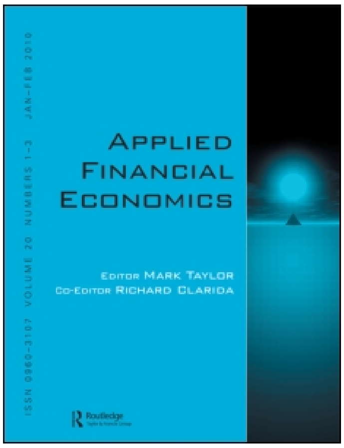

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Financial panic and emerging market funds

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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

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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 analyse the US and a handful of industrial markets tend to find supports of momentum trading and predictive power of flows on returns.[1] 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.[2] 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.[3] 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.[4] Approximately 70% of these assets is made of institutional investors; mainly pension funds and insurance companies. *EPFR* aggregates investment by emerging market funds into

[1] See Gruber (1996) and Zheng (1999) for empirical evidence on positive predictive power of flow on return as well as Frazzini and Lamont (2008) for an opposite argument, and also Carhart (1997), Daniel *et al*. (1997), Greene and Hodges (2002), Chan *et al*. (2005) and Hau and Rey (2006).
[2] See, for example, Froot *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.

Table 1. Weekly average statistics

	Asia	*EMEA*	*Latin*	*GEM*
tna (billion USD)	79.2	27.5	17.4	113.2
log(tna)	10.9	9.9	9.2	11.5
flow (million USD)	96.6	−0.6	40.9	38.9
flow (%)	0.23	0.08	0.32	0.02
return (%)	0.25	0.21	0.49	0.28

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 US$, seven times the size of *Latin*. On average, *Asia* registers the largest positive *flow*, +97 million US$ per week, whereas *EMEA* registers –0.6 million US$ 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

$$\mathbf{X}_t = C + \sum_k^p H_k \mathbf{X}_{t-k} + \boldsymbol{\epsilon} \tag{1}$$

where $\mathbf{X}_t = (X_{Asia,t}, X_{EMEA,t}, X_{Latin,t}, X_{GEM,t})$ vector; $X \in \{flow, return\}$, p is a number of lags, C is the 4×1 constant matrix, H_k is the 4×4 coefficient matrix of k-*week* lag and $\boldsymbol{\epsilon}$ is the 4×1 (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; Bekaert *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)

$$\begin{pmatrix} flow_{i,t} \\ return_{i,t} \end{pmatrix} = C + \sum_k^p A_k \begin{pmatrix} flow_{i,t-k} \\ return_{i,t-k} \end{pmatrix} + B \begin{pmatrix} \log tna_t \\ \Delta vix_t \end{pmatrix} + \varepsilon \tag{2}$$

where p is a number of lags; ε is i.i.d. disturbance matrix (bivariate normal distribution); C is 2×1 constant matrix; A_k is 2×2 coefficient matrix of lagged *flow* and lagged *return*, capturing persistency of *flow* and *return* and B is 2×2 coefficient matrix of $\log tna$ and Δvix, 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 $flow_{\{-12 \text{ to } -1\}}$ and $return_{\{-12 \text{ to } -1\}}$ 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

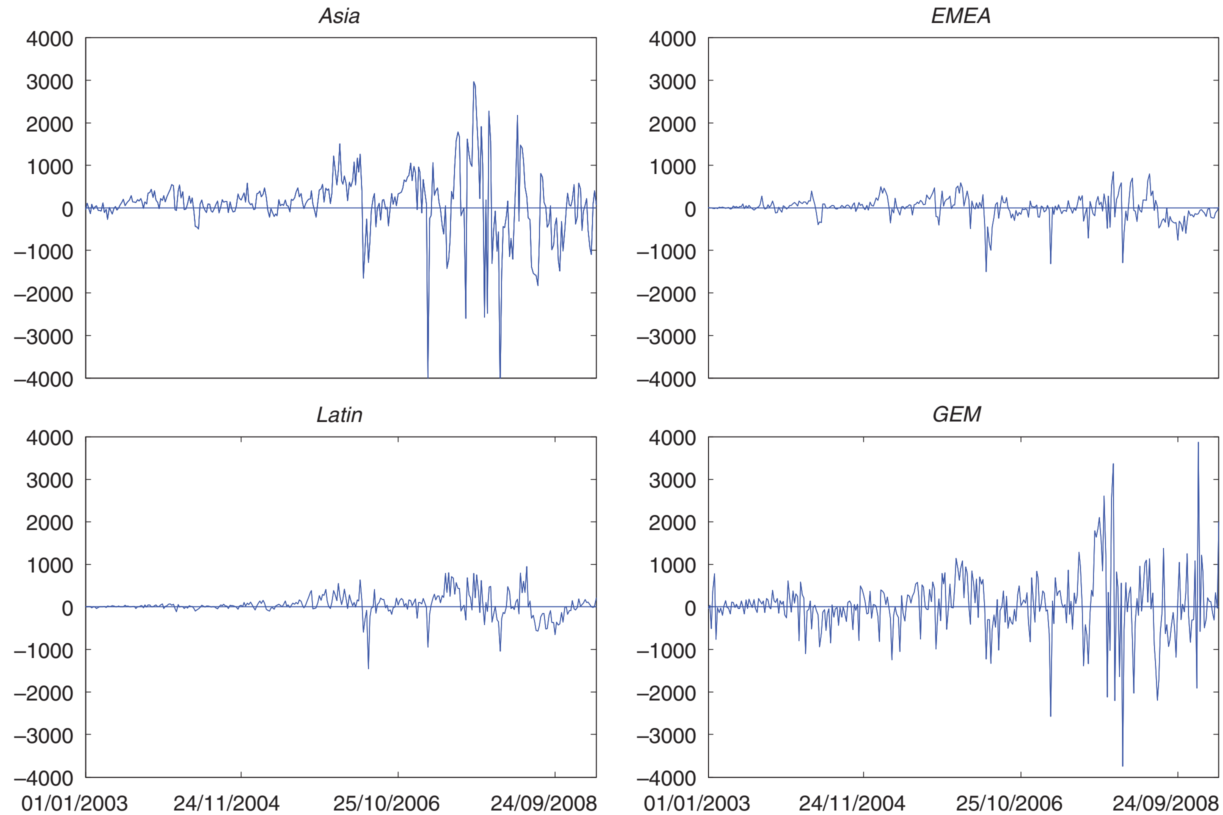

Fig. 1. Schematic representation of *flow*

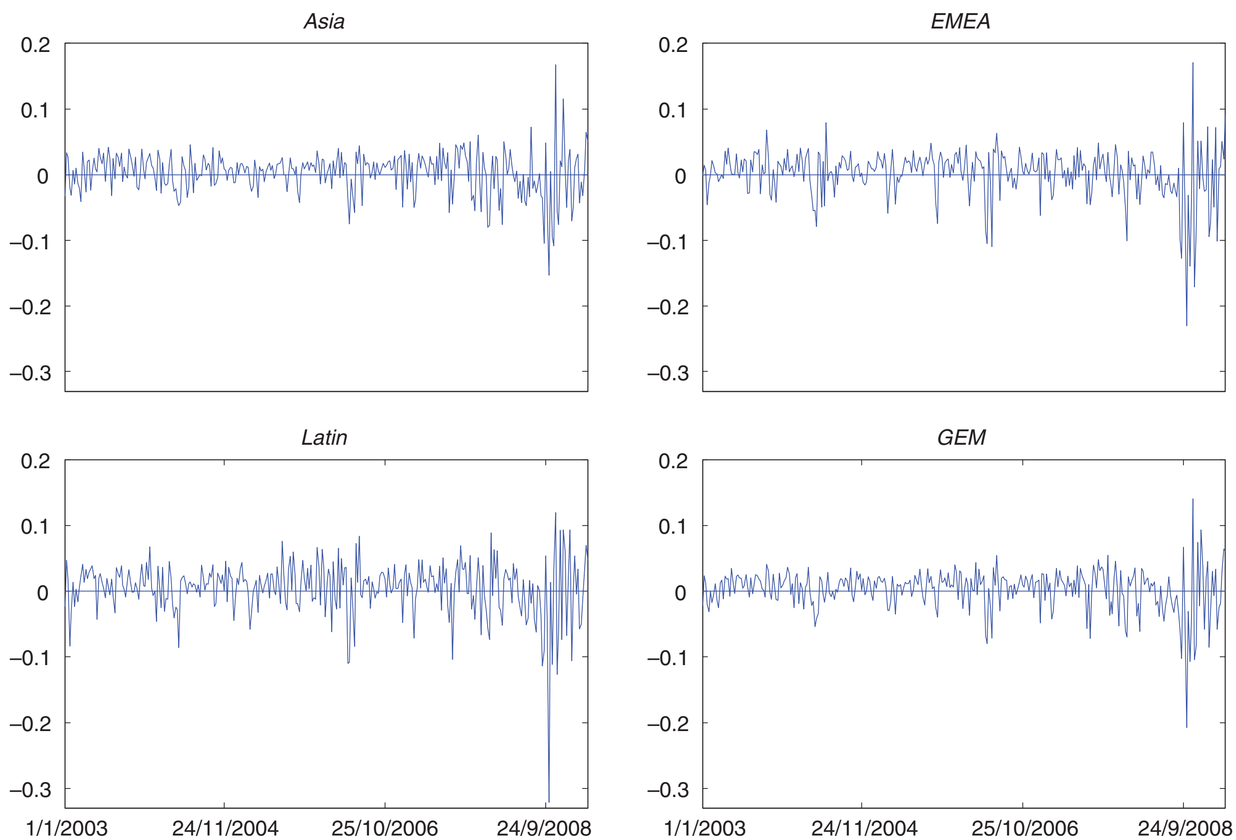

Fig. 2. Schematic representation of *return*

Table 2. Granger-causality test (*p*-values) for cross-regional co-movements

	flow					*return*			
Cause/effect	*Asia*	*EMEA*	*Latin*	*GEM*	Cause/effect	*Asia*	*EMEA*	*Latin*	*GEM*
$flow_{Asia,\{-12\ \text{to}\ -1\}}$	0.00	0.55	0.00	0.00	$return_{Asia,\{-12\ \text{to}\ -1\}}$	0.00	0.01	0.26	0.08
$flow_{EMEA,\{-12\ \text{to}\ -1\}}$	0.04	0.00	0.00	0.05	$return_{EMEA,\{-12\ \text{to}\ -1\}}$	0.58	0.86	0.55	0.37
$flow_{Latin,\{-12\ \text{to}\ -1\}}$	0.11	0.55	0.00	0.11	$return_{Latin,\{-12\ \text{to}\ -1\}}$	0.21	0.16	0.51	0.14
$flow_{GEM,\{-12\ \text{to}\ -1\}}$	0.03	0.68	0.28	0.42	$return_{GEM,\{-12\ \text{to}\ -1\}}$	0.22	0.04	0.22	0.56

association between *flow* and *return*, we follow Froot *et al*. (2001), extending Equation 2 as

$$\begin{pmatrix} flow_{i,t} \\ return_{i,t} \end{pmatrix} = C + \sum_{k}^{p} A_k \begin{pmatrix} flow_{i,t-k} \\ return_{i,t-k} \end{pmatrix} + B \begin{pmatrix} \log tna_t \\ \Delta vix_t \end{pmatrix} + \alpha \begin{pmatrix} 0 \\ flow_{i,t} \end{pmatrix} + \mathbf{e} \qquad (3)$$

where α measures the contemporaneous effect of unexpected current *flow* on *return*; **e** 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 fall to reflect the real information in *flow*. Under the ordering that *flow* precedes *return*, we identify from Equation 3, $flow_{\{0\}}$, 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*).[5]

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 $flow_{\{-12\ \text{to}\ -1\}}$ 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.[6] In addition, F-*return* and $return_{\{-12\ \text{to}\ -1\}}$ in the *flow* equations provide supportive evidence of positive feedback (contrarian) trading strategies across regions, with the average coefficient of lagged return, $return_{\{-12\ \text{to}\ -1\}}$, of 0.912 for *Asia*, 0.290 for *EMEA* and *Latin* and 0.421 for *GEM*.[7] In *return* equations, F-*return* is statistically significant in all regions, while $return_{\{-12\ \text{to}\ -1\}}$ is also statistically significant and positive: *return* is a persistent series. In the full-sample estimation, F-*flow* and $flow_{\{-12\ \text{to}\ -1\}}$ 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 $flow_{\{0\}}$ 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 *tna* are insignificant for all regions in both *flow* and *return* equations: there appears no evidence that a larger market (*tna*) attracts greater fund inflows nor does it improve

[5] 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).
[6] See Warther (1995), Froot *et al*. (2001), Kim and Wei (2002), Kaminsky *et al*. (2004) and Jinjarak *et al*. (in press).
[7] As $return_{\{-12\ \text{to}\ -1\}}$ 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).

Table 3. Flow-return relationship – full sample

	Asia		*EMEA*		*Latin*		*GEM*	
	flow	*return*	*flow*	*return*	*flow*	*return*	*flow*	*return*
Constant	−0.184	0.026	0.037	0.033	−0.179	0.031	−1.048	0.032
t-stat	−0.376	1.125	0.219	1.307	−1.627	1.705	−1.240	1.059
log(*tna*)	0.020	−0.002	−0.004	−0.003	0.020	−0.003	0.093	−0.003
t-stat	0.444	−1.001	−0.253	−1.218	1.710	−1.434	1.268	−0.961
Δvix	−0.971	−0.128	−0.205	−0.140	−0.319	−0.206	−1.215	−0.148
t-stat	−3.037	−8.613	−1.780	−8.133	−3.154	−12.319	−3.357	−11.365
$flow_{\{-12\text{ to }-1\}}$	0.038	0.000	0.041	−0.001	0.040	0.002	0.029	0.000
t-stat	3.494	0.011	3.758	−0.769	4.250	1.561	2.190	0.166
$return_{\{-12\text{ to }-1\}}$	0.912	0.029	0.290	0.043	0.290	0.003	0.421	0.033
t-stat	2.436	1.644	2.556	2.511	2.926	0.187	1.278	2.789
$flow_{\{0\}}$		0.018		0.055		0.053		0.009
t-stat		7.284		6.947		6.014		4.716
Granger causality (*p*-value)								
F-*flow*	0.000	0.518	0.004	0.566	0.000	0.013	0.007	0.617
F-*return*	0.000	0.000	0.000	0.000	0.000	0.005	0.000	0.000
R^2	0.475	0.312	0.419	0.319	0.469	0.441	0.247	0.444
N		314		314		314		314

fund performance in the emerging markets. As for the volatility effect, the coefficients of Δvix 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 Δvix (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 Δvix is statistically significant and negative. As Δvix 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; $s_t \in \{l = l, m = 2, h = 3\}$. We estimate the transition probabilities applying 3-state qth-order Markov-switching ARCH model (Hamilton and Susmel, 1994) to differentiate l, m, h states[9]

$$y_t = \sqrt{g_{st}}\tilde{u}_t + \tilde{y}_t \tag{4}$$

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

$$\tilde{y}_t = \sum_k^q \phi_k \tilde{y}_{t-k} + \varepsilon_t \tag{5}$$

The variable $\tilde{u}_t$ is assumed to follow an $\text{ARCH} - L(q)$ process

$$\tilde{u}_t t = h_t \upsilon_t \tag{6}$$

where $\upsilon_t \sim N(0, 1)$ and h_t is guaranteed by

$$h_t^2 = a_0 + \sum_k^q a_k \tilde{u}_{t-k}^2 \tag{7}$$

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 $g_j \geqslant 1$ for $j = 2, 3$. $\sqrt{g_{st}}\tilde{u}_t$ 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

[9] We thank the referee for suggesting a Markov switching process to identify noncrisis (tranquil) and crisis (panic) periods.

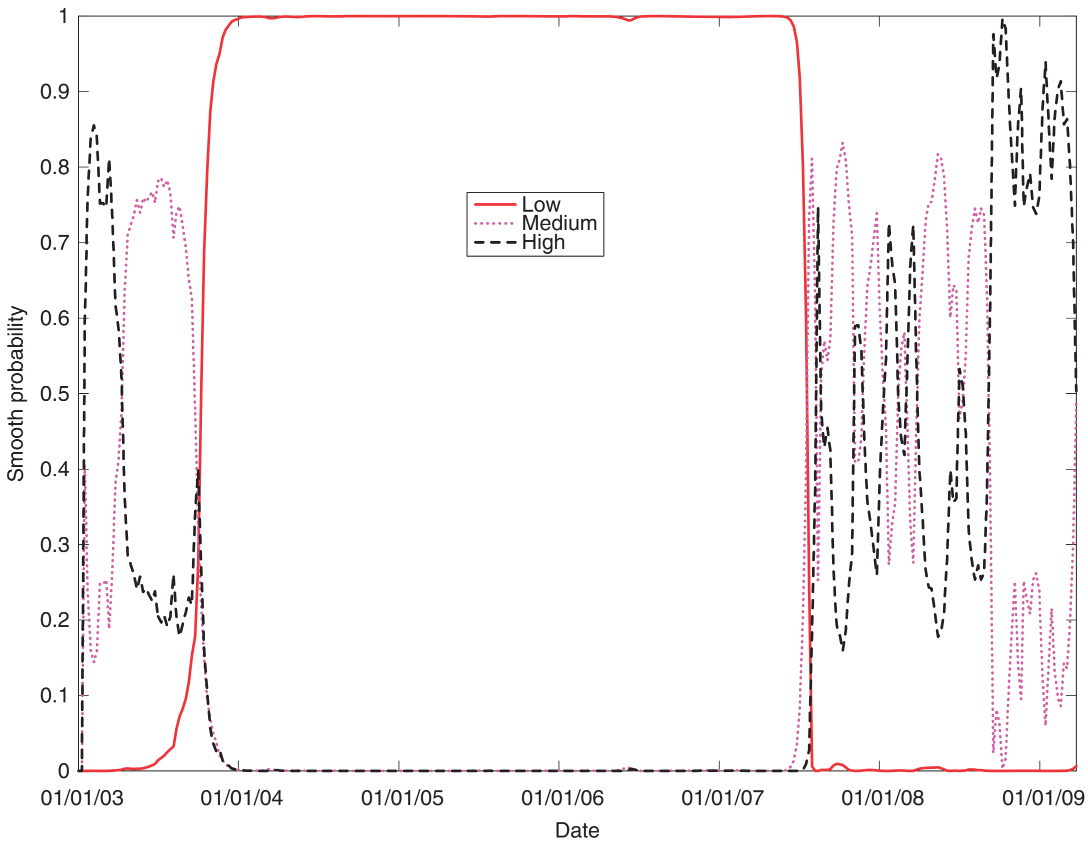

Fig. 3. Smooth transition probability of aggregate volatility based on *vix* (high volatility (dash line), moderate volatility (dotted) and low volatility (solid line) states)

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

	$flow_t$					$return_t$			
	Asia	*EMEA*	*Latin*	*GEM*		*Asia*	*EMEA*	*Latin*	*GEM*
Tranquil period									
$flow_{1,\{-12\ \text{to}\ -1\}}$	0.00	0.00	0.00	0.12	$return_{1,\{-12\ \text{to}\ -1\}}$	0.96	0.18	0.72	0.95
$flow_{2,\{-12\ \text{to}\ -1\}}$	0.41	0.00	0.00	0.05	$return_{2,\{-12\ \text{to}\ -1\}}$	0.12	0.01	0.03	0.01
$flow_{3,\{-12\ \text{to}\ -1\}}$	0.00	0.01	0.00	0.01	$return_{3,\{-12\ \text{to}\ -1\}}$	0.53	0.37	0.96	0.61
$flow_{4,\{-12\ \text{to}\ -1\}}$	0.90	0.31	0.12	0.18	$return_{4,\{-12\ \text{to}\ -1\}}$	0.94	0.29	0.71	0.78
Panic period									
$flow_{1,\{-12\ \text{to}\ -1\}}$	0.28	0.73	0.50	0.02	$return_{1,\{-12\ \text{to}\ -1\}}$	0.30	0.07	0.25	0.30
$flow_{2,\{-12\ \text{to}\ -1\}}$	0.01	0.11	0.01	0.05	$return_{2,\{-12\ \text{to}\ -1\}}$	0.61	0.47	0.58	0.48
$flow_{3,\{-12\ \text{to}\ -1\}}$	0.07	0.20	0.00	0.03	$return_{3,\{-12\ \text{to}\ -1\}}$	0.64	0.04	0.10	0.28
$flow_{4,\{-12\ \text{to}\ -1\}}$	0.89	0.99	0.94	0.67	$return_{4,\{-12\ \text{to}\ -1\}}$	0.37	0.06	0.30	0.42

Table 5. Flow-return relationship: tranquil subsample

	Asia		*EMEA*		*Latin*		*GEM*	
	flow	*return*	*flow*	*return*	*flow*	*return*	*flow*	*return*
Constant	−0.419	−0.003	0.102	0.014	−0.280	−0.006	−1.022	0.001
t-stat	−0.998	−0.123	0.626	0.593	−2.471	−0.281	−1.603	0.044
log(*tna*)	0.038	0.001	−0.011	−0.001	0.031	0.002	0.081	0.000
t-stat	0.969	0.349	−0.632	−0.236	2.445	0.711	1.444	0.124
Δvix	−0.769	−0.084	−0.212	−0.078	−0.340	−0.149	−0.565	−0.087
t-stat	−2.554	−5.439	−1.658	−4.114	−3.142	−7.896	−1.923	−6.354
$flow_{\{-12\ \text{to}\ -1\}}$	0.048	−0.001	0.051	0.000	0.051	−0.001	0.031	0.000
t-stat	4.219	−1.709	4.730	0.114	4.442	−0.285	2.118	0.082
$return_{\{-12\ \text{to}\ -1\}}$	1.286	0.048	0.147	−0.023	0.291	0.013	1.641	0.025
t-stat	3.456	2.546	0.761	−0.788	2.215	0.568	3.540	1.155
$flow_{\{0\}}$		0.016		0.077		0.054		0.007
t-stat		5.017		9.084		4.936		2.391
Granger causality (*p*-value)								
F-*flow*	0.000	0.036	0.000	0.622	0.000	0.217	0.111	0.081
F-*return*	0.000	0.053	0.000	0.116	0.000	0.297	0.000	0.029
R^2	0.505	0.233	0.518	0.206	0.564	0.335	0.359	0.276
N		227		227		227		227

Table 6. Flow-return relationship: panic subsample

	Asia		*EMEA*		*Latin*		*GEM*	
	flow	*return*	*flow*	*return*	*flow*	*return*	*flow*	*return*
Constant	1.713	0.071	−0.235	0.149	1.258	0.070	4.815	0.066
t-stat	0.347	0.329	−0.229	0.959	1.204	0.426	0.734	0.354
log(*tna*)	−0.143	−0.006	0.024	0.014	−0.118	−0.007	−0.384	−0.006
t-stat	−0.344	−0.342	0.247	−0.967	−1.189	−0.431	−0.714	−0.355
Δvix	−1.571	−0.197	−0.060	0.195	−0.330	−0.258	−2.013	−0.220
t-stat	−1.843	−5.315	−0.220	−4.772	−1.274	−6.365	−2.011	−7.697
$flow_{\{-12\ \text{to}\ -1\}}$	0.039	0.001	0.009	0.001	0.035	0.004	0.014	0.000
t-stat	1.397	0.880	0.232	0.220	1.839	1.314	0.430	0.064
$return_{\{-12\ \text{to}\ -1\}}$	0.753	−0.013	0.573	0.046	0.406	−0.009	0.911	0.031
t-stat	0.616	−0.241	1.781	0.950	1.700	−0.251	0.813	0.960
$flow_{\{0\}}$		0.017		0.038		0.057		0.009
t-stat		3.834		2.435		3.637		2.987
Granger causality (*p*-value)								
F-*flow*	0.141	0.926	0.603	0.999	0.340	0.370	0.575	0.990
F-*return*	0.021	0.404	0.062	0.076	0.220	0.366	0.483	0.040
R^2	0.541	0.469	0.473	0.528	0.499	0.611	0.320	0.655
N		87		87		87		87

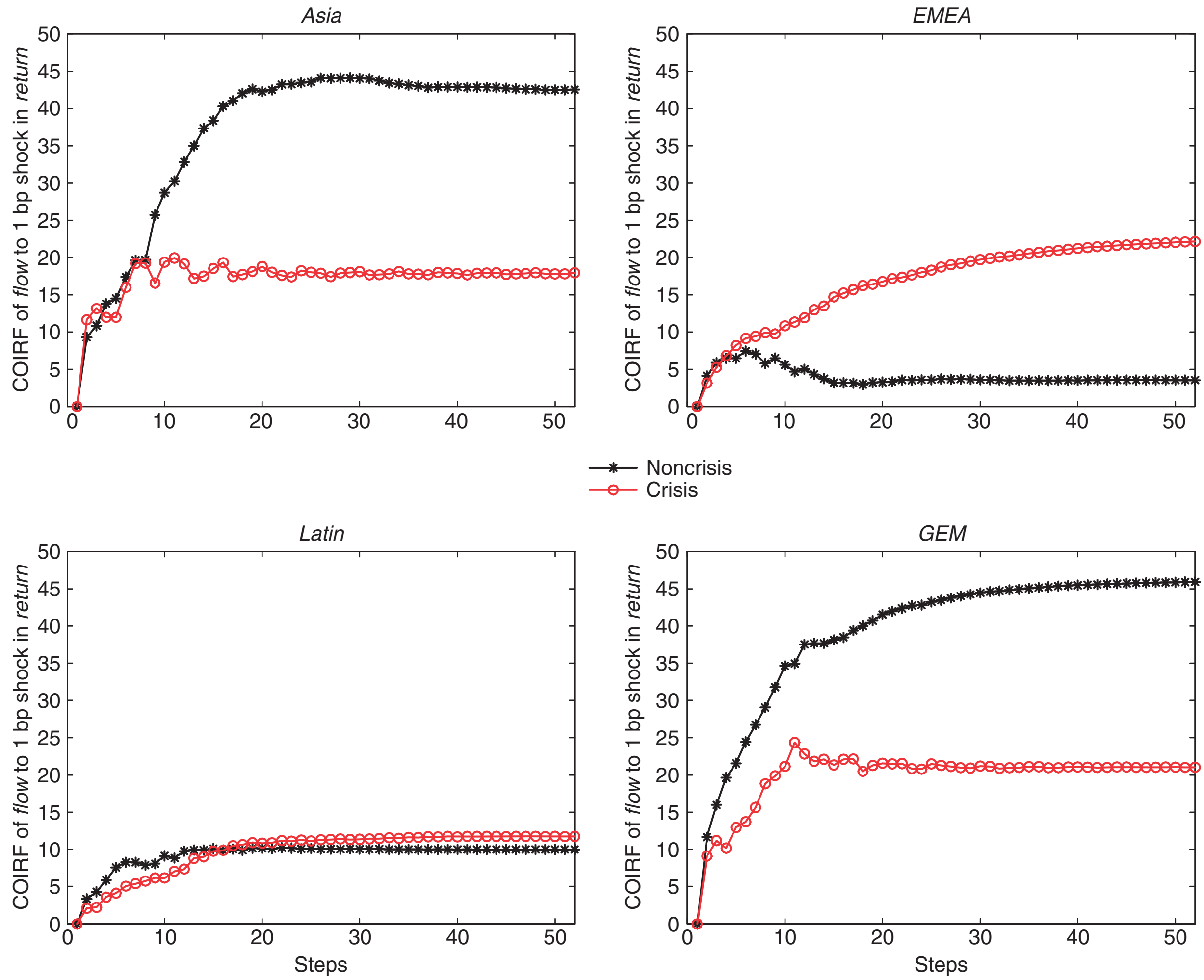

Fig. 4. The COIRE of *flow* to 1 bp shock in *return*

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 $return_{\{-12 \text{ to } -1\}}$ 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

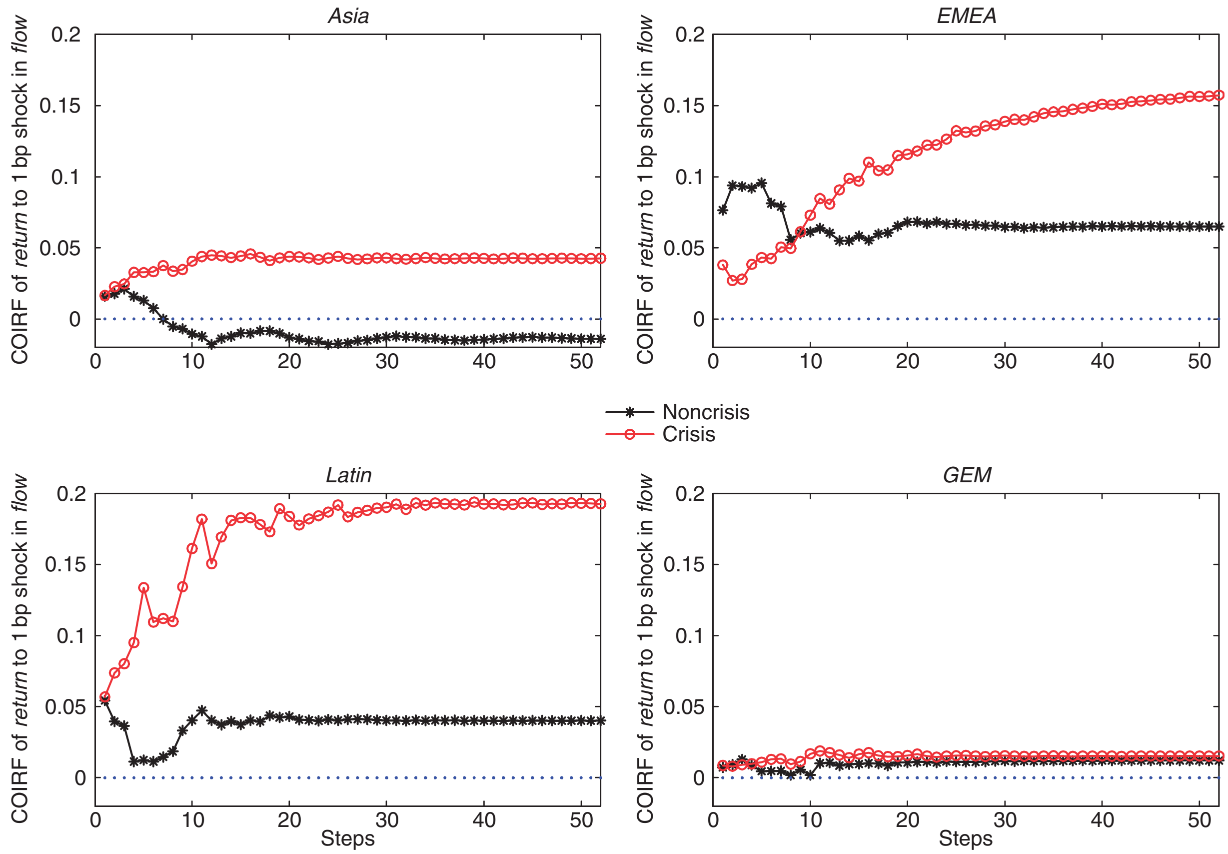

Fig. 5. The COIRE of *return* to 1 bp shock in *flow*

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 $flow_{\{0\}}$ 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*, 54 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

Table 7. Joint significant test (*p*-values)

	Asia		*EMEA*		*Latin*		*GEM*	
	flow	*return*	*flow*	*return*	*flow*	*return*	*flow*	*return*
Tranquil period								
F-*flow*	0.000	0.986	0.000	0.646	0.000	0.377	0.150	0.168
F-*return*	0.017	0.361	0.000	0.544	0.001	0.000	0.044	0.438
Panic period								
F-*flow*	0.813	0.966	0.026	0.865	0.163	0.914	0.842	0.854
F-*return*	0.340	0.936	0.306	0.441	0.894	0.217	0.300	0.868

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).[10] 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 work-horse VAR to better account for contagion as

$$\begin{pmatrix} flow_{i,t} \\ return_{i,t} \end{pmatrix} = C + \sum_{k}^{p} A_k \begin{pmatrix} flow_{i,t-k} \\ return_{i,t-k} \end{pmatrix} + \sum_{j \neq i}^{4} B \begin{pmatrix} flow_{j,t} \\ return_{j,t} \end{pmatrix} + B \begin{pmatrix} \log tna_t \\ \Delta vix_t \end{pmatrix} + \varepsilon \quad (8)$$

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, after controlling for the contagion effect, the benchmark evidence of positive feedback trading remains robust in *tranquil period*. The F-*flow* statistics in the *return* 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.

[10] See also Karolyi and Stulz (1996), Forbes and Rigobon (2001), Kyle and Xiong (2001), Kodres and Pritsker (2002), Yuan (2005), Boyer *et al*. (2006), Hau and Rey (2008) and Pavlova and Rigobon (2008).

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References

Ang, A., Hodrick, R. J., Xing, Y. and Zhang, X. (2006) The cross-section of volatility and expected returns, *Journal of Finance*, **61**, 259–99.

Bekaert, G., Hodrick, R. J. and Zhang, X. (2009) International stock return comovements, *Journal of Finance*, **64**, 2591–626.

Boyer, B. H., Kumagai, T. and Yuan, K. (2006) How do crises spread? Evidence from accessible and inaccessible stock indices, *Journal of Finance*, **61**, 957–1003.

Broner, F. A., Gaston Gelos, R. and Reinhart, C. M. (2006) When in peril, retrench: testing the portfolio channel of contagion, *Journal of International Economics*, **69**, 203–30.

Brunnermeier, M. K. (2009) Symposium: early stages of the credit crunch: deciphering the liquidity and credit crunch 2007–2008, *Journal of Economic Perspectives*, **23**, 77–100.

Brunnermeier, M. K. and Pedersen, L. H. (2009) Market liquidity and funding liquidity, *Review of Financial Studies*, **22**, 2201–38.

Calvo, G. A. and Mendoza, E. G. (2000) Rational contagion and the globalization of securities markets, *Journal of International Economics*, **51**, 79–113.

Carhart, M. M. (1997) On persistence in mutual fund performance, *Journal of Finance*, **52**, 57–82.

Chan, K., Covrig, V. and Ng, L. (2005) What determines the domestic bias and foreign bias? Evidence from mutual fund equity allocations worldwide, *Journal of Finance*, **60**, 1495–534.

Chen, J., Hong, H., Huang, M. and Kubik, J. D. (2004) Does fund size erode mutual fund performance? The role of liquidity and organization, *American Economic Review*, **94**, 1276–302.

Chiang, T. C., Jeon, B. N. and Li, H. (2007) Dynamic correlation analysis of financial contagion: evidence from Asian markets, *Journal of International Money and Finance*, **26**, 1206–28.

Coval, J. and Stafford, E. (2007) Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics*, **86**, 479–512.

Daniel, K., Grinblatt, M., Titman, S. and Wermers, R. (1997) Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance*, **52**, 1035–58.

Forbes, K. and Rigobon, R. (2001) Measuring contagion: conceptual and empirical issues, in *International Financial Contagion* (Ed.) S. Claessens, Kluwer Academic Publishers, Boston, pp. 43–66.

Frazzini, A. and Lamont, O. A. (2008) Dumb money: mutual fund flows and the cross-section of stock returns, *Journal of Financial Economics*, **88**, 299–322.

Froot, K. A., O'Connell, P. G. J. and Seasholes, M. S. (2001) The portfolio flows of international investors, *Journal of Financial Economics*, **59**, 151–93.

Froot, K. A. and Ramadorai, T. (2008) Institutional portfolio flows and international investments, *Review of Financial Studies*, **21**, 937–71.

Goldstein, I. and Pauzner, A. (2004) Contagion of self-fulfilling financial crises due to diversification of investment portfolios, *Journal of Economic Theory*, **119**, 151–83.

Greene, J. T. and Hodges, C. W. (2002) The dilution impact of daily fund flows on open-end mutual funds, *Journal of Financial Economics*, **65**, 131–58.

Gruber, M. J. (1996) Another puzzle: the growth in actively managed mutual funds, *Journal of Finance*, **51**, 783–810.

Hamilton, J. D. and Susmel, R. (1994) Autoregressive conditional heteroskedasticity and changes in regime, *Journal of Econometrics*, **64**, 307–33.

Hasbrouck, J. (1991) Measuring the information content of stock trades, *Journal of Finance*, **46**, 179–207.

Hau, H. and Rey, H. (2006) Exchange rates, equity prices, and capital flows, *Review of Financial Studies*, **19**, 273–317.

Hau, H. and Rey, H. (2008) *Global Portfolio Rebalancing Under the Microscope*, London Business School, London.

Heiko, H. and Brenda, G.-H. (2009) Financial crisis, global conditions, and regime changes. Available at http://www.voxeu.org/index.php?q=node/3472 (accessed 11 October 2010).

Ilyina, A. (2006) Portfolio constraints and contagion in emerging markets, *IMF Staff Papers*, **53**, 351–74.

Jinjarak, Y., Wongswan, J. and Zheng, H. (in press) International fund investment and local market returns. *Journal of Banking and Finance*.

Kaminsky, G., Lyons, R. K. and Schmukler, S. L. (2004) Managers, investors, and crises: mutual fund strategies in emerging markets, *Journal of International Economics*, **64**, 113–34.

Kaminsky, G. L. and Reinhart, C. M. (2000) On crises, contagion, and confusion, *Journal of International Economics*, **51**, 145–68.

Karolyi, G. A. and Stulz, R. M. (1996) Why do markets move together? An investigation of US-Japan stock return comovements, *Journal of Finance*, **51**, 951–86.

Keswani, A. and Stolin, D. (2008) Which money is smart? Mutual fund buys and sells of individual and institutional investors, *Journal of Finance*, **63**, 85–118.

Kim, W. and Wei, S. J. (2002) Foreign portfolio investors before and during a crisis, *Journal of International Economics*, **56**, 77–96.

Kodres, L. E. and Pritsker, M. (2002) A rational expectations model of financial contagion, *Journal of Finance*, **57**, 769–99.

Kyle, A. S. and Xiong, W. (2001) Contagion as a wealth effect, *Journal of Finance*, **56**, 1401–40.

Lutkepohl, H. and Reimers, H.-E. (1992) Granger-causality in cointegrated VAR processes: the case of the term structure, *Economics Letters*, **40**, 263–8.

Mendoza, E. G. and Terrones, M. E. (2008) An anatomy of credit booms: evidence from macro aggregates and micro data, NBER Working Paper No. 14049.

Pavlova, A. and Rigobon, R. (2008) The role of portfolio constraints in the international propagation of shocks, *Review of Economic Studies*, **75**, 1215–56.

Sapp, T. and Tiwari, A. (2004) Does stock return momentum explain the 'smart money' effect?, *Journal of Finance*, **59**, 2605–22.

Taylor, J. B. and Williams, J. C. (2009) A black swan in the money market, *American Economic Journal: Macroeconomics*, **1**, 58–83.

Warther, V. A. (1995) Aggregate mutual fund flows and security returns, *Journal of Financial Economics*, **39**, 209–35.

Yuan, K. (2005) Asymmetric price movements and borrowing constraints: a rational expectations equilibrium model of crises, contagion, and confusion, *Journal of Finance*, **60**, 379–411.

Zheng, L. (1999) Is money smart? A study of mutual fund investors' fund selection ability, *The Journal of Finance*, **54**, 901–33.