Working Papers

Equity Fund Flows and Stock Market Returns in the US before and after the Global Financial Crisis: A VAR-GARCH-in-mean Analysis

Vassilios Babalos
Guglielmo Maria Caporale
Nicola Spagnolo

CESIFO WORKING PAPER NO. 5932
CATEGORY 7: MONETARY POLICY AND INTERNATIONAL FINANCE
JUNE 2016

ISSN 2364-1428

CESifo *Working Paper No. 5932*

Equity Fund Flows and Stock Market Returns in the US before and after the Global Financial Crisis: A VAR-GARCH-in-mean Analysis

Abstract

The 2008—2009 global financial crisis has raised new questions about the relationship between equity fund flows and stock market returns. This paper analyses it using US monthly data over the period 2000:1-2015:08. A VAR-GARCH(1,1)-in-mean model with a BEKK representation is estimated, and a switch dummy for the global financial crisis is also included. We find causality-in-mean from stock market returns to equity fund flows (consistently with the feedback-trading hypothesis) only in the post-September 2008 period. There are also volatility spillovers from stock market returns to equity fund flows both before and after the crisis; however, this relationship is not stable, becoming weaker in the crisis period. As a robustness check we augment the model with a a set of macroeconomic control variables. Their inclusion does not affect the main results.

JEL-Codes: G230, C320.

Keywords: equity fund flows, stock market returns, VAR-GARCH-in-mean model, volatility.

Vassilios Babalos
Accounting and Finance
Technological Educational Institute of Peloponnese / Kalamata / Greece
vbabalos@teikal.gr

*Guglielmo Maria Caporale**
Department of Economics and Finance
Brunel University London
United Kingdom – London, UB8 3PH
Guglielmo-Maria.Caporale@brunel.ac.uk

Nicola Spagnolo
Department of Economics and Finance
Brunel University London
United Kingdom – London, UB8 3PH
Nicola.Spagnolo@brunel.ac.uk

*corresponding author

May 25, 2016

1 Introduction

It has long been recognised that capital markets are dominated by institutional investors: in the US the demand for mutual fund shares has experienced a steadily, upward trend from 2006 to 2015; households invested an annual average of $366 billion in long-term registered investment companies, these being the largest investors in the US financial markets for much of the past twenty years. However, the exact nature of the dynamic linkages between mutual fund flows and stock market returns is yet to be investigated thoroughly (Edwards and Zhang, 1998). There are two main approaches in the literature. The micro approach analyses mutual funds flows on an individual basis and finds that investors typically move cash into the funds that had the highest returns in the preceding years (see, e.g., Ippolito (1992), Sirri and Tufano (1993), and Hendricks, Patel, and Zeckhauser (1993), Rakowski and Wang (2009)). By contrast, the macro approach investigates the dynamic relationship between stock market returns and aggregate fund flows. Finance theory suggests that stock market returns and equity fund flows should be contemporaneously correlated, with positive market returns being linked to flows into equity funds, and negative returns to outflows or lower inflows instead.

Different explanations have been offered for the observed co-movement between these two variables. According to the feedback-trader hypothesis market returns are the driving force behind trading and fund flows; in particular investors buy equity fund shares when stock prices increase and sell them when prices fall. However, Remolona et al. (1997) using instrumental variables found only limited evidence of short-term returns affecting mutual fund flows. In a related study, Edwards and Zhang (1998) reported unidirectional Granger causality running from stock market returns to aggregate equity fund flows. It is also possible, though, for fund flows to affect stock market returns as mutual fund investors may follow sentiment unrelated to fundamentals (Brown et al., 2003), and as a result of their uninformed demand stock prices may temporarily diverge from their fundamental values. This is the so-called price-pressure hypothesis, according to which fund flows cause stock market returns. In an influential paper, Edelen and Warner (2001) reported a strong positive contemporaneous relationship between aggregate fund flows and share market returns for the US market, and found a price impact of mutual fund flows. They concluded that at the daily frequency stock market returns contain information about future aggregate fund flows, whilst aggregate fund flows cannot be used to predict next period's stock market returns. More evidence in favour of the price-pressure hypothesis was provided by Ben-Rephael et al. (2011) and Ben-Rephael et al. (2012) for Israeli and US funds, using daily and monthly data respectively. Warther (1995) found a positive relationship between aggregate fund flows and stock market returns in US at the weekly frequency, and a negative one at the monthly frequency. Fant (1999) used a VAR framework to analyse the effects on stock market returns of different investors' actions such as new sales, redemptions, exchanges-in, and exchanges-out of funds, and found a relationship only between returns and exchanges-in and-out.

A third hypothesis is that fund flows and market returns are both driven by the arrival of new information, without any direct causal linkage between them. Jank (2012) examined this hypothesis employing quarterly data on US fund flows. He concluded that variables that forecast the real economy as well as the equity premium (such as the dividend-price ratio, the default spread, the relative T-Bill rate and the consumption-wealth ratio) can account for the correlation between fund flows and market returns. A few studies examine the fund flows-stock market returns relationship in countries other than the US. For instance, both Caporale et al. (2004) and Alexakis et al. (2005) found bi-directional linkages in the case of the Greek market. Oh and Parwada (2007) and Watson and Wickramanayake (2012) reported unidirectional (positive) causality running from stock market returns to mutual fund flows in Korea and Australia respectively. Alexakis et al. (2013) carried out asymmetric cointegration tests and found that in Japan there are two-way effects in periods with rising prices and unidirectional causality from fund flows to stock returns when prices are falling.

The present study is related to those of Warther (1995), Edwards and Zhang (1998), and Ben-Rephael et al. (2012) examining the Investment Company Institute (ICI) data on monthly aggregate flows to US mutual funds, as well as to the literature on the transaction costs of institutional investors. If fund flows exert price pressure, fund managers will buy "high" and sell "low"; Edelen's (1999) showed that in fact mutual fund flows are responsible for their negative market timing. However, the existing literature mainly focuses on first-order causality. The only exception is the study by Cao et al. (2008), who estimated a VAR using daily data and found that daily market volatility is negatively related to contemporaneous and lagged flows; further, their impulse response analysis suggests that shocks to fund flows have a negative impact on market volatility. In their paper volatility is measured first using high-frequency volatility estimators and then included in a bivariate model containing fund flows as well. Our study improves on theirs by modelling endogenously both the conditional mean and variance in the context of a VAR-GARCH(1,1)-in-mean model for which a BEKK representation is adopted given its well-known advantages (see below). Moreover, the chosen specification also allows for possible effects of the second moments of the series on their first moments. Therefore we are able to investigate causality-in-mean, causality-in-variance and GARCH-in-mean effects within the same framework and to shed new light on both mean and volatility spillovers between aggregate fund flows and stock returns. Further, we include a dummy variable allowing the parameters to shift in September 2008, at the time of the collapse of Lehman Brothers, since the recent global financial crisis could have affected the relationship between the two variables. It should be also noted that, according to the Investment Company Institute, over the past 10 years US investors have increasingly moved towards equity funds that invest primarily in foreign markets (world equity funds), with net outflows totalling \$834 billion, which makes an analysis of the dynamic linkages between domestic stock market returns and domestic equity fund flows particularly interesting. In brief, we find causality-in-mean from stock market returns to equity fund flows (consistently with the feedback-trading hypothesis) only in the post-September 2008 period. There are also volatility spillovers from stock market returns to equity fund flows both before and after the crisis; however, this relationship is not stable, becoming weaker in the crisis period. Following earlier studies arguing that mutual fund flows and stock market returns might be correlated through a common response to market-wide fundamentals (Jank, 2012), we perform a robustness test by augmenting our model with a set of variables that predict the future state of the economy. In contrast to Jank (2012), we find that equity fund flows and stock market returns are not related to market-wide fundamentals. Overall, the inclusion of the control variables does not affect the main results.

The layout of the paper is as follows. Section 2 outlines the econometric modelling approach. Section 3 describes the data and presents the empirical findings. Section 4 reports some robustness checks. Finally, Section 5 summarises the main findings and offers some concluding remarks.

2 The model

We represent the first and second moments of stock market returns and equity fund flows using a VAR-GARCH(1,1)-in-mean [1] In its most general specification the model takes the following form:

$$\boldsymbol{y}_t = \boldsymbol{\alpha} + \boldsymbol{\beta}\boldsymbol{y}_{t-1} + \boldsymbol{\delta} h_{t-1} + \boldsymbol{u}_t \tag{1}$$

where $\boldsymbol{y}_t = (MutualFund_t, Stock\,\mathrm{Re}\,t_t)$ and $\boldsymbol{y}_{t-1}$ is a corresponding vector of lagged variables. The residual vector $\boldsymbol{u}_t = (u_{1,t}, u_{2,t})$ is bivariate and normally distributed $\boldsymbol{u}_t \mid I_{t-1} \sim (\mathbf{0}, H_t)$ with its corresponding conditional variance covariance matrix given by:

$$H_t = \begin{bmatrix} h_{11t} & h_{12t} \\ h_{12t} & h_{22t} \end{bmatrix} \tag{2}$$

The parameter vectors of the mean return equation (1) correspond to the constant $\boldsymbol{\alpha} = (\alpha_1, \alpha_2)$, the autoregressive term, $\boldsymbol{\beta} = (\beta_{11}, \beta_{12} + \beta_{12}^* \mid \beta_{21} + \beta_{21}^*, \beta_{22})$, which allows for bi-directional causality effect, and the GARCH-in-mean parameters $\boldsymbol{\delta} = (\delta_{12} + \delta_{12}^* \mid \delta_{21} + \delta_{21}^*)$ which allow for bi-directional effects of volatilities on returns.

We adopt a BEKK representation and therefore the second moment takes the following form[2]:

$$H_t = C_0{}' C_0 + A_{11}' \begin{bmatrix} u_{1,t-1}^2 & u_{2,t-1}u_{1,t-1} \\ u_{1,t-1}u_{2,t-1} & u_{2,t-1}^2 \end{bmatrix} A_{11} + G_{11}' H_{t-1} G_{11} \tag{3}$$

where

$$A_{11} = \begin{bmatrix} a_{11} & a_{12} + a_{12}^* \\ a_{21} + a_{21}^* & a_{22} \end{bmatrix}; G_{11} = \begin{bmatrix} g_{11} & g_{12} + g_{12}^* \\ g_{21} + g_{21}^* & g_{22} \end{bmatrix}$$

Equation (3) models the dynamic process of H_t as a linear function of its own past values H_{t-1} and past values of the squared innovations $\left(u_{1,t-1}^2, u_{2,t-1}^2\right)$. The parameters of (3) are given by C_0, which is restricted to be upper triangular, and the two matrices A_{11} and G_{11}. The BEKK representation guarantees by construction that the covariance matrix in the system is positive definite. In order to account for the possible effects of the recent financial crisis, we also include a dummy variable (denoted by*) with a switch in September 2008 (since Lehman Brothers collapsed on the 15th of that month).

Given a sample of T observations, a vector of unknown parameters θ and a 2×1 vector of variables $\boldsymbol{y}_t$, the conditional density function for model (1) is:

$$f\left(\boldsymbol{y}_t | I_{t-1}; \theta\right) = (2\pi)^{-1} \left|H_t\right|^{-1/2} \exp\left(-\frac{\boldsymbol{u}_t{}' \left(H_t^{-1}\right) \boldsymbol{u}_t}{2}\right) \tag{4}$$

[1] The model is based on the GARCH(1,1)-BEKK representation proposed by Engle and Kroner (1995).

[2] The parameters (a_{21}) and (a_{11}) in Equation (3) measure the causality effect of mutual funds and stock return volatility respectively, whereas $(a_{21} + a_{21}^*)$ and $(a_{12} + a_{12}^*)$ the possible effect of the 2008 financial crisis.

The log-likelihood function is:

$$L = \sum_{t=1}^{T} \log f\left(\boldsymbol{y}_t | I_{t-1}; \theta\right) \tag{5}$$

where θ is the vector of unknown parameters. The standard errors are calculated using the quasi-maximum likelihood method of Bollerslev and Wooldridge (1992), which is robust to the distribution of the underlying residuals.

3 Empirical Analysis

3.1 Data

Monthly data on aggregate equity fund flows have been obtained from the Investment Company Institute (ICI). Following other studies flows are normalised using the previous month's aggregate assets. US stock market returns are proxied by the Wilshire 5000 Total market index over the period 2000:1 - 2015:8, for a total of 188 observations. We construct monthly returns as the logarithmic differences of stock prices and the first differences of fund flows. The descriptive statistics, presented in Table 1, Panel A, show that the 2008 crisis had a noticeable impact on the distribution of both variables. In particular, the volatility of stock returns increased post-September 2008, whereas for equity fund flows the opposite is true. Furthermore, stock returns are higher in the post-September 2008 period, whilst equity flows have been negative during the same period.

Please Insert Table 1 and Figure 1

3.2 Hypotheses Tested

We test for mean and volatility spillovers by imposing restrictions on the relevant parameters; specifically we consider the following three sets of null hypotheses[3] H_0:

1. Tests of no mean spillovers between equity fund flows and stock returns
H_{01}:Equity fund flows on stock returns before the 2008 crisis: $\beta_{12} = 0$
H_{02}:Equity fund flows on stock returns after the 2008 crisis: $\beta^*_{12} = 0$
H_{03}:Stock returns on equity fund flows before the 2008 crisis: $\beta_{21} = 0$
H_{04}:Stock returns on equity fund flows after the 2008 crisis: $\beta^*_{21} = 0$

2. Tests of no volatility spillovers between equity fund flows and stock returns
H_{05}:Equity fund flows volatility on stock volatility before the 2008 crisis: $a_{21} = g_{21} = 0$
H_{06}:Equity fund flows volatility on stock volatility after the 2008 crisis: $a^*_{21} = g^*_{21} = 0$
H_{07}:Returns volatility on equity fund flows volatility before the 2008 crisis: $a_{12} = g_{12} = 0$
H_{08}:Returns volatility on equity fund flows volatility after the 2008 crisis: $a^*_{12} = g^*_{12} = 0$

3. Tests of no spillovers from volatility into returns (GARCH-in-mean effects)
H_{09}:Equity fund flows volatility on stock returns before the 2008 crisis: $\delta_{21} = 0$
H_{10}:Equity fund flows volatility on stock returns after the 2008 crisis: $\delta^*_{21} = 0$

[3] The joint restrictions $H_{05} - H_{08}$ are tested by means of a Wald test.

H_{11}:Stock returns volatility on equity fund flows before the 2008 crisis: $\delta_{12} = 0$
H_{12}:Stock returns volatility on equity fund flows after the 2008 crisis: $\delta_{12}^{*} = 0$

3.3 Discussion of the Results

In order to assess the adequacy of the models, Ljung–Box portmanteau tests were performed on the standardized and squared residuals. Overall, the results indicate that the VAR-GARCH(1,1) specification captures satisfactorily the persistence in returns and squared returns of both variables. The estimated VAR-GARCH(1,1) model with the associated robust p-values and likelihood function values are presented in Table 2. We select the optimal lag length of the mean equation using the Schwarz information criterion.

The following points are noteworthy. There does not appear to be any significant causality-in-mean at the standard 5% level before the 2008 crisis. In the post-September 2008 period causality running from stock markets returns to equity fund flows is found ($\beta_{12}^{*} = 0.9478$), consistently with the results of Remolona et al. (1997) and Edwards and Zhang (1998). This supports the feedback trading hypothesis that implies that equity fund investors respond to positive returns with inflows and to negative returns with outflows.

The model specification allows us to control and test for the presence of reverse causality running from volatility to returns (GARCH-in-mean effects), which is measured by the parameter vector $\boldsymbol{\delta}$. We only find a significant (positive) effect from stock markets returns to equity fund flows ($\delta_{12} = 0.0349$). The 2008 crisis seems to have affected the relationship between stock market volatility and equity fund flows, with a negative effect of the former on the latter post-September 2008 ($\delta_{12} + \delta_{12}^{*} = -0.0164$). This points to a shift in the risk appetite of US equity fund investors, who appear to have reduced their degree of exposure in the context of a more volatile stock market. The volatility of equity fund flows does not appear to affect stock market returns post-September 2008 either.

Please Insert Table 2 about here

Concerning the conditional variance equations, the estimated “own-market” coefficients are statistically significant with $g_{11} = 0.4862$ and $g_{22} = 0.9784$ suggesting a high degree of persistence, especially in the case of stock market returns. Their volatility has a significant influence on that of equity fund flows both before ($g_{21} = -0.0455$) and after the crisis ($g_{21} + g_{21}^{*} = -0.0084$), but it is smaller in the latter period. There is no evidence of causality-in-variance in the opposite direction.

Squared stock market returns have a significant influence on the volatility of equity fund flows before the crisis ($a_{12} = -3.9733$). Squared equity fund returns also affect the volatility of stock market returns before the crisis ($a_{21} = 0.0872$). Furthermore, there is evidence of this affecting the causality-in-variance dynamics. In particular, the post-crisis coefficient on squared stock market returns is lower, in absolute value ($a_{12} + a_{12}^{*} = -0.6535$), compared to the pre-September 2008 period. The same is true of the coefficient on squared equity fund returns, that falls ($a_{21} + a_{21}^{*} = 0.0553$).

Finally, the conditional correlations confirm the previous results. While they are positive for the whole sample, they shift downward in the post-September 2008 period, when they have an average value of 0.4071 compared to 0.6585 in the earlier period. Furthermore, their standard deviation increases from 0.1187 in the earlier period to 0.1611 in the following one (see Table 1), which is further evidence of a regime shift.

4 Robustness Checks

According to the information-response hypothesis, the documented relationship between stock market returns and equity fund flows could be just the result of both variables responding to the arrival of new information (Jank, 2012). In order to test this hypothesis we augment the baseline specification with a set of control variables in the conditional mean equation (Eq.1): the US Economic Policy Uncertainty Index (EPU) and the US Equity market uncertainty index (EMU) that are obtained from the site http://www.policyuncertainty.com/; the three-month Treasury Bill rate (TBill), the Term spread (Aaa corporate bond yield minus the three-month bill yield - TSpread), and the Default spread (Baa corporate bond yield minus the Aaa corporate bond yield - Default), both from Moody's - these series are taken from the Federal Reserve of Saint Louis (FRED) Database. The US Economic Policy Uncertainty index attempts to capture policy-related economic uncertainty that stems from three different sources: newspaper coverage of policy-related economic uncertainty, the number of Federal tax code provisions expiring in the coming years and disagreement between economic forecasters. Baker et al. (2015) argue that shifts in their policy uncertainty index are associated with greater stock price volatility and their index appears to have predictive power for future output, investment and unemployment in the US. The stock market uncertainty index is instead constructed employing news articles from leading US newspapers with a focus on the stock market.

Proponents of the information-response hypothesis argue that equity fund investors adjust their strategies on the basis of new information which is also fully incorporated into prices in an efficient market; consequently, the demand for equity fund shares should shift in response to news about fundamentals, and equity fund flows should be driven by such news (by contrast, according to the price pressure hypothesis there should be no relationship between flows and news). Therefore the information-response hypothesis has two testable implications (Jank, 2012): first, variables that contain information about the future state of the economy should be related to equity fund flows; second, if the latter respond to the arrival of information about the real economy, then they should also predict real economic activity. In the present study we test the first of the two hypotheses. All variables are lagged and differenced once before being included in the model, with the exception of the Treasury Bill rate (lagged but not in first differences); descriptive statistics are presented in Table 1, Panel B. The extended specification has the following form:

$$\boldsymbol{y}_t = \boldsymbol{\alpha} + \boldsymbol{\beta}\boldsymbol{y}_{t-1} + \boldsymbol{\delta}h_{t-1} + \boldsymbol{\gamma}z_{t-1} + \boldsymbol{u}_t \qquad (6)$$

where $\boldsymbol{y}_t = (MutualFund_t, Stock\,\mathrm{Re}\,t_t)$, $\boldsymbol{y}_{t-1}$ is the corresponding vector of lagged variables and z_{t-1} is the matrix containing the lagged control variables. Therefore, $\gamma\,' = (\gamma_{11}, \gamma_{12}, \gamma_{13}, \gamma_{14}, \gamma_{15} \mid \gamma_{21}, \gamma_{22}, \gamma_{23}, \gamma_{24}, \gamma_{25})$ is the matrix of control parameters[4] that ap-

[4] These variables are treated as exogenous in order to obtain a system of equations of manageable dimensions; they are lagged in order to control for any potential endogeneity and to capture possible noncontemporaneous effects. Please note that a switch dummy was not included for the control variables, again in order

pear in both equations. The conditional variance equation is the same as before (see Eq. 2).

Overall, the new set of results confirms the previous ones as far as the dynamics linkages between equity funds to stock returns are concerned. Further, they do not support Jank's (2012) hypothesis that market returns and equity fund flows react simultaneously to macroeconomic news. More specifically, we find that the Economic Policy Uncertainty Index has a positive effect on equity fund flows; this could reflect a preference on the part of investors for professionally managed collective schemes over individual stock market investments when uncertainty about the future state of the economy grows. On the other hand, default spread has the expected negative effect on stock market returns.

Please Insert Table 3 about here

5 Conclusions

This paper examines the effects of the global financial crisis on the relationship between equity fund flows and stock market returns in the US employing monthly data for the period January 2000- August 2015. In particular, a VAR-GARCH-in-mean model with a BEKK representation is estimated to test for both mean and volatility spillovers; the specification also includes a switch dummy to take into account the possible effects of the crisis. We find statistically significant causality-in-mean running from stock market returns to equity fund flows in the post-September 2008 period only. This finding lends support to the feedback-trading hypothesis over that period. Net flows to equity funds tend to rise with stock prices and the opposite tends to occur when stock prices fall. Cao at al. (2008) had concluded that daily market volatility is negatively related to concurrent and lagged aggregate flows. Our study shows that the crisis significantly affected the relationship between the two series. In particular, the GARCH-in-mean effects of stock market volatility on equity fund flows turned from positive before the crisis to negative post-September 2008. Further, the volatility of stock market returns has a significant influence on that of equity fund flows both before and after the crisis, but less so in the latter period, namely the relationship is not stable over time. Finally, we carry out robustness checks by including in the model exogenous factors, namely the US Economic Policy Uncertainty Index, the US Equity market uncertainty index, the three-month Treasury Bill rate, and Moody's Term spread and Default spread. The augmented model yields very similar findings, and lends support to the price-pressure rather than information-response hypothesis. This evidence can be usefully exploited by both policy makers and market participants for their respective purposes.

References

[1] Alexakis, C., Niarchos, N., Patra,T. Poshakwale, S. 2005. The dynamics between stock returns and mutual fund flows: empirical evidence from the Greek market. International Review of Financial Analysis 14, 559–569.

to reduce the number of parameters to be estimated.

[2] Alexakis, C., Dasilas, A., Grose.C. 2013. Asymmetric dynamic relations between stock prices and mutual fund units in Japan. An application of hidden cointegration technique. International Review of Financial Analysis 28 ,1-8.

[3] Baker,S.,Bloom,N., Davis,S.2015. Measuring Economic Policy Uncertainty. NBER Working Paper 21633, Cambridge, MA.

[4] Ben-Rephael, A., Kandel, S.,Wohl,A. 2012. Measuring investor sentiment with mutual fund flows. Journal of Financial Economics 104,363-382.

[5] Ben-Rephael, A., Kandel, S.,Wohl,A. 2011. The Price Pressure of Aggregate Mutual Fund Flows. Journal of Financial and Quantitative Analysis 46, 585-603.

[6] Brown,S.J., Goetzmann,W.N. Hiraki, T. Shirishi, N., Watanabe, M., 2003. Investor Sentiment in Japanese and U.S. Daily Mutual Fund Flows. NBER Working Paper No. 9470.

[7] Cao, C., Chang ,E.C., Wang,Y. 2008.An empirical analysis of the dynamic relationship between mutual fund flow and market return volatility. Journal of Banking and Finance 32, 2111-2123.

[8] Caporale, G., Philippas, N., Pittis, N., 2004. Feedbacks between mutual fund flows and security returns: evidence from the Greek capital market. Applied Financial Economics 14, 981–989.

[9] Edelen, R., Warner, J., 2001. Aggregate price effects of institutional trading: a study of mutual fund flow and market returns. Journal of Financial Economics 59, 195–220.

[10] Edwards, F., Zhang, X., 1998. Mutual funds and stock and bond market stability. Journal of Financial Services Research 13,257–282.

[11] Engle, R.F., and K.F. Kroner, 1995, Multivariate simultaneous generalized ARCH, Econometric Theory, 11, 122-150.

[12] Fant, L.F., 1999. Investment behavior of mutual fund shareholders: The evidence from aggregate fund flows. Journal of Financial Markets 2, 4, 391–402.

[13] Hendricks, D, Patel,J., Zeckhauser, R., 1993, Hot hands in mutual funds: Short-run persistence of relative performance, 1974-1988, Journal of Finance 48(1), 93-130.

[14] Jank, S. 2012. Mutual fund flows, expected returns, and the real economy. Journal of Banking and Finance 36, 3060-3070.

[15] Ippolito, R. A., 1992, Consumer reaction to measures of poor quality: Evidence from the mutual fund industry, Journal of Law and Economics 35, 45-70.

[16] Ljung, G.M. and G.E.P. Box, 1978, On a measure of lack of fit in time series models, Biometrika, 65, 297–303.

[17] Mosebach, M., Najand, M., 1999. Are the structural changes in mutual funds investing driving the US stock market to its current level. Journal of Financial Research 22, 317–329.

[18] Oh, N., and Parwada, J., 2007. Relations between mutual fund flows and stock market returns in Korea. Journal of International Financial Markets, Institutions and Money 17, 140–151.

[19] Rakowski, D, Wang, X., 2009. The dynamics of short-term mutual fund flows and returns: A time-series and cross-sectional investigation. Journal of Banking and Finance 33, 11,2102–2109.

[20] Remolona, E.M., Kleiman, P., Gruenstein, D., 1997. Market returns and mutual fund flow. Economic Policy Review 3, 33–52.

[21] Sirri, E.R., Tufano, P., 1993, Buying and selling mutual funds: Flows, performance, fees, and services, Working Paper, Harvard Business School.

[22] Warther, V., 1995. Aggregate mutual fund flows and security returns. Journal of Financial Economics 39, 209–235.

[23] Watson, J., Wickramanayake., J., 2012.The relationship between aggregate managed fund flows and share market returns in Australia. Journal of International Financial Markets, Institutions and Money 22, 451– 472. .

TABLE 1: Descriptive Statistics

Panel A	Pre-2008		Post-2008	
	Stock Returns	Mutual Funds	Stock Returns	Mutual Funds
Mean	0.115	0.193	0.959	−0.065
Median	1.031	0.201	1.710	−0.017
St. Dev	4.186	0.437	4.822	0.316
Skewness	−0.481	−0.866	−0.824	−1.192
Kurtosis	2.956	6.195	4.794	6.244
Jarque-Bera	4.001	57.251	20.544	56.071
Min.	−10.030	−1.722	−17.611	−1.446
Max.	8.231	1.444	11.531	0.624
No. Obs.	102	102	85	85

	Conditional Correlations	Conditional Correlations
Mean	0.6585	0.4071
St. Dev	0.1187	0.1611

Panel B	Control Variables				
	△EPU	△EMU	TBill	△Default	△TSpread
Mean	0.017	1.193	0.017	0.008	0.009
Median	−0.019	0.051	0.009	0.000	−0.008
St. Dev	0.192	3.841	0.193	0.098	0.128
Skewness	2.141	4.942	0.871	1.803	2.393
Kurtosis	13.119	33.201	2.354	11.333	13.762
Jarque-Bera	940.1	786.7	26.946	642.29	1081.1
Min.	−0.474	−0.951	0.001	−0.251	−0.339
Max.	1.231	30.547	0.061	0.566	0.747
No. Obs.	187	187	187	187	187

Note: The sample size covers the period 2000:1-2015:8, for a total of 187 observations.

TABLE 2: Estimated VAR-GARCH(1,1) model

	Pre-crisis			Post-crisis	
Parameters	Coefficient	p-values	Parameters	Coefficient	p-values
		Conditional Mean Equation			
α_1	0.0157	(0.7506)			
α_2	1.3313	(0.0569)			
β_{11}	0.4618	(0.0001)			
β_{12}	-0.1449	(0.8688)			
			β^*_{12}	0.9478	(0.0004)
β_{21}	0.0088	(0.4539)			
			β^*_{21}	0.0078	(0.5539)
β_{22}	-0.0791	(0.4051)			
δ_{12}	0.0349	(0.0141)			
			δ^*_{12}	-0.0513	(0.0001)
δ_{21}	-0.5731	(0.7717)			
			δ^*_{21}	-0.7795	(0.5819)
		Conditional Variance Equation			
c_{11}	0.1512	(0.0001)			
c_{12}	0.1553	(0.0038)			
c_{22}	0.0001	(0.0009)			
g_{11}	0.4862	(0.0002)			
g_{21}	-0.0445	(0.0001)			
			g^*_{21}	0.0361	(0.0009)
g_{12}	0.8845	(0.2688)			
			g^*_{12}	3.1591	(0.4061)
g_{22}	0.9784	(0.0001)			
a_{11}	-0.2799	(0.0285)			
a_{21}	0.0872	(0.0001)			
			a^*_{21}	-0.0319	(0.0193)
a_{12}	-3.9733	(0.0001)			
			a^*_{12}	3.3188	(0.0212)
a_{22}	0.1173	(0.0002)			
LogLik	-514.1839				
$LB_{Mutual,(10)}$		14.419	$LB_{Stock,(10)}$		12.573
$LB_{Mutual,(10)}$		1.714	$LB_{Stock,(10)}$		4.497

Note: P-values are calculated using the quasi-maximum likelihood method of Bollerslev and Wooldridge (1992), which is robust to the distribution of the underlying residuals. Parameters not statistically significant at 5% level are not reported. LB $_{(10)}$ and LB $^2_{(10)}$ are the Ljung-Box test (1978) of significance of autocorrelations of ten lags in the standardized and standardized squared residuals respectively. The parameters β_{12} and β_{21} measure the causality effect of mutual funds flow on stock returns and of stock returns on mutual funds flow, respectively, .a_{21} and a_{12} measure the causality in variance effect. The effect of the 2008 financial crises on stock returns is measured by $(\beta_{12}+\beta^*_{12})$, and on mutual funds flow by $(\beta_{21}+\beta^*_{21})$ whereas $(a_{21}+a^*_{21})$

and $(a_{12}+a_{12}^{*})$ capture the effect on stock return volatilities and mutual funds flow volatilities. The covariance stationarity condition is satisfied by all the estimated models, all the eigenvalues of $A_{11} \otimes A_{11} + G_{11} \otimes G_{11}$ being less than one in modulus. Note that in the conditional variance equation the sign of the parameters cannot be determined.

TABLE 3: Estimated VAR-GARCH(1,1) model with Control Variables

Pre-crisis			Post-crisis		
Parameters	Coefficient	p-values	Parameters	Coefficient	p-values
Conditional Mean Equation					
α_1	-0.0262	(0.4936)			
α_2	0.8955	(0.0936)			
β_{11}	0.5414	(0.0001)			
β_{12}	0.3773	(0.6647)			
			β_{12}^*	0.1481	(0.0423)
β_{21}	0.0056	(0.4125)			
			β_{21}^*	0.0043	(0.5254)
β_{22}	-0.1070	(0.1893)			
δ_{12}	0.0355	(0.0031)			
			δ_{12}^*	-0.0334	(0.0013)
δ_{21}	-1.7205	(0.3181)			
			δ_{21}^*	2.3514	(0.2038)
Control on Mutual Fund			Control on Stock Returns		
$\gamma_{11}(\triangle\text{EPU}_{\ t-1})$	0.0024	(0.0278)	$\gamma_{21}(\triangle\text{EPU}_{\ t-1})$	0.0235	(0.2001)
$\gamma_{12}(\triangle\text{EMU}_{\ t-1})$	0.0001	(0.3547)	$\gamma_{22}(\triangle\text{EMU}_{\ t-1})$	0.0003	(0.3721)
$\gamma_{13}(\text{TBill}_{\ t-1})$	-0.0031	(0.7563)	$\gamma_{23}(\text{TBill}_{\ t-1})$	-0.0215	(0.8677)
$\gamma_{14}(\triangle\text{Default}_{\ t-1})$	0.0045	(0.0903)	$\gamma_{24}(\triangle\text{Default}_{\ t-1})$	-0.0861	(0.0225)
$\gamma_{15}(\triangle\text{TSpread}_{\ t-1})$	0.0011	(0.3159)	$\gamma_{25}(\triangle\text{TSpread}_{\ t-1})$	-0.0172	(0.2754)
Conditional Variance Equation					
c_{11}	-0.1087	(0.0001)			
c_{12}	0.6351	(0.0081)			
c_{22}	-0.0001	(0.0009)			
g_{11}	0.1646	(0.0102)			
g_{21}	0.0585	(0.0101)			
			g_{21}^*	-0.0410	(0.0032)
g_{12}	0.5992	(0.3725)			
			g_{12}^*	-2.8891	(0.1883)
g_{22}	0.8555	(0.0001)			
a_{11}	0.9353	(0.0001)			
a_{21}	-0.0499	(0.0061)			
			a_{21}^*	0.0305	(0.0111)
a_{12}	-2.3773	(0.0162)			
			a_{12}^*	6.4028	(0.0083)
a_{22}	0.5298	(0.0001)			
LogLik	-502.7511				
$LB_{Mutual,(10)}$		10.331	$LB_{Stock,(10)}$		9.443
$LB_{Mutual,(10)}$		5.169	$LB_{Stock,(10)}$		3.981

Note: See notes Table 2. EPU, EMU, TBill, TSpread and Default are respectively the US Economic Policy Uncertainty Index, the US Equity market uncertainty index, three months Treasury Bills, Term spread by Moody's Aaa corporate bond yield minus the three-month bill yield and the Default spread by Moody's Baa corporate bond yield minus the Aaa corporate bond yield.

Figure 1: Mutual Fund Flow, Stock Market Returns and Conditional Correlations