative as the returns series are very persistent. Therefore, we also report standard errors estimated by bootstrap that show that the negative performance gap of funds investing in the US and emerging market is statistically significant. Sharpe-ratios of buy-and-hold are always larger than for return-chasing. Therefore, buy-and-hold strategies are superior even after controlling for risk. In the last column, we report the fraction of quarters in which the performance gap is strictly

Figure 7: Performance gap



Notes: This figure plots the performance gap between return-chasing and buy-and-hold strategies. Shaded areas represent US and Euro Area official recessions. Returns are at quarterly frequency. Data are from Bloomberg and Assogestioni for the period 2003:Q3-2015:Q4.

negative. For funds investing in the US market, the performance gap is always negative, while for funds investing in the Euro Area and Emerging Markets the performance gap is negative in about 70 percent of the quarters.

We have so far showed that a simply buy-and-hold investment over-performs return-chasing in terms of average returns and Sharpe ratios. However, returns from the two strategies might represent compensations for exposure to different risk-factors. Therefore, we further compare the two strategies looking at risk-adjusted performance using a 3-factor model as in [Fama and French \(1993\)](#). In particular, we run the following regression:

$$\bar{r}_{t,t+hh}^{s,m} = \alpha^{s,m} + \beta_1^{s,m} RMRF_{t,h} + \beta_2^{s,m} SMB_{t,h} + \beta_3^{s,m} HML_{t,h} + \epsilon_t^{s,m}, \quad (11)$$

where  $s = BH, RC$ . The three factors correspond to the geometric average, over the same holding period equal to 12 quarters, of the excess returns on the value-weighted market portfolio ( $RMRF$ ); the returns on zero-investment factor-mimicking portfolios for size and book-to-market ( $SMB, HML$ ). All the factors are from [Kenneth French's data library](#), for

Table 17: Buy-and-hold vs. Return-chasing

	Mean	St. dev.	SE	Sharpe ratio	Skewness	Kurtosis	% quarters
<hr/>							
Euro Area							
Buy-and-hold	0.87	2.96	0.48	0.30	-0.65	2.10	–
Return-chasing	0.62	2.76	0.45	0.23	-0.42	1.92	–
Performance gap	-0.24	0.71	0.11	-0.35	1.30	3.70	71.05
<hr/>							
US							
Buy-and-hold	1.22	3.31	0.52	0.37	-0.39	1.91	–
Return-chasing	0.34	3.10	0.50	0.11	-0.32	1.93	–
Performance gap	-0.87	0.44	0.07	-2.02	-0.17	1.89	100.00
<hr/>							
Emerging Markets							
Buy-and-hold	1.57	2.74	0.44	0.58	0.28	2.53	–
Return-chasing	1.16	2.41	0.40	0.49	0.49	2.84	–
Performance gap	-0.41	0.65	0.10	-0.64	-0.94	4.22	71.05

*Notes:* This table reports mean, standard deviation, standard error estimated by bootstrap, sharpe ratio, skewness, kurtosis of quarterly returns of buy-and-hold and return-chasing strategies with a holding period of 12 quarters. In addition, we report the same statistics for the performance gap, defined as the spread between the returns on the two strategies. For the performance gap we additionally report the fraction of quarters in which buy-and-hold outperforms return-chasing (i.e., in which the performance gap is strictly negative). Returns are at quarterly frequency. Data are from Bloomberg and Assogestioni for the period 2003:Q3-2015:Q4.

the European market and converted in Euro. While we do not report all the results from the estimation of the 3-factor model, table 18 reports the estimates for the alphas for both strategies, and the three areas of investment. For buy-and-hold, alphas are always zero or not statistically significant from zero. On the contrary, the alphas for the market-timing strategy are negative and significant for investments in the Europe and the Euro Area and the US market. The point estimates are also economically large and equal to -1% per quarter, approximately 4% per year. As for buy-and-hold, the alphas for the return-chasing strategy investing in Emerging Markets is not significantly different from zero. Note that the 3-factor model explains a smaller fraction of the total variance when applied to strategies investing in Emerging Markets (the  $R^2$  is approximately 55%), while explain most of the variation in returns for investments in Europe and the euro area and the US market (the  $R^2$ s are above 90%).

Table 18: 3-factor alphas

	Europe and Euro Area	US	Emerging Markets
$\alpha^{BH}$	0.00 (0.00)	0.00 (0.35)	0.01 (0.10)
$\alpha^{RC}$	-0.01 (0.04)	-0.01 (0.00)	0.00 (0.20)

Notes: This table reports alphas from regressions of quarterly returns from buy-and-hold and return-chasing, with horizon 12 quarters, on a 3-factor model. P-values computed using HAC standard errors in parentheses. Data are from Kenneth French's website, Bloomberg and Assogestioni for the period 2003:Q3-2015:Q4.

In this section we showed that returns from market-timing strategies are lower than those obtained by simple buy-and-hold strategies, even after accounting for differences in risk. Returns from market-timing strategies are estimated assuming no transaction costs, which would further increase the gap. At the same time, by assuming that all funds, *de facto*, track broad market indices we neglect the possibility that some funds outperform the others, for example because of better management. Therefore, if investors were able to effectively separate good from bad funds, and put their money mostly in the former, we would underestimate the returns from market-timing strategies. Unfortunately, we cannot resolve this problem given our data on aggregate equity mutual fund net flows.

### 3.4 Robustness

In this section, we show that our results are robust to different investment horizons, and alternative measures of returns from return-chasing strategies. First, since the computation of the IRR, when net flows change sign multiple times, can be problematic, [Dietz \(1966\)](#) suggests the use of the following approximation:

$$\bar{r}_t^m = \left[ \frac{AUM_{t+h} - AUM_t - \sum_{i=1}^h Flow_{s_{t+i}}}{AUM_t + \frac{1}{2} \sum_{i=1}^h Flow_{s_{t+i}}} + 1 \right]^{1/h} - 1, \quad (12)$$

where *AUM* are the asset under management and *Flows* mutual funds' net flows. This approximation has been, for example, recently used by [Venanzi \(2016\)](#) to estimate the performances of Italian mutual funds. We computed again returns from return-chasing, using [Dietz \(1966\)](#)'s approximation, and the new values for the performance gap, and found that results are not affected. For example, the performance gap, using [Dietz \(1966\)](#)'s approximation to estimate the performance of market-timing strategies, become -0.22% per quarter for investments in Europe and the euro area; -0.82% per quarter in the US market; and -0.35% per quarter in Emerging Markets.

Second, table 19 shows that our results are robust to changing the investment horizon. In fact, the quarterly spread in returns between the two strategies is approximately invariant to a shortening, or a lengthening, of the holding period (i.e, for  $h = 4, 8, 12, 16$ ).

Table 19: Performance gap for different investment horizons  $h$

N. quarters	4	8	12	16
Euro Area	-0.22 (0.15)	-0.27 (0.11)	-0.24 (0.11)	-0.22 (0.11)
US	-0.86 (0.11)	-0.86 (0.07)	-0.87 (0.07)	-0.90 (0.08)
Emerging Markets	-0.43 (0.19)	-0.48 (0.13)	-0.41 (0.10)	-0.41 (0.07)

*Notes:* This table reports the performance gap, i.e., the mean spread between a return-chasing and a buy-and-hold investment strategy, as a function of the investment horizon (in quarters). Standard errors are in parentheses. Returns are quarterly. The sample is 2003:Q3-2015:Q4. Data are from Bloomberg and Assogestioni.

### 3.5 Conclusions

In this chapter we compare the returns from buy-and-hold and market-timing strategies effectively used by Italian equity mutual fund investors. We use data on aggregate net flows into equity mutual funds to estimate the returns from market-timing strategies. We show that returns from market-timing are smaller than those obtained by simple, passive, buy-and-hold strategies. These results are robust to differences in risk exposure and holding periods.



The estimation of a 3-factor model on the returns from the two strategies confirms our results: the alphas from market-timing strategies tend to be negative, and statistically significant, indicating that investors would be better off following passive strategies corresponding to different weights on the 3 mimicking portfolios of the 3-factor model, and thereby paying less in fees. Note that the Italian financial market has been recently hit by the alleged scandal of very complicated and not appropriate financial products being sold to financially uneducated investors. Similar events have been uncovered in the US during the Great Recession. Our results, on one hand suggest that investors should follow simple and passive strategies, on the other might convince financial regulators to force intermediaries to offer more simple products, and to introduce tax benefits for investors who "buy-and-hold".

## 4 Future research. Insights from a discrete asset pricing model with extrapolation<sup>40</sup>

Future research on extrapolation in the mutual fund market seems to be a very promising area of research. In order to address the issue, this chapter presents a modified version of the model in Barberis et al. (2015). It uses elements of bounded rationality from Barberis et al. (2016) and Adam et al. (2016) and it aims to determine the price of a risky asset endogenously. This framework allows to easily explicitate both the demand and the dividend price ratio, moreover it is linear and it can be thought as a CAPM.

I consider an economy set in discrete time with  $T + 1$  dates,  $t = 0, 1, 2, \dots, T$  with two assets: a risk-free asset and a risky asset. The risk-free asset has a fixed gross return and is perfectly elastically supplied, while the risky asset is a claim to a liquidating cash flow (i.e. dividend) at a fixed time in the future  $T$  and it has a fixed supply of  $Q$  shares. At each period, news about the value of final cash flow is publicly released. There are two types of traders: fundamentalists with bounded rationality and chasers, henceforth I refer to each agent using superscripts  $F$  and  $C$ . Both types maximize expected utility defined over next period's wealth, while they differ only in their expectations about the future stock market price. In the model there are no transaction costs or entry/exit fees. The value of the dividend at time  $T$ ,  $\tilde{D}_T$ , is given by:

$$\tilde{D}_T = D_0 + \tilde{\epsilon}_1 + \dots + \tilde{\epsilon}_T, \quad (13)$$

where  $\tilde{\epsilon}_t \sim N(0, \sigma_\epsilon^2)$  is i.i.d. over time. The value of  $D_0$  is public information at time 0, while the realized value of  $\epsilon_t$  becomes public at  $t$ . I assume the variance of the price changes equal to the variance of the dividend (i.e.  $\sigma_\epsilon^2$ ) and equal among agents. The assumption of homogeneous and constant beliefs on variance, primarily made for analytic tractability,

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<sup>40</sup>I thank participants at 2016 international meeting of the Academy of Behavioral Finance & Economics, Ca Foscari University and seminar participants at LUISS University.

makes sense in reality. In fact, since volatility can be easily estimated from past data, I assume that chasers know the true value of  $\sigma_\epsilon^2$ <sup>41</sup>. The generic budget constraint for agent  $i$ , with  $i \in [F, C]$  is:

$$W_{t+1} = R(W_t - C_t - P_t N_t^i) + (\tilde{P}_{t+1} + \tilde{D}_{t+1}) N_t^i, \quad (14)$$

where  $W$  is the per-capita exogenous wealth of the agent,  $C$  is the per-capita consumption,  $R$  is the gross return of the risk-free asset,  $P$  denotes the price of the risky asset,  $D$  is the dividend and  $N^i$  is the demand of each agent  $i$ . Since in this case  $D$  is paid only at date  $T$ , the constraint reduces to:

$$W_{t+1} = (RW_t - RC_t + N_t^i(\tilde{P}_{t+1} - RP_t)). \quad (15)$$

I assume a CARA utility function, therefore each type  $i$ , with  $i = [F, C]$ , maximizes:

$$\max_{N_t^i} \mathbb{E}_t^i [-e^{-\gamma(W_{t+1})}], \quad (16)$$

where  $\gamma$  is the coefficient of absolute risk aversion equal across agents<sup>42</sup>. Substituting the constraint in the objective, 16 becomes:

$$\max_{N_t^i} \mathbb{E}_t^i \left[ -e^{-\gamma(RW_t - RC_t + N_t^i(\tilde{P}_{t+1} - RP_t))} \right]. \quad (17)$$

With normally distributed returns to holding a unit of the risky asset, maximizing the expected value of 16 is equivalent (see Appendix 1) to maximizing :

$$\max_{N_t^i} \mathbb{E}_t^i(W_{t+1}) - \frac{\gamma}{2} Var_t^i(W_{t+1}). \quad (18)$$

---

<sup>41</sup>Nelson (1992) provides empirical justification for homogeneity of beliefs on variance in a diffusion context, arguing that the variance can be estimated with high precision by repeated sampling within a fixed period of time, whereas this is not the case for the mean. Poon and Granger (2003), after a comparison of over 90 papers that forecast volatility from past data, show that financial market volatility has a clear component of forecastability.

<sup>42</sup>The model remains analytically tractable even if the two traders have different values for  $\gamma$ .

The generic demand for agent  $i$  at time  $T - 1$ , with  $i \in [F, C]$  is:

$$N_{T-1}^i = \frac{\mathbb{E}_{T-1}^i(\tilde{P}_T) - RP_{T-1}}{\gamma \text{Var}_{T-1}^i(\tilde{P}_T - RP_{T-1})}. \quad (19)$$

Therefore the demand for the fundamentalist at time  $T - 1$  is:

$$N_{T-1}^F = \frac{\mathbb{E}_{T-1}^F(\tilde{P}_T) - RP_{T-1}}{\gamma \text{Var}_{T-1}^F(\tilde{P}_T - RP_{T-1})} = \frac{D_{T-1} - RP_{T-1}}{\gamma \sigma_\epsilon^2}. \quad (20)$$

In fact, in order to determine his time  $t$  demand for the risky asset, the fundamentalist considers that at time  $T$ ,  $P_T = D_T$ , while at time  $T - 1$ ,  $\mathbb{E}_{T-1}^F(\tilde{P}_T) = D_{T-1}$ . Each type  $i$ , with  $i \in [F, C]$  respectively make up a fraction  $\mu^F$  and  $\mu^C = (1 - \mu^F)$  of the population; each fraction does not depend on time and both values are public information. Therefore, the market clearing (MCC) condition at period  $T - 1$  implies:

$$\mu^F \left( \frac{D_{T-1} - RP_{T-1}}{\gamma \sigma_\epsilon^2} \right) + \mu^C N_{T-1}^C = Q, \quad (21)$$

which implies:

$$P_{T-1} = \frac{D_{T-1}}{R} - \frac{\gamma \sigma_\epsilon^2}{R \mu^F} (Q - \mu^C N_{T-1}^C). \quad (22)$$

At time  $T - 2$ , the fundamentalist demand is:

$$N_{T-2}^F = \frac{\mathbb{E}_{T-2}^F(\tilde{P}_{T-1}) - RP_{T-2}}{\gamma \sigma_\epsilon^2}. \quad (23)$$

Here the bounded rationality of the fundamental trader comes into play. Computing  $\mathbb{E}_{T-2}^F(\tilde{P}_{T-1})$  (i.e. the expectation price in 22), the fundamentalist has to come up with an estimate of  $\mathbb{E}_{T-2}^F(N_{T-1}^C)$ . If the agent was fully rational he should solve a dynamic system with both his demand and the demand of the other agent as unknowns. In order to simplify the mechanism, without losing much of the economic intuition of the result, I assume that  $\mathbb{E}_{T-2}^F(N_{T-1}^C) = Q$ .

From the fundamentalist viewpoint, the chaser holds period-by-period his per-capita

share of the risky asset supply; this can also be read as a lack of information of the fundamentalist that does not have a detailed understanding of how the chaser form his share demand. Under this assumption I can easily solve for the demand of fundamentalist at time  $T - 2$ :

$$N_{T-2}^F = \frac{D_{T-2} - \gamma\sigma_\epsilon^2 Q - RP_{T-2}}{\gamma\sigma_\epsilon^2}, \quad (24)$$

and iterating I get the demand of fundamantalist at generic time  $t$ :

$$N_t^F = \frac{D_t - \gamma\sigma_\epsilon^2(T - t - 1)Q - RP_t}{\gamma\sigma_\epsilon^2}. \quad (25)$$

If in the economy there were only fundamentalists the MCC would be  $N_t^F = Q$ , getting:

$$P_t^F = \frac{D_t}{R} - \frac{\gamma\sigma_\epsilon^2(T - t)Q}{R}. \quad (26)$$

Let  $P_t^F$  be the *fundamental value* of the price of the risky asset at time  $t$ . Substituting the fundamental value in the demand of the rational agent is easy to show that this trader strongly counteracts period-by-period any mispricing. The main economic difference with a model with fully rational traders, is that in this case fundamentalists cannot bear any mispricing and they lean against the wind at each time. This is due to the fact that fundamentalists assume that chasers demand period-by-period their share of the total supply. [Barberis et al. \(2015\)](#) find that in a model with fully rational traders, in case of overvaluation of the risky asset (due to the demand of chasers), rational traders do not aggressively counteract the overvaluation. It happens mainly because rational traders have a multi-period perspective, therefore, since in the near future chasers continue to have bullish expectations for the stock market they continue to exhibit a strong demand. In their scenario rational traders only partially counteract the overpricing, seeing profit opportunities due to the predictability of future returns. While in this model fundamentalists expect the price of the risky asset to revert to fundamental value within one period, they trade against any mispricing (i.e against

chasers). From 19, the optimal demand for chasers at time  $t$  is:

$$N_t^C = \frac{\mathbb{E}_t^C(\tilde{P}_{t+1}) - P_t}{\gamma \text{Var}_t(\tilde{P}_{t+1} - P_t)}. \quad (27)$$

Now I include the main feature for chasers assuming that chasers form their expectation learning from past prices, similar to Adam et al. (2016)<sup>43</sup>:

$$\mathbb{E}_t^C(\tilde{P}_{t+1} - RP_t) = (P_t - RP_{t-1}) + \alpha[(P_{t-1} - RP_{t-2}) - (P_t - RP_{t-1})] \equiv X_t. \quad (28)$$

Define  $\beta_t = (P_{t+1} - RP_t)$ , I can equivalently write:

$$X_t = \beta_{t-1} + \alpha(\beta_{t-2} - \beta_{t-1}), \quad (29)$$

It means that if past prices growth has been high, each chaser expects the risky asset will continue to perform well and he will have bullish expectation on price growth. The second part of the 29 include the main learning feature. In fact, chasers learn from past prices until 2 periods before and the second term counterbalance the first. This dynamic is linearly reflected into chaser demand:

$$N_t^C = \frac{X_t}{\gamma \sigma_\epsilon^2}. \quad (30)$$

In order to have a more reasonable expectation function for the chasers I allow for them to be concerned about the price of the risky asset compared to its fundamental value. Therefore the chaser demand becomes:

$$N_t^C = w \left( \frac{D_t - \gamma \sigma_\epsilon^2 (T - t - 1) Q - RP_t}{\gamma \sigma_\epsilon^2} \right) + (1 + w) \left( \frac{X_t}{\gamma \sigma_\epsilon^2} \right), \quad (31)$$

with  $w \in (0, 1)$ . It is possible to split the demand of the chasers in 31 in two parts. Each part can be seen as a signal for the chaser: the first one is a value signal, while the second

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<sup>43</sup>Other works do not explicitly assume a learning feature since in their model agents are not aware about their own beliefs.

one is a growth signal <sup>44</sup>. Note the two signals point in opposite directions. Through the MCC at time  $t$  (i.e.  $\mu^F N_t^F + \mu^C N_t^C = Q$ ) I get the aggregate demand  $\bar{N}$  at time  $t$ :

$$\bar{N}_t = (\mu^F + \mu^C w) \left( \frac{D_t - \gamma \sigma_\epsilon^2 (T - t - 1) Q - R P_t}{\gamma \sigma_\epsilon^2} \right) + \mu^C (1 + w) \left( \frac{X_t}{\gamma \sigma_\epsilon^2} \right), \quad (32)$$

Equation 32 reflects one of the predictions of this model: the aggregate demand depends negatively from contemporaneous price and positively from past prices. Solving the MCC for  $P_t$ , I get:

$$P_t = \frac{D_t}{R} + \frac{\mu^C (1 - w)}{R(\mu^F + \mu^C w)} X_t - \gamma \sigma_\epsilon^2 Q \frac{(\mu^F + \mu^C w)(T - t - 1) + 1}{R(\mu^F + \mu^C w)}. \quad (33)$$

The RHS of 33 has three terms. The first term links the equilibrium price to the expected value of the final dividend, the second term refers to the impact of past prices on actual price (through chaser demand). The third term is a price reduction that compensates agents for bearing the risk. Future work could be focused on the estimation of the model, verifying whether the extrapolation feature with learning, matches empirical regularities in the mutual fund market both on prices and flows.

The framework presented in this chapter provides a basic structure that incorporates empirical findings and at the same time remains simple and easily tractable. However it presents some limitations that have to be addressed in the future formulations of the model and few of them deserve to be briefly discussed hereafter. A first point regards the estimation of equation 32. A tempting solution would be that of using aggregate net flow as a proxy for aggregate demand. However there are key differences between the two, since the first is expected to be downward sloped with respect to price, while flow time-series float around zero. Any empirical estimation of the aggregate demand should overcome the issue.

A second point refers to the fact that the model includes an extrapolative mechanism in 28

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<sup>44</sup>Interestingly Barberis et al. (2016) in their model end up with similar terms that they interpret as *greed* and *fear* that give the trader conflicting signals.

and 29 without motivating that in terms of consumption stream. This point is linked to a general critique by [Cochrane \(2011, 2016\)](#) to behavioral models. [Cochrane \(2011\)](#) points out that: “[...] behavioral theories are also discount-rate theories. A distorted probability with risk-free discounting is mathematically equivalent to a different discount rate [...]”. In fact, in a consumption-based model risk-neutral probability is the actual probability times marginal utility:

$$\pi_s^* = \pi_s \beta \frac{u'(C_s)}{u'(C_0)} R^f, \quad (34)$$

where  $s$  denote states of nature,  $\pi_s^*$  are true probabilities and  $\pi_s$  are distorted probabilities. Under risk-neutral probabilities, price is the expected payoff, discounted at the risk free rate:

$$P_0 = \frac{1}{R^f} \sum_s \pi_s^* X_s = \frac{1}{R^f} E^*(X), \quad (35)$$

where  $X_s$  is the asset payoff in state  $s$ . [Cochrane \(2011\)](#) points out that: “[...] It is therefore pointless to argue *rational* versus *behavioral* in the abstract. There is a discount rate and equivalent distorted probability that can rationalize any (arbitrage-free) data”<sup>45</sup>. Properly address the last point is worth of great interest due to the fact that there are still open questions and key issues left unsolved, concerning the reconciliation of behavioral biases with consumption-based asset pricing models<sup>46</sup>.

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<sup>45</sup>Following this approach, any behavioral theory could be linked to other macro-finance frameworks, as habits or long run risk models.

<sup>46</sup>See for example [Cochrane \(2016\)](#).



## Appendix 1

This appendix reports the demonstration of 18. The negative exponential utility function, coupled with normally distributed wealth, yields an elegant representation of expected utility. In particular, I assume a negative exponential utility function of the form  $U = -e^{-\gamma W}$  and that agent's wealth is normally distributed with mean  $\mu$  and variance  $\sigma^2$ . The agent's expected utility can be simplified as follows:

$$\begin{aligned}
& \int -e^{-\gamma W} f(W) dW, \\
& \int -e^{-\gamma W} \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left[-\frac{(W-\mu)^2}{2\sigma^2}\right]} dW, \\
& - \int \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left[-\frac{W^2 - 2\mu W + 2\gamma W\sigma^2 + \mu^2}{2\sigma^2}\right]} dW, \\
& - \int \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left[-\frac{W^2 - 2(\mu - \gamma\sigma^2)W + \mu^2}{2\sigma^2}\right]} dW, \\
& - \int \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left[-\frac{W^2 - 2(\mu - \gamma\sigma^2)W + (\mu - \gamma\sigma^2)^2 - (\mu - \gamma\sigma^2)^2 + \mu^2}{2\sigma^2}\right]} dW, \\
& - \int \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left[-\frac{(W - (\mu - \gamma\sigma^2))^2 + \gamma\sigma^2(2\mu - \gamma\sigma^2)}{2\sigma^2}\right]} dW, \\
& - e^{\left[-\frac{\gamma\sigma^2(2\mu - \gamma\sigma^2)}{2\sigma^2}\right]} \int \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left[-\frac{(W - (\mu - \gamma\sigma^2))^2}{2\sigma^2}\right]} dW, \\
& - e^{\left[-\frac{\gamma(2\mu - \gamma\sigma^2)}{2}\right]}, \\
& - e^{\left[-\gamma\left(\mu - \frac{\gamma}{2}\sigma^2\right)\right]}.
\end{aligned}$$

The utility function is monotone increasing in  $\mu - (\frac{\gamma}{2})\sigma^2$ , which is convenient because the choice variable of interest for the agent only affects the mean and the variance of the agent's wealth. Maximizing the expected utility is equivalent to maximizing  $\mu - (\frac{\gamma}{2})\sigma^2$ , as in 18.

## References

- ADAM, K., A. MARCET, AND J. P. NICOLINI (2016): “Stock market volatility and learning,” *Journal of Finance*, 71, 33–82.
- BANCA D’ITALIA (2015): “La ricchezza delle famiglie italiane 2014,” Supplementi al bollettino statistico. Indicatori monetari e finanziari No. 69.
- BANEGAS, A., G. MONTES-ROJAS, AND L. SIGA (2016): “Mutual fund flows, monetary policy and financial stability,” Federal Reserve Finance and Economics Discussion Series No. 71.
- BARBERIS, N., R. GREENWOOD, L. JIN, AND A. SHLEIFER (2015): “X-CAPM: An extrapolative Capital Asset Pricing Model,” *Journal of Financial Economics*, 115, 1–24.
- (2016): “Extrapolation and bubbles,” NBER Working Paper No. 21944.
- BEKAERT, G., C. R. HARVEY, AND R. L. LUMSDAINE (2002): “The dynamics of emerging market equity flows,” *Journal of International Money and Finance*, 21, 295–350.
- BEN-REPHAEL, A., S. KANDEL, AND A. WOHL (2012): “Measuring investor sentiment with mutual fund flows,” *Journal of Financial Economics*, 104, 363–382.
- BERK, J. B. AND R. C. GREEN (2002): “Mutual fund flows and performance in rational markets,” NBER Working Paper No. 9275.
- BRANDT, M. W. (1999): “Estimating portfolio and consumption choice: a conditional Euler equations approach,” *Journal of Finance*, 54, 1609–1645.
- BROCK, W. A. AND C. H. HOMMES (1998): “Heterogeneous beliefs and routes to chaos in a simple asset pricing model,” *Journal of Economic Dynamics and Control*, 22, 1235–1274.
- BRONER, F., T. DIDIER, A. ERCE, AND S. L. SCHMUKLER (2013): “Gross capital flows: dynamic and crises,” *Journal of Monetary Economics*, 60, 113–133.
- BRUNO, V. AND H. S. SHIN (2015): “Capital flows and the risk-taking channel of monetary policy,” *Journal of Monetary Economics*, 71, 119–132.
- CALVO, G. A., L. LEIDMAN, AND C. M. REINHART (1993): “Capital inflows and real exchange rate appreciation in Latin America: the role of external factors,” IMF Staff Papers: 108-151.

- (1996): “Capital flows to developing countries in the 1990s: causes and effects,” *Journal of Economic Perspectives*, 10, 123–139.
- CAMPBELL, J. Y. AND L. M. VICEIRA (2002): *Strategic asset allocation: portfolio choice for long-term investors*, Oxford University Press, USA.
- CASHMAN, G. D., D. N. DELI, F. NARDARI, AND S. VILLUPURAM (2012): “Investors do respond to poor mutual fund performance: evidence from inflows and outflows,” *Financial Review*, 47, 719–739.
- CHABOT, B., E. GHYSELS, AND R. JAGANNATHAN (2014): “Momentum trading, return chasing, and predictable crashes,” NBER Working Paper No. 20660.
- CHEN, J., H. HONG, M. HUANG, AND J. D. KUBIK (2004): “Does fund size erode mutual fund performance? The role of liquidity and organization,” *American Economic Review*, 94, 1276–1302.
- CHEVALIER, J. AND G. ELLISON (1997): “Risk taking by mutual funds as a response to incentives,” *Journal of Political Economy*, 105, 1167–1200.
- CHIARELLA, C. AND X. HE (2003): “Heterogeneous beliefs, risk and learning in a simple asset pricing model with a market maker,” *Macroeconomic Dynamics*, 7, 503–536.
- CHIEN, Y. (2014): “The cost of chasing returns,” *Economic Synopses Federal Reserve Bank of St. Louis*.
- COCHRANE, J. H. (2011): “Discount rates,” *Journal of Finance*, 66, 1047–1108.
- (2016): “Macro-Finance,” NBER working paper no. 22485.
- DE VITA, G. AND K. S. KYAW (2008): “Determinants of capital flows to developing countries: a structural VAR analysis,” *Journal of Economic Studies*, 35, 304 – 322.
- DEL GUERCIO, D. AND P. A. TKAC (2002): “The determinants of the flow of funds of managed portfolios: mutual funds vs. pension funds,” *Journal of Financial and Quantitative Analysis*, 37, 523–557.
- (2008): “Star power: the effect of Morningstar ratings on mutual fund flow,” *Journal of Financial and Quantitative Analysis*, 43, 907–936.
- DELONG, B., A. SHLEIFER, L. H. SUMMERS, AND R. J. WALDMANN (1990): “Noise trader risk in financial markets,” *Journal of Political Economy*, 98, 703–738.

- DIETZ, P. O. (1966): "Pension funds: measuring investment performance," *Free Press*.
- EDELEN, R. M. (1999): "Investor flows and the assessed performance of open-end mutual funds," *Journal of Financial Economics*, 53, 439–466.
- EDELEN, R. M. AND J. B. WARNER (2001): "Aggregate price effects of institutional trading: a study of mutual fund flow and market returns," *Journal of Financial Economics*, 59, 195–220.
- EUROPEAN CENTRAL BANK (2016): "Recent developments in capital flows to emerging market economies," ECB Economic Bulletin, Issue 5.
- FAMA, E. AND K. FRENCH (1993): "Common risk factors in the return on bond and stocks," *Journal of Financial Economics*, 33, 3–53.
- FAMA, E. F. (1999): "Efficient markets II," *Journal of Finance*, 46, 1575–1617.
- FANT, L. F. (1999): "Investment behaviour of mutual fund shareholders: The evidence from aggregate fund flows," *Journal of Financial Markets*, 2, 391–402.
- FERNÁNDEZ-ARIAS, E. (1996): "The new wave of private capital inflows: push or pull?" *Journal of Development Economics*, 2, 389–418.
- FERREIRA, M. A., A. KESWANI, A. F. MIGUEL, AND S. B. RAMOS (2012): "The flow-performance relationship around the world," *Journal of Banking & Finance*, 36, 1759–1780.
- FRATZSCHER, M. (2012): "Capital flows, push versus pull factors and the global financial crisis," *Journal of International Economics*, 88, 341–356.
- FRAZZINI, A. AND O. A. LAMONT (2008): "Dumb money: mutual fund flows and the cross-section of stock returns," *Journal of Financial Economics*, 88, 299–322.
- FRIESEN, G. C. AND T. R. SAPP (2007): "Mutual fund flows and investor returns: an empirical examination of fund investor timing ability," *Journal of Banking & Finance*, 31, 2796–2816.
- GALLANT, A. R., L. P. HANSEN, AND G. TAUCHEN (1990): "Using conditional moments of asset payoffs to infer the volatility of intertemporal marginal rates of substitution," *Journal of Econometrics*, 45, 141–179.
- GELOS, G. (2011): "International mutual funds, capital flow volatility, and contagion. A survey," IMF Working Paper, No. 11/92.

- GHOSH, A. R., M. S. QURESHI, J. I. KIM, AND J. ZALDUENDO (2014): “Surges,” *Journal of International Economics*, 92, 266–285.
- GREENWOOD, R. AND A. SHLEIFER (2014): “Expectations of returns and expected returns,” *Review of Financial Studies*, 27, 714–746.
- INTERNATIONAL MONETARY FUND (2016): “Understanding the slowdown in capital flows to emerging markets,” *World Economic Outlook*, April.
- IVKOVIC, Z. AND S. WEISBENNER (2009): “Individual investor mutual fund flows,” *Journal of Financial Economics*, 92, 223–237.
- JEGADEESH, N. AND S. TITMAN (1993): “Returns to buying winners and selling losers: implications for stock market efficiency,” *Journal of Finance*, 48, 65–91.
- KINDLEBERGER, C. P. (1978): *Manias, panics and crashes: A history of financial crises*, New York: Basic Books Inc. Publishers.
- KOEPKE, R. (2015): “What drives capital flows to Emerging Markets? A survey of the empirical literature,” IIF Working Paper, Institute of International Finance.
- KOEPKE, R. AND S. MOHAMMED (2014): “Portfolio flows tracker FAQ,” IIF Research note.
- LOU, D. (2012): “A flow-based explanation for return predictability,” *Review of Financial Studies*, 25, 3457–3489.
- MIAO, Y. AND M. PANT (2012): “Coincident indicators of capital flows,” IMF Working Paper, No. 12/55.
- MILESI-FERRETTI, G.-M. AND C. TILLE (2011): “The great retrenchment: international capital flows during the global financial crisis,” *Economic Policy*, 26, 289–346.
- NELSON, D. B. (1992): “Filtering and forecasting with misspecified ARCH models: getting the right variance with the wrong model,” *Journal of Econometrics*, 51, 61–90.
- POON, S.-H. AND C. W. GRANGER (2003): “Forecasting volatility in financial markets: A review,” *Journal of Economic Literature*, 41, 478–539.
- PUY, D. (2016): “Mutual funds flows and the geography of contagion,” *Journal of International Money and Finance*, 60, 73–93.
- QIU, L. AND I. WELCH (2004): “Investor sentiment measures,” NBER Working Paper No. 10794.

- RADDATZ, C. AND S. SCHMUKLER (2012): “On the international transmission of shocks: micro-evidence from mutual fund portfolios,” *Journal of International Economics*, 88, 357–374.
- REMOLONA, E. M., P. KLEIMAN, AND D. GRUENSTEIN (1997): “Market returns and mutual fund flows,” *Federal Reserve Bank of New York Economic Policy Review*, 3, 33–52.
- SHILLER, R. J. (2005): *Irrational exuberance*, 2nd ed. Princeton University Press, Princeton.
- SIRRI, E. AND P. TUFANO (1998): “Costly search and mutual fund flows,” *Journal of Finance*, 53, 1589–1622.
- VAN ROOIJ, M., A. LUSARDI, AND R. ALESSIE (2011): “Financial literacy and stock market participation,” *Journal of Financial Economics*, 101, 449–472.
- VENANZI, D. (2016): “The performance of the Italian mutual funds: does the metric matter?” *Research in International Business and Finance*, 37, 406–421.
- WARTHER, V. A. (1995): “Aggregate mutual fund flows and security returns,” *Journal of Financial Economics*, 39, 209–235.
- YAGAN, D. (2014): “Riding the bubble? Chasing returns into illiquid assets,” NBER working paper no. 20360.