Financial panic and emerging market funds

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This article studies equity investment of emerging-market funds based on the 2003–2009 weekly data and compares the dynamics of flow and return between tranquil period and financial panic based on the experience of the latest 2008–2009 global financial crisis. First, we find that the well-documented positive feedback trading is a tranquil-period phenomenon such that it is more difficult in general for emerging-market funds to attract new investment in financial panic. Second, the predictive power of flow on return is driven by a combination of price pressure and information effects in tranquil period, while the information effect dominates in financial panic. Third, the underlying co-movements or contagion of flow across the emerging-market funds influence the association between flow and return. Overall, the findings highlight the importance of accounting for state-dependent dynamics as well as cross-regional co-movements in the analysis of flow and return.

I. Introduction

The financial globalization of portfolio investment is an ongoing process that over the past three decades has frequently been associated with financial panics, market crashes and the resultant welfare losses: the 1997 Asian Crisis, the 1998 Long-Term Capital Management (LTCM) Collapse, the 2002 Banking and Currency Crisis of Argentina, the 2008–2009 Subprime Crisis. To this date, understanding the behaviour of portfolio flows and investment funds is a challenge that merits more of both academic and policy attention. A large body of empirical works has explored characteristics of fund investment, potential interaction between flow, return, influence of fund size and aggregate market volatility. Insofar as the existing works provide evidence only on funds investing mainly the US and a few industrial countries, it remains difficult to generalize such findings to funds investing internationally, in particular those with mandated focus on emerging markets and developing regions. Naturally, new data and empirical tests are called upon.

This article uses a unique dataset on equity investment of international funds directing towards emerging markets. At weekly frequency we study the dynamics of flow and return across regions, taking into account fund size, its focus and aggregate volatility in the global equity markets. After presenting investment dynamics based on the full-sample series, the analysis explores regime-varying nature of flow-return relationship, comparing the subsamples of tranquil and financial panic periods. The empirical approach is to study persistency of flow and return investing mainly the US and a few industrial countries, it remains difficult to generalize such findings to funds investing internationally, in particular those with mandated focus on emerging markets and developing regions. Naturally, new data and empirical tests are called upon.

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series as well as interaction between the two, both across and within regions, in the Vector Autoregressive (VAR) framework that controls for fund size and aggregate volatility. In a full-sample estimation, our results suggest that there are cross-regional co-movements of flow and the fund investment can be characterized by (i) positive feedback trading (inflow towards funds that have recently performed well); (ii) influence of private information and price pressure (forecasting power of contemporaneous flow on return) and (iii) negative effects of aggregate volatility on flow and return. Applying the Markov-switching Autoregressive Conditional Heteroscedastic (ARCH) model to identify the onset of 2008–2009 financial crisis, we find that positive feedback trading characterizes the tranquil period, while the predictive power of flow on return is relatively larger in financial panic, whereby the predictive power is a combination of price pressure and information effects in tranquil period, while the information effect dominates in financial panic.

For the finance literature, our study provides new evidence on the dynamics of fund flow and return for emerging markets. Previous works that analyze the US and a handful of industrial markets tend to find supports of momentum trading and predictive power of flows on returns. According to this strand of the literature, investment is directed to equity funds that subsequently perform well; flow contains information useful to predict return. However, the predictive power of flow on return may as well be an artefact of investors’ momentum trading strategies: investing in funds that have recently perform well and selling those that have done poorly would realize above-average return because fund performance is persistent. It follows that momentum trading could create a spurious co-movement between past flows and current returns. By and large, previous findings on the flow-return relationship vary from one market to the others: for instance, Keswani and Stolin (2008) point out that for mutual funds in the UK, large flow predict high future return even after accounting for the return momentum, in contrast to the US evidence provided by Sapp and Tiwari (2004). Our new estimates from the emerging markets suggest that the predictive power of flow on return is state dependent, varying with aggregate volatility in the global equity markets.

In macroeconomics, our work is related to existing studies on the association between cross-border equity flow and financial panic. According to this strand of the literature, market panic could spread across localities (being contagious) that have common share of investors (Goldstein and Pauzner, 2004), overexposed funds (Broner et al., 2006) and credit constraints (Calvo and Mendoza, 2000; Ilyina, 2006). As the market contagion could be associated with a combination of changing investment strategy of cross-border investors, an empirical challenge is to identify whether the dynamics of flow and return are significantly different between financial tranquil and panic periods. Using monthly equity flow of the late 1990s, Kaminsky et al. (2004) show that the contemporaneous correlation of flow and return is stronger during market turbulence for fund investment in Latin America. Our new evidence is based on the latest 2008–2009 global financial crisis, the episode the highly leverage nature of financial institutions is likely to magnify the impact of aggregate volatility on the credit constraints of portfolio investment across industrial countries and emerging markets. We find that the dynamics of flow and return depend critically on whether the analysis controls for potential contagion effect across markets.

The rest of this article is organized as follows. Section II describes the data. Section III provides full-sample dynamics of fund investment in emerging markets. Section IV explores the difference between financial tranquil and panic periods. Section V concludes.

II. Data Description

The weekly data, acquired from Emerging Portfolio Fund Research (EPFR), covers equity fund investing in emerging markets from 1 January 2003 to 25 March 2009 (326 weeks). Each week, fund managers and advisors report their investment and holding directly to EPFR, whose database records both open- and closed-end funds, of which the latter accounts for about 10% of assets being tracked. Approximately 70% of these assets is made of institutional investors; mainly pension funds and insurance companies. EPFR aggregates investment by emerging market funds into

2 See, for example, Frooth et al. (2001), Kim and Wei (2002), Chiang et al. (2007) and Froot and Ramadorai (2008).
3 See Mendoza and Terrones (2008) for macro-micro level linkages of credit boom and financial leverages, and Brunnermeier (2009) for the analysis of the liquidity squeeze and the credit crunch.
4 This number has become less than 5% since 2009.
four regions: (1) Emerging Asia (Asia, including funds investing only in Asian countries except Japan); (2) Emerging Europe regional, Middle East and Africa (EMEA); (3) Latin America (Latin) and (4) Global Emerging Market (GEM, including funds investing across Asia, EMEA and Latin). Funds classified under GEM are allowed to invest in a broad global market, whereas Asia, EMEA and Latin are mandated to invest only in their specific regions.

We define total net assets (tna) as a sum of total net assets held by all funds investing in a corresponding region; for example, tna of Asia is the total net assets (million US Dollar (USD)) under management of funds in the Asia group as recorded by EPFR. Fund flow (flow) is calculated as a net purchase of all funds investing in a corresponding region, a positive value signifies inflows. flow% is flow divided by tna. Fund return (return) is calculated as a sum of weekly change in total net asset value and dividends, divided by total net asset value of a previous week.

Table 1 presents the summary statistics of the full sample. In term of tna, GEM accounts for 113 billion USS, seven times the size of Latin. On average, Asia registers the largest positive flow, +97 million USS per week, whereas EMEA registers –0.6 million USS per week. In terms of flow%, Latin receives on average 0.32% of its tna, followed by Asia 0.23% and GEM 0.02%. Latin, the smallest in term of tna, registers 4.9 basis points (bp) weekly return, quite remarkable in comparison to other regions. Plots of flow and return in Figs 1 and 2 suggest that the former has become more volatile since 2007, while the volatility of return began to increase significantly by late 2008.

### III. Full-sample Dynamics of flow and return

We first examine cross-regional co-movements of flow series and return series. To identify the cross-regional co-movements for each of these series, we employ the Granger-causality

\[ X_t = C + \sum_k^p H_k X_{t-k} + \epsilon \]  

where \( X_t = (X_{Asia,t}, X_{EMEA,t}, X_{Latin,t}, X_{GEM,t}) \) vector; \( X \in \{flow, return\}, p \) is a number of lags, \( C \) is the \( 4 \times 1 \) constant matrix, \( H_k \) is the \( 4 \times 4 \) coefficient matrix of \( k\)-week lag and \( \epsilon \) is the \( 4 \times 1 \) (independent and identically distributed (i.i.d.)) normally distributed residual matrix.

Table 2 reports \( p \)-values of Granger causality test for the influence of a region in rows on a region in columns. The \( F \)-tests of joint significance suggest that in the case of flow, Asia and EMEA have significant influence on flow of other regions, whereas Latin and GEM have relatively little. In the case of return, the cross-regional co-movements seem to be small, consistent with recent findings that correlations of return tend to be regional rather than global (Kaminsky and Reinhart, 2000; Bektaert et al., 2009; Jinjarak et al., in press).

Next, we formally model the dynamics and interaction of flow and return as a vector autoregressive system (Hasbrouck, 1991), controlling for the well-documented effects of ’fund size’ (Chen et al., 2004) and ‘aggregate financial volatility’ captured in the Chicago Board Option Exchange’s vix Index – known as Wall Street’s ‘fear gauge’ (Ang et al., 2006)

\[
\begin{align*}
(flow_{i,t} & ) = C + \sum_k^p A_k (flow_{i,t-k}) + B (\log tna_i) \\
& + B (\log return_{i,t-k}) + \epsilon
\end{align*}
\]

(2)

where \( p \) is a number of lags; \( \epsilon \) is i.i.d. disturbance matrix (bivariate normal distribution); \( C \) is \( 2 \times 1 \) constant matrix; \( A_k \) is \( 2 \times 2 \) coefficient matrix of lagged flow and lagged return, capturing persistency of flow and return; and \( B \) is \( 2 \times 2 \) coefficient matrix of \( \log tna \) and \( \Delta vix \), the latter is calculated as return on the vix index from week \( t-1 \) to week \( t \). We estimate Equation 2 for each of the four regions: Asia, EMEA, Latin and GEM.

In providing the results, we report average coefficients of lagged flow and of lagged return (denoted as \( flow_{[-12 to -1]} \) and \( return_{[-12 to -1]} \) for each of the four regions, with \( p=12 \) based on Box–Jenkins information criteria and model parsimony consideration. We denote F-flow and F-return as \( p \)-values of the \( F \)-test of joint significance for lagged flow and for lagged return, respectively.

While Equation 2 could adequately model the dynamics of flow and return as well as capture serial correlation and potential delayed responses in each series, one can extend it by including an unexpected contemporaneous flow to study its potential impacts on return. To account for the contemporaneous
Fig. 1. Schematic representation of flow

Fig. 2. Schematic representation of return
association between flow and return, we follow Froot et al. (2001), extending Equation 2 as

\[
\begin{align*}
\text{flow}_{i,t} & = C + \sum_k A_k \left( \text{flow}_{i,-t-k} \right. \\
& \quad + B \left( \log \text{tna}_i \right) + \alpha \left( 0 \right) + \epsilon \quad (3)
\end{align*}
\]

where \(\alpha\) measures the contemporaneous effect of unexpected current flow on return; \(\epsilon\) is the residual matrix. Essentially, this is an orthogonalized decomposition of covariance under the ordering of flow preceding return. If contemporaneous flow contains useful information on asset value, fund investment could push asset price according to that informational content: flow contemporaneously affects asset price and thus return. For example, if a fund manager overestimates the informational content of contemporaneous flow, the asset price would fail to reflect the real information in flow. Under the ordering that flow precedes return, we identify from Equation 3, \(\text{flow}_{i0}\), the contemporaneous effect of flow on return (note that it appears only in the return equation following the above-mentioned ordering that flow precedes return).²

Predictability of flow and return

Table 3 presents full-sample results for each of the four regions. In flow equations, \(F\)-flow is statistically significant in all regions, while \(\text{flow}_{i-12} \to \) is also statistically significant and positive. Hence flow is persistent, the evidence of momentum trading of international funds in emerging markets that is consistent with the literature on fund flow dynamics based on the evidence from US and industrial countries. In addition, \(F\)-return and \(\text{return}_{i-12} \to \) in the flow equations provide supportive evidence of positive feedback (contrarian) trading strategies across regions, with the average coefficient of lagged return, \(\text{return}_{i-12} \to \), of 0.912 for Asia, 0.899 for EMEA and Latin and 0.421 for GEM. In return equations, \(F\)-return is statistically significant in all regions, while \(\text{return}_{i-12} \to \) is also statistically significant and positive: return is a persistent series. In the full-sample estimation, \(F\)-flow and \(\text{flow}_{i-12} \to \) in the return equations show that the lagged effect of flow on return is insignificant in all regions (a marginal one for Latin).

Delving further the return equations, coefficient estimates of \(\text{flow}_{i0}\) shows that the contemporaneous effect of flow on return is significant and positive for all four regions, ranging from 0.009 for GEM to 0.055 for EMEA. There are two plausible explanations. First, flow contains real information on asset price in emerging markets so that price increases (decreases) with good (bad) news as soon as the information reveals itself through flow, the information effect. Second, fund managers may increase their holdings in emerging-market asset in response to large inflows, which would then drive the asset price up, the price pressure effect.⁸

Size and volatility effects

Table 3 also reports effects of fund size and aggregate volatility. The coefficients of \(\log \text{tna}\) are insignificant for all regions in both flow and return equations: there appears no evidence that a larger market \((\text{tna})\) attracts greater fund inflows nor does it improve

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² As both flow and return series are stationary, we model the process and VAR and Structural VAR (SVAR) as well as conduct the Granger-causality test in the co-movements of flow, return across regions and between flow and return within region. With longer and higher frequency series, possibly with fund-level data, it is important to distinguish long-run and short-run components of the underlying relation even if short-run (causal) relations are to be examined as one should take into account cointegration effects (Lutkepohl and Reimers, 1992).


⁷ As \(\text{return}_{i-12} \to \) is a simple average of lagged coefficients, it is more useful to compare empirical intensity of positive feedback trading in Impulse Response Functions (IRFs).

⁸ If the positive effect of contemporaneous flow is originated from the price pressure effect, existing investors benefit from inflows, whereas new investors pay higher prices for the asset than they would have to (see also Coval and Stafford, 2007).
fund performance in the emerging markets. As for the volatility effect, the coefficients of $\Delta vix$ in flow and return equations are statistically significant and negative for all regions. The volatility effect on flow is relatively large for GEM: a one bp increase in $\Delta vix$ (e.g., the risk appetite declines globally) would reduce fund flow into GEM by US$1.215 million on a weekly basis. In the regression of return, the coefficient of $\Delta vix$ is statistically significant and negative. As $\Delta vix$ increases by one bp, return decreases by 0.206, 0.148, 0.140 and 0.128 for Latin, GEM, EMEA and Asia, respectively: Latin seems to be the most vulnerable to global market volatility, while Asia is the least sensitive.

IV. Financial Panic and Fund Dynamics

Our sample covers the 2008–2009 global financial crisis, an episode that the highly leverage nature of financial institutions is likely to magnify the impact of aggregate volatility on the credit constraints of portfolio investment across industrial countries and emerging markets. Continuing from the previous section, we classify the aggregate volatility based on $vix$ into three states: low ($l$), moderate ($m$) and high ($h$). We dub the low-volatility state as tranquil period, whereas moderate and high states as financial panic. With this state-dependent distribution of aggregate volatility, the three states can be described by a discrete and unobserved variable $s_t$, $s_t \in \{l = 1, m = 2, h = 3\}$. We estimate the transition probabilities applying 3-state $q$th-order Markov-switching ARCH model (Hamilton and Susmel, 1994) to differentiate $l$, $m$, $h$ states:

$$y_t = \sqrt{g_{st}}u_t + \tilde{y}_t$$

The variable $\tilde{y}_t$ is assumed to follow a zero-mean $q$th-order autoregression

$$\tilde{y}_t = \sum_{k=1}^{q} \phi_k \tilde{y}_{t-k} + \varepsilon_t$$

The variable $u_t$ is assumed to follow an ARCH–$L(q)$ process

$$u_{t} \sim \text{N}(0, 1)$$

where $u_t \sim \text{N}(0, 1)$ and $h_t$ is guaranteed by

$$h_t^2 = a_0 + \sum_{k=1}^{q} a_k \tilde{u}_{t-k}^2$$

where $g_{st}$ denotes the parameter when the process is in the state represented by $s_t$, with $g_1$ normalized to 1 so that $g_1 \geq 1$ for $j = 2, 3$. $\sqrt{g_{st}}h_t$ captures occasional and abrupt shifts in the average level of $y_t$. The estimate of interests is the transition probability $vix$ among the three states.

Estimating the three-state second-order Markov-switching ARCH model on the daily $vix$ series, we

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**Table 3. Flow-return relationship – full sample**

<table>
<thead>
<tr>
<th></th>
<th>Asia</th>
<th>EMEA</th>
<th>Latin</th>
<th>GEM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>flow</td>
<td>return</td>
<td>flow</td>
<td>return</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.184</td>
<td>0.026</td>
<td>0.037</td>
<td>0.033</td>
</tr>
<tr>
<td>t-stat</td>
<td>-0.376</td>
<td>1.125</td>
<td>0.219</td>
<td>1.307</td>
</tr>
<tr>
<td>log(tna)</td>
<td>0.020</td>
<td>-0.002</td>
<td>-0.004</td>
<td>-0.003</td>
</tr>
<tr>
<td>t-stat</td>
<td>0.444</td>
<td>-1.001</td>
<td>-0.253</td>
<td>-1.218</td>
</tr>
<tr>
<td>$\Delta vix$</td>
<td>-0.971</td>
<td>-0.128</td>
<td>-0.205</td>
<td>-0.140</td>
</tr>
<tr>
<td>flow$_{-12}$ to $-1$</td>
<td>0.038</td>
<td>0.000</td>
<td>0.041</td>
<td>-0.001</td>
</tr>
<tr>
<td>t-stat</td>
<td>3.494</td>
<td>0.011</td>
<td>3.758</td>
<td>-0.769</td>
</tr>
<tr>
<td>return$_{-12}$ to $-1$</td>
<td>0.912</td>
<td>0.029</td>
<td>0.290</td>
<td>0.043</td>
</tr>
<tr>
<td>t-stat</td>
<td>2.436</td>
<td>1.644</td>
<td>2.556</td>
<td>2.511</td>
</tr>
<tr>
<td>flow$_{[0]}$</td>
<td>0.018</td>
<td>0.055</td>
<td>0.055</td>
<td>0.055</td>
</tr>
<tr>
<td>t-stat</td>
<td>7.284</td>
<td>6.947</td>
<td>6.014</td>
<td>4.716</td>
</tr>
</tbody>
</table>

Granger causality (p-value)

<table>
<thead>
<tr>
<th></th>
<th>F-flow</th>
<th>F-return</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-flow</td>
<td>0.000</td>
<td>0.518</td>
<td>0.475</td>
</tr>
<tr>
<td>F-return</td>
<td>0.000</td>
<td>0.000</td>
<td>0.312</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.475</td>
<td>0.312</td>
<td>0.419</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Asia</th>
<th>EMEA</th>
<th>Latin</th>
<th>GEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>314</td>
<td>314</td>
<td>314</td>
<td>314</td>
</tr>
</tbody>
</table>
obtain the smoothed conditional probabilities that date t aggregate volatility was in low state (solid line), moderate state (dotted line) and high state (dashed line). Figure 3 shows that vix moved from a low state to a moderate state in 1 August 2007, fluctuated between moderate- and high-volatility states, then switched to the high-volatility state right after the collapse of Lehman Brothers in September 2008 and remain in the high state until the end of March 2009. Based on these transition probabilities, we split the sample into two subsamples of tranquil period: 1 January 2003 to 25 July 2007; and financial panic: 1 August 2007 to 25 March 2009. Note that our dating of 2008–2009 global financial crisis is similar to that of Heiko and Brenda (2009) which applied Markov-switching ARCH model in vix, TED spread, and Euro/USD foreign exchange swap to identify the starting point of the crisis, as well as that of Taylor and Williams (2009) which, based on the spread between 3-month London Interbank Offered Rate (Libor) and the Fed’s overnight federal funds rate target, marked 9 August 2007 as the onset of the crisis.

For tranquil period and financial panic subsamples, we re-estimate Equation 1 for each of them separately and report results in Table 4. The F-tests of joint significance suggest that in the case of flow during tranquil period, Asia, EMEA and Latin have significant influence on flow of other regions, while during financial panic, only EMEA and Latin maintain their cross-regional influence. In the case of return, only EMEA has significant influence on return of other regions during tranquil period, while Asia, Latin and GEM have little influence on return of other regions, for both tranquil and panic periods, as they were in the full-sample estimation. Overall, these results suggest that cross-regional co-movements of flow exist only in tranquil period, while return correlations are regional rather than global.

Positive feedbacks

Applying Equation 3 on our new subsamples, we report in Tables 5 and 6 the estimates of tranquil period and financial panic, respectively. As done in Section III, we emphasize the significance of F-return
Table 4. Granger-causality tests for co-movements for tranquil and panic periods

<table>
<thead>
<tr>
<th></th>
<th>flow</th>
<th></th>
<th></th>
<th>return</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Tranquil period</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$flow_{t-12 \rightarrow t}$</td>
<td>Asia</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.12</td>
<td>return$_{t-12 \rightarrow t}$</td>
<td>0.96</td>
<td>0.18</td>
<td>0.72</td>
<td>0.95</td>
</tr>
<tr>
<td>$flow_{t-1 \rightarrow t}$</td>
<td>EMEA</td>
<td>0.41</td>
<td>0.00</td>
<td>0.00</td>
<td>0.05</td>
<td>return$_{t-1 \rightarrow t}$</td>
<td>0.12</td>
<td>0.01</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>$flow_{t-12 \rightarrow t}$</td>
<td>Latin</td>
<td>0.00</td>
<td>0.01</td>
<td>0.00</td>
<td>0.01</td>
<td>return$_{t-12 \rightarrow t}$</td>
<td>0.53</td>
<td>0.37</td>
<td>0.96</td>
<td>0.61</td>
</tr>
<tr>
<td>$flow_{t-1 \rightarrow t}$</td>
<td>GEM</td>
<td>0.90</td>
<td>0.31</td>
<td>0.12</td>
<td>0.18</td>
<td>return$_{t-1 \rightarrow t}$</td>
<td>0.94</td>
<td>0.29</td>
<td>0.71</td>
<td>0.78</td>
</tr>
<tr>
<td>Panic period</td>
<td></td>
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<tr>
<td>$flow_{t-12 \rightarrow t}$</td>
<td>Asia</td>
<td>0.28</td>
<td>0.73</td>
<td>0.50</td>
<td>0.02</td>
<td>return$_{t-12 \rightarrow t}$</td>
<td>0.30</td>
<td>0.07</td>
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<tr>
<td>$flow_{t-1 \rightarrow t}$</td>
<td>EMEA</td>
<td>0.01</td>
<td>0.11</td>
<td>0.01</td>
<td>0.05</td>
<td>return$_{t-1 \rightarrow t}$</td>
<td>0.61</td>
<td>0.47</td>
<td>0.58</td>
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<td>$flow_{t-12 \rightarrow t}$</td>
<td>Latin</td>
<td>0.07</td>
<td>0.20</td>
<td>0.00</td>
<td>0.03</td>
<td>return$_{t-12 \rightarrow t}$</td>
<td>0.64</td>
<td>0.04</td>
<td>0.10</td>
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<td>$flow_{t-1 \rightarrow t}$</td>
<td>GEM</td>
<td>0.89</td>
<td>0.99</td>
<td>0.94</td>
<td>0.67</td>
<td>return$_{t-1 \rightarrow t}$</td>
<td>0.37</td>
<td>0.06</td>
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Table 5. Flow-return relationship: tranquil subsample

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<tr>
<td>log($na$)</td>
<td>-0.419</td>
<td>-0.003</td>
<td>0.102</td>
<td>0.014</td>
<td>-0.280</td>
<td>-0.006</td>
<td>-1.022</td>
<td>0.001</td>
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<td>r-stat</td>
<td>-0.998</td>
<td>-0.123</td>
<td>0.626</td>
<td>0.593</td>
<td>-2.471</td>
<td>-0.281</td>
<td>-1.603</td>
<td>0.044</td>
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<tr>
<td>F-flow</td>
<td>0.000</td>
<td>0.036</td>
<td>0.000</td>
<td>0.622</td>
<td>0.000</td>
<td>0.217</td>
<td>0.111</td>
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<td>F-return</td>
<td>0.000</td>
<td>0.053</td>
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<td>0.116</td>
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<td>0.297</td>
<td>0.000</td>
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<td>$R^2$</td>
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<td>0.233</td>
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<td>0.564</td>
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Table 6. Flow-return relationship: panic subsample

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<td>log($na$)</td>
<td>-0.143</td>
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<td>-0.342</td>
<td>0.247</td>
<td>-0.967</td>
<td>-1.189</td>
<td>-0.431</td>
<td>-0.714</td>
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<tr>
<td>F-flow</td>
<td>0.141</td>
<td>0.926</td>
<td>0.603</td>
<td>0.999</td>
<td>0.340</td>
<td>0.370</td>
<td>0.575</td>
<td>0.990</td>
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<td>F-return</td>
<td>0.021</td>
<td>0.404</td>
<td>0.062</td>
<td>0.076</td>
<td>0.220</td>
<td>0.366</td>
<td>0.483</td>
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<tr>
<td>$R^2$</td>
<td>0.541</td>
<td>0.469</td>
<td>0.473</td>
<td>0.528</td>
<td>0.499</td>
<td>0.611</td>
<td>0.320</td>
<td>0.655</td>
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in the flow equation as an indicator of positive feedback trading, and on the significance of F-flow in the return equation as an indicator of the predictive power of flow on return. An empirical challenge is to identify whether the dynamics of flow and return are significantly different between tranquil period and financial panic.

Table 5 reports the estimation results for tranquil period, showing that F-return in the flow equation is statistically significant at 1% as well as return_{[-12 to -1]} is positive across regions. On the contrary, positive feedback is relatively weak for financial panic period, as shown by the statistics in Table 6. Figure 4 plots 52-week Cumulative Impulse Response Function (CIRF) of flow to a return shock. Over the long run, the CIRF of tranquil (noncrisis) period is larger than that of financial panic (crisis) for Asia and GEM, suggesting fund investment of EMEA and Latin chase returns (positive feedback) more aggressively than Asia and GEM during financial panic. Nonetheless, for financial panic, these CIRFs are statistically insignificant at conventional confident level as reported in Table 6.

One possible explanation for the weak positive feedback during financial panic is that it is more difficult in general for emerging-market funds to attract new investment in the volatile markets. As noted by Brunnermeier and Pedersen (2009), market liquidity and funding liquidity are mutually reinforcing. In the present context, the constrained market liquidity tightens the funding liquidity, thereby limiting the availability of cash flows during the 2008–2009 credit crunch, the period of financial panic, and rendering international funds to be more cautious of their equity investment in emerging markets.

Predictive power of flows

Table 5 shows that in the return equation, F-flow is statistically significant for Asia and GEM during financial panic.
tranquil period, but becomes insignificant for all regions in financial panic. Hence, there is little evidence that lagged flow is informative in predicting return (supportive to the full-sample estimation). However, the effect of contemporaneous flow on return is highly significant across regions for both tranquil period and financial panic as shown by coefficient estimates of flow	extsubscript{0} in Tables 5 and 6, respectively. Specifically, in tranquil period, an unexpected US$1 million increase of flow pushes return up in the same period by 77 bp in EMEA, 46 bp in Latin, 16 bp in Asia and 7 bp in GEM. Figure 5 plots 52-week Cumulative Orthogonalized Impulse Response Function (COIRF), under the ordering that flow precedes return (Equation 3). Across all regions, in the long run, the positive predictive power of flow on return in financial panic is even larger than that in tranquil period. On the one hand, flow might contain more private information useful to predict return at the time of financial distress. Alternatively, the predictive power of flow could be due to stronger price pressure during the credit squeeze.

Price pressure or information effect? If the predictive power of flow is due to price pressure, we should observe that return increases in response to positive flow, followed by a complete price reversal (a decrease in return) that brings the price to its original level as the positive sentiment fades away. If flow contains private information about return, then we would expect a price increase (and therefore an increase in return) in response to positive flow without any price reversal afterwards. If the predictability arises from a combination of private information and price pressure effects, then there would be some evidence of reversal, but not a complete one.

During tranquil period, in response to a shock to flow, the COIRF of return generally decreases in the first few weeks, then reverses and stabilizes 10–20 weeks after, though not back to its origin, which suggests the presence of both price pressure and information effects. In addition, the COIRF of return suggests that information contained in flow tends to be noise, which misleads investors to direct money into (out of) funds that perform poorly (well). During financial panic, the COIRFs trend upward, with occasional short-term reversal for all regions, suggesting that the flow contain useful information which guides investors to channel their investment into (out of) emerging-market funds that
subsequently perform well (poorly). In sum, the predictive power of flow on return is a combination of price pressure and information effects in tranquil period, while the information effect dominates in financial panic.

More on contagion

While we try to be comprehensive in accounting for cross-regional co-movements of fund investment, there are many channels through which financial panic could transmits across markets. Conceptually, the panic tends to be contagious to other localities that share common investors (Goldstein and Pauzner, 2004) and/or that is subject to rebalancing portfolio exposure (Broner et al., 2006). Such behaviour spread the market sentiment from one to another and causes the contagion effect from the channel of portfolio flows. Below, we further extend our workhorse VAR to better account for contagion as

\[
\begin{align*}
\left( \frac{\text{flow}_{i,t}}{\text{return}_{i,t}} \right) &= C + \sum_{k} A_k \left( \frac{\text{flow}_{i,t-k}}{\text{return}_{i,t-k}} \right) + \sum_{j \neq i} B \left( \frac{\text{flow}_{j,t}}{\text{return}_{j,t}} \right) + B \left( \log \text{tna}_t \right) + \epsilon
\end{align*}
\]

where \( \beta_{j,k} \) is the coefficient matrix of contemporaneous flow and return from market \( j \).

This extended configuration of Equation 2 allows for both lagged and contemporaneous interaction of flow and return, as well as essentially captures the contagion effect from market \( j \) in \( \beta_{j,k} \). We report \( p \)-values of joint significant tests in Table 7. The F-return statistics in the flow equation suggest that the predictive power of flow on return during financial panic is due to the underlying co-movements or contagion of flow across the emerging-market funds, which could be driven either by private information, price pressure or a combination of the two.

V. Conclusion

This article studies the equity investment of emerging-market funds based on the 2003–2009 weekly data. We compare the dynamics of flow and return between tranquil period and financial panic and produce several contribution to the literature based on the experience of the latest 2008–2009 global financial crisis. First, we find that the well-documented positive feedback trading is a tranquil-period phenomenon such that it is more difficult, in general, for emerging-market funds to attract new investment in financial panic. Second, the predictive power of flow on return is driven by a combination of price pressure and information effects in tranquil period, while the information effect dominates in financial panic. Third, the underlying co-movements or contagion of flow across the emerging-market funds influence the association between flow and return. Overall, our findings highlight the importance of accounting for state-dependent dynamics as well as cross-regional co-movements, or contagion, in the analysis of flow and return. From the policy perspective, this study offers a framework for estimating the flow-return dynamics as well as a battery of tests, which could be useful to policymakers in monitoring portfolio investment of international funds at the regional level.

\[\text{Table 7. Joint significant test (p-values)}\]

<table>
<thead>
<tr>
<th></th>
<th>Asia</th>
<th>EMEA</th>
<th>Latin</th>
<th>GEM</th>
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<tr>
<td></td>
<td>flow</td>
<td>return</td>
<td>flow</td>
<td>return</td>
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<tr>
<td>Tranquil period</td>
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<tr>
<td>F-flow</td>
<td>0.000</td>
<td>0.986</td>
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<td>0.646</td>
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<td>0.017</td>
<td>0.361</td>
<td>0.000</td>
<td>0.544</td>
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<tr>
<td>F-flow</td>
<td>0.813</td>
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<td>F-return</td>
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We would like to thank an anonymous reviewer, Itay Goldstein (discussant) and participants at the AEA and Econometric Society Meetings in Atlanta (January 2010) as well as the Economics Brownbag at NTU. Any remaining errors are ours.

References


