Aggregate Mutual Fund Flow and Stock Market Return. Evidence from the U.S. Market

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ABSTRACT

This study contributes new empirical evidence on the dynamic relation between mutual fund flow and stock market return using a multivariate GARCH model. Data consists of daily domestic US mutual funds from 1998 to 2012, while the result robustness is tested under alternative GARCH specifications and sub-periods that cover the US financial crisis, bear/bull and cyclical market phases. In the pre-crisis period, the effect of past mutual fund flows on S&P stock returns is negative indicating that higher inflows (outflows) lead to lower (higher) future stock returns. For the post-crisis period, the correlation between lagged fund flows and S&P returns is positive. Interestingly the negative effect from past flows to stock returns is significantly more pronounced in bearish periods compared to bullish ones. Moreover, a positive relationship between mutual fund flows and past stock market returns is reported across all periods and market phases. Finally, the simultaneous relation between returns and fund flows is uniformly positive and significant. However, the dynamic conditional correlations reveal a few concentrated instances of negative simultaneous correlations between flows and returns.

Keywords: mutual fund flows, stock returns, feedback trading, price pressure

JEL classification: G10, G12, G14

1. Introduction

Chalmers et al. (2013) find that mutual fund investors allocate less (more) to equity funds and more (less) to money market funds when economic conditions are subject to an expected decline (improvement). Also, Jank (2012) finds a positive co-movement of flows into equity funds and stock market returns which is largely explained by a common response to macroeconomic news. On the theory front, Vayanos and Wooley (2013) show that institutional fund flows are not only caused by stock market returns but also trigger changes in stock market returns. Two principal hypotheses are used in the literature to explain the impact of mutual fund flows on security returns; the information revelation hypothesis and the price pressure hypothesis[1]. However, the impact of security return on mutual fund flow is largely explained by the feedback-trader hypothesis which addresses the question of whether mutual fund investors move money into a market as a response to recent performance in this market (DeLong et al, 1990). Empirical evidence on the feedback effects between mutual fund flows and stock returns are mixed. For example, Fortune (1998), Mosebach and Najand (1999), and Cha and Kim (2010) find a positive relation between mutual fund flows and returns, while Braverman et al. (2005) observe that this relation is significantly negative.

This study contributes new empirical evidence on the aggregate stock return – mutual fund flow relationship in the U.S. securities market. A multivariate GARCH model is applied which allows for conditional correlations (constant or dynamic), own and cross feedback effects to be estimated between the two variables simultaneously. Results robustness is tested under alternative GARCH specifications and sub-periods that cover the US financial crisis of 2007-

[1] The information revelation hypothesis claims that prices move (at new equilibrium levels) in the same direction with the new information contained in the mutual fund inflows or outflows, thus, creating a positive relation between security return and fund flow (Warther,1995). The price pressure hypothesis states that an increase in mutual funds' inflows results in a higher demand to hold stocks which further increases stock prices. Eventually, security returns exhibit reversals as prices return to fundamental levels after the sentiment or pressure wave has passed (Harris and Gurel,1986; Shleifer,1986).

8, bear/bull and cyclical market phases of the US stock market. Data spans from 1998 to 2012 (3,538 daily observations) and mutual fund flows consist mainly of U.S. domestic mutual funds selected using the Morningstar category classifications.

Key findings are as follows. Across the whole period, the effect of past mutual fund flows on S&P stock returns is negative indicating that higher inflows (outflows) lead to lower (higher) future stock returns and being consistent with the price pressure hypothesis. Similar results are obtained for the pre-crisis period and the bear/bull and cyclical market phases it includes. For the post-crisis period, the correlation between lagged fund flows and S&P returns is positive, demonstrating that higher inflows (outflows) lead to higher (lower) stock market returns in the future. This result is in line with the information revelation hypothesis where prices move at new equilibrium levels and in the same direction with the new information contained in the mutual fund inflows or outflows (Warther,1995). This positive effect from lagged flows to stock returns largely reflects the trading behavior of mutual fund investors during the bull, rather than the bear, market phase. Interestingly, the negative effect from past flows to stock returns is significantly more pronounced in bearish periods compared to the bullish ones, indicating the higher expected return demanded by liquidity providers to hold stocks that they wouldn't otherwise buy, especially in a downward market. Moreover, a positive relationship between mutual fund flows and past stock market returns is also reported across all the periods and market phases considered. Finally, the simultaneous relation between returns and flows are positive and significant, ranging from 0.02 to 0.22, across the pre/post-crisis periods, bear/bull and cyclical market phases. However, the dynamic conditional correlations reveal a few concentrated instances of negative simultaneous correlations between flows and returns. In other words, outflows of funds are associated with increasing stock market returns, while flows into mutual funds can't stop index returns from falling.

This paper is organized as follows. The second section reviews the existing literature and outlines the hypothesis. The third section introduces the data and describes the method of constructing both aggregate mutual fund flow and stock market return. The fourth section displays the econometric approach. Empirical findings are reported and discussed in the fifth section. The sixth section concludes the paper.

2. Empirical evidence and theoretical explanations

The literature on the mutual fund flow and stock market return relationship is extensive and covers both developed and developing market economies. Warther (1995), using monthly data from 1984 to 1992 for stock, bond and money market funds finds a positive relation between flows and subsequent returns but a negative one between returns and subsequent flows. Fortune (1998) provides evidence of a mixed causal relationship between mutual fund flows and market returns. For some mutual funds, flows have an impact on future security returns, while, for others, fund flows only are affected by past stock returns.[2] Remolona et al. (1997) find only a weak effect of past security returns on fund flows with the effect being stronger for the funds with relatively conservative investment objectives (government bond funds, income stock funds) than for those with relatively risky objectives (growth stock funds, high yield bond funds). Edwards and Zhang (1998) find that bond and stock returns significantly affect the magnitude of flows into both bond and stock funds.[3] Similarly, Mosebach and Najand (1999), find that the level of the stock market in the previous month has a significant impact on the net flow of funds invested in the stock market.

[2] Additionally, he has provided –by applying VAR models with seven variables and monthly data for the period January 1984 through December 1996-strong evidence of positive linkage between contemporaneous returns and mutual fund flows.

[3] Also, they provide evidence that flows into bond and stock funds were not affected either bond or stock returns for the period 1971-1981 (when stock returns were considerably depressed by widespread redemptions from equity mutual funds).

Edelen and Warner (2001), using daily data for a sample of 424 U.S. equity funds from 1998 to 1999, report a concurrent flow-return relation and that flows follow returns with one-day lag. The response of fund flows to returns or to the information driving returns indicates that investors require an overnight period to react either to positive feedback trading or new public information releases.[4] Cha and Lee (2001) also show that the performance of the stock market has a direct impact on the equity fund flows.[5] However, investors change their demand for stocks through their attempt to forecast the fundamentals of firms rather than responding to positive feedback trades. Goetzmann and Massa (2003) find strong contemporaneous correlation between inflows and returns, no evidence for positive feedback trading, and evidence that negative market returns may induce subsequent sales. Boyer and Zheng (2004) show that the contemporaneous relation between mutual fund flows and return is significant and positive. Their findings suggested that the mutual fund sector might exert price pressure on the market through its demand for stocks. Braverman et al. (2005) examine the relationship between monthly US aggregate net flows and subsequent returns and find that this link is significantly negative.[6] Cha and Kim (2010) provide empirical evidence of a positive relation between mutual fund flows and one-day lagged returns in the US market, which is consistent with the feedback trader hypothesis. Rakowski and Wang (2009) report a significant negative impact from lagged returns on the current day's flow in the US market[7]. They also provide evidence of a positive interaction between daily returns and lagged flows which indicates either

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[4] In addition, they provide evidence of a significant correlation between concurrent market returns and aggregate mutual fund flow at daily frequency. This concurrent relation indicates that both institutional trading and fund flows affect returns.

[5] Further, they find no evidence, for the price-pressure hypothesis, that equity fund flows have a direct influence on stock market prices.

[6] This negative relationship causes mutual fund investors, as a group, to realize a lower long-term accumulated return than the long-term accumulated return on a "buy and hold" position in these funds.

[7] This implies that less mutual fund investors are following a strategy consistent with momentum behaviour than with short-term contrarian behaviour. The authors also distinguish between contrarian and momentum traders. While contrarian investors act –when flows are preceded by negative returns- as if they are buying funds that have previously suffered a price decline but selling those funds whose prices have increased, momentum traders are those who are chasing hot funds, and –as a result- flows will be positively related to the lagged returns.

a temporary price pressure effect or a permanent information impact. Alexakis et al. (2013), using a hidden cointegration model for Japan, find a bi-directional causal relationship between positive stock returns and fund flows, whereas for negative changes in the two variables, causality runs only from fund flows to stock prices.

In the case of emerging markets, Alexakis et al. (2005) report that inflows and outflows of cash into and out of equity funds seem to cause ascending and descending stock returns in the Greek stock market, respectively. Oh and Parwada (2007) find that net flows display a negative relationship with market returns suggesting negative feedback trading by the Korean mutual fund industry. Standard causality tests suggest that it is predominantly returns that drive flows, while stock sales may contain information about returns.[8] In the case of the Australian market, Watson and Wickramanayake (2012) provide evidence that stock market returns Granger-cause managed fund flows but not the opposite. Also, unexpected fund flows are simultaneously positively related to excess stock returns demonstrating herding behavior in the Australian market. Mishra (2011) finds evidence of unidirectional causality running from the stock market returns to mutual funds investment flow for the India market.

2.1 Theoretical explanations and hypothesis

Warther (1995) utilizes two principal finance theories to explain the relationship amongst mutual fund flows and stock returns. The first one is the information revelation hypothesis. If mutual fund investors possess information, then their trades will be associated with new information and the market will respond to this information revelation. As a result, prices move in the same direction as the fund flow and the returns will be positively correlated with mutual fund flows. In this scenario, the market is responding efficiently to new information rather than

[8] After controlling for declining markets, results suggest that Korean equity fund managers tend to increase stock purchases in times of rising market volatility, possibly disregarding fundamental information, and to sell in times of wide dispersion in investor beliefs.

reacting to fund flow because of price pressure. Jank (2012) finds a positive co-movement of flows into equity funds and stock market returns which is largely explained by a common response to macroeconomic news.[9] The second one, the price-pressure hypothesis, asserts that an increase in mutual funds' inflows results in a higher demand to hold stocks and stimulates the stock prices to go up. If mutual fund flows exert price pressures, then security returns should exhibit reversals as prices should return to fundamental levels after the sentiment or pressure wave has passed.[10] The price pressure effect (downward sloping demand curves) is even more pronounced when investors disagree over the value of the securities (Shleifer, 1986). Ben-Rehael et al (2011) find strong support for the "temporary price pressure hypothesis" regarding mutual fund flows and that, approximately, one-half of the price change is reversed within 10 trading days. An essential factor affecting the mutual fund market is also investor sentiment. If flows into mutual funds is a good measure of this sentiment, then security returns should have a significant and positive correlation with flows into mutual funds[11] (Indro, 2004; Ben-Rephael et al., 2012; Jiang and Yuksel, 2019).

Mutual fund investors may attempt to lock in higher returns in previous months by shifting monies out of domestic equity funds, and to retain exposure to domestic equities following months of lower returns. The impact of security return on mutual fund flow is largely explained by the feedback-trader hypothesis which addresses the question of whether mutual fund

[9] Variables that predict the real economy as well as the equity premium – such as dividend-price ratio, default spread, relative T-Bill rate and consumption-wealth ratio – are related to fund flows and can account for the correlation of flows and market returns. Furthermore, consistent with the information-response hypothesis, mutual fund flows are forward-looking and predict real economic activity.

[10] It appears that an immediate increase in price (price pressure) is necessary to induce passive demanders to offer their shares, while the subsequent decrease allows them to re-establish their position (if desired) at a net profit (Harris and Gurel, 1986; Scholes,1972).

[11] Indro (2004) provide evidence that the behavior of equity fund investors is influenced not only by economic fundamentals, but also by investor sentiment. In particular, the net aggregate equity fund flow in the current week is higher when individual investors have become more bullish in both the previous and current weeks. Ben-Rephael et al (2012) find that aggregate net exchanges between bond and equity funds (proxy for investor sentiment) in the US market are positively contemporaneously correlated with aggregate stock market excess returns. Moreover, 85% (all) of the contemporaneous relation is reversed within four (ten) months, while their findings support the notion of ''noise'' in aggregate market prices induced by investor sentiment.

investors move money into a market as a response to recent performance in this market (DeLong et al, 1990). Fant (1999) provides evidence of feedback from returns to exchanges-out.[12] Clifford et al. (2014), using a data set of over 500 ETFs from 2001 to 2010, show that ETF investors chase returns in the same way as mutual fund investors.

Vayanos and Wooley (2013) also propose a link between institutional fund flows, triggered by changes in manager's efficiency, and stock returns. For instance, investment funds holding assets, which have been hit by negative fundamental news, will realize low returns, triggering outflows by investors who update negatively about the efficiency of the managers running these funds. As a consequence of the outflows, funds sell assets they own, and this further depresses the prices of the assets hit by the original shock[13]. Momentum arises in stock returns if outflows are gradual, and if they trigger a gradual price decline and a drop in expected returns. Reversal arises because outflows push prices below fundamental values, and so expected returns eventually rise. Another key feature of their model is that fund flows not only cause stock returns but are also caused by them. In other words, momentum and reversal arise conditional not only on past returns but also on past cash-flow shocks. For example, a negative cash-flow shock to a stock that the active fund overweighs lowers the active fund's performance relative to the index fund. The investor then infers that the cost has increased, and funds flow out of the active and into the index fund. This lowers the stock's price, amplifying the effect of the original shock. In Dasgupta, Prat, and Verardo (2011) reputation concerns of fund managers give rise to an endogenous tendency to imitate past trades, which impacts the prices of the assets they

[12] His findings indicate that mutual fund investors use exchanges to time the market and/or engage in tactical asset allocation. New sales/redemptions, on the other hand, would appear to reflect long-term, unconditional risk premia. Further, he finds that returns are positively related to concurrent exchanges-in and negatively related to exchanges out. Further, the contrarian relation between aggregate flows and returns exists solely between returns and exchanges-out.

[13] Rational investors absorb the outflows, buying assets whose expected returns have decreased and despite expecting a further price drop in the short run, to hedge against a reduction in the mispricing. Assets that experience a price drop and are expected to continue underperforming in the short run are those held by investment funds expected to experience outflows. The anticipation of outflows causes these assets to be underpriced and to guarantee investors an attractive return over a long horizon.

trade. As a result, institutional herding positively predicts short-term returns (momentum) but negatively predicts long-term returns (reversals) under the additional assumptions that the market makers trading with the managers are either monopolistic or myopic and that institutional traders dominate trading volume.

3. Data

3.1 Mutual fund flows

Mutual fund flows data is obtained from Trim Tabs Investment Research. The dataset primarily consists daily data on total net assets (TNAs), net asset values (NAVs) and flow for 8,135 individual mutual funds. The net flow of each mutual fund is calculated as follows:

$$Flow_t = TNA_t - NAV_t \frac{TNA_{t-1}}{NAV_{t-1}}.$$

The sample consists of all the traded mutual funds within the US stock market and counts 4,829,466 daily mutual funds flow observations. Specifically, the dataset covers U.S. domestic mutual funds for the period spanning from February 3rd 1998 to March 20th 2012 (1,774,367 daily mutual fund observations). In addition, selection criteria are applied depending on Morningstar category classifications (discussed subsequently in detail). The final aggregated sample is observed by obtaining the daily sum of mutual funds flows and the sum of total net assets. This selection process produced a final sample of 3,538 daily observations.[14] Because the number of mutual funds is not constant over time (it varies from 31 to 2533 daily individual mutual funds), the aggregate flow (NFlow) is normalized by dividing the sum of daily mutual funds flow by the sum of daily total net assets (aggregate flow is expressed as a percentage of

[14] To eliminate the possible outliers that could occur as a result of recording errors, a five standard-deviation filter is applied as suggested by Chalmers et al. (2001) to identify a potential error in the total net assets' data series. If the daily change in TNA was more than five standard deviations for each single fund, we hand-checked TNA against alternative sources because a five-standard-deviation change is an extremely rare case.

the aggregate total net assets, see also Figure 3 in the appendix): $Flow_t = \sum_{i=1}^{K} flow_{it}, where\ K = 31, \dots, 2533$

$$NFlow_t = \frac{Flow_t}{TNA_t},$$

3.2 Fund classifications

With regards to the Morningstar Category Classifications (2012), the funds mainly considered are domestically operated such as U.S. stock, sector stock and balanced asset classifications and all other funds that are internationally operated are excluded (funds which invest their money to international stocks). The U.S. stock asset classifications consist of large/mid/small-cap value, large/mid/small-cap blend, large/mid/small-cap growth categories.[15] Meanwhile, the categories of sector stock are communications, equity energy, equity precious metals, financial, global real estate, health, industrials, natural resources, real estate, technology and utilities. The balanced asset classification contains solely aggressive allocation category.[16] Finally, data on S&P 500 stock index is obtained from Thomson Reuters Database (see Figure 1 and 2 in the appendix). Stock market returns are calculated as the natural logarithm of adjacent daily closing prices (P_t) of S&P 500: $Return_t = Ln(P_t) - Ln(P_{t-1})$.

3.3 Sub-samples

The data set examined in this paper covers the period from 3rd February 1998 to 20th March 2012 (3,538 daily observations). Analysis is performed on the whole sample and different

[15] Large/mid/small-cap stocks are defined as the stocks in the top 70%, mid 20% and bottom 10% of the capitalization of the U.S. equity market, respectively. Value is defined based on both slow growth (low growth rates for sales, book value, earnings and cash flow) and low valuations (high dividend yields and low price-earnings ratios). Growth is normally defined based on both high valuations (low dividend yields and high price-earnings ratios) and rapid growth (high growth rates for sales, book value, earnings and cash flow). Blend portfolios are representative of the overall U.S. stock market in growth rates, price and size.

[16] Aggressive-allocation portfolios primarily seek to provide both income and capital appreciation through investing in three principal areas which are cash, stocks and bonds. These portfolios typically have 10% to 30% of assets in cash and fixed income and the remainder is in equities.

subsamples considering major financial events (the dotcom bubble of 2000, the financial crisis of 2007, the European sovereign debt crisis of 2009), bull and bear market phases and cyclical (trough-peak-trough) S&P index behavior. First, the total sample is divided into subsamples A and B. Sample A, covers the pre-crisis period from 3rd February 1998 to 25th July 2007 (2,369 observations) and sample B data spans from 26th July 2007 to 20th March 2012 (1169 observations), the post-crisis one. Second, the total sample is split into five up-and-down (UP, DN) sub-samples based on the bull and bear market phases of the S&P 500 index. Specifically, samples UP1, UP2 and UP3 cover the bullish S&P marker phases while samples DN1 and DN2 cover the bearish ones.[17] Finally, two cyclical (CYs) subsamples are considered, CY1 and CY2, with an aim to unravel the relation between returns and mutual fund flows over adjacent up and down periods.[18] Overall, the sub-samples analysis will shed more light on the uniformity of the fund flow-return relationship across different times and market phases.

3.4 Descriptive statistics

The number of funds used to calculate the aggregate flow ranges from as little as 31 to a maximum of 2533. Interestingly, the growth in the number of mutual funds, investing in domestic equity, is slow and linear until the 2007-8 financial crisis. Specifically, the minimum and maximum number of funds included in the fund flow calculations is 143 and 347, respectively. However, after the financial crisis, the number of funds included in the study increased enormously reaching an average of 2054 towards the last two months of the sample. This also indicates that during and after the US financial crisis, investor demand for equity

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[17] The first bull market phase, sample UP1, extends from 3rd February 1998 to 1st September 2000, while the first bear market, sample DN1, spans from 5th September 2000 to 7th October 2002. The period from 8th October 2002 until 19th July 2007 is characterised by the second bull market, sample UP2, while the period from 20th July 2007 to 9th March 2009 is dominated by the second bear phase of the S&P, sample DN2. Finally, sample UP3 is the last bull phase of the sample and spans from 10th March 2009 until 20th March 2012.

[18] The CY1 and CY2 sub-samples cover the periods from 3rd February 1998 until 7th October 2002 and 8th October 2002 to 9th March 2009, respectively. In other words, sample CY1 includes both sub-samples UP1 and DN1, while sample CY2 comprises of both sub-samples UP2 and DN2.

stocks is largely realised through mutual funds. Most importantly, more than half (about 60%) of the $3.6 trillion in 401(k) assets at year-end 2012 was invested in mutual funds, primarily in stock funds as reported by the Investment Company Institute. In addition, the Trim Tabs asset base used in this study increased from $250 billion to almost a trillion dollars.

Table 1 presents the descriptive statistics for the flow and return data.[19] The average daily flow is negative (outflow) for the whole sample and subsamples A and B. When the sample is split into bull/bear market phases, the average daily flow turns into positive for up-markets 1 and 3 and for down-market 1 (only slightly though possibly due to a few very large inflows). Moreover, the average daily flow is positive for cyclical phase 1 (CY1) and negative for cyclical phase 2 (CY2). Regarding stock market returns, the daily average over the whole sample is 0.01%, while for the pre- and post-crisis periods is 0.018% and -0.007%, respectively. During the up-market phases, the average daily return is positive (0.064, 0.057, 0.096) but it turns to negative (-0.127, -0.203) across the down-market ones. Also, the return standard deviation is considerably higher in bear market times compared to bullish market periods.

Table 1. Descriptive statistics: Mean – Standard deviation

	S&P returns		**Mutual fund flows**	
Samples	**Mean**	**Std. deviation**	**Mean**	**Std. deviation**
Whole Sample	0.010	1.358	-0.005	0.128
Panel A:				
A	0.018	1.128	-0.001	0.116
B	-0.007	1.731	-0.012	0.149
Panel B:				
UP1	0.064	1.265	0.022	0.158
DN1	-0.127	1.466	0.005	0.138
UP2	0.057	0.840	-0.017	0.066
DN2	-0.203	2.283	-0.041	0.196
UP3	0.096	1.332	0.003	0.114
Panel C:				
CY1	0.011	1.246	0.007	0.126
CY2	-0.009	1.366	-0.023	0.115

Notes: This table reports the mean and standard deviation of aggregate mutual fund flows and S&P500 returns across the different samples.

[19] Dollar flow is expressed as a percentage of the previous day's asset base, while returns are the percentage change in the S&P500 index price.

Table 2 shows the time series properties of the fund flows and daily index returns. Fund flows are negatively autocorrelated at lag 1 and positively autocorrelated at lags 2, 3 and 5 when the whole sample is considered. The same autocorrelation pattern is observed across the subsamples examined, although not all autocorrelation lags appear to be uniformly significant. Overall, current flows are positively linked to two, three and five-day old fund flows. The autocorrelations for daily S&P500 index returns are significant and negative for the whole sample and most of the subsamples. For the bull and bear market phases, returns are also negatively serially correlated but not all lags are significant. Sentana and Wadhwani (1992) find evidence, when volatility is low, that stock returns at short horizons exhibit positive serial correlation but when volatility is rather high, returns exhibit negative autocorrelation. As volatility increases, the positive feedback traders have a greater influence on the price (more positive than negative feedback trading), which then manifests itself in greater negative serial correlation in returns.[20] Finally, at very short horizons like daily or weekly, there is evidence of negative autocorrelation (Jegadeesh,1990; Lehmann,1990), but a large literature attributes this to microstructural biases such as non-synchronous trading and the bid-ask bounce (Lo and Mackinlay,1990; Kaul and Nimalendran,1990). Mutual fund flows and S&P returns are both stationary processes (ADF t-statistic is -18.4 and -46.1 for fund flows and returns, respectively).

[20] The authors also find some evidence which suggests that the extent of positive feedback trading is greater following price declines than it is after price rises.

Table 2. Descriptive statistics: Partial autocorrelations

	S&P returns				Mutual fund flows			
Samples	Lag1	Lag2	Lag3	Lag5	Lag1	Lag2	Lag3	Lag5
Whole Sample	-0.077*	-0.057*	0.010	-0.047*	-0.033*	0.031*	0.067*	0.082*
Panel A:								
A	-0.019	-0.032	-0.023	-0.050*	-0.037	-0.001	0.040*	0.108*
B	-0.127*	-0.084*	0.033	-0.046	-0.027	0.069*	0.010*	0.046
Panel B:								
UP1	-0.008	-0.009	-0.071	-0.042	-0.102*	-0.060	-0.030	0.053
DN1	0.025	-0.090*	0.022	-0.049	0.042	-0.034	0.056	0.156*
UP2	-0.087*	0.006	-0.011	-0.048	0.014	0.207*	0.189*	0.099*
DN2	-0.150*	-0.169*	0.010*	-0.006*	-0.015	0.049	0.159*	0.103*
UP3	-0.092*	0.046	-0.085*	-0.069*	-0.048	0.106*	0.002	-0.021
Panel C:								
CY1	0.009	-0.051	-0.025	-0.050	-0.048	-0.045	0.004	0.098*
CY2	-0.132*	-0.117*	0.073*	-0.025	-0.007	0.087*	0.168*	0.103*

Notes: This table reports partial autocorrelations of lag order 1, 2, 3 and 5 for aggregate mutual fund flows and S&P500 returns. * denotes significance at 5% level.

4. Econometric approach

A bivariate GARCH model is used to examine the bi-directional relation between U.S. mutual funds flows and S&P 500 stocks returns.[21] The estimates of the various formulations are obtained by quasi maximum likelihood estimation (QMLE) as implemented by James Davidson (2007) in Time Series Modelling (TSM).[22] To capture the potential interactions between stock return and flow, stock return (y_{1t}) and mutual funds flow (y_{2t}) follow a bivariate VAR model as follows:

$$\boldsymbol{\Phi}(L)\boldsymbol{y_t} = \boldsymbol{\mu} + \boldsymbol{\varepsilon_t}, \qquad 3.1$$

with $\boldsymbol{y_t} = \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix}$, $\boldsymbol{\mu} = \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \end{bmatrix}$, $\boldsymbol{\varepsilon_t} = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$ and $\boldsymbol{\Phi}(L) = \begin{bmatrix} (1-\Phi_{11}(L)) & -\Phi_{12}(L) \\ -\Phi_{21}(L) & (1-\Phi_{22}(L)) \end{bmatrix}$,

[21] Bollerslev et al. (1992) show that the univariate and multivariate GARCH model has been extensively applied in finance problems and reasonably capturing the time variation in the volatility of daily stock market returns.
[22] To check for the robustness of the estimates, a range of starting values is employed to ensure that the estimation procedures converge to a global maximum. Furthermore, the minimum value of the information criteria has been considered when choosing the best fitting specification.

where $\Phi_{ij}(L) = \sum_{l=1}^{l_{ij}} \phi_{ij}^{l} L^{l}$ and (L) denotes the lag operator. The coefficients of the significant own lag effects for stock return and flow are represented by $\Phi_{11}(L)$ and $\Phi_{22}(L)$ respectively, while $\Phi_{12}(L)$ and $\Phi_{21}(L)$ denote the significant lags of the cross effects between the two variables.[23] The bi-directional causality between return and flow is represented by the lag polynomials $\Phi_{12}(L)$ and $\Phi_{21}(L)$.

Regarding the variance equations, the bivariate vector of innovations ε_t is conditionally normal with mean zero and variance-covariance matrix $\mathbf{H_t}$. That is $\varepsilon_t|\Omega_{t-1} \sim N\ (\mathbf{0}, \mathbf{H_t})$:

$$\mathbf{H_t} = \begin{bmatrix} h_{1t} & h_{12,t} \\ h_{21,t} & h_{2t} \end{bmatrix}, \qquad 3.2$$

where $h_{it}, i = 1,2$ denotes the conditional variance of stock return and mutual funds flow respectively and $h_{12,t}$ denotes the conditional covariance of the two variables. Specifically, $\mathbf{H_t}$ follows the bivariate constant conditional correlation (CCC) GARCH (1,1) model of Bollerslev et al. (1992). That is, h_{it} is given by equation (3.4) and $h_{12,t}$ is given by

$$h_{12,t} = \rho\sqrt{h_{1t}}\sqrt{h_{2t}}, \qquad 3.3$$

where ρ denotes the constant conditional correlation. In matrix form, the variance-covariance matrix $\mathbf{H_t}$ can be written as $\mathbf{H_t} = \boldsymbol{D_t R D_t}$, where $D_t = diag\{\sqrt{h_{i,t}}\}$ and $\boldsymbol{R}$ is the correlation matrix containing the conditional correlations[24]. Further, the dynamic conditional correlation model (DCC) is applied which differs only in allowing $\boldsymbol{R}$ to be time varying $\mathbf{H_t} = \boldsymbol{D_t R_t D_t}$ (see also Engle, 2002; Engle and Sheppard, 2001). Moreover, two alternative conditional variance models for h are examined. First, the study assume that h_{it} follows a GARCH (1,1) processes:

[23] The polynomial $\Phi_{12}(L)$ in equation (3.1) represents the effect of flow on return, while the polynomial $\Phi_{21}(L)$ captures the impact of return on flow in the mean equation.
[24] We can rewrite R as $E_{t-1}(\varepsilon_t \varepsilon_t') = D_t^{-1} H_t D_t^{-1} = R$, since $\varepsilon_t = D_t^{-1} r_t$. A simple estimate of R is also the unconditional correlation matrix of the standardized residuals.

$$h_{it} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}, i = 1,2, \qquad 3.4$$

where $\omega_i > 0$, $\alpha_i > 0$, and $\beta_i \geq 0$ such that $h_{it} > 0$ for all t and $\alpha_i + \beta_i < 1$ for the unconditional variance to exist. Bollerslev's (1986) GARCH model allows the conditional variance to depend on the past conditional variances and past squared residuals.[25] Secondly, it is assumed that h_{it} follows a FIGARCH (1,d,1) processes:

$$(1 - \beta_i L) h_{it} = \omega_i + [(1 - \beta_i L) - (1 - c_i L)(1 - L)^{d_i}] \varepsilon_{i,t-1}^2, i = 1,2, \quad 3.5$$

where $c_i = \alpha_i + \beta_i$ and d_i is the long memory parameter. Note that if $d_i = 0$, then the above FIGARCH (1,d,1) model reduces to the GARCH (1,1) model in equation (3.7). [26] The presence of long-memory in the autocorrelations of absolute returns of many financial asset prices is widely reported (Dacorogna et al., 1993; Ding et al.,1993; Breidt et al., 1998).[27] Brunetti and Gilbert (2000) extend the multivariate GARCH (1,1) model to the multivariate FIGARCH (1,d,1) model by using the constant correlation parameterization.[28]

5. Empirical Results

5.1 The stock return – mutual fund flow relation

This section presents the empirical findings of the return-flow relationship examined from utilizing the bivariate VAR-CCC GARCH model. Specifically, we examine the feedback (own and cross) effects in the mean equations and the persistence (or GARCH) coefficients in the

[25] The autoregressive components capture the persistence in the conditional variance of flow and return, while the past squared residual components capture the information shocks to flow and return (see also Engle,1982; Bollerslev,1986; Bollerslev et al.,1992; Bollerslev et al.,1994).

[26] The sufficient conditions of Bollerslev and Mikkelsen (1996) for the positivity of the conditional variance of a FIGARCH (1,d,1) model: $\omega_i > 0$, $\beta_i - d_i \leq c_i \leq \frac{2 - d_i}{3}$, and $d_i \left(c_i - \frac{1 - d_i}{2} \right) \leq \beta_i (c_i - \beta_i + d_i)$ should be satisfied for both i (see also Conrad and Haag, 2006, Conrad, 2010, and Karanasos et al. 2016,).

[27] The FIGARCH model was introduced by Baillie et al. (1996) as a flexible class of processes for the conditional variance that are more capable of representing and explaining the observed dynamic dependencies in the financial market's volatility.

[28] Their choice has fundamentally been motivated by three principal considerations which are: it is considered as the most parsimonious of the available specifications, stationarity is being ensured by restrictions on the diagonal elements of the variance-covariance parameters matrices only and the variance-covariance matrices are positive definite under weak conditions.

variance equations. Table 3 reports the chosen lags for the own (Φ_{11}, Φ_{22}) and cross (Φ_{12}, Φ_{21}) effects accordingly. For the whole sample, the first lag of stock market returns adequately captures the autocorrelation of the series, while for some of the subsamples the lag order is extended up to six. Regarding the mutual fund flows, the first, second and third lags seem to capture the fund flow dynamic dependence in most of the cases with higher order lags (up to 8) used only in a few periods. In other words, there is information in past flow that is relevant for future flow. Specifically, there is statistically significant negative autocorrelation at lag 1 and positive autocorrelation at higher lags. In table 3, the lag order with the highest significance is also reported for the cross-feedback effect of flows on returns (Φ_{12}) and returns on flows (Φ_{21}). Three and four-day old fund flows predict current stock market returns, while occasionally fund flows up to two weeks old can be affecting current S&P500 index returns. For the effect of past return on fund flows, results show that five (three) day lagged returns predict current mutual fund flows when the whole and pre-(post) crisis periods are considered. Interestingly, for the bear/bull and cyclical market phases, mutual fund flows are only affected by one day lagged returns.

Table 3. Mean Equations: Own and cross lag orders

	S&P returns		**Mutual fund flows**	
Sample	$\Phi_{11}(L)$	$\Phi_{12}(L)$	$\Phi_{22}(L)$	$\Phi_{21}(L)$
Whole	1	4	2,3	5
Panel A:				
A	5	10	1,3,4,5,6,7,8	5
B	1	3	2,3	3
Panel B:				
UP1	3,6	4	1,2	1
DN1	2	3	3,4,5	1
UP2	1,5	4	2,3,4,5	1
DN2	1	7	3	1
UP3	1	3	2,3	1
Panel C:				
CY1	5	6	1,2	1
CY2	1,2	2	1,2,3	1

Notes: This table reports significant own and cross lag orders as represented by $\Phi_{ii}(L)$ and $\Phi_{ij}(L)$ in equations (3.1) respectively.

Table 4 reports a bidirectional feedback relationship between aggregate mutual fund flow and stock market returns. For the whole sample, the effect of past mutual fund flows on stock returns is negative implying that higher inflows (outflows) lead to lower (higher) future stock returns. This is consistent with the price pressure hypothesis where temporary price changes are necessary to compensate investors who accommodate changes in demand (Harris and Gurel,1986)[29]. Similar results are obtained for the pre-crisis period (sample A) as well as for the bear/bull (UP1, DN1, UP2) and cyclical (CY1) market phases it includes. However, when the post-crisis period is considered, the correlation between lagged fund flows and S&P returns is positive, which implies that higher inflows (outflows) lead to higher (lower) stock market returns in the future. This result agrees with the information revelation hypothesis where prices move at new equilibrium levels and in the same direction with the new information contained in the mutual fund inflows or outflows (Warther,1995). The positive effect from lagged flows to stock returns, in the after-crisis period, appears to reflect the trading behavior of mutual fund investors during the bull (UP3), rather than the bear (DN2), market phase. The second downward phase (DN2) is characterized by the onset of the financial crisis and the increased uncertainty over the scale of investment bank losses during the credit crunch period. The negative correlation between lagged flows and returns confirms the increasing pressure for prices to drop following mutual fund outflows. Most importantly, the negative effect from past flows to stock returns is significantly more pronounced in bearish periods compared to the bullish ones, indicating the higher expected return demanded by liquidity providers to hold stocks that they wouldn't otherwise buy, especially in a downward market. This is also consistent with Vayanos and Wooley (2013) who show that rational investors absorb the outflows, buying assets whose expected returns have decreased and despite expecting a further

[29] It seems that an immediate increase in price (price pressure) is necessary to induce passive demanders to offer their shares, while the subsequent decrease allows them to reestablish their position (if desired) at a net profit.

price drop in the short run, to hedge against a reduction in the mispricing. The positive autocorrelation in mutual fund flows together with their negative impact on stock index returns further supports the momentum and reversal patterns predicted by Vayanos and Wooley (2013), when institutional flows are gradual.

A related issue here is also how much investors' inflows or outflows are affected by past S&P index price changes. Column 2 of Table 4 reports a positive relationship between mutual fund flows and past stock market returns for the whole sample. The correlation is also positive across the pre/post-crisis periods, bull/bear and cyclical market phases examined. This result is consistent with the feedback trader hypothesis where mutual fund investors move money into a fund in response to recent performance in the market (Delong et. al, 1990). However, this does not preclude Brenan and Cao's (1996) explanation that it can be rational for uninformed investors to chase returns if these returns are a sufficient statistic for public information releases. Finally, in line with the one day lagged effect of returns to fund flows, trading in the direction of fund returns would allow fund investors a profit opportunity if there is one-day positive autocorrelation in S&P returns (Edelen and Warner, 2001). Empirical evidence shows that there is no positive autocorrelation in stock index returns across the bear/bull and cyclical market periods.

Table 4. The Return-Flow Link (VAR-CCC-GARCH)

Samples	Flows on Returns	Returns on Flows
Whole Sample	**-0.49 (0.21)****	**0.01 (0.00)***
Panel A:		
A	**-0.65 (0.26)****	**0.01 (0.00)*****
B	**0.10 (0.04)****	**0.04 (0.02)*****
Panel B:		
UP1	**-0.59 (0.35)*****	**0.08 (0.00)***
DN1	**-0.84 (0.56)****	**0.04 (0.00)***
UP2	**-0.60 (0.32)*****	**0.01 (0.00)***
DN2	**-1.26 (0.56)****	**0.01 (0.00)*****
UP3	**1.24 (0.47)****	**0.02 (0.00)***
Panel C:		
CY1	**-0.13 (0.28)*****	**0.06 (0.00)***
CY2	**-0.12 (0.31)***	**0.01 (0.00)***

Notes: This table reports parameters' estimates for the Φ_{12} and Φ_{21} respectively. ***, **, and * stand for significance at the 1%, 5% and 10% significant levels respectively. The numbers in parentheses are standard errors.

5.2 Volatility persistence and correlation coefficients

Table 5 reports estimates of ARCH, GARCH and CCC parameters. Following equation (4), the sum of the coefficients of the ARCH parameter (α) and the GARCH parameter (β) for the total sample and all the other sub-samples respectively is less than one. Additionally, the persistence coefficients are positive and significant in all cases. With regards to equation (3), the conditional correlations between returns and flows, in the whole sample and the sub-samples considered, are positive and significant. In the pre/post-crisis period, bear/bull and cyclical market phases the return-flow conditional correlation estimates range from 0.02 to 0.22. The highest concurrent return-flow correlation is evident during the second bearish market (onset of the financial crisis period) while the lowest one is observed in the upward phase that followed the end of the financial crisis period. The simultaneous relation between flows and returns is likely to reflect the causal relation from flows to returns. For example, under a temporary price pressure hypothesis, high unexpected mutual fund inflows are associated with increased current stock returns and lower future ones when the price pressure disappears. Results on the effect of past flows on returns provide support for the price pressure hypothesis. However, explanations such as extremely rapid feedback trading by fund investors (returns causing flows), or a joint same-day reaction of both returns and flows to economic news can't be precluded. The mild dependence of daily flow on one day lagged returns in Table 4 makes intraday feedback trading explanations not too plausible, though. Moreover, stock returns are expected to react instantly to economic news, whereas an overnight delay (at the least) seems more reasonable for mutual fund flows. Finally, looking at the dynamic conditional correlations of Figure 4, a few concentrated instances of negative simultaneous correlations between flows and returns are demonstrated. For example, towards the end of the second bull market phase, outflows of funds are associated with increasing stock market returns, while, at the outcry of the financial crisis, flows into mutual funds can't stop index returns from falling.

Table 5. Variance Equations: GARCH and Correlation Coefficients

Samples	**Return -** h_{1t}	**Flows -** h_{2t}
Whole Sample		
$\boldsymbol{\alpha_i}$	**0.08 (0.01)***	**0.08 (0.03)***
$\boldsymbol{\beta_i}$	**0.91 (0.01)***	**0.91 (0.03)***
$\boldsymbol{\rho}$	**0.01 (0.01)***	-
<u>Panel A:</u>		
Sub-Sample A		
$\boldsymbol{\alpha_i}$	**0.06 (0.01)***	**0.12 (0.04)***
$\boldsymbol{\beta_i}$	**0.93 (0.01)***	**0.87 (0.03)***
$\boldsymbol{\rho}$	**0.02 (0.02)**	-
Sub-Sample B		
$\boldsymbol{\alpha_i}$	**0.11 (0.02)***	**0.10 (0.05)**
$\boldsymbol{\beta_i}$	**0.88 (0.01)***	**0.89 (0.05)***
$\boldsymbol{\rho}$	**0.07 (0.04)***	-

Panel B:		
Sub-Sample UP1		
α_i	**0.06 (0.03)****	**0.12 (0.04)*****
β_i	**0.92 (0.03)*****	**0.69 (0.11)*****
ρ	**0.11 (0.05)****	**-**
Sub-Sample DN1		
α_i	**0.10 (0.03)*****	**0.08 (0.02)*****
β_i	**0.86 (0.04)*****	**0.90 (0.02)*****
ρ	**0.08 (0.05)***	**-**
Sub-Sample UP2		
α_i	**0.04 (0.01)*****	**0.11 (0.40)****
β_i	**0.94 (0.01)*****	**0.73 (0.54)****
ρ	**0.05 (0.03)****	**-**
Sub-Sample DN2		
α_i	**0.09 (0.02)*****	**0.12 (0.04)*****
β_i	**0.90 (0.02)*****	**0.87 (0.04)*****
ρ	**0.22 (0.08)*****	**-**
Sub-Sample UP3		
α_i	**0.11 (0.02)*****	**0.04 (0.02)***
β_i	**0.87 (0.02)*****	**0.95 (0.03)*****
ρ	**0.01 (0.03)***	**-**
Panel C:		
Sub-Sample CY1		
α_i	**0.08 (0.02)*****	**0.13 (0.03)*****
β_i	**0.89 (0.03)*****	**0.84 (0.04)*****
ρ	**0.12 (0.04)***	**-**
Sub-Sample CY2		
α_i	**0.06 (0.01)*****	**0.14 (0.05)*****
β_i	**0.93 (0.01)*****	**0.84 (0.05)*****
ρ	**0.09 (0.03)***	**-**

Notes: This table reports parameters' estimates for the ARCH ($\boldsymbol{\alpha_i}$), GARCH ($\boldsymbol{\beta_i}$) and ccc ($\boldsymbol{\rho}$) coefficients. ***, ** and * stand for significance at the 1%, 5% and 10% significant levels respectively. The numbers in parentheses are standard errors.

5.3 Alternative GARCH specification

Results in the previous section show that the conditional volatility of mutual fund flows and stock market returns is highly persistent. Now, empirical evidence is provided for the return-flow relationship by using a bivariate-ccc-FIGARCH model which better captures the persistence or long memory in volatility[30]. In Table 6, the first (and fifth lags) of stock market returns sufficiently capture the autocorrelation of the series in most of the cases. Further, lags 1 up to 5 describe the fund flow dynamic dependence across the samples investigated. For example, there is statistically significant positive autocorrelation at lags 3 and beyond. The lag order with the highest significance for the cross-feedback effects (Φ_{12}, Φ_{21}) is also reported in Table 6. Similar to the results in Table 2, three and four-day old fund flows predict current stock market returns, while only one day lagged returns affect current fund flows across the different periods. Specifically, when the pre- and post-crisis periods are examined, feedback effects are observed from fund flows (returns) to returns (fund flows) of lag orders as high as 10 (5) and 9 (3), respectively.

Table 6. Mean Equations: Own and cross lag order

	S&P returns		**Mutual fund flows**	
Sample	$\Phi_{11}(L)$	$\Phi_{12}(L)$	$\Phi_{22}(L)$	$\Phi_{21}(L)$
Whole	1,5	4	2,3,4,5	1
Panel A:				
A	5	10	1,3,4,5,6,7,8	5
B	1	9	2,3,4,5	3
Panel B:				
UP1	3,7	4	1,2,7	1
DN1	2	3	3,4,5	1
UP2	1	4	2,3,4	1
DN2	1	7	3	1
UP3	3	3	2,3	1
Panel C:				
CY1	5	6	1,2	1
CY2	1,2	2	1,2,3	1

Notes: This table reports significant own and cross lag orders as represented by $\Phi_{ii}(L)$ and $\Phi_{ij}(L)$ in equations (3.1) respectively.

Following the results presented in Table 7, there is bidirectional feedback between aggregate mutual fund flows and stock market returns like the bivariate-ccc-GARCH model above. In particular, past flows affect returns negatively whereas past returns impact mutual

[30] Moreover, having the correct description of the conditional variance is important for valid hypothesis testing about the mean and substantially more efficient estimates of the conditional mean (Hamilton, 2008).

fund flows in a positive way. In the former case, an inflow of funds would lead to lower stock market returns in the future, a result consistent with the pressure price hypothesis (Harris and Gurel,1986, Shleifer, 1986). In the latter case, an increase in stock market returns today leads to higher fund inflows tomorrow which agrees with mutual fund investors rationally (irrationally) chasing returns depicting new public information (positive feedback trades of informed investors). Moreover, a positive correlation between past flow and return is only realized during the post-crisis upward market phase. This result is consistent with the information revelation hypothesis where prices move to new equilibrium levels and in the same direction with the new information contained in the mutual fund inflows or outflows (Warther,1995). This result is in line with the finding reported by Cha and Kim (2010).

Overall, comparing the results of the bivariate-ccc-FIGARCH model with those of the bivariate-ccc-GARCH one, it is evidenced that the return-flow feedback relationships are very similar in terms of significance and signs. In most of the cases, past flows affect stock returns negatively while lagged returns have a positive impact on mutual fund flows. Furthermore, the positive effect from past fund flows to returns turns into negative in the post-crisis period for the FIGARCH model (lag order also changes from 3 to 9). However, when the bull and bear market times are considered individually, during the post crisis period, the feedback relationship between stock returns and flows remains nearly the same regardless of the conditional variance specification. Finally, the positive effect from one day lagged returns to flows remains weakly significant for the bull/bear market phases across the whole sample. Yet, in the pre- and post-crisis periods three and five-day old returns have a (significant) positive effect on fund flows respectively.

Table 7. The Return-Flow Link (VAR-CCC-FIGARCH)

Samples	Flows on Returns	Returns on Flows
Whole Sample	**-0.44 (0.22)****	**0.02 (0.00)***
Panel A:		
A	**-0.65 (0.27)****	**0.01 (0.00)*****
B	**-0.09 (0.05)****	**0.04 (0.02)*****
Panel B:		
UP1	**-0.56 (0.32)*****	**0.08 (0.00)***
DN1	**-0.87 (0.57)****	**0.04 (0.00)***
UP2	**-0.66 (0.34)*****	**0.01 (0.00)***
DN2	**-0.79 (0.54)****	**0.02 (0.00)***
UP3	**1.44 (0.60)****	**0.02 (0.00)***
Panel C:		
CY1	**-0.04 (0.29)*****	**0.06 (0.00)***
CY2	**-0.14 (0.29)****	**0.02 (0.00)***

Notes: This table reports parameters' estimates for the Φ_{12} and Φ_{21} respectively. ***, **, and * stand for significance at the 1%, 5% and 10% significant levels respectively. The numbers in parentheses are standard errors.

Estimates of the ARCH and the GARCH parameters of the FIGARCH conditional volatility model for S&P returns and mutual fund flows are reported next (Table 8). Results show that the sum of the ARCH (α) and GARCH (β) coefficients for the total sample and the sub-samples examined is less than one. Additionally, they are positive and significant in all cases. In other words, the GARCH coefficients satisfy the sufficient and necessary conditions for the non-negativity of the conditional variances (see, for instance, Conrad and Haag, 2006,). Moreover, Table 9 reports estimates of the long memory parameter d_i $(i = 1,2)$ which governs the long-run dynamics of the conditional heteroscedasticity. Results show that the long memory parameters for S&P returns range from 0.11 to 0.40, while for mutual fund flows they range from 0.13 to 0.43, across the different samples. In other words, the conditional variances of the two variables are characterized by stationary long memory GARCH behavior.

Table 8. Variance Equations: FIGARCH Coefficients

Samples	h_{1t} **(Return)**	h_{2t} **(Flow)**
Whole Sample		
$\boldsymbol{\alpha_i}$	**0.29 (0.35)****	**0.02 (0.01)***
$\boldsymbol{\beta_i}$	**0.70 (0.35)****	**0.79 (0.01)*****
Panel A:		
Sub-Sample A		
$\boldsymbol{\alpha_i}$	**0.05 (0.01)*****	**0.12 (0.24)***
$\boldsymbol{\beta_i}$	**0.94 (0.07)*****	**0.87 (0.23)*****
Sub-Sample B		
$\boldsymbol{\alpha_i}$	**0.36 (0.06)*****	**0.02 (0.01)****
$\boldsymbol{\beta_i}$	**0.63 (0.06)*****	**0.97 (0.01)*****
Panel B:		
Sub-Sample UP1		
$\boldsymbol{\alpha_i}$	**0.23 (0.08)*****	**0.14 (0.09)*****
$\boldsymbol{\beta_i}$	**0.31 (0.14)****	**0.68 (0.10)*****
Sub-Sample DN1		
$\boldsymbol{\alpha_i}$	**0.24 (0.19)*****	**0.13 (0.04)*****
$\boldsymbol{\beta_i}$	**0.73 (0.17)*****	**0.85 (0.04)*****
Sub-Sample UP2		
$\boldsymbol{\alpha_i}$	**0.26 (0.08)*****	**0.18 (0.14)***
$\boldsymbol{\beta_i}$	**0.55 (0.12)*****	**0.32 (0.25)***
Sub-Sample DN2		
$\boldsymbol{\alpha_i}$	**0.27 (0.05)*****	**0.06 (0.03)****
$\boldsymbol{\beta_i}$	**0.70 (0.05)*****	**0.93 (0.02)*****
Sub-Sample UP3		
$\boldsymbol{\alpha_i}$	**0.08 (0.02)*****	**0.28 (0.26)*****
$\boldsymbol{\beta_i}$	**0.90 (0.02)*****	**0.56 (0.09)*****
Panel C:		
Sub-Sample CY1		
$\boldsymbol{\alpha_i}$	**0.07 (0.03)*****	**0.05 (0.04)****
$\boldsymbol{\beta_i}$	**0.68 (0.33)****	**0.71 (0.17)*****
Sub-Sample CY2		
$\boldsymbol{\alpha_i}$	**0.16 (0.04)*****	**0.10 (0.11)***
$\boldsymbol{\beta_i}$	**0.83 (0.04)*****	**0.78 (0.10)*****

Notes: This table reports parameters' estimates for the ARCH ($\boldsymbol{\alpha_i}$) and GARCH ($\boldsymbol{\beta_i}$) coefficients. ***, ** and * stand for significance at the 1%, 5% and 10% significant levels respectively. The numbers in parentheses are standard errors.

The conditional correlations between returns and flows across the different samples are positive and significant. In the pre/post-crisis period, bear/bull and cyclical market phases the return-flow conditional correlation estimates range from 0.05 to 0.30. The highest simultaneous return-flow correlation happens during the whole pre-crisis period, while the lowest one is realized in the upward phase that preceded the start of the financial crisis period. The simultaneous relation between flows and returns potentially reflects the causal relation from flows to returns. Recall here that under a temporary price pressure hypothesis, high unexpected mutual fund inflows are associated with increased current stock returns and lower future ones when the price pressure disappears. Results on the effect of past flow on return provide support for the price pressure hypothesis (see also Table 7). Alike the main results, the weak dependence of daily flow on one day lagged returns constitutes the intraday feedback trading explanation not too plausible[31]. Overall, the correlation coefficients of the bivariate CCC FIGARCH model are comparable to the bivariate GARCH ones and even more significant in the pre- and post-crisis periods alone[32].

[31] The simultaneous return-flow relationship can also be explained by a joint same-day reaction of both returns and flows to economic news. Though, stock returns react instantly to economic news, but an overnight delay (at the least) seems more sensible for mutual fund flows.

[32] The FIGARCH model better captures long run changes in the conditional variance and interferes considerably less with the short-run dynamics of the series.

Table 9. Variance Equation: FIGARCH Persistence and Correlation Parameters

Samples	Returns	Flows
Whole Sample		
d_i	**0.31 (0.07)*** **	**0.39 (0.05)** **
$\boldsymbol{\rho}$	**0.21 (0.02)*** **	-
Panel A:		
Sub-Sample A		
d_i	**0.22 (0.02)** **	**0.36 (0.03)** **
$\boldsymbol{\rho}$	**0.30 (0.02)*** **	-
Sub-Sample B		
d_i	**0.39 (0.06)*** **	**0.22 (0.08)*** **
$\boldsymbol{\rho}$	**0.25 (0.04)*** **	-
Panel B:		
Sub-Sample UP1		
d_i	**0.28 (0.07)*** **	**0.19 (0.08)*** **
$\boldsymbol{\rho}$	**0.12 (0.05)** **	-
Sub-Sample DN1		
d_i	**0.37 (0.02)** **	**0.17 (0.06)*** **
$\boldsymbol{\rho}$	**0.08 (0.05)** **	-
Sub-Sample UP2		
d_i	**0.11 (0.08)*** **	**0.13 (0.02)** **
$\boldsymbol{\rho}$	**0.05 (0.03)** **	-
Sub-Sample DN2		
d_i	**0.40 (0.05)*** **	**0.31 (0.09)*** **
$\boldsymbol{\rho}$	**0.16 (0.06)** **	-
Sub-Sample UP3		
d_i	**0.34 (0.04)** **	**0.32 (0.02)** **
$\boldsymbol{\rho}$	**0.11 (0.04)*** **	-
Panel C:		
Sub-Sample CY1		
d_i	**0.30 (0.07)*** **	**0.41 (0.04)** **
$\boldsymbol{\rho}$	**0.21 (0.04)* **	-
Sub-Sample CY2		
d_i	**0.22 (0.04)** **	**0.35 (0.03)** **
$\boldsymbol{\rho}$	**0.08 (0.03)* **	-

Notes: This table reports parameters' estimates for the long-memory (d_i), $i = 1,2$ and ccc ($\boldsymbol{\rho}$) coefficients. ***, ** and * stand for significance at the 1%, 5% and 10% significant levels respectively. The numbers in parentheses are standard errors.

6. Conclusion

This study investigates the dynamic interactions between S&P500 index returns and aggregate (domestic) mutual fund flows. The variables under consideration are inextricably linked and several key behavioural features arise across the different (bivariate) models and samples considered. The predictions of the information revelation hypothesis and the price pressures hypothesis, about the impact of mutual fund flows on stock returns, are thoroughly examined (Warther,1995; Harris and Gurel,1986; Scholes,1972). Further, the feedback-trader hypothesis is investigated by looking at how mutual fund flows are affected by lagged index returns (DeLong et al,1990). A bivariate GARCH model is applied with different specifications on the conditional variance equation, conditional correlation (constant, dynamic) and over a long span of daily data from 1998 to 2012.

Results show that a bidirectional feedback relationship between S&P500 stock returns and aggregate mutual fund flows exists over the long period of fifteen years examined. For the whole sample, the effect of past mutual fund flows on S&P stock returns is negative which indicates that higher inflows (outflows) lead to lower (higher) future stock returns. This is consistent with the price pressure hypothesis where temporary price changes are necessary to compensate investors who accommodate changes in demand (Harris and Gurel,1986)[33]. Similar results are obtained for the pre-crisis period (sample A) and the bear/bull (UP1, DN1, UP2) and cyclical (CY1) market phases it incorporates. Moreover, when the post-crisis period is considered, the correlation between lagged fund flows and S&P returns is positive, which implies that higher inflows (outflows) lead to higher (lower) stock market returns in the future. This result is in line with the information revelation hypothesis where prices move at new

[33] It seems that an immediate increase in price (price pressure) is necessary to induce passive demanders to offer their shares, while the subsequent decrease allows them to reestablish their position (if desired) at a net profit.

equilibrium levels and in the same direction with the new information contained in the mutual fund inflows or outflows (Warther,1995). Nevertheless, the positive effect from lagged flows to stock returns, in the after-crisis period, appears to reflect the trading behavior of mutual fund investors during the bull (UP3), rather than the bear (DN2), market phase. Interestingly, it is noticed that the negative effect from past flows to stock returns is significantly more pronounced in bearish periods compared to the bullish ones indicating the higher expected return demanded by liquidity providers to hold stocks that they wouldn't otherwise buy especially in a downward market[34]. The positive autocorrelation in mutual fund flows together with their negative impact stock index returns further supports the momentum and reversal patterns predicted by Vayanos and Wooley (2013) when institutional flows are gradual. A positive relationship between mutual fund flows and past stock market returns is also reported across the pre/post-crisis periods, bull/bear and cyclical market phases considered. This result is consistent with the feedback trader hypothesis where mutual fund investors move money into a fund in response to recent performance in the market (Delong et. al, 1990).

Finally, the simultaneous relation between returns and flows is positive and significant ranging from 0.02 to 0.22 across the pre/post-crisis periods, bear/bull and cyclical market phases examined.[35] However, the dynamic conditional correlations reveal a few concentrated instances of negative simultaneous correlations between flows and returns. For example, towards the end of the second bull market phase, outflows of funds are associated with increasing stock market returns, while, at the outcry of the financial crisis, flows into mutual funds can't stop index returns from falling. Overall, most of the bidirectional (own and cross

[34] This is also consistent with Vayanos and Wooley (2013) who show that rational investors absorb the outflows, buying assets whose expected returns have decreased and despite expecting a further price drop in the short run, to hedge against a reduction in the mispricing.

[35] The simultaneous relation between flows and returns is likely to reflect the causal relation from flows to returns. Under the temporary price pressure hypothesis, high unexpected mutual fund inflows are associated with increased current stock returns and lower future ones when the price pressure disappears.

lag) effects are found to be quite robust to the dynamics of the different GARCH models employed in this study.

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8. Appendix

A. Trim Tabs Data Collection

The collection procedures of Trim Tabs' data could be summarized as follows: mutual fund investors send orders for redemption or purchase to the transfer agent or the fund customer service centre daily. At the time, when a fund receives an order from an investor, then the order –by law- must be executed at the next calculated net asset value (NAV). The day's net asset value is considered as the day's closing prices of securities held by the previous trading day's fund and shares outstanding. Afterwards, net asset value is reported to both the transfer agent and the National Association of Security Dealers before 5:30 P.M. EST. The transfer agent promptly processes all orders overnight after the net asset value has been calculated and employs this net asset value at the process of computing the change in the fund's receivables, payables, cash and shares outstanding. Consequently, the transfer agent reports back these varied numbers to fund managers to be entered into the fund's balance sheet on the subsequent morning. Furthermore, each morning, Trim Tabs receives funds' data of the previous day's net asset values and total net assets (see Edelen and Warner, 2001; Cao et al., 2008).

B. Figures

Figure 1. S&P500 Index Price

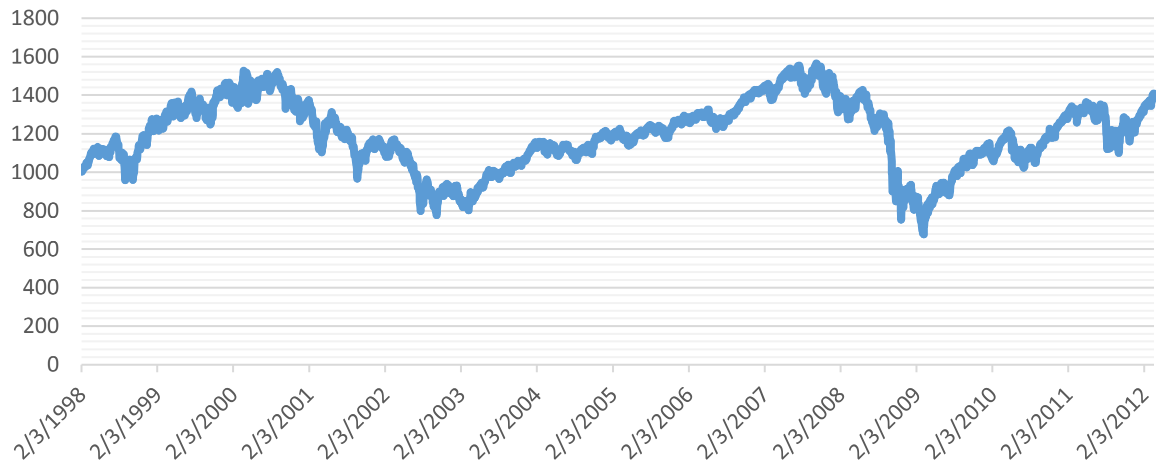
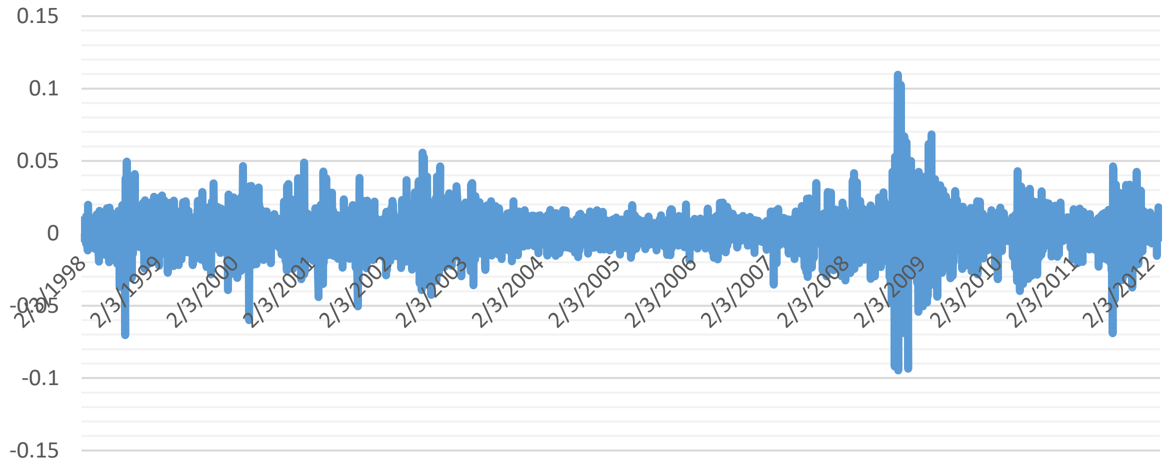


Figure 2. S&P500 Index Returns



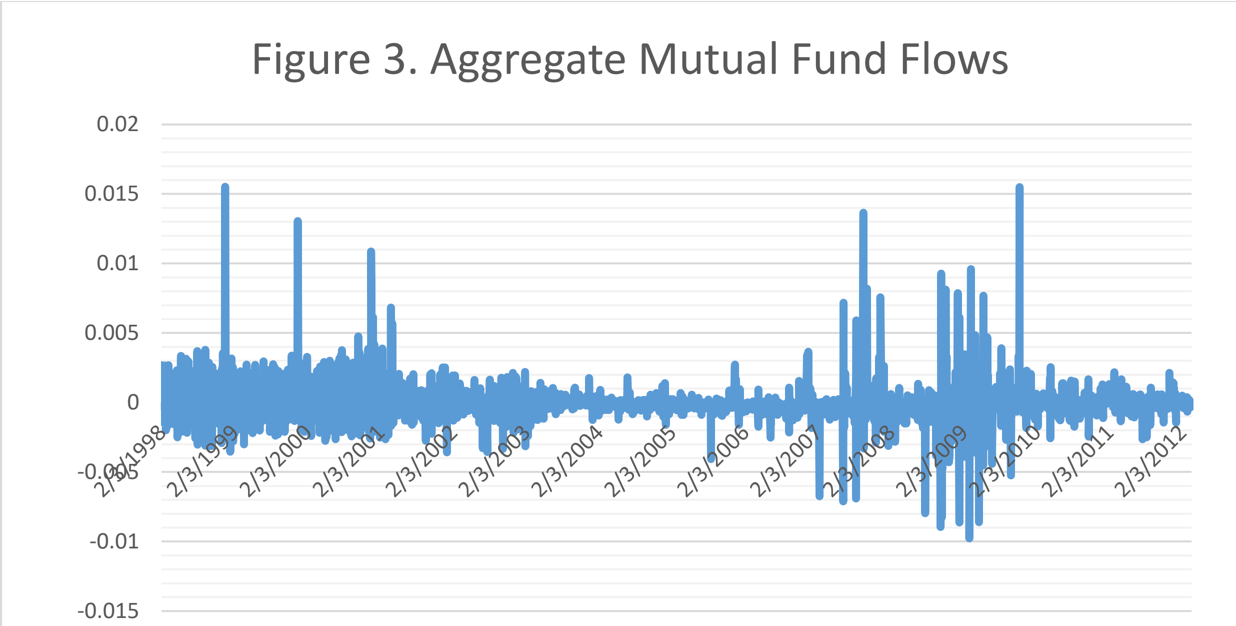


Figure 3. Aggregate Mutual Fund Flows
0.02
0.015
0.01
0.005
0
-0.005
-0.01
-0.015
2/3/1998
2/3/1999
2/3/2000
2/3/2001
2/3/2002
2/3/2003
2/3/2004
2/3/2005
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2/3/2010
2/3/2011
2/3/2012

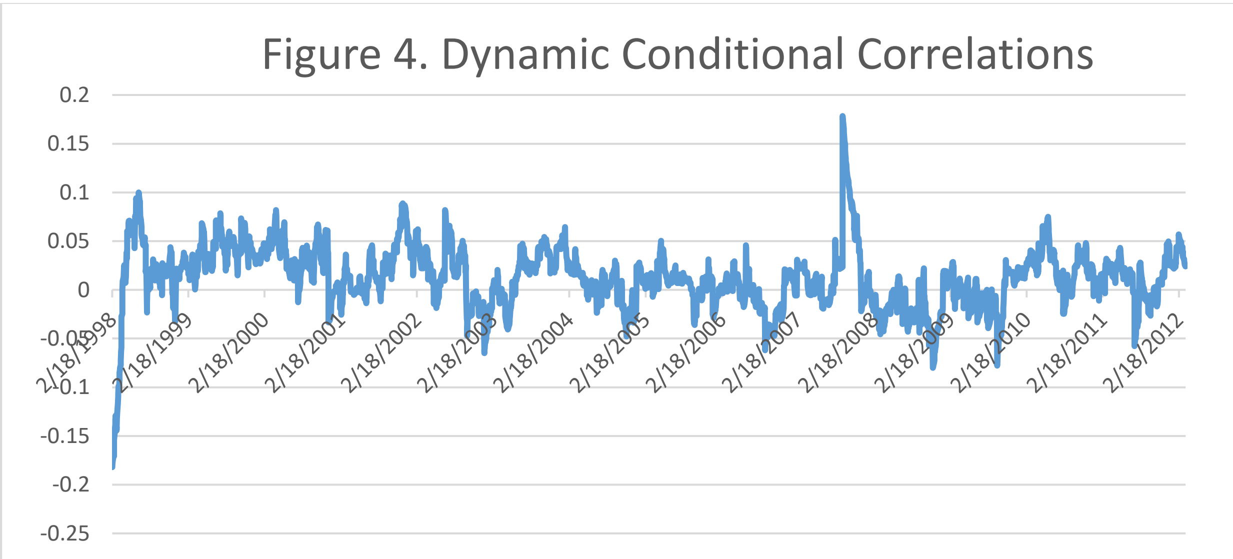

Figure 4. Dynamic Conditional Correlations
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
-0.25
2/18/1998
2/18/1999
2/18/2000
2/18/2001
2/18/2002
2/18/2003
2/18/2004
2/18/2005
2/18/2006
2/18/2007
2/18/2008
2/18/2009
2/18/2010
2/18/2011
2/18/2012