Available online at www.sciencedirect.com
ScienceDirect
Journal of Banking & Finance 32 (2008) 2111–2123
Journal of BANKING & FINANCE
www.elsevier.com/locate/jbf

An empirical analysis of the dynamic relationship between mutual fund flow and market return volatility ☆

Charles Cao [a,b,*], Eric C. Chang [c], Ying Wang [d]

[a] Department of Finance, Smeal School of Business, Pennsylvania State University, 338 Business Building, University Park, PA 16802, United States
[b] CCFR, Beijing, China
[c] School of Business, University of Hong Kong, Hong Kong, China
[d] Department of Finance, School of Business, State University of New York at Albany, 1400 Washington Avenue, Albany, NY 12222, United States

Received 18 September 2007; accepted 17 December 2007
Available online 11 January 2008

Abstract

We study the dynamic relation between aggregate mutual fund flow and market-wide volatility. Using daily flow data and a VAR approach, we find that market volatility is negatively related to concurrent and lagged flow. A structural VAR impulse response analysis suggests that shock in flow has a negative impact on market volatility: An inflow (outflow) shock predicts a decline (an increase) in volatility. From the perspective of volatility–flow relation, we find evidence of volatility timing for recent period of 1998–2003. Finally, we document a differential impact of daily inflow versus outflow on intraday volatility. The relation between intraday volatility and inflow (outflow) becomes weaker (stronger) from morning to afternoon.

JEL classification: G10; G11; G19

Keywords: Mutual fund flow; Market volatility; Volatility timing; Fund inflow and fund outflow

1. Introduction

We have witnessed an unprecedented growth in mutual funds since the 1980s. Shares in mutual funds now represent a major part of household wealth, and the funds themselves have become important intermediaries for savings and investments. Over the past 10 years, several studies have examined aggregate mutual fund flow into US (or, international) equity funds. We now know that (1) flow into equity funds is positively correlated with concurrent and subsequent market returns, while market returns are negatively related to subsequent flow in the monthly data (Warther, 1995); (2) daily flow is positively associated with concurrent and previous day's market return, but daily returns are not associated with lagged flow (Edelen and Warner, 2001); and (3) the documented relation between market returns and flow for US equity funds is uncovered in other developed markets and emerging markets (Froot et al., 2001). These findings suggest that flow and flow-induced trade have an effect on market returns, and this effect is not idiosyncratic. Also there is evidence of positive feedback trading by mutual fund investors in daily data, but not in monthly data. These studies concentrate, exclusively, on the relation between flow and market returns.

The purpose of this paper is to offer new insights on aggregate mutual fund flow. We focus on the relation

☆ This paper was reviewed and accepted while Professor Giorgio Szego was the Managing Editor of The Journal of Banking and Finance and by the past Editorial Board.

* Corresponding author. Address: Department of Finance, Smeal School of Business, Pennsylvania State University, 338 Business Building, University Park, PA 16802, United States. Tel.: +814 865 7891; fax: +814 865 3362.
E-mail address: qxc2@psu.edu (C. Cao).

0378-4266/$ - see front matter © 2008 Elsevier B.V. All rights reserved.
doi:10.1016/j.jbankfin.2007.12.035

between aggregate flow and market volatility and answer three questions that are not addressed by the previous literature. First, we examine the dynamic relation between flow and market volatility and investigate whether market volatility is associated with concurrent and past aggregate flow. Second, we study whether mutual fund investors time market volatility by moving money into (or out of) equity funds in response to a decrease (or an increase) in market volatility. Finally, we examine the relation between intraday market volatility and daily flow and assess the differential impact of inflow versus outflow on intraday market volatility.

We use a data set of daily mutual fund flow provided by Trim Tabs Investment Research. Using the data from 1998 to 2003, we estimate the dynamic relation between market volatility and flow by using a vector autoregression (VAR) approach. Our primary finding is that daily market volatility is negatively related to concurrent and lagged flow. We also find a negative contemporaneous relationship between innovations in flow and market volatility. A structural VAR impulse response analysis suggests that shock in flow has a negative impact on market volatility. This effect is particularly significant over the next ten days, and gradually disappears. In other words, an inflow shock induces lower market volatility, while an outflow induces higher volatility. Further, daily flow is negatively related to lag-1 volatility, providing evidence that mutual fund investors time market volatility. Finally, our test results suggest that the relation between intraday volatility and inflow becomes weaker, while the relation between intraday volatility and outflow becomes stronger, from morning to afternoon.

This paper is the first that presents direct evidence on the relation between flow and market volatility, and contributes to the literature on mutual funds in several aspects. First, the daily flow data allows us to study the dynamic relation between aggregate flow and market volatility at a daily interval. Second, existing literature focuses on the relation between flow and market returns, and suggests that such a relation may arise from information revelation by mutual fund flow, price pressure, or investor sentiment. However, it is unclear how flow is related to volatility at the aggregate level. Presumably, common components to flow should have an impact on market volatility if flow (and flow-induced trading) is highly correlated. However, the impact of flow on market volatility can be strictly idiosyncratic in nature if flow is driven by the pursuit of different investment strategies/styles. We fill this gap by providing evidence of the dynamic relationship between flow and volatility. Third, this paper highlights the asymmetric relation between flow and market volatility: inflow is associated with lower volatility, and outflow is associated with higher volatility on the next day. Last, this study extends research on the issue of volatility timing by using a larger sample of more than 800 domestic equity funds for the most recent period. Busse (1999) provides evidence of volatility timing at an individual fund level for a sample of 230 funds and for the period of 1985–1995. Since the percentage of US households owning mutual funds has increased from about 30% in 1995 to 50% in 2003, it is important to re-examine volatility timing for this more recent period.

The remainder of the paper is organized as follows. In Section 2 we discuss related literature. Section 3 presents the mutual fund flow data and alternative measures of market volatility. Our main empirical results are presented in Section 4 with the results of robustness checks in Section 5. Concluding remarks are provided in Section 6.

2. Related literature and background

There is a large body of literature on mutual fund flow. Earlier studies have focused on the micro-level relation between individual fund performance and the flow of money into or out of a mutual fund. For example, Sirri and Tufano (1998) analyze annual fund flow and document a striking performance-flow relationship. They conclude that "Mutual fund consumers chase returns, flocking to funds with the highest recent returns, though failing to flee from poor performers." Other studies, including Ippolito (1992), also conclude that mutual fund investors move cash into funds that had the best performance in the preceding year. Coval and Stafford (2007) study asset fire sales and institutional price pressure by examining stock transactions of mutual funds. They find supporting evidence that widespread selling by financially distressed mutual funds leads to transaction prices that occur below fundamental value. They also find that price effects are long-lived and last two quarters.

Recent papers by Warther (1995) and Edelen and Warner (2001) extend earlier studies by studying the relation between flow and returns at the macro-level (e.g., the relation between aggregate fund flow and market returns). According to Warther (1995), there is a fundamental difference between the micro-level and macro-level analyses. Since investors often take money out of one fund and then invest in another fund, much of the cash into one fund is at the expense of another fund. The micro-level analysis helps understand how funds compete against each other to increase their respective market share. At the macro-level, in contrast, flows among funds are offsetting, so only the aggregate flow into (or out of) all funds is relevant. The current paper studies the relation between aggregate flow and market-wide volatility.

There are at least two channels through which the fund flow and stock return volatility are related. First, we observe lumpy cash infusion (or withdraw) into (or out of) funds at the individual fund level over a short period of time (e.g., at daily frequency). Such exogenous cash flow might be related to past performance. Take positive feedback strategies as an example. Fund managers who follow such strategies rely on past performance to predict future returns. They buy securities in up markets and sell in down markets, pushing security prices away from their fundamental values. Other fund managers may follow negative feedback (contrarian) strategies, and their trades drive security prices toward their fundamental values. Since positive (negative) feedback strategies increase (decrease) short-term volatility, the extent to which flow-induced trades depend on past return is important. As fund managers pursue a variety of investment strategies, their aggregate actions may be offsetting. The overall impact of these effects on market volatility is an open empirical question, which is the focus of our study.

Second, studies of Black (1996) and Lee et al. (1991) conclude that noise traders cause wide swings away from fundamentals, and that investor sentiment and noise traders are an important factor in the overall market movement. It is a common belief that mutual fund investors are the least informed investors. Thus, it is reasonable to use mutual fund flow as a proxy for uninformed investor sentiment. Reports in the popular press claim that fund flow is a good indicator of retail investor sentiment, and this sentiment is often irrational. To the extent that investor sentiment is important in the market place and aggregate flow is a good proxy of the sentiment, flow into (or out of) mutual funds will be related to market-wide returns and volatility.

The current paper is also related to Busse (1999) who sheds light on the question of whether mutual funds time market volatility. Using a proprietary dataset and a sample of 230 domestic equity funds during 1985 and 1995, Busse shows that mutual funds do time market volatility and funds change market exposure when volatility changes. According to a survey conducted by Investment Company Institute and US Census Bureau, there has been a dramatic increase in the ownership of mutual funds by US households in the past decade, up from about 30% in 1995 to 50% in 2003. Given the fact that the increase in ownership of mutual funds over time is significant, and that daily fund return data is not available to academia, we extend Busse's work by studying the question of volatility timing from the perspective of the flow–volatility relationship. Our test is based on flow data for more than 800 domestic equity funds and is for a recent period of 1998–2003.

3. Data

3.1. Mutual fund flow

Our daily mutual fund flow data come from Trim Tabs Investment Research of Santa Rosa, CA. The sample spans the period from February 1998 to December 2003. Starting from February 1998, the vendor collects daily data on net asset values (NAVs), total net assets (TNAs), and flow for a sample of over 1600 mutual funds.

Trim Tabs' data collection procedures are briefly summarized as the follows: Each day, mutual fund investors send orders for purchase or redemption to the fund customer service center (or the transfer agent). Whenever a fund receives an order from an investor, the order, by law, should be executed at the next calculated net asset value. Each day, the NAV is determined by the day's closing prices of securities held by the fund and shares outstanding on the previous trading day. Before 5:30 p.m. EST, the NAV is reported to the National Association of Security Dealers and the transfer agent. After the NAV is calculated, the transfer agent processes all orders overnight and uses this NAV to compute the change in the fund's payables, receivables, cash and shares outstanding. The transfer agent then reports these numbers back to fund managers and these numbers are entered into the fund's balance sheet the next morning. Trim Tabs receives data of the previous day's total net assets and net asset values from each fund every morning (We refer readers to Edelen and Warner (2001) who provide a detailed description of Trim Tabs data). Relying on these data on date t and $t-1$, Trim Tabs calculates the net flow on date t for a single fund as

$$Flow_t = \mathrm{TNA}_t - \mathrm{NAV}_t \frac{\mathrm{TNA}_{t-1}}{\mathrm{NAV}_{t-1}}. \tag{1}$$

Since the focus of this paper is on the relationship between aggregate fund flow and market return volatility, we include only domestic equity mutual funds in our sample. We match our sample with funds in the Center for Research in Security Prices (CRSP) survivor-bias free US mutual fund database and include the funds with the following Investment Company Data Institute (ICDI) investment objectives: aggressive growth (AG), growth and income (GI), income (IN), long-term growth (LG), sector funds (SF), total return (TR), and utility funds (UT). The final sample contains 859 domestic equity mutual funds. Funds with other investment objectives (e.g., bond funds and international funds, etc.) are excluded.

Trim Tabs advises that mutual funds do not make adjustment in distributions (e.g., dividends and capital gains) in a uniform manner. For this reason, we obtain the distribution data from the CRSP mutual fund database and adjust the NAVs accordingly. Recent studies using Trim Tabs data report solitary typographical errors in NAVs and TAVs (see Edelen and Warner, 2001; Chalmers et al., 2001; Greene and Hodges, 2002).

We use the two filters suggested by Chalmers et al. (2001) to identify potential data error in NAV and TNA series. The first is a five-standard-deviation filter intended to eliminate outliers that occur as a result of recording errors. If the daily change in NAV (or in TNA) for a single fund is more than five standard deviations, we hand-check NAV (or TNA) against alternative sources, because a five-standard-deviation change is an extremely rare event. The second filter captures observations when a three-standard-deviation move is followed by a reversal to within 1.5 standard deviations (or by a further 1.5 standard deviations move in the same direction) the next day. This filter intends to catch false reversals or continuations. Chalmers et al. (2001) recommend using both filters to spot potential errors. We keep those observations if they can be corrected or verified and discard the remaining spurious observations. In total, we eliminate 0.34% of our sample observations. After filtering, we use Eq. (1) to calculate the net flow for each fund.

Finally, the dollar value of the Trim Tabs asset base varied dramatically from 280 to 810 billion during our six-year sample period. Therefore, we aggregate the fund flow and normalize the aggregate flow by expressing it as a percentage of the previous day's total asset base for our sample of 859 funds.

Summary statistics of normalized flow data are presented in Table 1. Panel A reports the characteristics of aggregate net flow for our sample funds. The mean of aggregate flow over the sample period is −0.20 basis points (−0.002%) per day, or −0.5% in annualized term. The median of the daily flow is −0.64 basis points and the standard deviation is 10.69 basis points. While the total asset base increased during our sample period, the mean and median daily fund flows are slightly negative because funds experienced a significant outflow after the burst of the internet bubble in early 2000.

Despite the average negative aggregate flow, we notice that among the 1484 observations of aggregate net flow data, 685 are positive, while 799 are negative. That is, during about 54% of trading days, aggregate cash flows out of, rather than into, equity mutual funds. We present summary statistics of aggregate net inflow and outflow, respectively, in Panel A. We observe that the average of net inflow (0.084% per day) is greater than that of net outflow (0.076% per day). Panel B shows that there are significant and negative partial autocorrelations (PAC) for aggregate flow at lags 1 and 2, and there are significant and positive PAC at lags 4 and 5. The time series of daily aggregate fund flow is plotted in Fig. 1.

Table 1
Summary statistics of daily aggregate mutual fund flow

	Obs.	Mean (b.p.)	Median (b.p.)	Std. (b.p.)	Min (b.p.)	Max (b.p.)
Panel A: Aggregate mutual fund flow						
Daily net flow	1484	−0.20	−0.64	10.69	−58.93	60.64
Daily net inflow	685	8.40	6.19	7.62	0.00	60.64
Daily net outflow	799	−7.57	−5.80	6.70	−58.93	0.00
Panel B: Partial autocorrelations of aggregate mutual fund flow						
	Lag	1	2	3	4	5
Daily Net Flow		−0.12*	−0.10*	0.02	0.06*	0.08*

Daily aggregate mutual fund flow from February 1998 to December 2003 for a sample of 859 domestic equity funds. Panel A reports summary statistics of aggregate net fund flow, inflow, and outflow, respectively. Aggregate flow is scaled by the total TNAs of our sample funds on the previous day. Panel B presents the partial autocorrelations of aggregate net equity fund flow.

* Significant at 5% level, two-tailed test.

3.2. Measurement of daily volatility

We use three measures of daily market volatility in this study. The first is the high-frequency volatility estimator proposed by Andersen et al. (2001). They develop the daily volatility estimator by summing intraday squared five-minute returns. They argue that this estimator is free of measurement errors and model-free.[1] The second volatility estimator is the extreme value estimator (σ_{HL}) developed by Parkinson (1980), while the third one is similar to the high-frequency volatility estimator, but we pre-filter the intraday return by using a GARCH model. To save space, we present our main results by using the high-frequency volatility estimator and extreme value estimator.[2]

The first and third volatility measures are calculated by using the intraday levels of the S&P 500 index, while we calculate the second volatility measure by using the daily high/low levels of the S&P 500 index. We obtain the intraday and daily levels of the S&P 500 index from Tick Data, Inc. The tick-by-tick futures and index database provided by Tick Data is comprised of over 85 symbols. The S&P 500 index and other data are collected via multiple real-time data feeds. Tick Data takes several steps to ensure the accuracy of its ongoing data collection process, beginning at the source. To ensure continuity, Tick Data collects data from two geographical locations. All data are passed through the Data Manager, a suite of scrubbing and verification programs developed for the purpose of producing clean and robust data.

Following Andersen et al. (2001), we construct the five-minute return series of the S&P 500 index from the logarithmic difference between the prices recorded at or immediately before the corresponding five-minute interval. Since the five-minute return is serially correlated, we estimate an AR (5) model for the five-minute return series each day to remove the serial correlation. We then construct the high-frequency volatility estimator as

$$\sigma_{\mathrm{High},t} = \sqrt{\sum\nolimits_{i=1}^{N} (r_{t+i\Delta})^2}, \tag{2}$$

where $\sigma_{\mathrm{High},t}$ denotes daily market volatility based on high-frequency data on day t, Δ is the observation interval length (i.e., five minutes), N is the number of five-minute intervals in one trading day ($N = 78$), and $r_{t+i\Delta}$ is the intraday de-meaned and filtered S&P 500 index return in interval Δ on day t.

Summary statistics of alternative volatility estimators are provided in Table 2. Panel A shows that the daily average of high-frequency volatility (σ_{High}) and high-low volatility (σ_{HL}) are 14.7% and 15.9%, respectively. These two volatility estimators are highly correlated, with a correlation of 0.78 (see Panel C). Both volatility estimators are negatively correlated with daily fund flow (The correlations are −0.19 and −0.16). Finally, both volatility estimators exhibit substantial positive autocorrelations. Thus, we

[1] Andersen et al. (2001) justify using a sampling frequency of five minutes, stating that this interval is long enough to avoid most measurement errors and short enough to avoid microstructure biases.

[2] To ensure that our inferences are not sensitive to the particular estimator used, we repeat all the analyses by using the extreme value estimator and the third volatility estimator, reporting our results in Section 5.

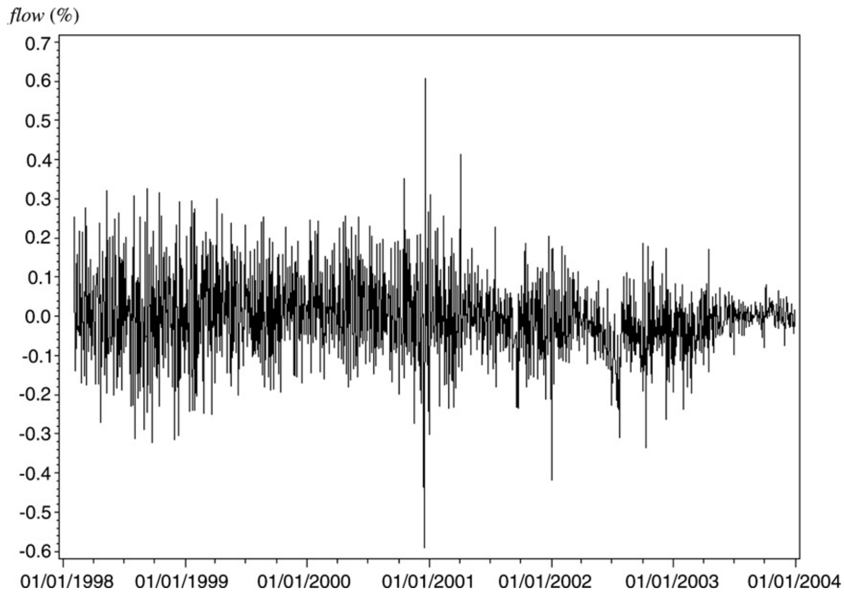

Fig. 1. Time series of daily aggregate US equity mutual fund flow. The figure plots the time series of daily aggregate domestic equity mutual fund flow from February 1998 to December 2003. Flow is scaled by the total TNAs on the previous day.

Table 2
Summary statistics of alternative volatility estimators

Panel A: Summary statistics	Mean (%)	Median (%)	Std. (%)	Min (%)	Max (%)
σ_{High}	14.7	13.4	6.2	3.5	52.2
σ_{HL}	15.9	14.2	8.3	2.7	80.9
Panel B: Partial autocorrelations	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
σ_{High}	0.70*	0.26*	0.10*	0.16*	0.07
σ_{HL}	0.41*	0.32*	0.19*	0.11*	0.10*

Panel C: Correlations	σ_{High}	σ_{HL}	*flow*
σ_{High}	1.00		
σ_{HL}	0.78*	1.00	
Flow	−0.19*	−0.16*	1.00

Summary statistics of high-frequency volatility (σ_{High}) and high-low volatility (σ_{HL}) from February 1998 to December 2003. σ_{High} is calculated using intraday S&P 500 index returns and σ_{HL} is based on the extreme value method of Parkinson (1980). Panels A and B present summary statistics and partial autocorrelations of both volatility estimators. Panel C reports the correlations of two volatility estimators and *flow*, where *flow* is the aggregate flow for a sample of 859 domestic equity funds.

* Significant at 5% level, two-tailed test.

control for the autocorrelations in our later tests. The time series of two volatility estimators are plotted in Fig. 2.

4. Empirical results

In the previous section, we provide correlation evidence for the co-movement between market volatility and mutual fund flow. Although these unconditional results suggest a relationship between volatility and flow, they do not clearly depict the structure of the relationship and do not control for other factors that are likely to influence volatility and flow. In this section, we use a VAR approach to examine the dynamic relationship between market volatility and flow.

4.1. VAR analysis

In its general form, a p-th order Gaussian VAR model can be represented as

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + e_t, \tag{3}$$

where $Y_t = (Y_{1,t}, \ldots, Y_{K,t})'$ is a vector time series of variables, μ is a k-vector of intercepts, ϕ_i $(i = 1, \ldots, p)$ are $k \times k$ parameter matrices with all eigenvalues of ϕ having moduli less than one so that the time series is stationary, and e_t is the error vector, which is assumed to be i.i.d. k-variate normally distributed with expectation the zero vector, and variance matrix Σ. Before conducting the VAR analysis, it is important to note that each time series should be a stationary process. To test the stationarity of the variables of our interest, we perform both Dickey-Fuller and Phillips-Perron unit root tests (with and without drift). The results, although not reported, suggest that the unit root hypotheses are strongly rejected in favor of the stationary hypotheses for all the variables of our interest. We obtain maximum likelihood estimates of ϕ and Σ using iterated least squares method. The selection of VAR lag length is based on a top-down approach.[3]

[3] Given an initial choice of the lag length p, the top-down approach entails conducting joint Wald tests of the null hypotheses that the lag length can be reduced to q for $q = p-1, p-2$, and so forth., up to the point where the null hypothesis is rejected.

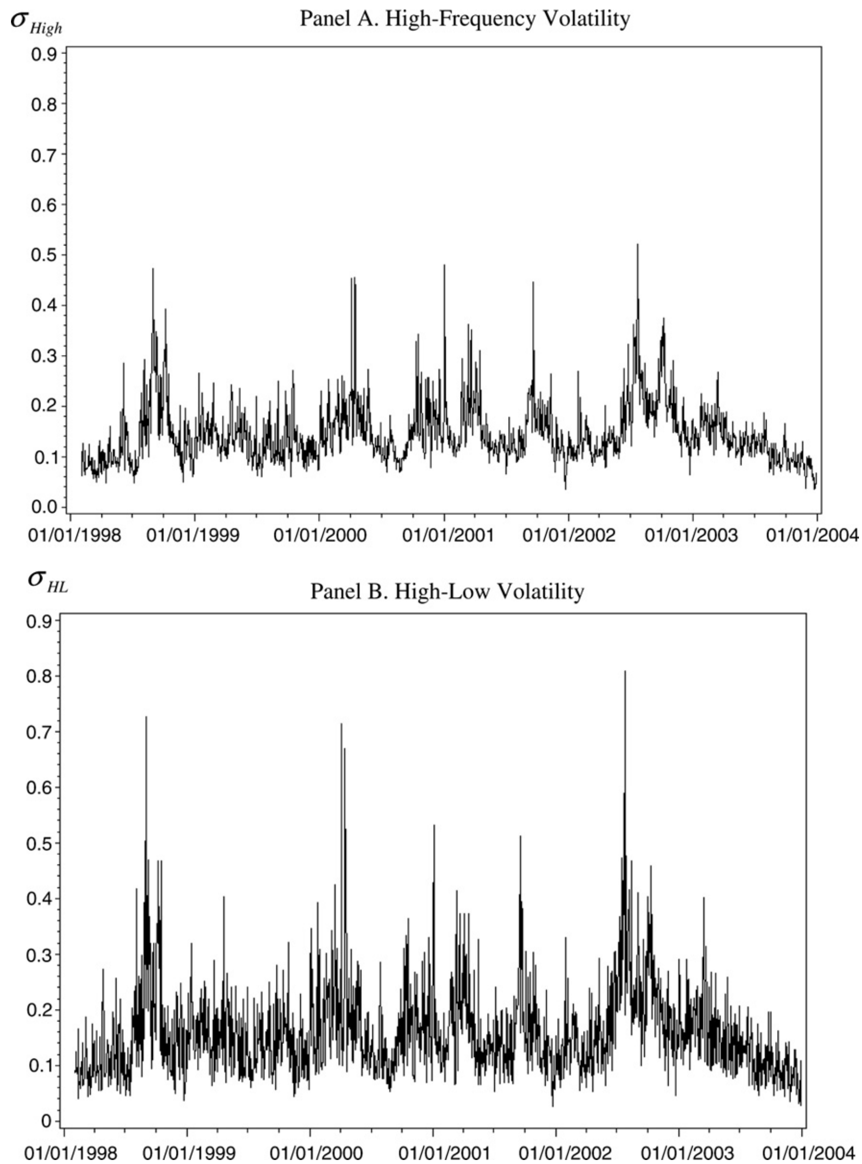

Fig. 2. Time series of alternative market volatility estimators. The figures plot time series of two market volatility estimators from February 1998 to December 2003: high-frequency volatility (σ_{High}) in Panel A and high-low volatility (σ_{HL}) in Panel B.

We first examine a bivariate model that consists of high-frequency volatility ($\ln(\sigma_{\mathrm{High}})$) and flow, i.e., $Y_t = (\ln(\sigma_{\mathrm{High},t}), flow_t)$, which provides a preliminary overview of the dynamic relationship between market volatility and flow. Given the well-documented negative correlation between market returns and volatility (see French et al., 1987; Nelson, 1991), it is possible that the volatility–flow relationship is a spurious result of the positive flow-return relationship documented by Edelen and Warner (2001). To address this issue, we examine a three-factor VAR model including S&P 500 returns (*mkret*) (i.e., $Y_t = (\ln(\sigma_{\mathrm{High},t}), flow_t, mkret_t)$) to determine whether meaningful changes occur after we control for market returns.

In our bivariate VAR specification, the coefficients of our main interest are the off-diagonal coefficients $\phi_1(1,2)$, $\phi_2(1,2)$, $\phi_3(1,2)$, etc. Specifically, the coefficient $\phi_1(1,2)$ characterizes the relationship between market volatility and fund flow with one-day lag. If $\phi_1(1,2)$ is negative and significant, then there exists an asymmetric relationship between volatility and inflow versus volatility and outflow: more inflow is associated with lower volatility while more outflow is associated with higher volatility on the next day. Other off-diagonal coefficients, such as $\phi_1(2,1)$, $\phi_2(2,1)$, $\phi_3(2,1)$, characterize the impact of lagged volatility on flow.

Table 3 reports coefficient estimates of the bivariate and three-factor VAR models. The top-down methodology indicates that we should use lag 13 and 11, respectively, for each model.[4] Looking first at the bivariate model, we find that market volatility is negatively related to flow at lags 1, 2, and 3, suggesting that flow has a negative impact

[4] For brevity, only the coefficients for the first three lags are reported in Table 3.

Table 3
Coefficient estimates of the bivariate and three-factor VAR models

	Bivariate model ($p = 13$)		Three-factor model ($p = 11$)		
	$\ln(\sigma_{\mathrm{High},t})$	$flow_t$	$\ln(\sigma_{\mathrm{High},t})$	$flow_t$	$mkret_t$
Intercept	−0.21*	0.01	−0.20*	−0.01	0.56*
	(−4.37)	(0.53)	(−4.41)	(−0.52)	(2.25)
$\ln(\sigma_{\mathrm{High},t-1})$	0.38*	−0.09*	0.30*	−0.04*	0.09
	(14.26)	(−8.28)	(10.88)	(−3.94)	(0.60)
$\ln(\sigma_{\mathrm{High},t-2})$	0.14*	0.06*	0.16*	0.03*	0.30*
	(4.95)	(4.85)	(5.50)	(2.98)	(1.97)
$\ln(\sigma_{\mathrm{High},t-3})$	0.04	0.02	0.05	0.01	−0.19
	(1.20)	(1.74)	(1.87)	(1.19)	(−1.23)
Wald test p-value	{0.00}	{0.00}	{0.00}	{0.00}	{0.41}
$flow_{t-1}$	−0.22*	−0.22*	−0.18*	−0.15*	0.16
	(−3.43)	(−8.37)	(−2.53)	(−5.61)	(0.40)
$flow_{t-2}$	−0.26*	−0.17*	−0.23*	−0.14*	0.16
	(−3.90)	(−6.02)	(−3.19)	(−5.43)	(0.40)
$flow_{t-3}$	−0.17*	−0.04	−0.12	−0.01	0.19
	(−2.43)	(−1.33)	(−1.61)	(−0.42)	(0.49)
Wald test p-value	{0.00}	{0.00}	{0.03}	{0.00}	{0.72}
$mkret_{t-1}$			−0.05*	0.04*	0.04
			(−9.90)	(22.80)	(1.47)
$mkret_{t-2}$			−0.01*	−0.01*	−0.02
			(−2.07)	(−5.64)	(−0.52)
$mkret_{t-3}$			−0.01	0.00	0.02
			(−1.80)	(1.01)	(0.55)
Wald test p-value			{0.00}	{0.00}	{0.54}
R^2	58.9%	13.8%	62.0%	37.9%	2.2%

The table reports the coefficient estimates of the VAR model

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + e_t$$

where $Y_t = (Y_{1,t}, \ldots, Y_{K,t})'$ is a vector time series of variables, μ is a k-vector of intercepts, $\phi_i(i = 1, \ldots, p)$are $k \times k$ parameter matrices, and e_t is the error vector. The bivariate model consists of ln (σ_{High}) and *flow*, where σ_{High} is the high-frequency volatility estimator, and *flow* is the aggregate flow for a sample of 859 domestic equity funds. The three-factor model includes $\ln(\sigma_{\mathrm{High}})$, flow and market returns (*mkret*) where *flow* and *mkret* are in percentage. The VAR lag length, p, is chosen using a top-down method. For brevity, only the coefficient estimates of the first three lags are reported. t-Statistics are reported in parentheses. The null hypothesis of the Wald test is that the coefficients of lagged variables are jointly 0. p-values for the Wald test are reported in braces. The sample period is from February 1998 to December 2003.

* Significant at 5% level, two-tailed test.

on subsequent market volatility. Since flow can take a positive value (inflow) or a negative value (outflow), our results indicate that, holding everything else constant, inflow is associated with lower volatility while outflow is associated with higher volatility on the next day.

Other results, including the positive autocorrelations in market volatility and negative autocorrelations in fund flow, are consistent with findings of Bollerslev et al. (1992) and Edelen and Warner (2001). Table 3 also shows that flow is negatively related to the previous day's volatility, which suggests that mutual fund investors might time market volatility (A test of volatility timing using impulse response analysis is presented in the next section.).

The estimation results from the three-factor VAR model provide additional evidence for the volatility–flow relation. First, the volatility–flow relationship obtained from the bivariate model still holds after we control for market returns. Thus, the uncovered flow–volatility relationship is not driven by the correlation between flow and returns. Second, concurrent flow is positively related to the previous day's market returns and negatively related to returns with a two-day lag, while concurrent return is not related to lagged flow. This flow-return relationship is consistent with Edelen and Warner (2001). This exercise not only validates our self-constructed flow data, but it also extends Edelen and Warner's tests to a more recent period and to a dynamic setting. Finally, we document that volatility is negatively related to lagged returns, but return is not related to lagged volatilities. This suggests that the documented negative volatility-return relationship might result from higher (lower) returns leading to lower (higher) volatility.

Based on the VAR results, we test the Granger-causality between volatility and flow. As the focus of this paper is on the dynamic relation between mutual fund flow and market volatility, we test (1) whether flow Granger-causes market volatility and (2) weather volatility Granger-causes flow. If flow does not Granger-cause volatility, the coefficients of volatility on the lagged flow should be jointly zeros. Similarly, if market volatility does not Granger-cause flow, the coefficients of flow on the lagged volatility should be jointly zeros.

Table 3 presents the Wald test results and corresponding p-values. The results reject the null hypothesis that flow does not Granger-cause market volatility at the 5% significance level for both VAR specifications. For example, for the bivariate VAR model, the Wald test statistic is 30.6 and the corresponding p-value is 0.00. For the three-factor VAR model, the p-value of the Wald test is 0.03. Further, the Wald test rejects the null hypothesis that the coefficients of flow on the lagged volatility are jointly zeros – all p-values of the Wald test are less than 5% significant level. These results reaffirm our earlier finding that flow has a significant impact on volatility and vice verse. The Granger-causality test implies that the level of flow and volatility Granger-cause each other, suggesting that we should study the inter-temporal relationship between innovations in flow and volatility in both directions.

4.2. Structural VAR impulse response analysis

In the previous section, the VAR results and the Granger-causality tests focus on the level of market volatility and flow. Since there are substantial autocorrelations in both flow and volatility, a natural question to ask is whether unexpected flow has an impact on subsequent unexpected volatility. We now investigate the dynamic relationship between innovations in market volatility and flow.

Table 4
Contemporaneous correlations between VAR innovations

	$\ln(\sigma_{\text{High},t})$	$flow_t$	$mkret_t$
$\ln(\sigma_{\text{High},t})$	1.00		
$flow_t$	-0.10^{*}	1.00	
$mkret_t$	-0.26^{*}	0.04	1.00

The table reports the contemporaneous correlations between innovations from the VAR (11) model consisting of $\ln(\sigma_{\text{High}})$, *flow*, and market returns (*mkret*), where σ_{High} is the high-frequency volatility estimator and *flow* is the aggregate flow for a sample of 859 domestic equity funds. The VAR lag length was chosen using a top-down approach. The sample period is from February 1998 to December 2003.

* Significant at 5% level, two-tailed test.

Table 4 reports the contemporaneous correlations between innovations of the three-factor VAR model. As shown in the table, volatility shocks are negatively correlated with flow shocks at the 5% significance level with a correlation of −0.10. Next, we assess the impact of flow shocks on volatility shocks using the structural VAR approach proposed by Bernanke (1986) and Sims (1986). Specifically, we examine the three-factor structural VAR model, which consists of high-frequency volatility ($\ln(\sigma_{\text{High}})$), *flow*, and market returns (*mkret*). Assuming that volatility shocks are determined by flow and return shocks, and that flow shocks are determined only by return shocks, we find volatility shocks respond negatively to concurrent flow shocks with a coefficient estimate of −0.284 and a *t*-Statistic of −4.44.[5]

To examine the dynamic relationship between innovations in volatility and innovations in flow, we study the impulse response functions, which provide the estimated dynamic response of a variable to a unit standard deviation shock in other variables. Fig. 3 plots the impulse response function of $\ln(\sigma_{\text{High}})$ to a unit shock in *flow* over a 60-day period. Two standard error bands are also provided to assess the significance of the impact of flow shocks on volatility. The figure indicates that flow shocks have a pronounced negative impact on market volatility, especially over the subsequent 10 days. For example, a positive unit standard deviation shock in *flow* generates an initial day decline of 0.06 standard deviation of volatility and its impact is less than 0.02 standard deviation of volatility after 20 days.

Therefore, much as we did for the VAR coefficient estimates we reported previously, we document an asymmetry between the impact of inflow shocks and outflow shocks on market volatility – A unit shock in inflow (outflow) predicts a decline (increase) in concurrent and next day volatility.

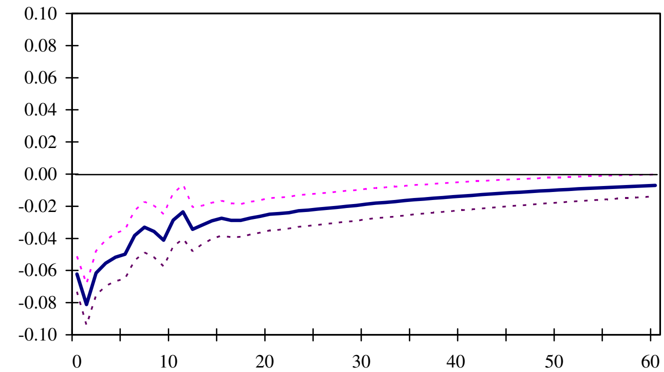

Fig. 3. Impulse responses of high-frequency volatility to flow. The figure plots the impulse responses of high-frequency volatility ($\ln(\sigma_{\text{High}})$) to a unit standard deviation shock in flow in a structural VAR(11) model that consists of ln (σ_{High}), *flow*, and market returns (*mkret*), assuming that volatility shocks are determined by flow and return shocks and that flow shocks are determined by return shocks. The VAR lag length is chosen using a top-down approach. The dotted lines represent the plus and minus two standard error bands. The sample period is from February 1998 to December 2003.

Further, the impact of flow shocks on volatility is large during the first few days and then gradually dissipates over two months.

4.3. Evidence of volatility timing

Busse (1999) investigates the question of whether mutual funds time market volatility using daily fund returns from 1985 to 1995, and finds that (1) there is a significant relation between volatility timing and a traditional measure of investment performance at individual fund level; (2) funds decrease market exposure when the market volatility is high; and (3) the systematic risk of surviving funds is sensitive to market volatility. In this subsection, we extend the test for volatility timing for a recent period (1998–2003) from the perspective of flow–volatility relationship for a recent period.

The estimation results reported in Table 3 suggest that flow is negatively related to the previous day's volatility. If the previous day's market volatility is high (low), the next day's flow tends to be low (high). Now we examine the ability of timing volatility by using the three-factor VAR model consisting of $\ln(\sigma_{\text{High}})$, *flow*, and *mkret*, and by analyzing impulse responses. We assume that flow shocks are determined by volatility and return shocks, and that volatility shocks are determined by return shocks.[6]

Our result indicates a significantly negative contemporaneous response of flow to shocks in volatility (the coefficient estimate is −0.04 with a *t*-statistic of −4.32). The impulse response function of flow to a unit standard devi-

[5] We reach similar conclusions under other assumptions that innovations in market volatility are determined by innovations in flow, and (1) innovations in returns are determined by innovations in volatility and flow; (2) innovations in flow are determined by innovations in returns, which are determined by innovations in volatility; or (3) innovations in volatility are determined by innovations in returns, which are determined by innovations in flow.

[6] We also consider other assumptions and find that our results remain unchanged.

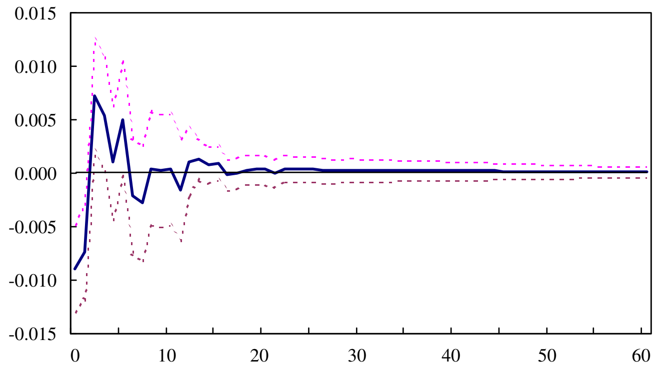

Fig. 4. Impulse responses of flow to high-frequency volatility. The figure plots the impulse responses of flow to a unit standard deviation shock high-frequency volatility ($\ln(\sigma_{\text{High}})$) in a structural VAR (11) model that consists of $\ln(\sigma_{\text{High}})$, *flow*, and market returns (*mkret*), assuming that flow shocks are determined by volatility and return shocks and that volatility shocks are determined by return shocks. The VAR lag length is chosen using a top-down approach. The dotted lines represent the plus and minus two standard error bands. The sample period is from February 1998 to December 2003.

ation shock in market volatility is plotted in Fig. 4. The plot suggests that a unit shock in market volatility has a significant, but temporary, impact on flow. In particular, a positive shock in market volatility results in less inflow one-day after the shock, and the impact dissipates to zero very soon thereafter. Therefore, the impact of volatility shock on flow is short-lived, compared to the impact of flow shock on volatility. Overall, the structural VAR impulse response analyses provide supporting evidence that mutual fund investors time volatility.

4.4. Trading volume

It is well known that trading volume is positively related to volatility (Karpoff, 1987). This correlation between volume and volatility raises the concern of whether the volatility–flow dynamic is a spurious manifestation of the volatility–volume dynamic. To rule out this possibility, we include market turnover rate (TR) as a control variable in the VAR model. The turnover rate is defined as the value-weighted average of daily trading volume for all NYSE/AMEX/Nasdaq stocks, divided by their shares outstanding at the end of the previous day.

Table 5 presents coefficient estimates of the VAR model which consists of $\ln(\sigma_{\text{High}})$, *mkret*, *flow*, and TR.[7] Our result shows that the flow–volatility dynamic still holds, even after controlling for market turnover. For example, volatility is negatively related to prior flows at the first two lags, with *t*-Statistics of -2.68 and -3.24, respectively. Additional result suggests that market turnover has little impact on the impulse responses of volatility to flow–flow shocks still have a negative impact on volatility after controlling for market turnover. We conclude that the impact of flow on market volatility is not a spurious manifestation of the impact of overall market volume on volatility.

4.5. Test for relationship between intraday volatility and daily flow

According to Edelen and Warner (2001), mutual fund managers may receive flow information provided by their transfer agent prior to the close of a trading day, and the information has some predictability. Some fund managers have informal arrangements with their transfer agent, who is expected to telephone fund managers about unusually large individual transactions by mid-afternoon. Further, institutional investors in a fund often give a one-day advance notice for large wire transfers. This common practice helps fund managers to predict flow and subsequent returns. Edelen and Warner (2001) find a stronger relation between market return and flow in the afternoon than in the morning.

Our previous results indicate that there is a negative concurrent relationship between daily market volatility and daily flow–inflow is associated with lower volatility, while outflow is associated with higher volatility. If fund managers have access to flow information prior to the end of a trading day, and if they make trades based on that flow information (fund-share transactions), we expect intraday volatility to decrease over the trading day, as fund managers receive additional information about fund inflow. On the other hand, we expect intraday volatility to increase as fund managers learn about outflow during a typical day. Now we examine the relation between intraday volatility and daily flow.

Table 6 presents estimates from the following regression equations:

$$\ln(\sigma^T_{\text{High},t}) = \alpha_0 + \alpha_1 flow_t + \sum_{i=1}^{5} \beta_i \ln(\sigma_{\text{High},t-i}) + \varepsilon_t, \tag{4}$$

$$\ln(\sigma^T_{\text{High},t}) = \alpha_0 + \alpha_1 \text{inflow}_t + \alpha_2 \text{outflow}_t + \sum_{i=1}^{5} \beta_i \ln(\sigma_{High,t-i}) + \varepsilon_t, \tag{5}$$

where $\text{inflow}_t = \begin{cases} flow_t, & \text{if} \quad flow_t >= 0 \\ 0, & \text{if} \quad flow_t < 0 \end{cases}$
and $\text{outflow}_t = \begin{cases} 0, & \text{if} \quad flow_t >= 0 \\ flow_t, & \text{if} \quad flow_t < 0 \end{cases}$.

The superscript T denotes an intraday period (Open-11:00, 11:00-15:00, or 15:00-close). The two regression models are estimated for each intraday period separately. The dependent variable is the high-frequency volatility, computed by using intraday returns on the S&P 500 index during a given intraday period. The lagged daily volatilities from previous days are used as control variables.

Table 6 reveals that the relation between intraday volatility and daily flow is negative for each of the three intraday periods. For the time periods of open-11:00,

[7] The lag length is set at seven using a top-down approach. For brevity, only the first three lags are reported.

Table 5
Coefficient estimates of the VAR model including market turnover

	$\ln(\sigma_{\mathrm{High},t})$		$flow_t$		$mkret_t$		TR_t	
	Estimate	t-Statistics	Estimate	t-Statistics	Estimate	t-Statistics	Estimate	t-Statistics
Intercept	−0.21*	−4.01	−0.01	−0.69	0.22	0.78	0.57	1.28
$\ln(\sigma_{\mathrm{High},t-1})$	0.28*	10.33	−0.03*	−3.34	0.11	0.74	0.18	0.76
$\ln(\sigma_{\mathrm{High},t-2})$	0.16*	5.50	0.03*	3.27	0.28	1.82	−0.48	−1.95
$\ln(\sigma_{\mathrm{High},t-3})$	0.05	1.84	0.01	1.28	−0.19	−1.18	−0.28	−1.10
$flow_{t-1}$	−0.19*	−2.68	−0.14*	−5.21	0.15	0.39	−0.55	−0.89
$flow_{t-2}$	−0.24*	−3.24	−0.13*	−5.07	0.15	0.38	−1.36*	−2.18
$flow_{t-3}$	−0.12	−1.65	0.00	−0.01	0.18	0.45	−0.87	−1.37
$mkret_{t-1}$	−0.05*	−10.11	0.04*	22.7	0.04	1.46	0.05	1.18
$mkret_{t-2}$	−0.01*	−2.16	−0.01*	−5.41	−0.02	−0.6	−0.06	−1.24
$mkret_{t-3}$	−0.01	−1.82	0.00	1.21	0.01	0.39	0.00	0.04
TR_{t-1}	0.01*	2.14	−0.00*	−2.09	−0.02	−1.34	0.21*	7.78
TR_{t-2}	−0.00	−0.72	0.00	−0.32	0.01	0.79	0.33*	12.35
TR_{t-3}	0.00	−0.15	−0.00	−0.45	0.01	0.26	−0.00	−0.08
R^2	62.2%		37.5%		3.0%		46.8%	

The table reports the coefficient estimates of the VAR model

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + e_t$$

where $Y_t = (Y_{1,t}, \ldots, Y_{K,t})'$ is a vector time series of variables, μ is a k-vector of intercepts, $\phi_i (i = 1, \ldots, p)$ are $k \times k$ parameter matrices, and e_t is the error vector. The model consists of high-frequency volatility ($\ln(\sigma_{\mathrm{High}})$), *flow*, market return (*mkret*), and market turnover rate (TR). *flow* and *mkret* are denominated in percentages. The VAR lag length, p, is set at 10 using a top-down method. For brevity, only the coefficient estimates of the first three lags are reported. The sample period is from February 1998 to December 2003.

* Significant at 5% level, two-tailed test.

Table 6
Test for the relationship between intraday volatility and daily flow

Intraday Period	Open_t- $11{:}00_t$		$11{:}00_t$–$15{:}00_t$		$15{:}00_t$-Close_t	
	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	−0.19*	−0.21*	−0.45*	−0.47*	−0.20*	−0.26*
	(−4.09)	(−4.14)	(−9.96)	(−9.69)	(−2.82)	(−3.30)
$flow_t$	−0.47*		−0.52*		−0.39*	
	(−6.62)		(−7.59)		(−3.54)	
inflow_t		−0.38*		−0.41*		−0.10
		(−3.07)		(−3.48)		(−0.55)
$\mathrm{outflow}_t$		−0.57*		−0.64*		−0.71*
		(−4.30)		(−4.97)		(−3.43)
$\ln(\sigma_{\mathrm{High},t-1})$	0.44*	0.44*	0.39*	0.39*	0.40*	0.40*
	(14.77)	(14.70)	(13.47)	(13.40)	(8.60)	(8.50)
$\ln(\sigma_{\mathrm{High},t-2})$	0.24*	0.23*	0.22*	0.22*	0.21*	0.20*
	(7.28)	(7.22)	(7.03)	(6.96)	(4.10)	(4.00)
$\ln(\sigma_{\mathrm{High},t-3})$	0.02	0.02	0.04	0.04	0.07	0.07
	(0.54)	(0.53)	(1.31)	(1.30)	(1.44)	(1.42)
R^2	51.3%	51.4%	53.9%	54.0%	32.0%	32.1%

The regression results are based on the following equations:

$$\ln(\sigma^T_{\mathrm{High},t}) = \alpha_0 + \alpha_1 flow_t + \sum_{i=1}^{5} \beta_i \ln(\sigma_{\mathrm{High},t-i}) + \varepsilon_t, \tag{4}$$

$$\ln(\sigma^T_{\mathrm{High},t}) = \alpha_0 + \alpha_1 \mathrm{inflow}_t + \alpha_2 \mathrm{outflow}_t + \sum_{i=1}^{5} \beta_i \ln(\sigma_{\mathrm{High},t-i}) + \varepsilon_t, \tag{5}$$

where $\mathrm{inflow}_t = \begin{cases} flow_t, & \text{if} \quad flow_t >= 0 \\ 0, & \text{if} \quad flow_t < 0 \end{cases}$ and $\mathrm{outflow}_t = \begin{cases} 0, & \text{if} \quad flow_t >= 0 \\ flow, & \text{if} \quad flow_t < 0 \end{cases}$

The superscript T denotes an intraday period (Open-11:00, 11:00–15:00, or 15:00-close). The two regression models are estimated for each intraday period. The dependent variable is the high-frequency volatility computed by using intraday returns on the S&P 500 index during an intraday period. The lagged daily volatility from previous days are used as control variables. t-Statistics are in parentheses.

* Significant at 5% level, two-tailed test.

11:00-15:00 and 15:00-close, the coefficient estimates are −0.47, −0.52 and −0.39, respectively (with t-Statistics being −6.62, −7.59 and −3.54). While there is a difference between early morning and late afternoon results, the difference appears to be small. One drawback of the regression specification in Eq. (4) is that it does not allow us to assess the differential impact of inflow versus outflow on volatility.

We decompose flow into inflow and outflow, and we include both variables in Eq. (5). The separation of inflow from outflow reveals several interesting results. For example, the two coefficients of inflow are close to each other for the time periods of open-11:00 and 11:00-15:00 (−0.38 versus −0.41) and both are significant at 5% level with t-Statistics being −3.07 and −3.48. However, the coefficient estimate (−0.10) becomes close to zero and insignificant during the period of 15:00-close (t-Statistic = −0.55). As a result, the relation between intraday volatility and inflow is significant and stable prior to 15:00, but non-exist in the last trading hour. A possible explanation for this result is that fund managers may decide, during the last trading hour, to wait until the next day to purchase more stocks, even though they learn more about inflow during the last hour than during earlier periods.

The coefficient estimate of outflow during each period shows a different pattern: it increases in the magnitude monotonically from morning to afternoon. For instance, the estimated coefficients are −0.57, −0.64 and −0.71 for the three time periods. The relation between intraday volatility and outflow becomes progressively stronger from morning to afternoon. The negative coefficient, together with outflow (which takes a negative value), implies that intraday volatility increases from morning to afternoon, assuming everything else is equal. One explanation for this finding is that as fund managers know more about outflow toward the end of a trading day, they may furiously sell securities before the market closes, in order to meet redemption requirements.

5. Robustness check

To ensure that our results are not sensitive to the particular volatility estimator used, we re-examine the volatility–flow relationship by using two alternative volatility estimators. The first one is the high-low volatility (σ_{HL}). Table 7 reports the VAR coefficient estimates and shows that the results using σ_{HL} are similar to the previously presented results. For example, σ_{HL} is negatively related to previous flow at lags 1 and 2, with t-Statistics being −3.25 and −2.86, respectively.

We then re-examine the structural VAR model consisting of $\ln(\sigma_{\mathrm{HL}})$, *flow*, and *mkret*. Under the hypothesis that flow causes volatility, we assume that volatility shocks are determined by both flow and return shocks, while flow shocks are only determined by return shocks. Similar to the results relying on high-frequency volatility estimator, σ_{High}, we find that flow shocks response significantly to shocks in σ_{HL} with a coefficient estimate of −0.396 (t-Statistic = −3.80). Fig. 5 plots the impulse response function of σ_{HL} to *flow*. The figure provides evidence that is qualitatively similar to that in Fig. 3, when the volatility is the high-frequency volatility estimator, σ_{High}.

The second alternative volatility estimator is obtained by using a GARCH model. Extant literature documents

Table 7
Coefficient estimates of the three-factor VAR model using high-low volatility

	$\ln(\sigma_{\mathrm{HL},t})$		$flow_t$		$mkret_t$	
	Estimate	t-Statistics	Estimate	t-Statistics	Estimate	t-Statistics
Intercept	−0.32*	−4.74	0.00	0.16	0.52*	2.14
$\ln(\sigma_{\mathrm{HL},t-1})$	−0.01	−0.50	−0.00	−0.32	−0.02	−0.21
$\ln(\sigma_{\mathrm{HL},t-2})$	0.16*	5.98	0.01*	1.97	−0.00	−0.03
$\ln(\sigma_{\mathrm{HL},t-3})$	0.10*	3.61	0.00	0.77	0.04	0.43
$flow_{t-1}$	−0.39*	−3.25	−0.10*	−3.97	0.12	0.43
$flow_{t-2}$	−0.35*	−2.86	−0.13*	−4.78	0.17	0.39
$flow_{t-3}$	−0.11	−0.95	0.01	0.19	0.04	0.08
$mkret_{t-1}$	−0.08*	−11.28	0.05*	28.57	−0.02	−0.67
$mkret_{t-2}$	−0.05*	−5.17	−0.01*	−6.20	−0.04	−1.19
$mkret_{t-3}$	−0.03*	−2.78	0.00	0.95	−0.05	−1.36
R^2	42.8%		43.8%		2.1%	

The table reports the coefficient estimates of the VAR model

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + e_t$$

where $Y_t = (Y_{1,t}, \ldots, Y_{K,t})'$ is a vector time series of variables, μ is a k-vector of intercepts, $\phi_i (i = 1, \ldots, p)$ are $k \times k$ parameter matrices, and e_t is the error vector. The model consists of $\ln(\sigma_{\mathrm{HL}})$, *flow*, and market return (*mkret*), where σ_{HL} is the high-low volatility estimator and *flow* is the aggregate flow for a sample of 859 domestic equity funds. *flow* and *mkret* are denominated in percentages. The VAR lag length, p, is set at 11 using a top-down method. For brevity, only the coefficient estimates of the first three lags are reported. The sample period is from February 1998 to December 2003.

* Significant at 5% level, two-tailed test.

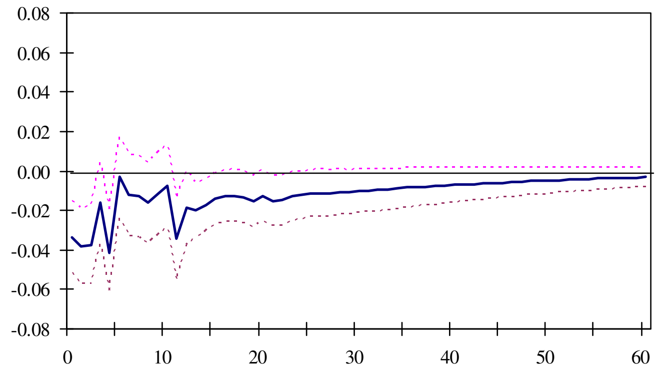

Fig. 5. Impulse responses of high-low volatility to flow. The figure plots the impulse responses of high-low volatility (ln (σ_{HL})) to a unit standard deviation shock in flow in a structural VAR (12) model that consists of ln(σ_{HL}), *flow*, and market returns (*mkret*), assuming that volatility shocks are determined by flow and return shocks and that flow shocks are determined by return shocks. The VAR lag length is chosen using a top-down approach. The dotted lines represent the plus and minus two standard error bands. The sample period is from February 1998 to December 2003.

that market returns exhibit conditional heteroskedasticity (French et al., 1987; Nelson, 1991). To take this property into account, we adopt a two-step procedure. In the first step, we estimate a GARCH(1,1) model with an AR(5) specification for the intraday return on the S&P 500 index. The estimation is done for each day in our sample. In the second step, we use the residual from the mean equation of the GARCH model and Eq. (2) to obtain a new volatility estimator each day. We then re-estimate the three-factor VAR model and re-do the impulse response analysis. Once again, the results are similar to those reported in Table 3 and Figs. 3 and 4. For example, the relation between market volatility and lag-1 flow is negative and significant (the coefficient estimate is -0.21 and the t-Statistic is -3.36).

The next robustness test addresses the concern of whether our results are driven by (1) a few large volatility spikes and (2) the events of September 11, 2001, which has a large impact on market volatility. Indeed, our sample period is characterized by five large volatility spikes related to the Russian financial crisis, the burst of the internet bubble, the 9/11 events, etc. We remove five observations corresponding to the five largest volatility outliers from the sample and find that our main results remain unchanged. To ensure that our results are robust and not being driven by the 9/11 events, we split our data into two sub-periods: one starting in February of 1998 and running through August of 2001, and the other starting in October of 2001 and running through the end of 2003. We find that the result of testing volatility–flow relationship is stronger during the first than during the second sub-period (a shorter period). The VAR coefficient that characterizes the relation between volatility and the lag-1 flow is -0.18 and significant at 5% level during the pre-9/11 period, however, this coefficient is -0.12 and only significant at the 10% level during the post-9/11 period. Overall, while a shorter sample could lead to less powerful tests, our analysis based on the two sub-samples yields findings similar to those presented in previous sections, suggesting that our results are not a byproduct of including the 9/11 events in our sample.

6. Conclusion

This paper empirically examines the dynamic relation between aggregate mutual fund flow and market-wide volatility. There are many arguments for and against the linkage between flow and market volatility, however, most of them are heuristic and judgmental. This paper is the first that provides direct evidence of the relation between flow and market volatility.

Our sample comprises 859 domestic equity funds and spans the time period from 1998 to 2003. Using a VAR approach, we show that market volatility is negatively related to concurrent and lagged flow, and that shock in flow has a negative impact on market volatility. One implication of this result is that a positive shock in flow (inflow shock) predicts a decline in volatility, while a negative shock in flow (outflow shock) predicts an increase in volatility on the next day. We also find evidence of volatility timing for a recent period of 1998–2003. Last, we uncover a differential impact of daily inflow versus outflow on intraday volatility. The relation between intraday volatility and daily flow is stable from morning until 15:00, but this relation disappears during the last trading hour. Further, the relation between volatility and outflow becomes stronger, progressively, from morning to afternoon. These results suggest that the response of fund managers to inflow is different from that to outflow as a trading day progresses.

Acknowledgements

This research is supported by the Research Grant Council of the Hong Kong Government (Earmarked Grant: HKU7141/02H). Special thanks go to Giorgio Szego and two anonymous referees for insights that greatly improved the quality of our paper. We thank Herman Bierens, Tim Simin, Michelle Lowry, Laura Field, Bill Kracaw and seminar participants at Pennsylvania State University and Financial Management Association Meetings for helpful comments.

References

Andersen, Torben, Bollerslev, Tim, Diebold, Francis, Ebens, Heiko, 2001. The distribution of realized stock return volatility. Journal of Financial Economics 61, 43–76.

Bernanke, Ben, 1986. Alternative explanations of the money-income correlation. Carnegie-Rochester Conference Series on Public Policy 25, 49–100.

Black, Fischer, 1996. Noise. Journal of Finance 41, 529–543.

Bollerslev, Tim, Chou, Ray, Kroner, Kenneth, 1992. ARCH modeling in finance: A review of the theory and empirical evidence. Journal of Econometrics 52, 5–59.

Busse, Jeffrey A., 1999. Volatility timing in mutual funds: Evidence from daily returns. Review of Financial Studies 12, 1009–1041.
Chalmers, John, Edelen, Roger, Kadlec, Gregory, 2001. On the perils of financial intermediaries setting security prices: The mutual fund wild card option. Journal of Finance 56, 2209–2236.
Coval, Joshua, Stafford, Erik, 2007. Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86, 101–125.
Edelen, Roger, Warner, Jerold, 2001. Aggregate price effects of institutional trading: A study of mutual fund flow and market returns. Journal of Financial Economics 59, 195–220.
French, Kenneth, Schwert, William, Stambaugh, Robert, 1987. Expected stock returns and volatility. Journal of Financial Economics 19, 3–29.
Froot, Kenneth, O'Connell, Paul, Seasholes, Mark, 2001. The portfolio flows of international investors. Journal of Financial Economics 59, 151–193.
Greene, Jason, Hodges, Charles, 2002. The dilution impact of daily fund flows on open-end mutual funds. Journal of Financial Economics 65, 131–158.
Ippolito, Richard, 1992. Consumer reaction to measures of poor quality: Evidence from the mutual fund industry. Journal of Law and Economics 35, 45–70.
Karpoff, Jonathan, 1987. The relation between price changes and trading volume: A survey. Journal of Financial and Quantitative Analysis 22, 109–126.
Lee, Charles, Shleifer, Andrew, Thaler, Richard, 1991. Investor sentiment and the closed-end fund puzzle. Journal of Finance 46, 75–109.
Nelson, Daniel, 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica 59, 347–370.
Parkinson, Michael, 1980. The extreme value method for estimating the variance of the rate return. Journal of Business 53, 61–66.
Sirri, Erik, Tufano, Peter, 1998. Costly search and mutual fund returns. Journal of Finance 53, 1589–1622.
Sims, Christopher, 1986. Are forecasting models usable for policy analysis? Federal Reserve Bank of Minneapolis Quarterly Review, 1–16.
Warther, Vincent, 1995. Aggregate mutual fund flows and security returns. Journal of Financial Economics 46, 103–131.