Investment Giants and Their Impacts in Emerging Markets

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Abstract

Non-resident portfolio flows into emerging markets are heavily concentrated among a few large institutional investors, termed "*investment giants*." Using monthly fund-level data, we demonstrate these giants' substantial influence on other investors and on aggregate market outcomes. Their contrarian investment decisions—measured by excess growth relative to smaller peers or the market—consistently predict future equity inflows, exchange rate movements, and stock market indices. To explain why investors follow investment giants, we build a strategic interaction model featuring a single investment giant and a continuum of typical investors. By observing the giant's initial actions, typical investors gain information on market fundamentals, reducing their uncertainty. Moving first, the investment giant sets a market direction that followers are inclined to align with, securing a strategic advantage. With strong strategic interaction and the giant's superior information quality allow both it and typical investors to achieve higher payoffs when the giant moves first, compared to reverse or simultaneous moves. These findings suggest the potential value of monitoring investment giants' actions as early indicators of market movements and financial instability in emerging economies.

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1 Introduction

In accordance with the increasing integration of international financial markets, there has been a consistent growth in portfolio flows across economies. Notably, following the global financial crisis (GFC), low market rates fueled substantial portfolio flows into emerging market economies as international investors reached for higher yields (Rajan 2006 and Summers 2016). From the perspective of emerging markets, non-resident portfolio inflows offer significant benefits, including increased opportunities for risk-sharing and external financing (Bonfiglioli 2008, Igan, Kutan and Mirzaei 2020, and Aristizabal-Ramirez, Leahy and Tesar 2023). However, greater external exposure also brings challenges. Capital inflows can amplify the vulnerability of local financial markets to global shocks, and their sudden reversal can intensify financial stress in emerging markets (Calvo and Reinhart 2002 and Gourinchas and Obstfeld 2012). Furthermore, foreign investors occasionally overreacted to the evolution of market fundamentals, leading to increased volatility in local financial conditions (Dornbusch and Park 1995). This situation could be further complicated by financial integration, which, while increasing the likelihood of financial crises, can also reduces their severity (Devereux and Yu 2019).

Capital flows and global asset allocations play crucial roles in financial and foreign exchange markets, particularly in emerging economies (e.g., Hau and Rey 2006, Gyntelberg, Loretan and Subhanij 2018, Wong 2017, and Goldberg and Krogstrup 2023). This relationship may also be relevant from the perspective of individual global investors' portfolio choices. Figure 1 illustrates the growth rates of Emerging Portfolio Fund Research (EPFR) global equity fund flows, stock market indices, and exchange rates (local currency per US dollar) in 20 emerging market economies. Although EPFR fund flows typically represent only 1–10% of each emerging market's capitalization (Jotikasthira, Lundblad and Ramadorai 2012), a rise in global equity flows shows a strong positive correlation with stock returns and a negative correlation with exchange rates, indicating their significant impact beyond market shares.

Despite the informative potential, our understanding of the underlying drivers of cross-border portfolio flows and their macro-financial consequences, particularly at the fund investor level, remains limited. This study seeks to address this gap by analyzing the investment choices made by institutional investors (mutual funds) in emerging equity markets. The EPFR data reveal a significant concentration of international portfolios among a few large investors, echoing patterns observed in previous studies on US and global financial markets (e.g., Corsetti, Dasgupta, Morris

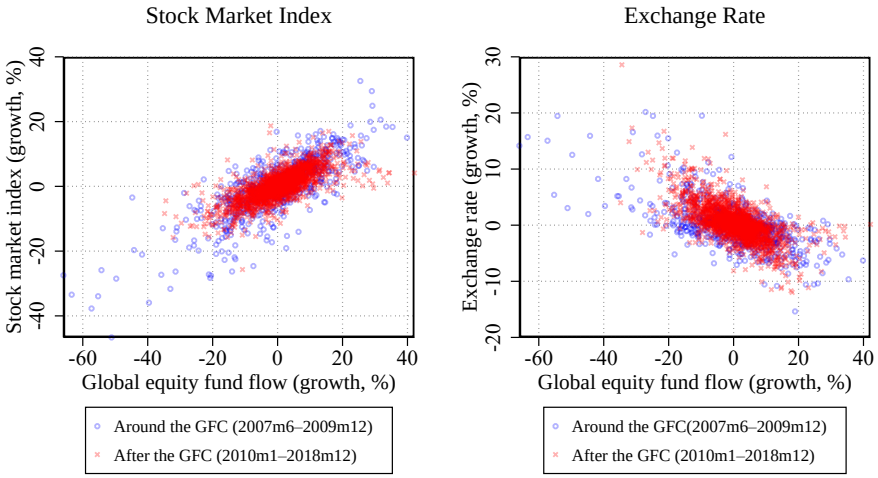


Figure 1: Global Equity Fund Flows, Stock Prices, and Exchange Rates in Emerging Economies

Notes: The figures plot the growth rates of EPFR global equity funds' aggregate investments, stock market indices, and nominal exchange rates (local currency per US dollar) in 20 emerging market economies. The blue circles and red crosses are observations around the global financial crisis (2007m6–2009m12) and after the crisis (2010m1–2018m12), respectively.

and Shin 2004, Buch, Koch and Koetter 2011, Ben-David, Franzoni, Moussawi and Sedunov 2021, and Coimbra, Kim and Rey 2022). Accordingly, we focus on identifying these dominant investors, often referred to as "*investment giants*," and their impacts on other investors, as well as on equity and currency markets. By doing so, we provide insights relevant to policymakers and market participants navigating the complexities of international capital flows in emerging markets. Our findings suggest the potential benefits of monitoring the activities of investment giants as early warning indicators in these economies.

In this paper, we examine how individual investors react to the decisions of investment giants using panel local projections. In more details, we investigate the dynamic effects of the investment giants' contrarian investment—measured by the average growth of giants' flows excessive to other investors or market growth—on individual investors' equity fund flows in 20 emerging markets.[1] We find that equity flows into emerging equity markets exhibit a persistent upsurge following an increase in investment giants flow shocks (the differential between the average equity flow of investment giants and other investors), implying that large investor flows relative to typical investors have strong predictive power for overall institutional equity flows. This underscores the

[1]We define the top 10 largest investors as investment giants. Given that there is no established rule-of-thumb for determining the threshold for large investors, we also compare the results by changing the criteria to include the top 7 or 15 largest investors.

importance of large investor flows in understanding the dynamics of global asset reallocation.

Notably, the observed influence of investment giants is particularly pronounced in the post-GFC period relative to the GFC period itself. This indicates that investors place greater reliance on the informational content of these giants' investment decisions during the post-crisis era. Our results align with previous research by Choe, Kho and Stulz (1999), which finds evidence of positive feedback trading by foreign investors in Korea before the 1997 Asian financial crisis, a pattern that dissipated during the crisis. In addition, Ahmed and Zlate (2014) and Ahmed, Coulibaly and Zlate (2017) document shifts in investment patterns and global financial conditions after the GFC.

Our empirical analysis also reveals a strong correspondence between fund-level and aggregate-level patterns. Aggregate equity flows demonstrate a positive response to investment giants' contrarian investment. The differential between investment giants' and typical investors' equity flows predicts increases in aggregate foreign equity inflows—computed from EPFR aggregate as well as from the International Institute of Finance (IIF) dataset. The congruence between fund-level and aggregate-level results suggests that, despite its small coverage in total market capitalization, EPFR data delivers useful information related to the future path of aggregate variables.

Furthermore, we observe a positive dynamic relationship between investment giants' contrarian investment and stock market returns. On the other hand, exchange rate is predicted negatively (i.e., currency depreciation) in response to less equity investments from investment giants than typical investors or aggregate investments. The strong predictability for market returns emphasizes the necessity of diligent monitoring of investment giants' transactions in equity and foreign exchange markets in emerging economies. Such monitoring can serve as a valuable tool for predicting foreign portfolio inflows and for detecting potential financial vulnerabilities.

Our theoretical work addresses why investment giants move first, with other investors following. To explore this, we construct a model that combines two key elements: a beauty contest framework (strategic interaction) and the presence of a dominant player, the investment giant. As in Morris and Shin (2002), investor payoffs decline as their actions deviate from both market fundamentals and the aggregate behavior of other investors. The market includes one large investor (the investment giant) and a continuum of smaller investors, similar to the setup in Corsetti et al. (2004). While individual actions by typical investors do not influence market aggregates, the investment giant's decisions do impact market equilibrium.

In this sequential move structure, typical investors benefit by observing the investment giant's initial actions, allowing them to refine their strategies and reduce reliance on private signals. For the

investment giant, moving first provides a strategic advantage in this beauty contest context, where payoffs are tightly connected to others' actions. Acting early, the giant sets a market direction that followers tend to align with, "locking in" momentum—especially when it commands a substantial market share. This advantage, however, remains inaccessible to typical investors, even if they move first, due to their limited influence on the market.

We analyze and compare payoffs for the investment giant and typical investors across different move structures, identifying the conditions under which observed market behavior aligns with theoretical predictions. When strategic interaction is strong, the investment giant's large market share and superior information quality lead both parties to achieve higher payoffs when the giant moves first and others follow, compared to reverse or simultaneous move structures.

Investigating investment decisions is essential for a comprehensive understanding of financial markets. Existing literature has provided valuable insights by examining investment decisions among institutional investors, particularly focusing on the collective decision-making processes and co-movements of portfolio investments. For instance, Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992) develop a sequential decision-making model where agents imitate the actions of predecessors while ignoring their private information. This model is combined with a pricing mechanism by Avery and Zemsky (1998) to analyze collective behavior. Furthermore, Lakonishok, Shleifer and Vishny (1992) study herding among investors in the pension fund market.

However, there are still unexplored dimensions in this research landscape that our paper seeks to contribute. Most of the existing studies rely on data from the US, which may not fully capture the international nature of investment strategies. As global investors may employ different decision strategies than domestic investors, there is a need for a more international perspective on these issues (Jotikasthira et al. 2012 and Raddatz and Schmukler 2012). Our paper takes this perspective into account, thereby contributing to a better understanding of portfolio allocations by fund investors. This broader view can be useful for ensuring financial stability in emerging economies closely integrated into the international financial market; e.g., designing macro-prudential or foreign exchange policy frameworks.

Furthermore, most of the existing literature lacks attention to the determinants of international portfolio flows at the fund level. While prior studies have predominantly concentrated on aggregate-level flows and the impact of external ("*push*") conditions (Calvo, Leiderman and Reinhart 1993, 1996, Fernandez-Arias 1996, Taylor and Sarno 1997, Forbes and Warnock 2012, Byrne and Fiess 2016, and many others), our research enhances this understanding by investigating both new

and unexplored determinants at the fund level. This aspect is particularly notable because global factors, including US monetary policy, significantly influence *inter alia* the global financial cycle, e.g., Rey (2015) and followed by Kalemli-Özcan (2019) and Goldberg and Krogstrup (2023). Our paper bridges this research void by providing insights into how these factors interact with the investment decisions of institutional investors in emerging equity markets.

The rest of the paper proceeds as follows: Section 2 provides a description of the dataset and relevant statistics regarding portfolio flows in emerging markets. Section 3 presents a detailed investor-level regression analysis, highlighting the critical role played by investment giants. In Section 4, the country-level regression analysis provides aggregate-level implications for investors and policymakers in emerging equity and currency markets. Section 5 presents a theoretical model with strategic interactions, dominant player, and sequential moves to offer economic interpretations about the observed influence of investment giants on typical investors. Section 6 concludes.

2 Data and Measurements

2.1 Mutual Funds Portfolio Data

Throughout the paper, we primarily use data from the EPFR global funds database. This database offers relatively high-frequency (monthly) information on portfolio investment at the individual investor level, with the caveat that it exclusively encompasses institutional investors.[2]

The EPFR database provides detailed information for each mutual fund, including its name, total net assets in US dollars, country allocation weights as a percentage of fund assets, investment destination countries/target regions, investment type (passive or active), and currency denomination. It also contains information on fund domiciles, of which the majority of funds located in advanced economies.

Emerging market-dedicated funds are categorized into specific target regions, including Asia ex-Japan, Emerging Europe, Europe, Middle East & Africa, Global Emerging, Latin America, and Middle East. Within these regions, we have selected funds that include a total of 20 host countries, namely Brazil, Chile, China, Colombia, Czech Republic, Hungary, Indonesia, India, Israel, South Korea, Mexico, Malaysia, Peru, the Philippines, Poland, Russia, Thailand, Turkey, Taiwan, and

[2]As in Koepke and Paetzold (2020), we find that the aggregate of EPFR fund flows at the country level exhibits similarities to traditional IMF Balance of Payment (BoP) statistics. See Fratzscher (2012), Kim and Lee (2020), Koepke and Paetzold (2020), and Chari, Stedman and Lundblad (2022) for the discussions and details of the EPFR global funds data. In addition, the sample period is selected based on the availability of reliable data, taking into consideration its volume as well as its freedom from exogenous non-financial impacts, including the pandemic.

South Africa. These 20 countries are chosen, considering that their equity fund investment accounts for a significant share of total emerging economy investment and their monthly macroeconomic indicators are available for the sample period.

For our analysis, we chose two distinct periods: the period from June 2007 to December 2009 and the period from January 2010 to December 2018, which follows the global financial crisis (GFC). We conducted a preliminary screening of the EPFR data by excluding funds with less than 12 months of observations or those with an average total investment of less than 100 million US dollars over the observed time series. After applying these filters, our dataset comprises approximately 100 mutual funds per month, with a range of 86 to 126 funds during the study period (June 2007–December 2018).

Table 1 provides the summary statistics of the data.[3] Our final dataset at the investor-country-month level comprises 56,460 observations for the period around the GFC (June 2007–December 2009) and 240,940 observations for the period after the GFC (January 2010–December 2018, before the COVID-19 pandemic).

2.2 Equity Investment Measurements

To track how each fund adjusts its investment behavior, we calculate the size of the fund i's equity investment or its estimated allocation to a particular country c at time (month) t, $\text{Equity}_{ic,t}$, using the information available in the EPFR database as follows:[4]

$$\text{Equity}_{ic,t} = \sum_{a \in \text{AssetClass}} \text{EquityShare}_{aic,t} \times \text{TotalNetAssets}_{ai,t}, \tag{1}$$

where $\text{TotalNetAssets}_{ai,t}$ is the total (equity) investment of mutual fund i's asset class a across all host countries, and $\text{EquityShare}_{aic,t}$ is the equity investment share of fund i's asset class a in country c in its total investment at time t. Each fund includes 12 class of assets, indexed by a.[5]

For instance, in December 2011, J.P. Morgan Asset Management held total net assets of 8,825.83 million US dollars under the asset class of Global Emerging Markets, with South Korea accounting

[3] See also Tables 3 for the summary statistics of active funds.

[4] The EPFR database also provides data on fund flows to each destination country, but their time-series quality is relatively lower than the country allocation data, marked by a higher incidence of missing observations.

[5] The list of the 12 asset classes is Global Emerging Markets-GEM-CA-Equity, Emerging Europe Regional-EMEA-CA-Equity, Asia ex-Japan Regional-Asia Ex-Japan-CA-Equity, Latin America Regional-LatAm-CA-Equity, Global-Global-CA-Equity, Middle East Regional-EMEA-CA-Equity, Global ex-US-Global-CA-Equity, Europe, Middle East & Africa Regional-EMEA-CA-Equity, Greater China-Asia Ex-Japan-CA-Equity, BRIC-GEM-CA-Equity, Africa Regional-EMEA-CA-Equity, and Middle East & Africa Regional-EMEA-CA-Equity.

for 10.1% of that total allocation. Similarly, the fund held 2,085.92 million US dollars in the Asia ex-Japan Regional, with South Korea accounting for 16.8% of the country weight. Hence, J.P. Morgan's equity investment in South Korea for that particular month amounted to 1,241.84 million US dollars (= 8,825.83×0.101 + 2,085.92×0.168). The same procedure is applied consistently across all funds and host countries.

There are instances where a fund does not invest in equities in a particular market or country. Since both the logarithmic value of equity investment and their time differences are not available in such cases, we employ the inverse hyperbolic sine (IHS) transformation ($\text{IHS}(x) = \ln[x+(x^2+1)^{0.5}]$) for the computation of the equity growths (flows) between t and $t+h$:

$$\Delta^h \text{IHS}(\text{Equity}_{ic,t}) = \text{IHS}(\text{Equity}_{ic,t+h}) - \text{IHS}(\text{Equity}_{ic,t}), \tag{2}$$

where the cumulative growth is winsorized at both ends by –h×100% and h×100% (i.e., 100% monthly growth rate), to prevent our regression results from being potentially influenced by a few extreme flows. This is similar to one that winsorizes the top and bottom 1% of observations in the case of $h = 1$.[6]

The cumulative equity growths of equation (2) include valuations resulting from equity returns and exchange rates. Hence, even when investors do not adjust their investment, high (low) equity returns and currency appreciation (depreciation) lead to an increase (decrease) in the investors' equity holdings. In this case, the equity growths overestimate (underestimate) investment allocation. To isolate this valuation channel, we compute the cumulative equity growth based on the adjusted equity growth with market returns:

$$\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = \text{IHS}\left(\text{Equity}_{ic,t+h} \times \frac{\text{StockIndex}_{c,t}}{\text{StockIndex}_{c,t+h}} \frac{\text{FX}_{c,t+h}}{\text{FX}_{c,t}}\right) - \text{IHS}(\text{Equity}_{ic,t}), \tag{3}$$

which controls the growths of stock market index and exchange rate growths for the fund i in country c at time $t+h$. The adjusted growth is also winsorized at both ends by –h×100% and h×100%.

[6] We checked the estimation results without winsorization, and found that the main results remain robust.

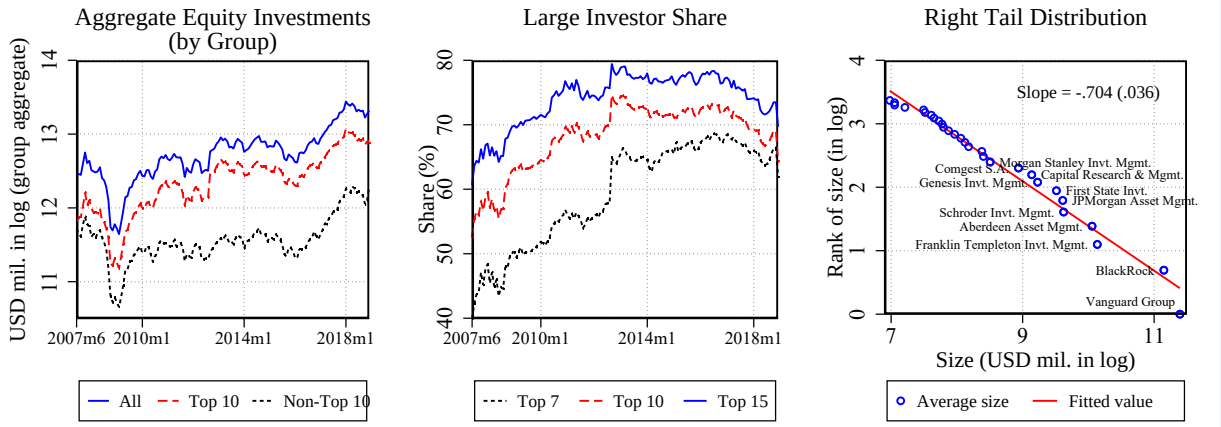


Figure 2: Trends of Equity Fund Flows to Emerging Markets

Notes: The first figure plots the total equity investment made by each investor group in the 20 emerging equities markets. The second figure displays the shares of the top 7, 10, and 15 largest investors in the total global equity funds allocated to the 20 emerging equity markets. The last figure plots the logged total equity investment size, averaged over the period of 2010m1–2018m12, and its logged rank in the emerging equity markets. The data includes 29 continuing investors with size exceeding one billion US dollars. The absolute value of slope of predictions (red line) implies the coefficients of power distribution.

2.3 Investment Giants

For our analysis of interplay among fund flows of different sizes, we should first set a criterion for categorizing individual funds as either *investment giants* (large investors, indexed by $i \in \mathcal{G}$) or *typical investors* (non-large investors, $i \notin \mathcal{G}$).[7] However, there is no precise cutoff point to distinguish large funds from non-large ones. To address this issue, we establish a reasonable rule of thumb by analyzing the size distribution of funds in relation to their equity investments in the 20 emerging markets.

Specifically, we first assort fund sizes based on the over-time average of each fund's total equity fund investments to the 20 emerging markets between January 2010 and December 2018. Then, we designate the top 10 largest funds as the investment giants throughout the study period. These 10 funds include Aberdeen Asset Management, BlackRock, Capital Research & Management, Comgest S.A., First State Investments, Franklin Templeton Investment Management, Genesis Investment Management, JPMorgan Asset Management, Schroder Investment Management, and Vanguard

[7]Throughout the paper, we use the term 'investment giants (typical investors)' and 'large investors (non-large investors)' interchangeably.

Group.[8] The funds not falling within the top 10 are categorized as typical (non-large) investors. Noticeably, these investment giants have consistently held the top-ranking positions over time due to their substantial assets under management.

Figure 2 provides an overview of the equity investments made by emerging market-focused funds. The first chart evidently indicates that, during the sample period, the total size of equity funds' allocations to emerging markets (expressed in logarithm), largely driven by investment giants, increased from 200 to 600 billion US dollars despite a sharp correction around the GFC in 2008. This pattern is further corroborated in the second chart which reports the share of large mutual funds' equity investments in emerging markets. Markedly, huge mutual funds have been increasingly dominant since the GFC, up until 2013. In short, the two charts collectively suggest that emerging equity markets have been incrementally dependent on capital inflows by the investment giants.

The distribution of equity investments made by mutual funds reaffirms the notable concentration of investments among a few large funds. In the final chart of Figure 2, there exists a pronounced right-tail fatness in the distribution for both periods around and after the GFC. The chart plots a log-log graph for the investment size against investor rank. The linear slope of the graph indicates a power-law relationship in the right tail of the distribution, where the rank changes as a constant power of the size, such that $\ln \text{Rank} \propto \text{Slope} \times \ln \text{Size}$. In our sample from January 2010 to December 2018 (post-GFC), the slope value is approximately –0.704 for the 29 largest investors. This suggests that investments are concentrated primarily among a handful of investment giants, while only a small portion is allocated to many typical investors.

Furthermore, we present the corresponding charts computed with the active fund flows data (excluding passive fund flows) in Figure 20. The patterns observed in the active fund data closely resemble those of all fund types. We also provide insights into the trends over time by breaking down the data on a monthly basis. Among them, Figure 21 displays the right tail distributions for three specific periods: September 2008, September 2010, and September 2015. The estimated slopes of log-log plots indicate a robust right heavy tail, ranging between –0.968 (robust standard error: 0.041) and –0.845 (0.017). The absolute values of the estimated slopes are smaller than two, implying granularity—meaning that idiosyncratic shocks to large funds cannot be diversified and

[8] Alternatively, we also consider the top 7 and 15 largest funds as investment giants. The top 7 largest funds are identical to the top 10 largest funds but excluding Capital Research & Management, Comgest S.A., and Genesis Investment Management. The top 15 largest funds include Deutsche Asset, Management, Invesco Asset Management, Morgan Stanley Investment Management, State Street Global Advisors, and Vontobel Asset Management, in addition to the top 10 largest funds.

therefore affect the aggregate.

2.4 Measure of Investment Giants' Contrarian Investment

Given that our primary focus is on the investment decisions of the giants, distinguished from the other investors, and their impacts on the markets, it is important to select an appropriate measure to capture their investment behaviors, in particular when they go against other investors or prevailing market trends. For the measurement, we mainly use the differential between the average equity flow of investment giants and typical investors, referring to as *the investment giant's contrarian investment*.[9]

$$\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}} = \frac{1}{N^{\mathcal{G}}} \sum_{i \in \mathcal{G}} \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}) - \frac{1}{N_t - N^{\mathcal{G}}} \sum_{i \notin \mathcal{G}} \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}), \tag{4}$$

where $\bar{g}_{c,t}^{\text{giant}}$ and $\bar{g}_{c,t}^{\text{typical}}$ are the average equity growth of investors between t and $t-1$ in two groups: investment giants ($i \in \mathcal{G}$) and typical investors ($i \notin \mathcal{G}$). Additionally, $N^{\mathcal{G}}$ and N_t are the number of investment giants and the total number of investors, respectively.[10]

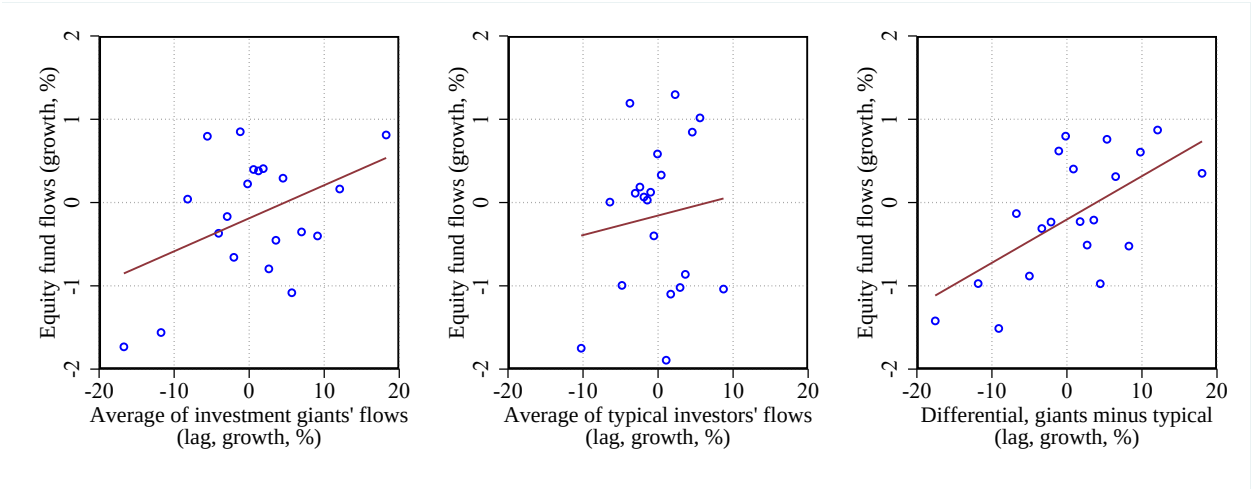
The investment giant's contrarian investment gauges the extent to which their investment size outpaces in emerging equity markets compared to that of typical investors. A positive differential, $\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}} > 0$, indicates that the average equity growth of investment giants exceeds that of typical investors. In other words, investment giants increased their equity investments to country c more significantly than typical investors. This suggests that investment giants are more aggressive or optimistic in their investment decisions compared to typical investors, potentially exerting a greater influence on overall market trends and the behavior of other investors.

Figure 3 presents binned scatter plots that show the average increase in investor equity within each ventile of investment giants' and typical investors' prior month growth rates, along with their differential. Panels (a) and (b) display the plots for the sub-samples corresponding to the periods during and after the GFC, respectively. The results indicate that when investment giants' equity investments increase in the prior month, global investor equity flows tend to grow accordingly. However, this pattern does not hold when typical investors increase their average investments in the previous month. Furthermore, this pattern becomes clearer when examining the differential of

[9] In a similar vein, investment giants share is also considered as a measure. See Section 3.3 for the details.

[10] Here, we use the valuation-adjusted equity growths. Similarly, the investment giants' and typical investors' averages of valuation-adjusted equity growth ($\bar{\tilde{g}}_{c,t}^{\text{giant}}$ and $\bar{\tilde{g}}_{c,t}^{\text{typical}}$) are derived from $\tilde{\Delta}^1$ rather than Δ^1. By construction, the non-adjusted contrarian investment by investment giants is close to the adjusted differential: $\bar{\tilde{g}}_{c,t}^{\text{giant}} - \bar{\tilde{g}}_{c,t}^{\text{typical}} \approx \bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}$.

(a) Around the GFC (2007m6–2009m12)



(b) After the GFC (2010m1–2018m12)

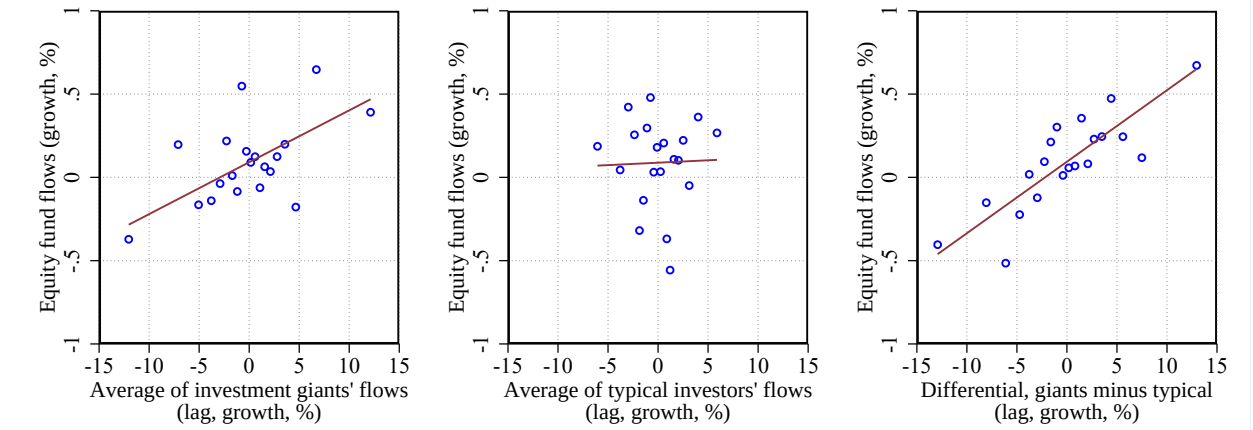


Figure 3: Equity Flows over the Lagged Investment Giants' and Typical Investors' Average Equity Flows

Notes: The figures are binned scatter plots of investors' equity flows, controlled for the aggregate equity flows ($\tilde{\Delta}^1 \ln \text{Equity}_{c,t-1}$), country and investor fixed effects. In the first and second figures of each panel, investors are divided into 20 bins on the x-axis based on their average one-month lagged equity investment growths ($\bar{\tilde{g}}^{\text{giant}}_{c,t-1}$ and $\bar{\tilde{g}}^{\text{typical}}_{c,t-1}$) as investment giants (top 10 largest investors) and typical investors (non-investment giants), respectively. The x-axis of last figure of each panel is the investment giants' equity flow differential, ($\bar{\tilde{g}}^{\text{giant}}_{c,t-1} - \bar{\tilde{g}}^{\text{typical}}_{c,t-1}$). The dots show the average equity investment growths of each group (ventile), and the lines present the fitted values. All equity flows are adjusted to remove valuation effects.

investment giants, as shown in the third charts of each panel (a) and (b). Global investors tend to increase their equity flows in response to investment giants' growths surpassing those of typical investors. These observations suggest that the decisions made by investment giants can play an important role in emerging equity markets by influencing other investors and aggregate trends.

2.5 Macroeconomic Variables

In addition to fund-level data, we incorporate country-level macroeconomic variables. These variables fall into two categories: pull and push factors. They are commonly employed in the literature to investigate or to control for the impacts of capital flows. Specifically, pull factor pertains to domestic features that reflect a country's macroeconomic fundamentals such as GDP, reserves, interest rates, and the stock market index. Push factor represents external conditions, including the supply of global liquidity (global risk premium), GDP, interest rates, and the stock market index in advanced economies or the US. We use the contemporaneous growth of these pull and push factors, along with their three lags. Further details regarding data collection and variable construction are available in Appendix B. Table 5 reports summary statistics for the macroeconomic variables.

3 The Roles of Investment Giants in Emerging Equity Markets

To understand the roles played by large institutional investors in emerging equity markets, this section examines how other investors react to the actions of these large players. Using panel local projections, we aim to assess the predictive power of large investors' decisions on the subsequent equity investments made by others. Our results establish that the decisions of investment giants carry significant information, and highlight their impacts on other investors within emerging equity markets.

3.1 Equity Fund Flow Dynamics with Investment Giants

As a first pass, we assess the predictability of investment giants' equity flow growth for subsequent other equity flow growth and its time-varying nature. This is done by testing the following two hypotheses.

The first hypothesis posits that individual fund flows were influenced by the investment giants' contrarian investments in emerging markets. The existing literature on capital flows, including portfolio flows, has typically focused on their correlation with business cycles. These studies

commonly investigate the determinants of capital or portfolio flows by examining their relationship with macroeconomic variables such as GDP and interest rates.[11] While this approach provides an overview of the broad-level relationship, it may not fully capture the complex interplays between institutional investors and their investment strategies. Recognizing these limitations of aggregate-level studies, we employ a demand estimation approach at the fund level to explore the impacts of investment giants' decisions on the other investors' reactions.

Another hypothesis postulates that the effects of investment giants were amplified after the GFC. Numerous studies, relying on gross-level data, have documented significant shifts in capital flow patterns in the aftermath of the GFC (Rey 2015). In particular, Shin (2014), Hardy and von Peter (2023), and others emphasize the importance of distinguishing between two phases of global liquidity. Following the GFC, global banks gradually ceded their dominant role to asset managers and other "buy-side" investors with global reach. Prolonged low-interest rates, primarily due to policy accommodation in the US and other advanced economies, arguably prompted global investors to take on more risk and search for higher yields. Investor-level investigations, as well as documented shifts in aggregate net inflows, particularly in portfolio flows before and after the GFC (Ahmed and Zlate 2014 and Ahmed et al. 2017), may provide additional insights into how interactions among individual investors contributed to the developments in capital flows during the post-GFC periods.

Regression specification To simplify our empirical model, we assume that each investor regards the overall stock market of each emerging economy as a representative asset. Hence, they determine their investment size in each market while considering the specific characteristics of that equity market. These characteristics systematically vary depending on the macroeconomic conditions of each country. We employ the investor-level demand model specified as a linear function of all covariates in equation (5). The model is estimated using panel local projection of *à la* Jordà (2005), separately for the sub-samples of the GFC and of the post-GFC periods:

$$\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = \beta^h \left(\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}\right) + \mathbf{\Gamma}^h_{\text{pull}} \mathbf{Pull}_{c,t} + \mathbf{\Gamma}^h_{\text{push}} \mathbf{Push}_t + \delta_i^h + \delta_c^h + \delta_m^h + \varepsilon_{ic,t}^h, \quad (5)$$

for the time horizon considered $h = 1, 2, \cdots, 10$, and where the dependent variable is the adjusted cumulative equity growth in equation (3).

[11] In our study, the influence of the cyclical common factors are taken consideration into by push and pull factors. For more comprehensive discussions and surveys, refer to Hannan (2017), Hannan and Cubeddu (2018) and Koepke (2019).

Most importantly among the right-hand side variables, we include the investment giants' contrarian investment (i.e., average equity growth differential between equity investments made by the top 10 largest investors and other investors; $\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}$) as a main regressor. As demonstrated in Section 2, the dominance of a handful of investment giants, presumably with substantial sway over other market participants, is a defining characteristic of the emerging portfolio market. As such, this regressor is to gauge the influence of investment giants' distinct portfolio decisions on the demand of individual investors for equity flows and its dynamics.

Besides, the local projection regression accounts for overall economic conditions by incorporating standard control variables. The vector $\mathbf{Pull}_{c,t}$ and $\mathbf{Push}_t$ includes other control variables, encompassing both pull and push factors at time t along with their three lags.[12] By controlling for the factors associated with economic and financial conditions, the regression excludes the latent impacts from spurious comovements or similar reactions among investors induced by the fundamentals (Bikhchandani and Sharma 2001). It is empirically important to isolate such correlated behavior because it merely reflects an efficient asset reallocation driven by common factors. Pull factors capture domestic aspects, consisting of real interest rates (per annum), growth rates of industrial production, total reserves, exchange rates, and the stock market index for each emerging country c. On the other hand, push factors encompass external or global conditions, including the corresponding US variables, such as US real interest rates (per annum) and growth rates of the VIX, US industrial production, and stock market index (Wilshire 5000).

There may be unobserved heterogeneity among investors and countries that is not captured by pull and push factors. Thus, we incorporates various fixed effects to account for unobserved heterogeneity among investors and emerging markets. Specifically, we include investor-specific fixed effects (δ_i^h) and market country fixed effects (δ_c^h) to capture time-invariant investor-specific characteristics and time-invariant market traits, respectively. Additionally, time (month) fixed effects (δ_m^h, 11 dummies) are considered to mitigate the effects of seasonality in the data.

Regression results Figure 4 provides the responses of equity flows to an increase in shocks of investment giant's contrarian investment. The impulse responses of equity growth are constructed based on the estimate of β^h at each horizon. The confidence intervals are drawn from the respective estimated standard errors. The results reported are based on the valuation-adjusted equity flows.[13]

[12] Similar push and pull factors have been commonly employed in empirical studies using EPFR data, including the work of Fratzscher (2012) and Chari et al. (2022).

[13] For comparison, we also provided the results with non-adjusted equity flows in Figure 3.

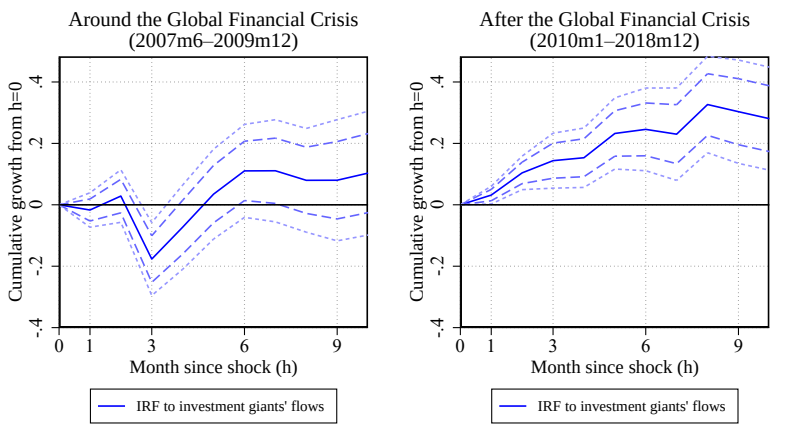


Figure 4: Investor-Level Response to the Equity Flow Differential between Investment Giants and Typical Investors

Notes: The figures depict the predictive capacity of average equity flows from the differential between investment giants' (the top 10) and typical investors' average equity growths where we use an individual investor's equity flows ($\tilde{\Delta}\text{IHS}(\text{Equity}_{ic,t})$) and the differential ($\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}$) are adjusted by stock market index and exchange rate growths to remove valuation effects. The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (5). In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. In each regression, singleton observations are dropped. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

The figure displays impulse responses for two distinct periods: the GFC periods (from June 2007 to December 2009; left chart) and the post-crisis periods (from January 2010 to December 2018; right chart).

Related to our two hypotheses, each figure reflects the impact of outpacing growth of large investor flow on the investment decisions by individual equity flows in emerging markets, taking into account current and future interactions between them. Hence, the impulse responses provide the information associated with the predictability of average growth rate differentials between large and non-large investor flows for subsequent equity flows among other individual investors. Furthermore, they allow us to capture the differences between the GFC period and the post-GFC period.

Two noteworthy findings emerge from the results. First, institutional investors tend to follow the lead of investment giants. An increase in the investment giant's disproportionate equity investment compared to typical investors has a positive impact on the equity investment of individual institutional investors. The result suggests that contrarian investment made by investment giants lead the overall market participants, presumably providing positive signals with them. This obser-

vation is also consistent with the feature presented in Figure 3, which suggests that international investors place more weight on the leading movements of investment giants when determining global portfolio allocation.

Second, the pattern of individual funds following investment giants' contrarian decision becomes more evident and persistent in the post-crisis periods compared to the GFC. During the GFC, equity flows initially exhibit insignificant or even negative responses for up to five months after the shocks. At $h = 6$, the responses revert to positive, but this effect is short-lived. In the post-GFC periods, however, the investment giants' contrarian flows have positive effects on other investors, and the responses become more persistent and stronger after the shock, peaking around 0.32% at $h = 8$ for valuation-adjusted flows.

Drawing the insights from the related literature, we can derive several potential explanations for this asymmetric response across investor flows and sub-sample periods. First, small-sized investors often grapple with a lack of information when making investment decisions. Consequently, the less informed investors are more likely to follow the observable fund flows of investment giants who have access to a richer information set (*informational cascade*, Deng, Hung and Qiao 2018 and Gelos 2011). This phenomenon can be rationalized by Billett, Garfinkel and Jiang (2023), who highlight the gains made by less-informed market participants in reducing asymmetric information costs in the US market. Additionally, individual investors may rely heavily on the investment trends of dominant players because the movements of these investment giants significantly influence aggregate fund flows in emerging equity markets. Hence, individual investors are prone to following the investment giants' decision to mitigate risk and to capitalize on important market signals.

Second, typical investors may mimic the behavior of investment giants due to the reputation they hold (Bikhchandani and Sharma 2001 and Villatoro 2009). Investment giants usually demonstrate a superior performance to smaller investors, leading the latter to emulate the former in the belief of achieving more returns. This inclination may be further intensified when compensation structures are linked to performance comparisons with others (Admati and Pfleiderer 1997 and Gümbel 2005). Typical investors are more likely to imitate the investment decisions of investment giants, regardless of their own private information, to avoid significant losses that could result from failing to follow the herd.

Third, during the crisis, investors in emerging markets may be suspicious of the actions taken by other investors and imitate to a lesser extent. Put differently, they tend to determine investment

based on their own information, or follow other specific investors rather than the market movements (Hwang and Salmon 2004 and Ferreruela and Mallor 2021). Furthermore, due to the prolonged low interest rates since the GFC, global investors has taken more risks, searching for higher yields. Such changes in investor's risk appetite may be attributed, at least in part, to their following of investment giants' contrarian decision in emerging markets in the aftermath of the GFC.

3.2 Equity Fund Responses with and without Stock Market Crashes

Shedding more lights on the role of investment giants in times of tail risks, we conduct an additional local projection estimation which takes into account stock market crashes. The local projection method has a strong advantage in that it is flexible in dealing with non-linearities and state dependency (see Ramey and Zubairy 2018 for example). Therefore, in addition to the baseline regression of equation (5), we consider a specification that condition the response of individual institutional equity flows on the market crash events.

The state-dependent specification we estimate is given by:

$$\begin{aligned}\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = &\beta^h_{nocrash}\big(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\big) \times \mathbb{1}_{\{\Delta^1 \ln \text{StockIndex}_{c,t} > -5\%\}} \\ &+ \beta^h_{crash}\big(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\big) \times \mathbb{1}_{\{\Delta^1 \ln \text{StockIndex}_{c,t} \leq -5\%\}} \\ &+ \mathbf{\Gamma}^h_{\text{pull}}\mathbf{Pull}_{c,t} + \mathbf{\Gamma}^h_{\text{push}}\mathbf{Push}_t + \delta^h_i + \delta^h_c + \delta^h_{m,t} + \varepsilon^h_{ic,t}, \end{aligned} \tag{6}$$

where $\mathbb{1}_{\{\Delta^1 \ln \text{StockIndex}_{c,t} > -5\%\}}$ and $\mathbb{1}_{\{\Delta^1 \ln \text{StockIndex}_{c,t} \leq -5\%\}}$ are indicator functions for stock market crashes (i.e., when the stock market index, $\text{StockIndex}_{c,t}$, declines by more than –5% on a monthly basis) and tranquil market conditions (no crashes), respectively. Similarly, we also consider 10%- and 15%-stock market crashes for comparison.[14]

This specification includes the same pull and push factors along with fixed effects as employed in regression equation (5).

Figure 5 illustrates the impulse responses of equity flow growth to the shocks in investment giants' contrarian flows after the GFC for 5%-, 10%-, and 15%-stock market crashes. Each chart compares the investor flow predictability in scenarios with market crashes (the estimates of β^h_{crash}, circled blue lines) and those without crashes (the estimates of $\beta^h_{nocrash}$, crossed red lines).[15]

[14] During the post-GFC period, the bottom 1%, 5%, and 10% of average growth rates of investment giants' equity flows were –11.9%, –7.3%, and –5.3%, respectively. Amid the GFC, however, the corresponding figures were much lower, recording –28.5%, –17.1%, and –11.5%, respectively, indicating more sizeable declines of investment giants' flows during the crashes.

[15] See Appendix Figure 5 for the responses around the global financial crisis (2007m6–2009m12).

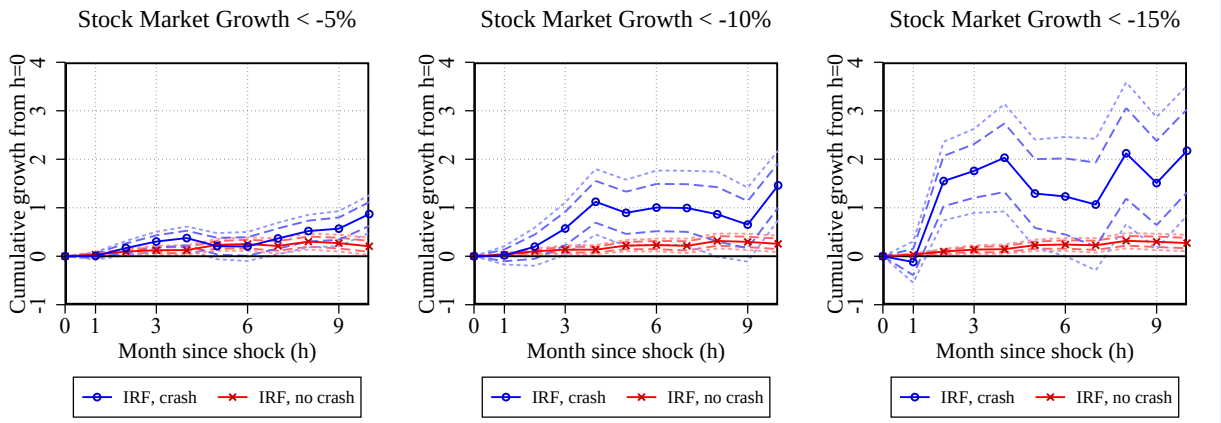


Figure 5: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis

Notes: The figures depict the predictive capacity of average equity flows from the differential between investment giants (the top 10) and typical investors' average equity growths with and without a stock market plunge of more than 5, 10, and 15%. The sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The responses to flows of investment giants relative to typical investors with and without stock market crashes are the estimates of β^h_{crash} (circled lines) and $\beta^h_{nocrash}$ (crossed lines), respectively, in equation (6). The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. In each regression, singleton observations are dropped. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

The key findings from these results are summarized as follows. First, the contrarian flows of investment giants *per se* predict subsequent positive equity flows, consistent with the patterns observed in the previous subsection. This positive predictability becomes more pronounced as the severity of the stock market crash increases. Second, there exist notable differences in predictability between scenarios with and without market crashes. In times of market crashes, the impacts of average changes in investor flows are predicted to be stronger compared to tranquil (no crash) market conditions.

More specifically, in the first chart of Figure 5, individual equity flows rise by up to 0.9%, peaking ten months after investment giants' contrarian flow shocks (1% increase) in a scenario with 5%-market crashes. In the absence of stock market crashes, equity flows exhibit the response of a more modest and sluggish increase, with the peak reaching less than 0.3%. Meanwhile, in cases of more severe market crashes, equity flows respond more strongly to shocks, reaching up to approximately 1.5% (for 10%-market crashes) and 2.1% (for 15%-crashes). Under normal market conditions without crashes, the increase in individual equity flows following shocks from investment giants' contrarian equity flows remains relatively moderate, around 0.3% across all

market crash scenarios.

These results highlight the dynamic and complex interplay at the fund level among institutional equity flows driven by investment giants and its state-dependence on market conditions in emerging economies. From a viewpoint of international financial architecture, fund-level interactions among market players presumably mirror the evolution in global financial landscape, characterized after the GFC. In particular, given that our fund-level analysis explicitly controls for macro-level push and pull factors, the results can be interpreted as evidence of a distinct, systemic relationship at the fund level among investors which drives non-resident portfolio flows into emerging equity markets.[16] As evidently shown in Section 2, the shares of investment giants in equity fund flows have sharply risen since the crisis. As such, this may heighten the influence of investment giants' decisions on the other investors (Arslanalp, Drakopoulos, Goel and Koepke 2020). In addition, as many emerging markets have been included in an international equity index over recent decades, fund flows' sensitivity to pull factors decreases while their sensitivity to global trends, substantially driven by investment giants, has increased.

3.3 Robustness Checks

In what follows, we summarize the results from a battery of exercises for robustness check. The strong predictability of investment giants' flows for equity market is greatly robust to (*i*) alternative data set, (*ii*) different fixed effects, (*iii*) different definitions of investment giants, and (*iv*) alternative main regressor (investment giants' share changes).

Active funds flows First of all, we estimate investor's responses with a sample including active fund flows but excluding passive ones. Passive funds, also known as passive index or index-style funds, indicate the investment vehicles which replicate a stock market index in their composition of investments.[17] Thus, their performance tends to follow the performance of the market index. Unlike passive funds, active funds select specific stocks for their own portfolios. Due to such different investment strategies, active and passive funds can indeed display different dynamics. For example, active funds can exhibit lower responsiveness to aggregate factors, including pull and

[16] Distinguishing from conventional push and pull factors, Carney (2019) refers to the institutional infrastructure of international financial system through which cross-border capital flows move as *pipes*. Hence, our findings are closely associated with the pipes at the investor level.

[17] Passive funds are closely related to benchmark-driven investments, and the two terms are sometimes used interchangeably.

push factors, in comparison to passive funds (Chari et al. 2022 and Chari 2023).[18]

To address this concern, we estimate regression equations (5) and (6) using active fund flows as the dependent and independent variables.[19] The estimation results with active funds data are broadly consistent with the full sample (active funds & passive funds) results. Specifically, as shown in Figure 4, the results from the estimation of equation (5) using active funds flows are by and large similar to those observed in Figure 4. Active fund flows increase in reaction to a rise in investment giants' flow shocks relative to typical investors, confirming high predictability of investment giants' contrarian decisions for tailing equity flows. In addition, the significant impacts of active fund flow differential between investment giants and typical investors are more pronounced and persistent after the GFC.

Next, in Figure 6, we report the results from state-dependent local projection similar to equation (6), exploiting the active fund flows data. This is to examine whether the asymmetric responses of active funds can be found in the presence or the absence of market crashes. The responses of active fund flows are, to a large extent, consistent with those of equity flows in the baseline, manifesting a sizeable increase when the stock market index sharply falls in the post-crisis era.

Investor-time fixed effects Regression equation (5) accounts for temporal fluctuations in push and pull factors by including the US and domestic country-level variables. Also, it controls for both firm and country fixed effects. However, there could remain the limitation that the baseline specification fails to capture heterogeneity in investor-level dynamics.

To address this potential issue, we carry out an additional regression by adjusting the equation (5). Specifically, given that EPFR data does not provide the detailed investor characteristics, we incorporate investor-time fixed effects ($\delta^h_{i,t}$):

$$\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = \beta^h \left(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\right) + \mathbf{\Gamma}^h_{\text{pull}} \mathbf{Pull}_{c,t} + \delta^h_{i,t} + \delta^h_c + \varepsilon^h_{ic,t}, \tag{7}$$

where we no longer need the push factors and month fixed effects ($\mathbf{Push}_t$ and δ^h_m). This modified specification offers a distinct advantage by enabling comprehensive control over all time-varying factors that affect investors.

Figure 7 summarizes the responses of equity flows based on the regression equation (7). The

[18] It is noteworthy, however, that the definitions of passive and active funds do not inherently imply that the portfolio choices of typical investors who opt for passive management follow the decisions of investment giants more or less closely than those of typical investors who choose active management.

[19] In the EPFR dataset, actively and passively managed fund flows can be distinctly identified.

left chart shows the results for the GFC-period, while the right chart depicts the results for the post-GFC period. Both results are qualitatively and quantitatively similar to those of the baseline specification. In response to the shock in the giant's contrarian investment on emerging equity markets, equity flows increase, more evidently after the GFC.

Definition of investment giants Another concern that may arise is whether our baseline results are contingent on the specific definition of investment giants. In our baseline specification, investment giants (or large investors) are arbitrarily defined as the top 10 largest investors in terms of the investment size in emerging equity markets. For the check of robustness, we depart from the definition by assigning two different thresholds for investment giants—top 15 and 7 largest investors. We then re-estimate the equation (5) using the fund data sorted out according to the two different definitions of investment giants.

The results corresponding to the alternative definitions are presented in Figure 8. Panels (a) and (b) display impulse responses of equity flows to shocks in the average growth differentials between investment giants' and typical investors' flows, based on the respective definition of the top 15 and 7 investors. Interestingly, regardless of the definition used, the impulse responses exhibit quite similar fluctuations to those observed in the baseline. In contrast to their insignificant responses during the GFC period, equity flows significantly increase in response to a rise in investment giants' flows (relative to typical investors) in the post-GFC era.

Taking the two different definitions of investment giants to equation (6), we further investigate the non-linearity of equity fund responses between crash and non-crash scenarios. Panels (a) and (b) in Figure 9 summarize the results when investment giants are defined as top 15 and 7 largest investors, respectively. Consistent with the observations in Figure 5, equity flows exhibit more pronounced responses during market collapses.

Investment giants share In our baseline estimation, we normalize investment giant flows by deducting the other (typical) investors' flows in order to isolate the unique effect of investment giants' decisions on emerging market equity flows. Alternative way for normalization is to employ the average change in the share of investment giants in equity market c at time t, given as:

$$\frac{1}{N^{\mathcal{G}}} \sum_{i \in \mathcal{G}} \Delta^1 \left(\frac{\text{Equity}_{ic,t-1}}{\text{Equity}_{c,t-1}} \right) \approx \bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{agg}} \tag{8}$$

where $\text{Equity}_{c,t-1}(\equiv \sum_i \text{Equity}_{ic,t-1})$ is the aggregate equity, and $\bar{g}^{\text{agg}}_{c,t}(\equiv \Delta^1 \ln \text{Equity}_{c,t-1})$ denotes the valuation-adjusted growth of aggregate equity between t and $t-1$ in country c. The share change is similar to the average of investment giants' growth normalized by the aggregate equity growth. The increase in the market share of investment giants implies that they invest to market c more than market aggregates, reflecting their contrarian stance.

We estimate the local projection of equations (5) and (6) by substituting the main regressor with the average change of investment giants' market share (8). Figure 10 reports the investor-level equity flow responses to changes in investment giants' share for the sub-sample of the GFC (left chart) and the post-GFC periods (right chart). Individual equity flows increase following the investment giants' contrarian flow shocks in the post-crisis periods, while they respond insignificantly or even negatively. This pattern is largely in line with our baseline results.

In addition, Figure 11 illustrates the predictability of average change in the share of investment giants for the scenarios of stock market crashes (blue circled line) and non-crashes (red crossed line). As in the baseline, we compare the results which take into account stock market crashes under three different criteria: 5%, 10%, and 15% declines in stock prices. The responses are largely consistent with the baseline results: equity flows react more sensitively to the shocks in large investors' contrarian flows during stock market crashes, compared to non-market crash conditions.

3.4 Further Investor-Level Investigation

Connecting our analysis to the conventional studies, we revisit the systemic relationship between equity flows and push and pull factors at the investor level. Indeed, the pull and push factors as the crucial drivers for cross-border capital movements have been extensively examined in international finance literature (e.g., Calvo et al. 1993, Fernandez-Arias 1996, Taylor and Sarno 1997, Forbes and Warnock 2012, Fratzscher 2012, Rey 2015, Byrne and Fiess 2016, Goldberg and Krogstrup 2023, and many others). Hence, this additional analysis is to investigate whether the well-documented relationship at aggregate level also holds when investigated with investor-level data.[20] Moreover, comparing to conventional predictions at the aggregate level, this exercise helps assess the validity of our baseline empirical framework.

As further detailed in Appendix C, we modify the specification of local projection by focusing on the growth of price factors, such as domestic and US stock price indices and nominal exchange rates.

[20] Our previous analyses focus on the pipes, in particular at the fund level, as they employ the push and pull factors as control variables. In contrast, this additional analysis places its focus squarely on the impacts of push and pull factors on fund-level flows.

Specifically, the price factors are iteratively employed as a main regressor in the local projection, while the other push and pull factors are used as control variables. Notably, the giants' contrarian investments are now included as a control variable.

The first finding from the regression is that equity fund flows respond positively to the domestic stock return shocks, but negatively to the US stock return shocks. These opposite responses, found at the fund level, collectively support the view that global equity investors are likely reach for higher yields (Rajan 2006, Choi and Kronlund 2017, and Caballero and Simsek 2020). This investment pattern is also found in the responses of equity flows to a currency depreciation shock. Upon the shock, individual equity flows decrease significantly, suggesting that the debased values of invested equities at the local markets lead to portfolio reallocation among international investors. Furthermore, we examine the responses of individual fund flows to the shock in relative stock returns, i.e., the differential between domestic stock returns denominated in US dollars and US stock returns.[21] The results show that equity flows rise significantly in response to an increase in relative stock return shocks, corroborating our earlier findings of international investors' search-for-yield behaviors.

4 Aggregate Dynamics and Implications

In this section, with our focus kept on the roles played by investment giants, we extend our analysis to investigate the aggregate-level relationships between investment giant flows and the conditions in emerging equity markets. We evaluate the extent to which decisions made by investment giants can predict future stock prices, exchange rates, and aggregate equity flows. Our aggregate-level analysis consistently reveals a significant pattern: reductions in investments by investment giants tend to precede substantial outflows of global capital and subsequent financial downturns in emerging equity markets.

4.1 Connecting the Dots: From Fund-level To Aggregate-level

Before elaborating our aggregate-level estimations, it would be imperative to discuss their importance and implications. Our aggregate analysis serves practical and substantial purposes, especially in relation to our previous fund-level findings.

[21] The relative stock returns can also be interpreted as a deviation from uncovered equity parity condition (Hau and Rey 2006 and Curcuru, Thomas, Warnock and Wongswan 2014), which is ex-post arbitrage opportunity.

First, aggregate analysis is practical because it can provide informative insights into the broader landscape of market variables such as future stock price indexes. Understanding the drivers of cross-border capital flows and their macro-financial repercussions at the aggregate level is of paramount significance not only for researchers but also for policymakers, particularly in emerging market economies. For instance, in a financially integrated world, capital flows driven by push factors from advanced economies determine local financial conditions in a large set of emerging economies. Hence, to mitigate the spillover effects of external shocks, foreign exchange-related macro-prudential policies, including capital flow management, should be carefully designed, grounded in a deep comprehension of the natures of capital flows at the fund- and aggregate-level (Basu, Boz, Gopinath, Roch and Unsal 2020).

Relatedly, prior studies have underscored the importance of investigating the relationship between capital flows and local and global financial factors, such as domestic and US stock market indices, as well as exchange rates. Among the studies centered on fund flows, Warther (1995) and Edelen (1999) have revealed the impact of aggregate mutual fund flows on contemporaneous stock returns. Meanwhile, Coval and Stafford (2007) have shown that large-scale fund flows exert substantial price pressures in the US equity market. Furthermore, Lilley, Maggiori, Neiman and Schreger (2022) have elucidated the significant explanatory power of US purchases of foreign bonds for currency dynamics since the GFC. Nevertheless, these relationships remain debatable and necessitate further in-depth investigation, as evidenced by Wardlaw (2020) and Gabaix and Maggiori (2015). Linked to the fund-level findings, our aggregate study reveal the factors that drive the dynamics of capital flows and market conditions. This may also underscore the critical importance of closely monitoring the activities of fund-level flows, in particular those of large investors, as an early warning indicator in emerging equity markets.

Second, the aggregate analysis is substantial because it helps confirm and generalize the consistency of our findings at the investor (or fund) level. In Section 3, we documented the strong positive predictability of investment giant flows for other investor flows. However, the predictive power of investment giants' flows concerning the flows of individual investors within the EPFR universe does not necessarily imply that investment giants' flows can offer predictive information for the entirety of equity flows. This is due to the limited scope of the EPFR global fund dataset, which covers only a relatively small portion of market capitalization for most emerging economies (typically from 1% to 8%, Jotikasthira et al. 2012). Hence, it is essential for determining whether the flows of investment giants also wield significant influence on the aggregate flows.

In addition, investor-level data can potentially illuminate the underlying rationale for aggregate behavior, while, reciprocally, insights gained at the aggregate level can enhance our understanding of individual investor behavior. Therefore, the aggregate study can help capture more generalized features of equity flow dynamics in emerging market economies.

4.2 The Impact of Investment Giants on Aggregate Flows

In the remainder of this section, we explore the extent of investment giants' impact and their ability to forecast emerging equity market dynamics, shining a light on their implications in connection with our fund-level findings.

Regression specification We begin by estimating country-month panel local projections for the aggregate flows using the equation, given as:

$$Y_{c,t}^{h} = \beta^{h}\left(\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}\right) + \mathbf{\Gamma}_{\text{pull}}^{h}\mathbf{Pull}_{c,t} + \mathbf{\Gamma}_{\text{push}}^{h}\mathbf{Push}_{t} + \delta_{c}^{h} + \delta_{m}^{h} + \varepsilon_{c,t}^{h}, \tag{9}$$

where $Y_{c,t}^{h}$ represents (either valuation-adjusted or non-adjusted) aggregate equity cumulative growth or aggregate net flows to GDP ratio change between t and $t+h$:

$$Y_{c,t}^{h} = \tilde{\Delta}^{h} \ln \text{Equity}_{c,t}, \quad \Delta^{h} \ln \text{Equity}_{c,t}, \quad \text{or} \quad \Delta^{h} \frac{\text{NetFlow}_{c,t}}{\text{GDP}_{c,t}}.$$

While the adjusted and non-adjusted aggregate equity flows are computed based on the EPFR data, the data for aggregate equity net flow is complemented with the Institute of International Finance (IIF) database from the IMF. In addition, identically to our fund-level estimations, the cumulative growth of equity flows between time t and $t+h$ is winsorized, ranging from $-h\times100\%$ to $h\times100\%$, to rule out the extreme values. Similar to previous regressions, equation (9) includes standard control variables—push and pull factors and various fixed effects. Other terms are defined comparably to those in equation (5).

Regression results Figure 6 presents the impulse responses of the three measures of aggregate equity flows ($Y_{c,t}^{h}$) to shocks in the differential between investment giant and typical investor flows, respectively. Overall, the results from the country-level data align with our earlier findings from investor-level regressions in Section 3. Both the valuation-adjusted (first chart) and non-adjusted average equity flow growths (second chart) react positively to changes in the investment

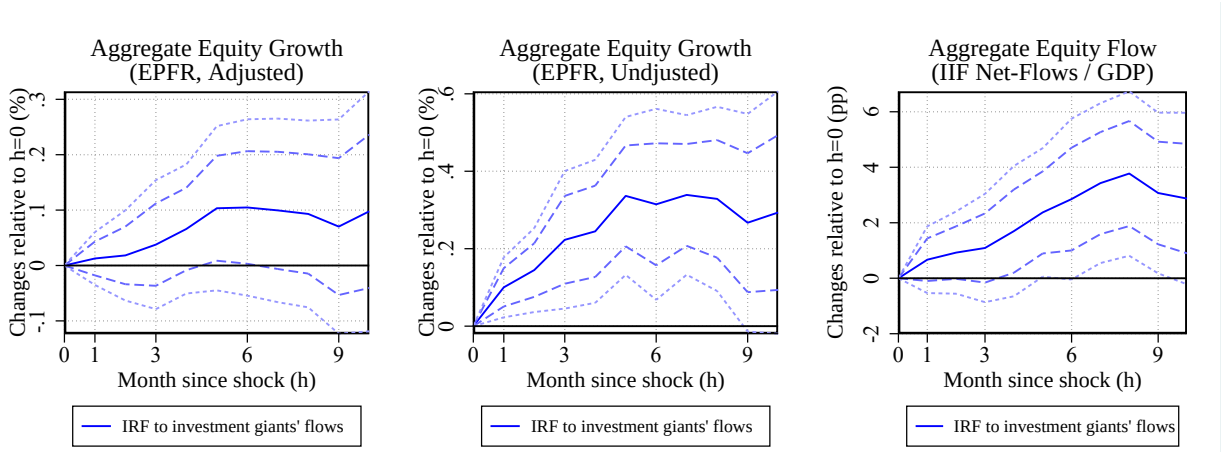


Figure 6: Aggregate Flow Responses to Investment Giants Flows

Notes: The figures depict the predictive content of the differential between investment giants' (the top 10) and typical investors' average equity growth for the valuation-adjusted and non-adjusted EPFR aggregate equity growths and and IIF aggregate equity net-flows (% of GDP). The sample periods are after the global financial crisis (2010m1–2018m12), respectively. The responses to investment giants flows are the estimates of β^h in equation (9). The specification controls for country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

giants' contrarian flows, although the former exhibits relatively short-lived and weaker responses. Similarly, aggregate net flows (IIF) relative to GDP increase persistently after the shock (third chart). The estimation results from aggregate funds data corroborate the predictability of investment giants' flows for other equity flows, consistent with the findings from the investor-level data. Put another way, the results collectively indicate that preceding contrarian movements by investment giants have strong predictive power for investor flows not only at the investor level but also at the entire aggregate level.

Robustness To ensure the robustness of these findings, we conduct additional analyses using alternative specifications similar to those in Section 3: (*i*) alternative dataset, (*ii*) different fixed effects, (*iii*) different definitions of investment giants, and (*iv*) alternative main regressor (changes in investment giants' share). We present the results for our robustness checks in Appendix E.

The results of aggregate-level regressions remain by and large robust across different data and specifications, reaffirming the substantial information embedded in the investment decisions of giants regarding the overall equity flow conditions in emerging equity markets. More specifically, we first compare our baseline results with those estimated using only active fund flows (Figure 12). Similar to our baseline results, although aggregate equity flows computed with valuation-adjusted

EPFR data exhibit to some extent weak or insignificant increase after the shock (first chart), those estimated with non-adjusted data (second chart) and IIF net flows (third chart) show significant and persistent increases.

Second, we carry out a regression which employs time fixed effect, given as:

$$Y_{c,t}^{h} = \beta^{h}\left(\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}\right) + \mathbf{\Gamma}_{\text{pull}}^{h}\mathbf{Pull}_{c,t} + \delta_{c}^{h} + \delta_{t}^{h} + \varepsilon_{c,t}^{h}, \tag{10}$$

where δ_t^h denotes the time fixed effect.[22] As summarized in Figure 14, the responses of aggregate equity flows, based on the three measures, to the giants' contrarian investment are consistent with our baseline when the the time fixed effect is explicitly accounted for.

Third, we test the sensitivity of the results to different definitions of investment giants. Panels (a) and (b) of Figure 16 report the impulse responses of aggregate flows to shocks in the contrarian flows of the top 15 and 7 large investors, respectively. Finally, we check the robustness of our results using an alternative main regressor—changes in investment giants' share in equation (8). The impulse responses of aggregate flows to the shocks are also in line with the baseline results, as presented in Figure 18.

In short, our aggregate-level analyses consistently reveals a noticeable pattern of aggregate equity flows in relation to investment giant flows: contrarian investments by investment giants precede movements in aggregate equity flows in emerging equity markets. This underscores the critical importance of closely monitoring the activities of investment giants as an early warning indicator for potential distress such as sudden stops and surges in emerging equity markets.

4.3 Investment Giants, Future Exchange Rate, Stock Price and Returns

In the previous sub-section, our analysis demonstrated the predictive power of investment giants' flows at the aggregate level, corroborating our investor-level findings. We now focus our attention to the relationship between aggregate flows and financial conditions in emerging markets.

Emerging market economies have witnessed capital flow volatility during various crises, including the global financial crisis and the recent pandemic, which led to domestic financial distress. Further, as the impacts of global factors, dubbed as *the global financial cycle*, have substantially grown, small open economies, in particular those which experienced more credit inflow, face

[22] Note that, similar to equation (7), push factor ($\mathbf{Push}_t$) and month fixed effect (δ_m^h) are excluded from the regression as the time fixed effect is included.

increasing challenges in insulating their financial markets from external shocks (*dilemma*, e.g., Rey 2015, Kalemli-Özcan 2019, and Goldberg and Krogstrup 2023).

Regression specification Against this backdrop, we investigate the responses of stock markets and foreign exchange markets to the investment giant flow shocks, using the regression (11).

$$Z^h_{c,t} = \beta^h \left(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\right) + \mathbf{\Gamma}^h_{\text{pull}} \mathbf{Pull}_{c,t} + \mathbf{\Gamma}^h_{\text{push}} \mathbf{Push}_t + \delta^h_c + \delta^h_m + \varepsilon^h_{c,t}, \tag{11}$$

where $Z^h_{c,t}$ denotes stock price indices, nominal exchange rates against US dollars, or relative stock returns denominated in US dollars change between t and $t+h$:

$$Z^h_{c,t} = \Delta^h \ln \text{StockIndex}_{c,t}, \quad \Delta^h \ln \text{FX}_{c,t}, \quad \text{or} \quad \Delta^h \ln \frac{\text{StockIndex}_{c,t}}{\text{StockIndex}_{\text{US},t}} \frac{1}{\text{FX}_{c,t}}.$$

Other terms are defined identically to those in equation (9).

Regression results Figure 7 summarizes the results, corresponding to the three measures of market returns. In the first chart, shocks in the investment giant flows have incremental effects on stock market indices in emerging markets. The response is the strongest around five months after the shock, rising around 0.14%. This finding is consistent with the literature which documents a strong positive link between capital flows and stock valuations in international financial markets (Bathia, Bouras, Demirer and Gupta 2020, Anaya, Hachula and Offermanns 2017, Gourinchas and Rey 2014, and many others).

Moreover, foreign exchange rates appreciate by up to 0.07% in response to a 1% increase in giant flow shocks (second chart). A large body of literature, has documented a similar positive relationship between (aggregate) capital flows and currency values in both advance economies (Hau and Rey 2006) and emerging market economies (Borio 2019). In conjunction with our previous finding—the positive predictability of investment giant flows on aggregate equity flows—the relationship between investment giant flows and exchange rates supports the earlier findings and further identifies investment giants as their important driving force.

Last, the third chart illustrates the responses of relative stock market returns, *viz.* the differentials between domestic returns in US dollars and US returns, to the shocks in investment giants' contrarian flows. According to the uncovered equity parity hypothesis, relative market returns represent an international arbitrage opportunities in emerging equity markets. Therefore, the

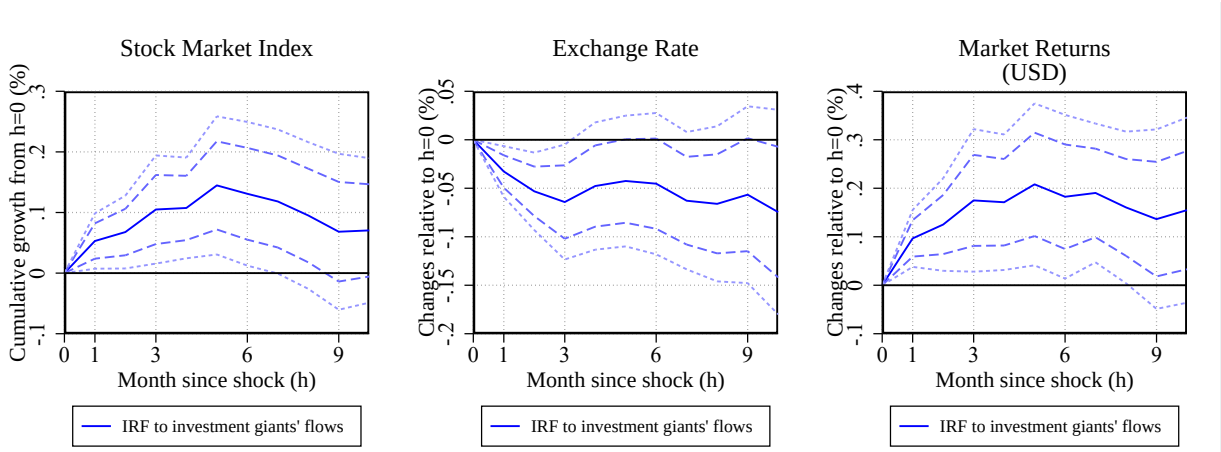


Figure 7: Stock and Currency Markets Responses to Investment Giants Flows

Notes: The figures depict the predictive content of the differential between investment giants' (the top 10) and typical investors' average equity growth for stock price indices, exchange rates, and stock market returns (USD). The sample periods are after the global financial crisis (2010m1–2018m12), respectively. The responses to investment giants flows are the estimates of β^h in equation (9). The specification controls for country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

results suggest that shocks in giant flows generate a positive reaction in relative returns, which in turn attract other investor flows.

Robustness As outlined in Appendix E, we estimate several alternative models to check the robustness of our empirical results. The baseline results are not sensitive to these alternative models or specifications. Our results consistently confirm the substantial information contained in the contrarian investment decisions by the giants concerning overall market conditions in emerging economies.

In more detail, the impulse responses of the stock and currency markets to active fund flows are first reported in Figure 13. Second, we carry out a regression similar to equation (10), which in particular takes into consideration time fixed effect. The estimation results are summarized in Figure 15. Third, we reckon with different definitions of investment giant flows. Specifically, labeling the top 7 and 15 largest investors in our EPFR dataset as investment giants, we assess whether our main findings remain consistent. The corresponding results are provided in panels (a) (top 15 largest investors) and (b) (top 7 largest investors) in Figure 17. Fourth, Figure 19 presents the responses of stock returns and exchange rate adjustments to shocks in the investment giants' share, as defined in equation (8).

Clearly, these consistent results hold important implications for emerging market economies, whereby policy frameworks have evolved to monitor and mitigate fluctuations in capital flows while enhancing early warning systems to detect underlying risk factors in the nascent stages. In this sub-section, we find that portfolio flows, led by investment giants, can drive return dynamics in emerging equity markets. This places specific emphasis on the importance of monitoring the activities of investment giants when formulating capital flow-related policies. As the impacts of the global financial cycle continues to grow, the need for a more integrated policy framework becomes increasingly essential, particularly for emerging market economies that are vulnerable to hot money flows.

5 Why and When Do Investors Follow Investment Giants? *(IN PROGRESS)*

In this section, we aim to understand our empirical findings by exploring why and when investors follow investment giants and the implications for market volatility. To address these questions, we construct a model that integrates three central elements: a beauty contest framework (strategic interaction), sequential moves, and a dominant player—the investment giant. Each investor receives a private, noisy signal regarding the underlying market fundamentals. Following Morris and Shin (2002), investors aim to maximize their payoffs, which decrease as their actions deviate from both the market fundamentals and the aggregate actions of other investors. Consequently, the payoff maximization problem is tightly linked to forecasting the fundamentals and market aggregates using both private and public information.

Our model introduces two primary assumptions in addition to this foundational setup. First, similar to Corsetti et al. (2004), an individual investor's actions do not impact market aggregates, while the investment giant's decisions do influence market equilibrium. Second, the investment giant moves first, and its information is observed by other investors. Typical investors then make their choices after observing both the investment giant's transactions and available public information. This sequential move assumption is flexible and could be adjusted as needed.

In a sequential move structure, followers benefit by refining their strategies based on the observable first mover's information and action, which offers insights into fundamental market conditions and reduces their reliance on private signals alone. For the investment giant, moving first offers a strategic advantage in this beauty contest setup, where payoffs are closely tied to others' actions. Acting early, the investment giant can set a market direction that followers tend

to align with, effectively "locking in" momentum, particularly when the investment giant holds substantial market share. This advantage, however, is unavailable to typical investors, even if they were to move first, due to their negligible market influence.

Through our model, we analyze how timing, information, and strategic interactions shape payoffs and decision-making, particularly under private information conditions. To assess these mechanisms, we compare the payoffs of the investment giant and typical investors across different move structures, identifying conditions under which observed market behavior aligns with theoretical predictions. Furthermore, we investigate how these behaviors contribute to excess market volatility.

5.1 The Model Environments

Investors and size There exists a continuum of investors indexed by i in a unit interval $[0, 1]$. We let a single investment giant be indexed by $i = 1$, whose market share is given by $\lambda_1 = \lambda \in [0, 1]$. Typical investors indexed by $j \in [0, 1)$ with $\lambda_j = 0$ are ex-ante identical. Their aggregate market share is $1 - \lambda$. Unlike the investment giants, the typical investors' idiosyncratic information and behavior have no aggregate implications because of diversification.

The beauty contest payoff An individual investor chooses an action s_j for the given predetermined large investor's action b. The payoff of investor $i \in [0, 1]$ is given by

$$\pi_i = -(1-\omega) \times (s_i - f)^2 - \omega \times \left\{ s_i - [\lambda s_1 = (1-\lambda)\bar{s}_0] \right\}^2, \tag{12}$$

where f represents the fundamentals, $\bar{s}_0 = \int_{[0,1)} s_j \mathrm{d}j$ is the average action of typical investors excluding the investment giants (indexed by $i = 1$). The beauty contest parameter, $\omega \in [0, 1])$, determines a degree of strategic interaction. In the right hand of equation (12), $(s_i - f)^2$ captures the (quadratic) loss of difference from the real fundamentals, and $\{s_i - [\lambda s_1 + (1-\lambda)\bar{s}_0]\}$ is the loss deviated from the average action of all investors, inducing strategic behavior. A zero beauty contest $\omega = 0$ means that an investor determines her action without worrying about the others', minimizing a signal extraction in the noise problem. By contrast, when $\omega = 1$, the investor only considers the others' behavior ignoring her own signal and chooses her action strategically.

Information and belief The fundamentals, denoted by f, are unobservable but follow a known distribution, $f \sim \mathcal{N}(0, \sigma_f^2)$. Investors choose their actions based on noisy signals about f. Each in-

vestor receives a private signal x_i with an additive noise term $\epsilon_{x,i}$ where f and $\epsilon_{x,i}$ are independent.

$$x_i = f + \epsilon_{x,i}, \tag{13}$$

where $\epsilon_{x,i} \sim \mathcal{N}(0, \sigma_{x,i}^2)$ is normally distributed noise, independent across investors, $\epsilon_{x,i} \perp \epsilon_{x,j}$ for all $i \neq j$. The investment giant and typical investors are ex-ante identical in signal structure, although the signal precision for the investment giant may differ, i.e., $\sigma_{x,1} \neq \sigma_{x,0} = \sigma_{x,j}$ for all $j \in [0, 1)$.

Using the conditional expectation formula for normally distributed variables, the beliefs about the fundamentals given the signals are as follows:

$$\mathbb{E}[f|x_1] = \theta_1 x_1, \quad \mathbb{E}[f|x_{j\neq 1}] = \theta_0 x_{j\neq 1}, \quad \text{and} \quad \mathbb{E}[f|x_{j\neq 1}, x_1] = \gamma_0 x_{j\neq 1} + \gamma_1 x_1, \tag{14}$$

where the coefficients are

$$\theta_0 \equiv \frac{\sigma_{x,0}^{-2}}{\sigma_f^{-2} + \sigma_{x,0}^{-2}},\ \theta_1 \equiv \frac{\sigma_{x,1}^{-2}}{\sigma_f^{-2} + \sigma_{x,1}^{-2}},\ \gamma_0 \equiv \frac{\sigma_{x,0}^{-2}}{\sigma_f^{-2} + \sigma_{x,0}^{-2} + \sigma_{x,1}^{-2}},\ \text{and}\ \gamma_1 \equiv \frac{\sigma_{x,1}^{-2}}{\sigma_f^{-2} + \sigma_{x,0}^{-2} + \sigma_{x,1}^{-2}}. \tag{15}$$

Furthermore, by the law of large numbers, agents can perfectly recover the unobserved fundamental f if they observe all typical investors' signals $\{x_j\}_{j\in[0,1)}$. The average signal of the typical investors provides an exact estimate of the fundamentals: $\bar{x}_0 \equiv \int_{j\in[0,1)} x_j \mathrm{d}j = f$.

5.2 The Sequential Moves: An Investment Giant Moves First

Reflecting observed patterns in emerging equity markets, we assume that the investment giant moves first, followed by typical investors. In this sequential setup, typical investors observe the investment giant's decision, treating it as public information that implicitly signals market fundamentals. This structure provides an informational advantage to typical investors, allowing them to reduce uncertainty by basing their decisions on both private signals and the giant's revealed action. In contrast, the investment giant maximizes its payoff solely based on its private signal.

This public information channel allows typical investors (the followers) to refine their strategies by leveraging the investment giant's initial move, thus gaining indirect insights into fundamental market conditions and reducing reliance on their private signals. The benefit of this information advantage becomes particularly significant when the investment giant's signal precision ($\sigma_{x,1}^{-2}$) is high and the precision of typical investors' signals ($\sigma_{x,0}^{-2}$) is relatively low.

For the investment giant, moving first offers a strategic advantage in our beauty contest

framework. By making an early decision, the investment giant can set a precedent, steering the market in a direction that followers are likely to align with. This capacity to "lock in" market momentum is especially powerful when the investment giant has a substantial market share (λ), as it discourages typical investors from deviating from its lead.

The extent of this advantage increases with the degree of strategic interaction (ω). When investors' actions strongly depend on others' choices, alignment with the investment giant's decision intensifies, amplifying the giant's leadership influence.

Typical investor Each typical investor $j \neq 1$ chooses an action s_j to maximize their expected payoff $\mathbb{E}[\pi_j|x_j, x_1, s_1]$ in equation (12), given the investment giant's signal and action. The first-order condition yields the following linear equilibrium:

$$s_j^* = (1-\omega)\mathbb{E}[f|x_j, x_1] + \omega\big\{\lambda s_1 + (1-\lambda)\mathbb{E}[\bar{s}_0^*|x_j, x_1, s_1]\big\}, \tag{16}$$

where $\bar{s}_0^* \equiv \int_{j\in[0,1)} s_j^* \mathrm{d}j$ is the average optimal action of the typical investors. This optimal strategy is a linear combination of expectations about the fundamentals (f) and the market outcome (the aggregate actions of other investors, s_1 and $\bar{s}_0^*$).

As shown in Morris and Shin (2002), the optimal strategy for a typical investor $j \in [0,1)$ can be expressed as a linear function of signals.[23]

$$s_j^*(x_j, x_1, s_1) \equiv \psi^* x_j + \eta_x^* x_1 + \eta_s^* s_1 \tag{17}$$

By substituting the typical investor's belief about the average investment of others, $\mathbb{E}[\bar{s}_0|x_j, x_1, s_1] = \psi^*\mathbb{E}[f|x_j, x_1] + \eta_x^* x_1 + \eta_s^* s_1$, into the first order condition equation (16), we derive the optimal responses to the private signal, the investment giant's signal, and the investment giant's action as follows:

$$\psi^* = \left[\frac{1-\omega}{1-\omega(1-\lambda)\gamma_0}\right]\gamma_0, \tag{18}$$

$$\eta_x^* = \left\{\frac{1-\omega}{[1-\omega(1-\lambda)][1-\omega(1-\lambda)\gamma_0]}\right\}\gamma_1 = \left[\frac{\psi^*}{1-\omega(1-\lambda)}\right]\frac{\gamma_1}{\gamma_0}, \tag{19}$$

$$\eta_s^* = \frac{\lambda\omega}{1-\omega(1-\lambda)} = 1 - \psi^* - \frac{\eta_x^*}{\theta_1}. \tag{20}$$

[23] In this equilibrium, the optimal action is a linear combination not only of private and public information as in Morris and Shin (2002) but also of the investment giant's action but also the investment giant's action s_1. Here, s_1 is distinguished from the public signal x_1 in that s_1 is the posterior outcome based on the prior information x_1.

The average (aggregate) action of typical investors is then given by:

$$\bar{s}_0^*(f, x_1, s_1) \equiv \int_{j\in[0,1)} s_j^* \mathrm{d}j = \psi^* f + \eta_x^* x_1 + \eta_s^* s_1. \tag{21}$$

Investment giant The investment giant chooses an action to minimize its deviation from the fundamental and the typical investor's action. Specifically, the giant's payoff maximization problem can be modified from the payoff in equation (12) as follows:

$$\max_{s_1} \mathbb{E}\big[-(1-\omega)(s_1-f)^2 - \omega(1-\lambda)^2[s_1 - \bar{s}_0^*(f, x_1, s_1)]^2 \big| x_1\big], \tag{22}$$

where $(1-\lambda)^2$ reflects the investment giant's advantage due to market dominance, decreasing as market share λ increases. The first-order condition yields:

$$s_1^* = (1-\omega)\mathbb{E}[f|x_1] + \omega\big\{\lambda s_1 + (1-\lambda)\mathbb{E}[\bar{s}_0^*(f, x_1, s_1)|x_1]\big\}(1-\lambda)\left\{1 - \frac{\partial \mathbb{E}[\bar{s}_0^*(f, x_1, s_1)|x_1]}{\partial s_1}\right\}, \tag{23}$$

where the investment giant's expectation of the typical investor's average action is a convex combination of its belief about the fundamentals and its own action:

$$\mathbb{E}[\bar{s}_0^*(f, x_1, s_1)|x_1] = (1-\eta_s^*)\mathbb{E}[f|x_1] + \eta_s^* s_1, \quad \text{where} \quad \mathbb{E}[f|x_1] = \theta_1 x_1. \tag{24}$$

Additionally, $\partial \mathbb{E}[\bar{s}_0^*|x_1]/\partial s_1 = \eta_s^*$. Thus, we obtain:

$$s_1^*(x_1) = \underbrace{\left\{\frac{(1-\omega) + \omega(1-\lambda)^2(1-\eta_s^*)\big(\psi^* + \eta_x^* x_1/\mathbb{E}[f|x_1]\big)}{(1-\omega) + \omega(1-\lambda)^2(1-\eta_s^*)^2}\right\}}_{=1 \quad \because \mathbb{E}[f|x_1]=\theta_1 x_1 \text{ and } \psi^*+\eta_x^*/\theta_1+\eta_s^*=1} \mathbb{E}[f|x_1] = \phi^* x_1, \text{ where } \phi^* = \theta_1. \tag{25}$$

Market volatility The investment giant's action s_1 can now be expressed as its signal $\phi^* x_1$ in the optimal decisions of both the individual and average typical investors (equations (17) and (21)). Substituting $\phi^* x_1$ yields:

$$\bar{s}_0^*(x_j, x_1) = \psi^* x_j + (1-\psi^*)\theta_1 x_1 \quad \text{and} \quad \bar{s}_0^*(f, x_1) = \psi^* f + (1-\psi^*)\theta_1 x_1 \tag{26}$$

Therefore, the market deviation from the fundamental can be expressed as:

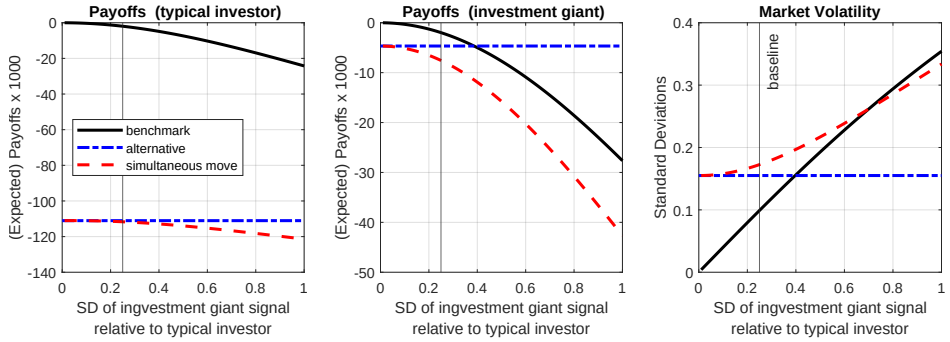
$$\begin{aligned} S^*(f, x_1) - f &\equiv \lambda\big[s_1^*(x_1) - f\big] + (1-\lambda)[\bar{s}_0^*(f, x_1) - f] \\ &= [1 - (1-\lambda)\psi^*](\theta_1 x_1 - f) = \left[\frac{1-(1-\lambda)\gamma_0}{1-\omega(1-\lambda)\gamma_0}\right](\theta_1 x_1 - f) \end{aligned} \tag{27}$$

Finally, the market volatility measure is:

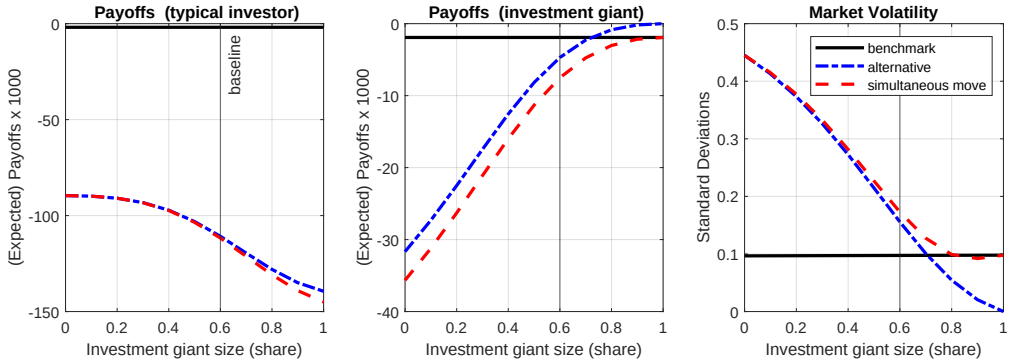
$$\sigma_{\text{mkt}}^* \equiv \text{sd}\big(S^*(f, x_1) - f\big) = [1 - (1-\lambda)\psi^*]\sqrt{1-\theta_1} \times \sigma_f \tag{28}$$

5.3 The Model Results *(IN PROGRESS)*

(a) Investment Giant's Signal Noise at Various Levels



(b) Investment Giant's Size at Various Levels



(c) Strategic Interactions at Various Levels

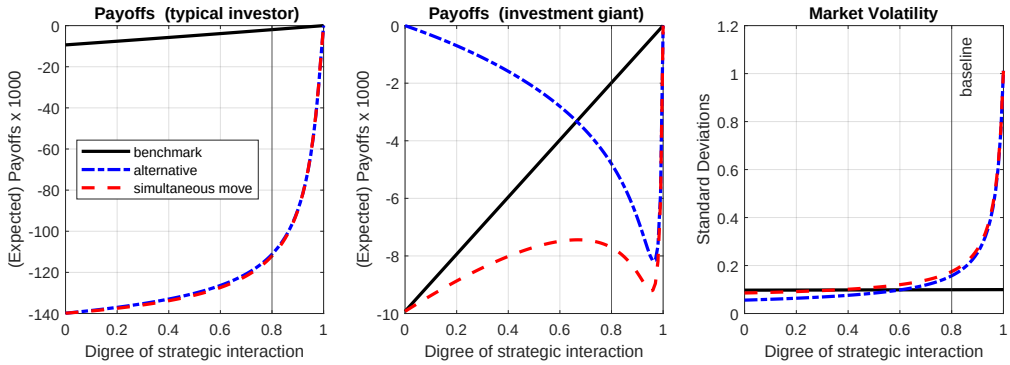


Figure 8: Investor's Payoffs and Market Volatility

Notes: In the benchmark model (black solid lines), the investment giant moves first, followed by typical investors. In the alternative case (blue short-dashed lines), typical investors are the first movers, with the investment giant as the follower. The red long-dashed lines plot results for the simultaneous moves of all investors. For details on the alternative and simultaneous cases, see Appendix A.

6 Conclusion

The global financial landscape has undergone significant shifts in recent decades, with changes in capital flows playing a critical role, particularly in emerging economies. Global factors, driven by the dominant currency US dollars and US monetary policy, shape and are shaped by capital flows, thereby impacting local financial markets. Since the GFC, cross-border capital flows have increasingly shifted toward market-based flows rather than bank-intermediated flows. More recently, the trajectory of global inflation has influenced the risk appetites of international investors as it has directly accounted for policy stances in major countries. In addition, heightened geopolitical risks have added pressure to international financial markets, thus raising the volatility of capital flows.

Despite its critical importance, however, our understanding of global portfolio allocations remains limited, with much of the focus concentrated on the aggregate-level interplay among the flows and macroeconomic factors. Fund-level studies are relatively scarce which examine the drivers of changes in aggregate flows and the mechanisms through which the channel operates. Particularly, in an environment where the composition of investors and investment strategies have been increasingly complex, this knowledge gap not only hampers our understanding of capital flows but also impedes policy reactions to capital flows in a proactive manner.

In this vein, our study lays the groundwork not only for in-depth fund-level analysis of global equity flows but also for well-informed decision-making by both policymakers and market participants. Specifically, this paper explores the investment choices of institutional investors operating in emerging equity markets, shedding light on the pivotal roles played by large and influential investors. Our analysis with fund-level flow data underscores the substantial impact of these investment giants on portfolio flows and their predictability for other investor flows. Notably, this tendency was observed to be more pronounced after the global financial crisis.

Our study addresses gaps in our understanding of fund-level flows stemming from strategic decisions made by international institutional investors. The results highlight the importance of developing a new framework to elucidate the determinants of international portfolio flows at the fund level.

From a policy perspective, our findings emphasize the potential value in closely monitoring the actions of these investment giants as early warning indicators for emerging market downturns. In a world of dilemma where policy options are limited (Rey 2015), this insight can serve as critical guideposts for policymakers and market participants navigating the intricate realm of

international portfolio flows. Moreover, by uncovering the micro-level determinants of fund flows, policymakers gain valuable implications for designing macro-prudential or foreign exchange-related policy frameworks aimed at ensuring financial stability, particularly in emerging economies deeply integrated into the global financial market.

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Appendix

A Two Alternative Model Setups

A.1 Alternative Case I: Simultaneous Move

In this case, each investor $i \in [0,1]$ independently and simultaneously makes an investment decision s_i, to maximize their expected payoff, $\mathbb{E}[\pi_i|x_i]$, based on their private signal, x_i. The first-order condition for each investor's optimization problem is:

$$s_i^{**}(x_i) = \frac{(1-\omega)\mathbb{E}[f|x_i] + \omega(1-\lambda_i)\big\{\lambda\mathbb{E}[s_1|x_i] + (1-\lambda)\mathbb{E}[\bar{s}_0|x_i]\big\}}{(1-\omega)+\omega(1-\lambda_i)}, \tag{1}$$

which represents a convex combination of the expectations of fundamentals and the aggregated market outcomes (i.e., the actions of other investors). Following the approach in Morris and Shin (2002), the optimal strategy can be expressed as a linear function of each investor's private signal:

$$s_1^{**}(x_1) = \phi^{**}x_1 \quad \text{and} \quad s_j^{**}(x_j) = \psi^{**}x_j \quad \text{for} \quad j \in [0,1), \tag{2}$$

where the coefficients ϕ^{**} and ψ^{**} satisfy the following relationships:

$$\phi^{**} = \left[\frac{(1-\omega)+\omega(1-\lambda)^2\psi^{**}}{(1-\omega)+\omega(1-\lambda)^2}\right]\theta_1 \quad \text{and} \quad \psi^{**} = \left[\frac{(1-\omega)+\omega\lambda\phi^{**}}{1-\omega(1-\lambda)\theta_0}\right]\theta_0. \tag{3}$$

A.2 Alternative Case II: Typical Investors Move First.

In contrast to the benchmark model, here we assume that the typical investors move first, and then the investment giant $i = 1$follows.

Investment giant The investment giant chooses its action s_1 to maximize its expected payoff, $\mathbb{E}[\pi_1|x_1, \{x_j, s_j\}_{j\in[0,1)}]$ in equation (12), given the typical investors' signals and decisions. After aggregating expectations, this maximization becomes $\mathbb{E}[\pi_1|f, \bar{s}_0]$. The first-order condition then provides a linear equilibrium as follows:

$$s_1^{***} = \frac{(1-\omega)f + \omega(1-\lambda)\big[\lambda s_1^{***} + (1-\lambda)\bar{s}_0\big]}{(1-\omega)+\omega(1-\lambda)}, \tag{4}$$

which leads to the investment giant's optimal response:

$$s_1^{***}(f, \bar{s}_0^*) = \phi^{***} f + (1 - \phi^{***})\bar{s}_0, \quad \text{where} \quad \phi^{***} \equiv \frac{1-\omega}{1-\omega+\omega(1-\lambda)^2}. \tag{5}$$

Typical investor Each typical investor $j \neq 1$ maximizes its expected payoff, $\mathbb{E}[\pi_j|x_j]$, based on its private signal. The first-order condition for a typical investor is:

$$s_j^{***} = (1-\omega)\mathbb{E}[f|x_j] + \omega\big\{\lambda\mathbb{E}[s_1^{***}|x_j] + (1-\lambda)\mathbb{E}[\bar{s}_0^{***}|x_j]\big\}, \tag{6}$$

where $\mathbb{E}[s_1^{***}|x_j] = \phi^{***}\mathbb{E}[f|x_j] + (1-\phi^{***})\mathbb{E}[\bar{s}_0^{***}|x_j]$. Assuming a linear optimal response for typical investors, we denote:

$$s_j^*(x_j) \equiv \psi^{***} x_j, \tag{7}$$

which implies $\mathbb{E}[\bar{s}_0^{***}|x_j] = \psi^{***}\mathbb{E}[f|x_j] = \psi^{***}\theta_0 x_j$ and $\mathbb{E}[s_1^{***}|x_j] = [\phi^{***} + (1-\phi^{***})\psi^{***}]\theta_0 x_j$. Thus, we obtain:

$$\begin{aligned}\psi^{***} &= (1-\omega)\theta_0 + \omega\big\{\lambda[\phi^{***} + (1-\phi^{***})\psi^{***}]\theta_0 + (1-\lambda)\psi^{***}\theta_0\big\} \\ &= \left[\frac{1-\omega(1-\lambda\phi^{***})}{1-\omega(1-\lambda\phi^{***})\theta_0}\right]\theta_0.\end{aligned} \tag{8}$$

B Macroeconomic Variables: Pull and Push Factors

We take into account various pull and push factors to investigate portfolio flows. The pull factor encompasses domestic features reflecting a country's macroeconomic fundamentals, while the push factor represents external circumstances, particularly U.S. macroeconomic variables.

More specifically, we calculate the ex-post real interest rates by subtracting the nominal interest rates from the year-over-year growth rate of the consumer price index (CPI). CPI data is sourced from the IMF's International Financial Statistics (IFS) dataset, with the exception of Taiwan, where CPI data is collected from Bloomberg. For nominal interest rates, we use treasury bill rates (or deposit rates) from the IFS dataset and supplement them with treasury bill yields from the Global

Financial Database for some countries where the data is not available in the IFS dataset.[24]

Besides, we obtain non-seasonally adjusted industrial production (in US dollars) from the World Bank's GEM (Global Economic Monitor) dataset. Total reserves excluding gold (in US dollars) are taken from the IFS dataset. Monthly exchange rates and stock market indices for each country are sourced from Bloomberg.[25] Finally, we use the Chicago Board Options Exchange Volatility Index (VIX) from Bloomberg. We calculate the month-over-month growth rates for these variables taking the first difference of logarithmic values rather than IHS because they do not contain zero value.

The monthly (country) aggregate equity flow is extracted from the International Institute of Finance (IIF) dataset. To facilitate cross-country comparisons, we standardize the equity flow by dividing it by nominal GDP. The nominal GDP is derived from quarterly data, which is then transformed into monthly data through cubic spline interpolation.

Table 5 provides the summary statistics for the macroeconomic variables. Our final dataset includes macroeconomic variables for all 20 countries over both the mid-GFC period (31 months) and the post-GFC period (108 months), with the exception of the net-flows of equity from IIF. The IIF data spans 351 observations during the crisis and 1,593 observations after the crisis within our sample.

[24]More pointedly, we take nominal interest rates from three sources as follows. First, for Brazil, Hungary, Israel, Mexico, South Africa, and Thailand, we use the treasury bill rate sourced from the IFS dataset. Second, for Chile, Colombia, Czech Rep., Indonesia, Korea Rep., Malaysia, Peru, Philippines, Russia, and Turkey, we choose the deposit rates from the IFS dataset. This is because the IFS dataset lacks treasury bill rate data for these countries, but the deposit rates closely resemble treasury bill rates. Third, for China, India, Poland, and Taiwan, we turn to the treasury bill yield from the Global Financial dataset. This alternative source is selected because their appropriate proxies for nominal interest rates are absent in the IFS dataset.

[25]The list of stock market index for each country that we employ is as follows: (US) Wilshire 5000, (Brazil) Bovespa, (Chile) S&P CLX IPSA, (China) Shanghai Composite, (Colombia) COLCAP, (Czech Rep.) PX, (Hungary) Budapest SE, (India) BSE Sensex 30, (Indonesia) Jakarta Stock Exchange Composite Index, (Israel) TA 35, (Korea Rep.) KOSPI, (Malaysia) FTSE Malaysia KLCI, (Mexico) S&P/BMV IPC, (Peru) S&P Lima General, (Philippines) PSEI Composite, (Poland) WIG 20, (Russia) MOEX Russia, (South Africa) South Africa Top 40, (Taiwan) Taiwan Weighted, (Thailand) SET Index, and (Turkey) BIST 10.

C The Role of Stock Prices and Exchange Rates in Equity Flows

The influence of pull and push factors on capital flows to emerging markets is a well-established topic in international finance literature (Fernandez-Arias 1996, Taylor and Sarno 1997, Forbes and Warnock 2012, Fratzscher 2012, Rey 2015, Byrne and Fiess 2016, Goldberg and Krogstrup 2023, and many others). Linking the existing findings with our fund-level data, we investigate the roles played by domestic and global factors in investment flows using the local projection framework.[26]

Among them, we focus on price factors, including domestic and US stock market indices as well as exchange rates by adjusting equation (5) as follows:

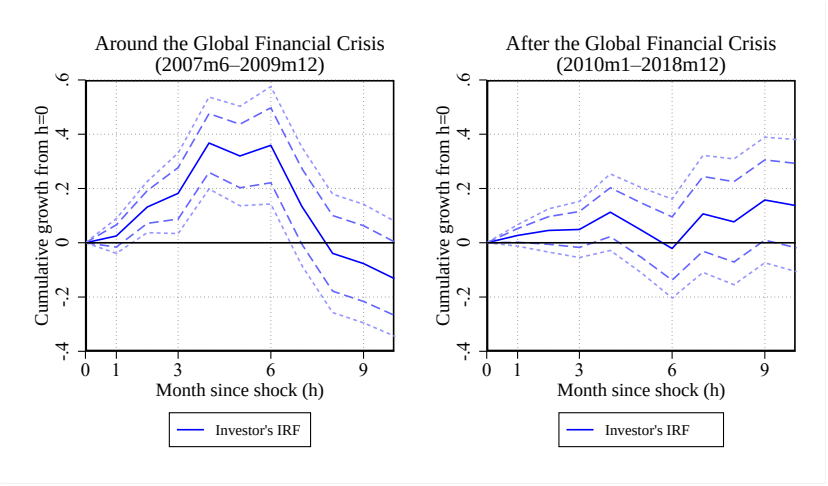
$$\begin{aligned}\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) =& \alpha^h \times \text{PriceFactorGrowth}_{c,t} + \sum_{l=0}^{3} \beta_l^h \left(\bar{g}_{c,t-l}^{\text{giant}} - \bar{g}_{c,t-l}^{\text{typical}}\right) \\ &+ \mathbf{\Gamma}_{\text{pull}}^h \mathbf{Pull}_{c,t} + \mathbf{\Gamma}_{\text{push}}^h \mathbf{Push}_t + \delta_i^h + \delta_c^h + \delta_m^h + \varepsilon_{ic,t}^h, \end{aligned} \tag{9}$$

where $\text{PriceFactorGrowth}_{c,t}$ represents the growth of price factors, encompassing domestic and US stock indices and nominal exchange rates against US dollar. Slightly different from the specifications in equation (5), $\mathbf{pull}_{c,t}$ and $\mathbf{push}_t$, a vector of pull and push factors, excludes the variables associated with $\text{PriceFactorGrowth}_{c,t}$. For instance, when exchange rate growth ($\ln \text{FX}_{c,t} - \ln \text{FX}_{c,t-1}$) is employed as $\text{PriceFactorGrowth}_{c,t}$, the vector of $\mathbf{pull}_{c,t}$ does not contain any exchange rate growths.

Figure 1 illustrates the impulse responses of equity flows to an 1% increase shocks in domestic (panel a) and US stock market indices (panel b). In each panel, the left chart displays the results for the mid-GFC period, whilst the right chart shows the results for the post-GFC samples. In response to an increase in domestic stock return shocks, equity flows initially surge in both the mid-GFC and post-GFC samples; peaking to approximately 0.15% around four months after the shock during the GFC period, and one month after the shock during the post-GFC period. Conversely, responding to an increase in the US stock return shock, equity investments in emerging markets decline over both periods up to around –2 to –1% at $h = 12$. This implies that global equity investors tend to reallocate their portfolios towards equities with higher returns, in line with prior research such as Rajan (2006), Choi and Kronlund (2017) and Caballero and Simsek (2020). The results also suggest that domestic and US stock returns are an important drivers of equity funds even at the

[26] It can be understood that our previous analyses investigated the pipes, in particular at the fund level, as they employed the push and pull factors as control variables. In contrast, this section places its focus squarely on the impacts of push and pull factors on the fund-level flows.

(a) Response to Domestic Stock Market Index Changes



(b) Response to US Stock Market Index Changes

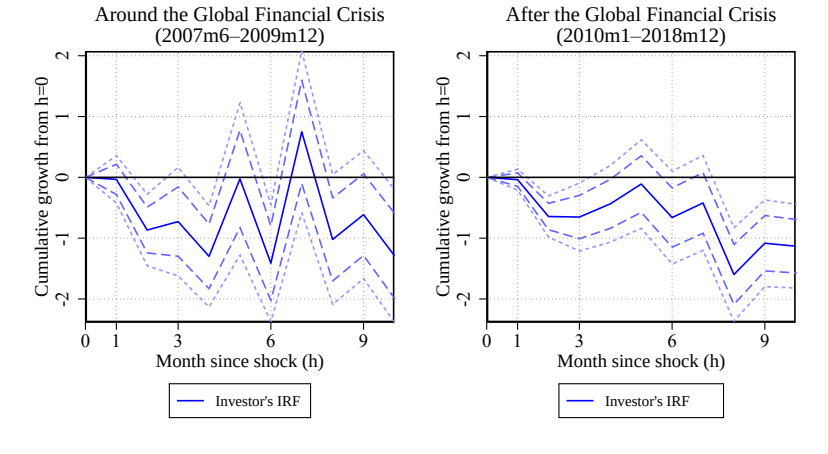


Figure 1: Investor-Level Response to Domestic and US Stock Market Indexes

Notes: The panels (a) and (b) plot the predictive content of domestic and US stock market index growths for individual investors, respectively. In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The responses to stock market indexes are the estimates of α^h in equation (9). The specification controls for investor and country fixed effects, and contemporaneous growth of other push and pull factors (additionally, investment giants' and typical investors' average equity flow growths), and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within investors. In each regression, singleton observations are dropped. The x-axis is time in months, and the y-axis is cumulative changes (growth, %).

fund level. Put another way, international institutional investors consider those price factors and relative returns between them as crucial factors when making decisions about equity investments in emerging markets.

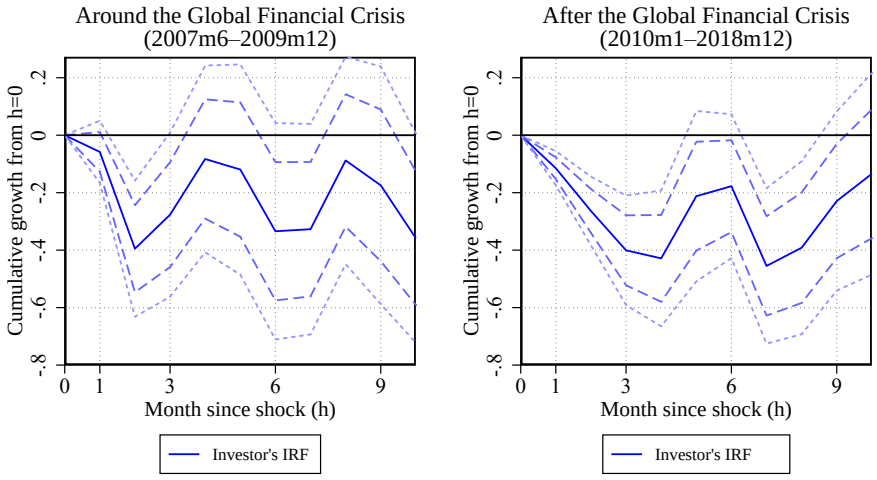
Furthermore, panel (a) of Figure 2 displays the impulse responses of individual equity flows to an increase in exchange rate (i.e., currency depreciation against US dollar) shocks. Other things being constant, when a currency depreciates, the values of locally-invested equities immediately decrease in US dollar terms, known as the *valuation effect* in the literature (Lane and Milesi-Ferretti 2007, Gourinchas and Rey 2014, Bénétrix, Lane and Shambaugh 2015, and many others). This leads international investors to reallocate their portfolios. Our results clearly illustrate this portfolio reallocation in investor-level fund flows due to exchange rate changes. Equity flows exhibit an initial decline of up to 0.25% within two months after the currency depreciation shock during the GFC period, but it is short-lived, partly reflecting the weakened market sentiments due to the crisis. In the post-GFC period, however, the negative responses of equity flows to the same shock are more evident and persistent, reaching to around 0.4%.

Taking these price factors together, we also consider the impacts of a linear combination of domestic and US stock returns along with exchange rates, i.e., the differentials between domestic stock returns denominated in US dollars and US stock returns.[27] They can be interpreted as the relative stock returns after subtracting valuation effect, or the deviations from the uncovered equity party condition (Hau and Rey 2006 and Kim 2011), which are closely linked to ex-post arbitrage opportunities. Hence, the analysis with the stock return differentials can offer a more direct interpretation related to the motivations behind international investors' portfolio reallocation, compared to analyzing stock returns and exchange rates separately.

The investor's reaction to the relative stock returns is estimated in a manner akin to the regression equation (9). In this regression, $\mathbf{X}_{c,t}$ does not include the exchange rate growths or the growth rates of both domestic and US stock market indices to avoid multicollinearity. The impulse responses are reported in panel (b) of Figure 2. In line with earlier observations, global investors exhibit pronounced search-for-yield behaviors by increasing their investments in emerging equity markets when the relative stock returns rise. Following an increase in relative return shocks, equity flows rise by 0.18% around two months after the shock during the GFC period, and by 0.22% around three months after the shock in the post-GFC period. Interestingly, the persistence of these

[27] More specifically, the stock return differentials are computed by taking the difference between the growth rates of the US stock market index and the exchange rate from those of the domestic stock market index.

(a) Response to Exchange Rate Depreciation



(b) Response to Stock Returns Relative to the US

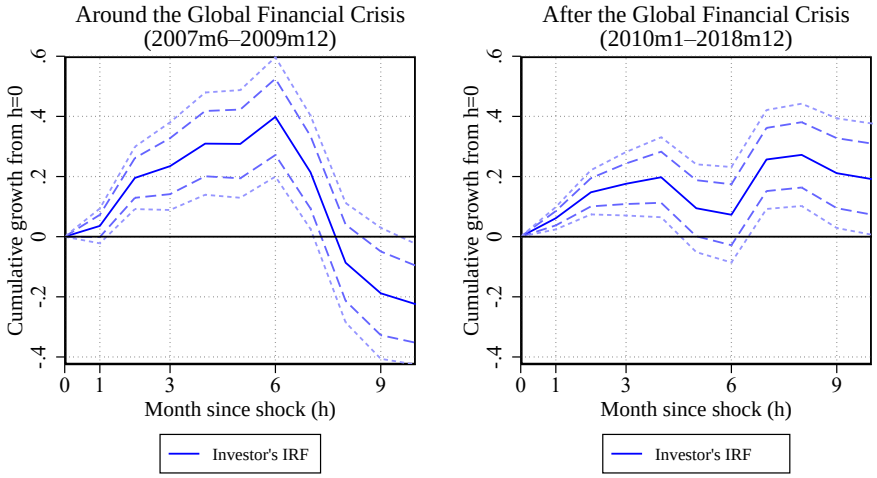


Figure 2: Investor-Level Response to Exchange Rates and Stock Returns Relative to the US

Notes: The panels (a) and (b) plot the predictive content of exchange rates and stock returns relative to the US for individual investors, respectively. In each panel, the left and right figures' sample periods are around the global financial crisis (2007m6–2009m12) and after the crisis (2010m1–2018m12), respectively. The responses to exchange rate and relative returns are the estimates of α^h in equation (9). In panel (a), an increase of exchange rates (local currency per US dollar) implies depreciation. In panel (b), the relative returns are derived by deducting the growth of the US stock market and exchange rate from the growth of the stock market index. The specification controls for investor and country fixed effects, and contemporaneous growth of other push and pull factors (additionally, investment giants' and typical investors' average equity flow growths), and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within investors. In each regression, singleton observations are dropped. The x-axis is time in months, and the y-axis is cumulative changes (growth, %).

investor behaviors varies across the two sample periods. During the GFC, the impacts of the relative return shocks on equity flows at the investor level are short lived, rapidly dissipating and even declining to –0.3% around eight months after the shock. Conversely, after the GFC, the shocks have far more persistent effects on equity flows, reflecting the strengthened risk-on investment strategy driven by prolonged low-for-long conditions in international financial markets (Lian, Ma and Wang 2019).

D Robustness Checks of Investor-Level Analyses

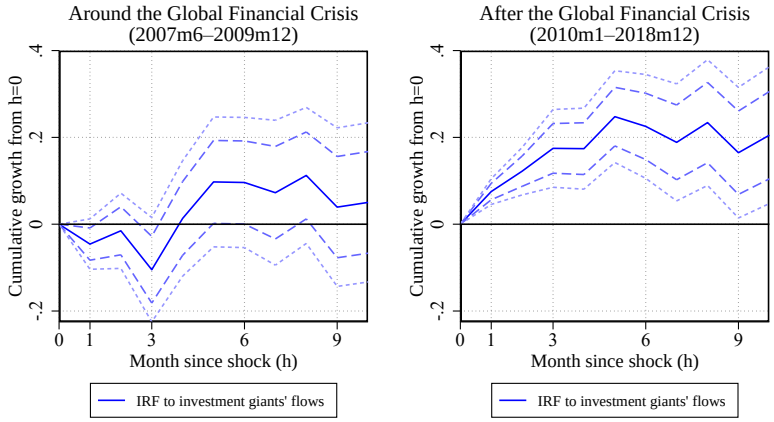


Figure 3: Investor-Level Response to the Unadjusted Equity Flow Differential between Investment Giants and Typical Investors

Notes: The figures depict the predictive capacity of average equity flows from the differential between investment giants' (the top 10) and typical investors' average equity growths where we use non-valuation-adjusted values ($\Delta\text{IHS}(\text{Equity}_{ic,t})$). The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (5). In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. In each regression, singleton observations are dropped. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

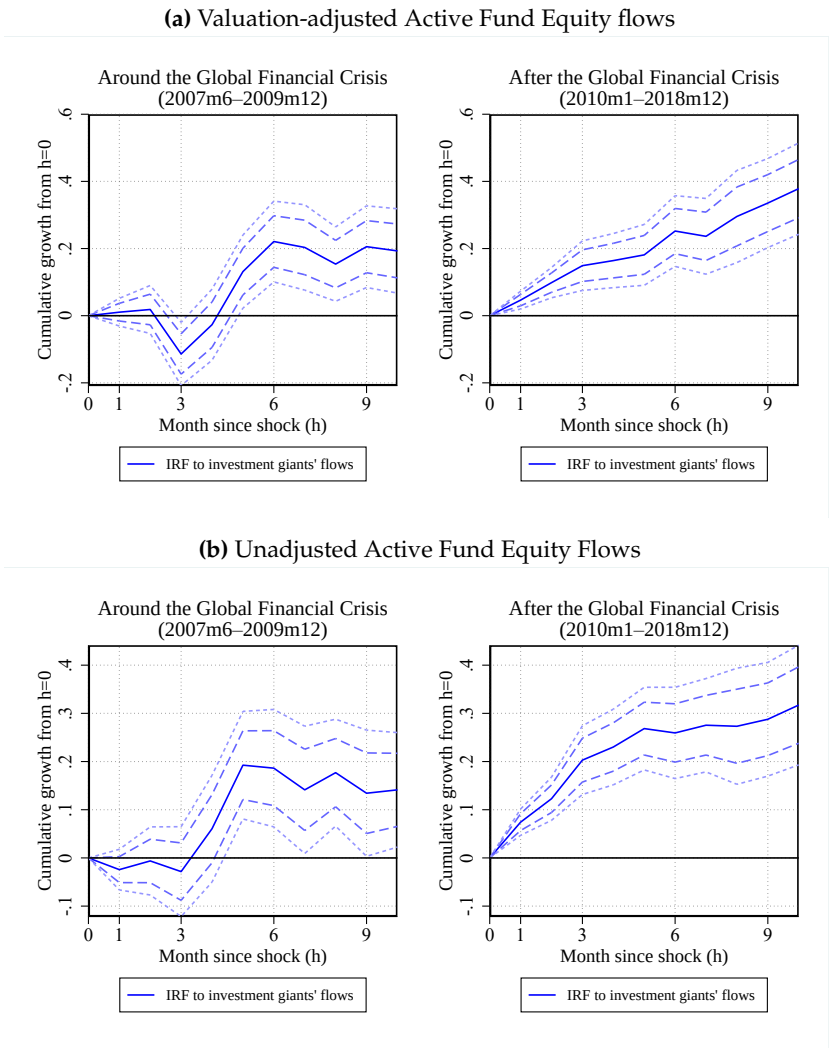


Figure 4: Investor-Level Response to the Equity Flow Differential between Investment Giants and Typical Investors: Active Fund Flows

Notes: The figures depict the predictive capacity of average active fund flows from the differential between investment giants' (the top 10) and typical investors' average active fund growths. In Panel (a), an individual investor's active fund flows ($\tilde{\Delta}\text{IHS}(\text{Equity}_{ic,t})$) and the differential ($\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}$) are adjusted by stock market index and exchange rate growths to remove valuation effects. Panel (b) uses unadjusted values ($\Delta\text{IHS}(\text{Equity}_{ic,t})$ and $\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}$). The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (5). In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

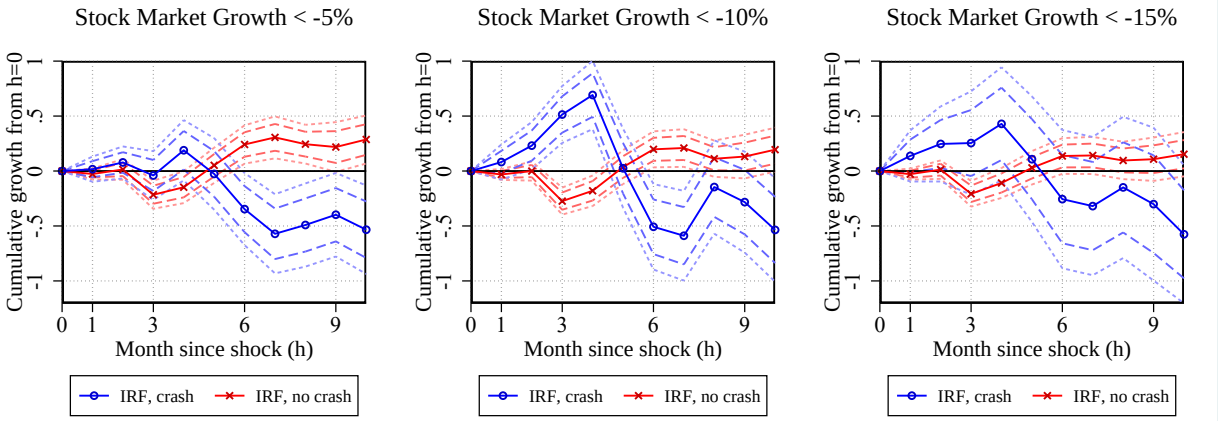


Figure 5: Investor-Level Response with and without Stock Market Crashes: 2007m6–2009m12

Notes: The figures depict the predictive capacity of average equity flows from the differential between investment giants' (the top 10) and typical investors' average equity growths with and without a stock market plunge of more than 5, 10, and 15%. The sample periods are around the global financial crisis (2007m6–2009m12). The responses to flows of investment giants relative to typical investors with and without stock market crashes are the estimates of β^h_{crash} (circled lines) and $\beta^h_{L,nocrash}$ (crossed lines), respectively, in equation (6). The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

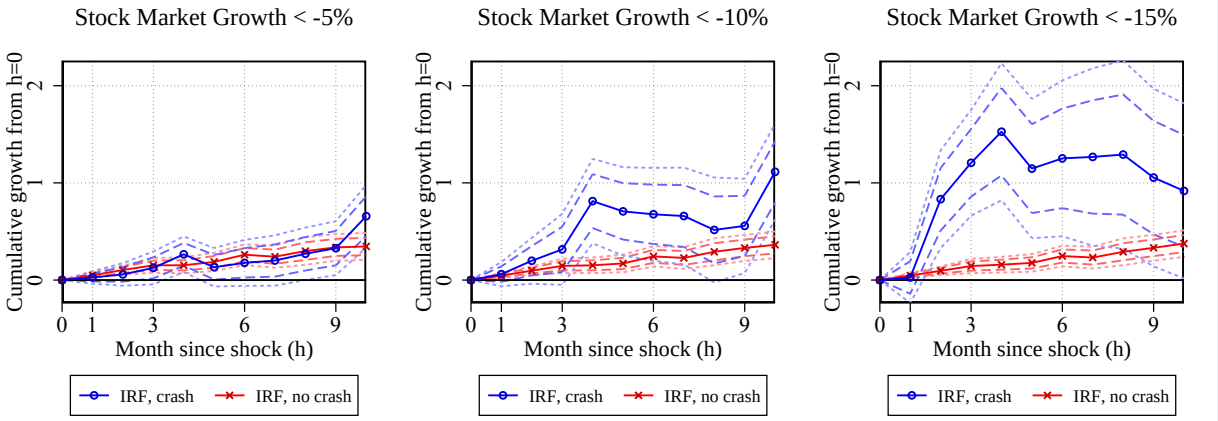


Figure 6: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis: Active Fund Flows

Notes: The figures depict the predictive capacity of average active fund flows from the differential between investment giants' (the top 10) and typical investors' average active fund growths with and without a stock market plunge of more than 5, 10, and 15%. The sample periods are after the crisis (2010m1–2018m12). The responses to flows of investment giants relative to typical investors with and without stock market crashes are the estimates of β^h_{crash} (circled lines) and $\beta^h_{nocrash}$ (crossed lines), respectively, in equation (6). The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

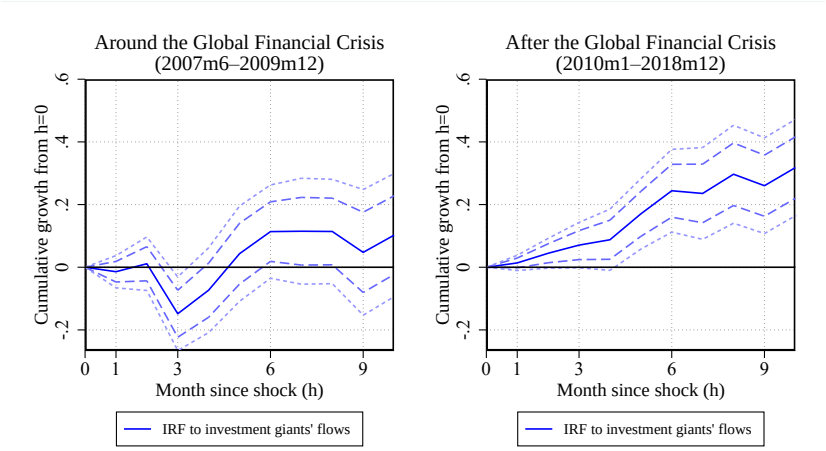
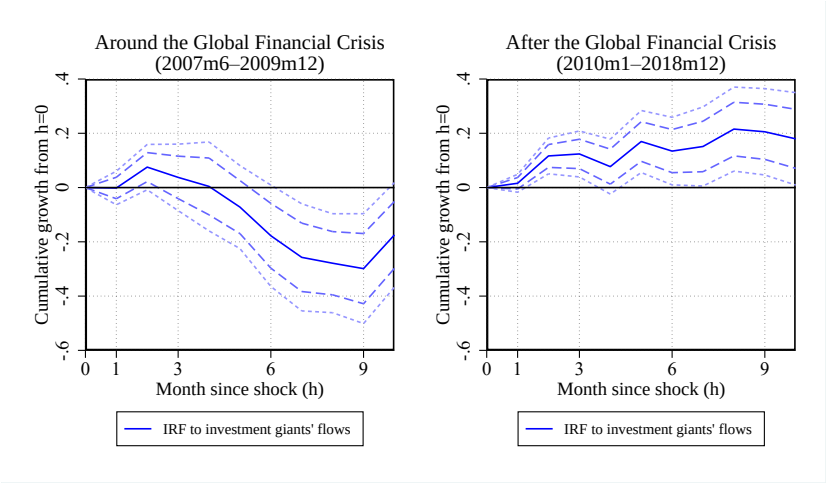


Figure 7: Investor-Level Response to the Equity Flow Differential between Investment Giants and Typical Investors: Alternative Specification

Notes: The figures depict the predictive capacity of average equity flows from the differential between investment giants' (the top 10) and typical investors' average equity growths. The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (7). In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The specification controls for investor-time and country fixed effects, and contemporaneous growth of pull factors, and their three lags. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

(a) Top 15 Largest Investors



(b) Top 7 Largest Investors

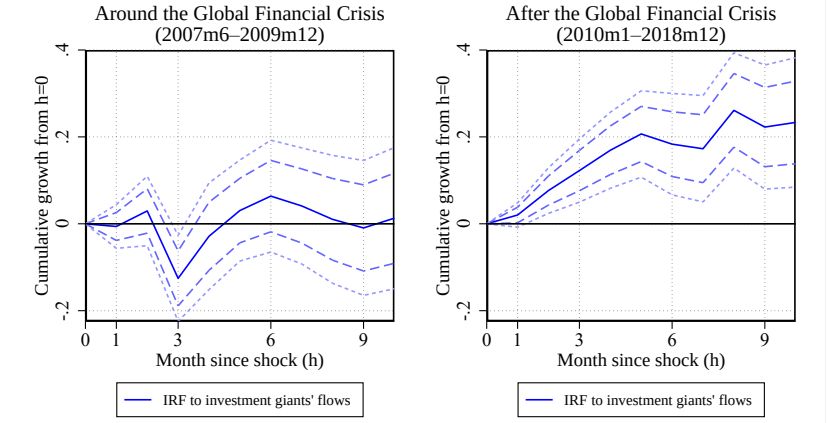
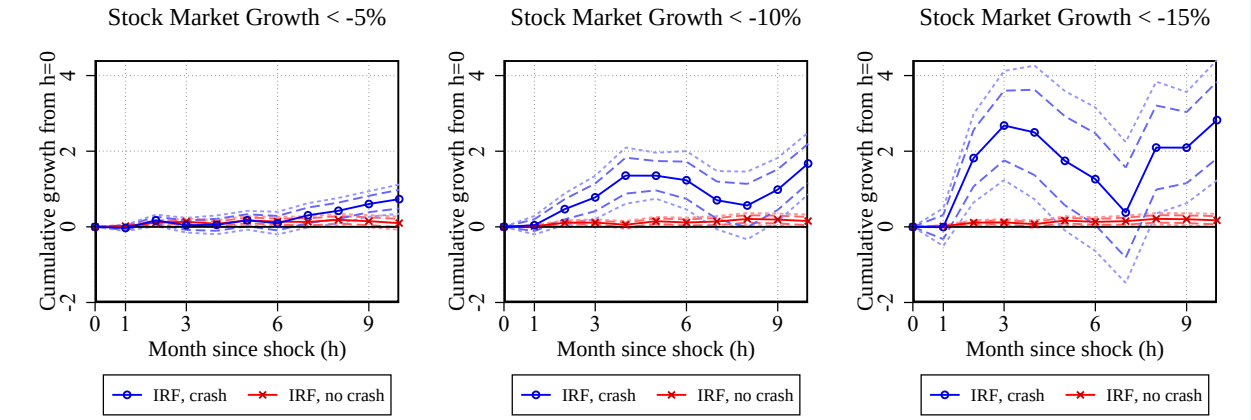


Figure 8: Investor-Level Response to the Equity Flow Differential between Investment Giants (Top 15 or 7 Largest Investors) and Typical Investors

Notes: The panels (a) and (b) plot the predictive capacity of average equity flows from the differential between investment giants' (the top 15 and 7, respectively) and typical investors' average equity growths. The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (5). In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

(a) Top 15 Largest Investors



(b) Top 7 Largest Investors

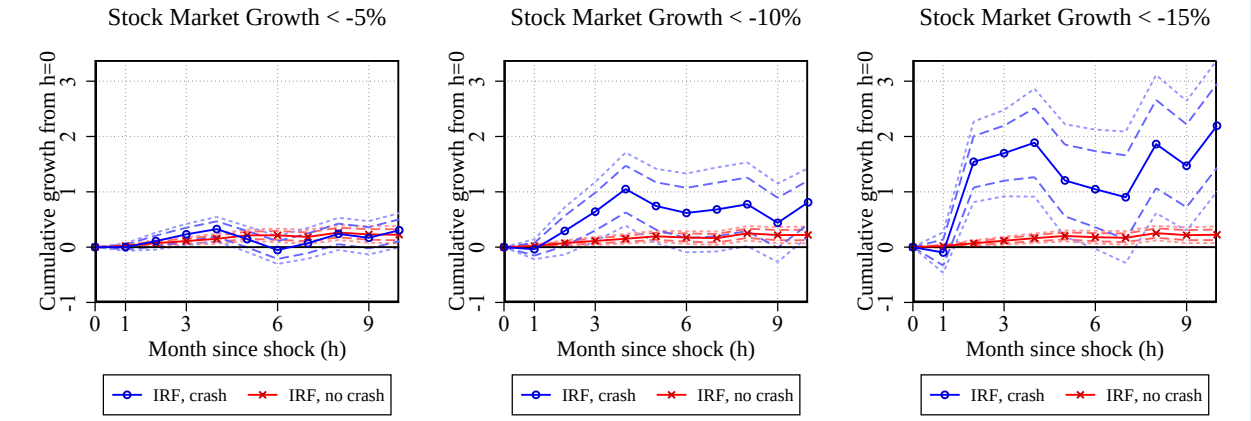


Figure 9: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis: Top 15 and 7 Largest Investors

Notes: The panels (a) and (b) plot the predictive capacity of average equity flows from the differential between investment giants' (the top 15 and 7, respectively) and typical investors' average equity growths with and without a stock market plunge of more than 5, 10, and 15%. The sample periods are after the crisis (2010m1–2018m12). The responses to flows of investment giants relative to typical investors with and without stock market crashes are the estimates of β^h_{crash} (circled lines) and $\beta^h_{nocrash}$ (crossed lines), respectively, in equation (6). The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

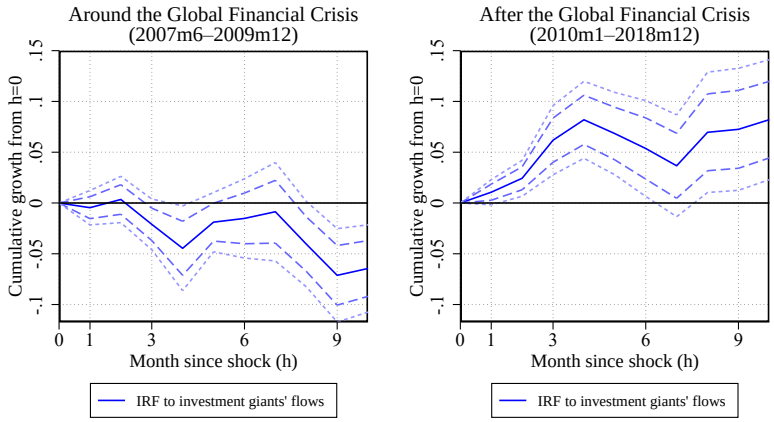


Figure 10: Investor-Level Response to Changes in Investment Giants Share

Notes: The figures depict the predictive capacity of average equity flows from the share of investment giants' (the top 10) equity investments. The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (5). In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

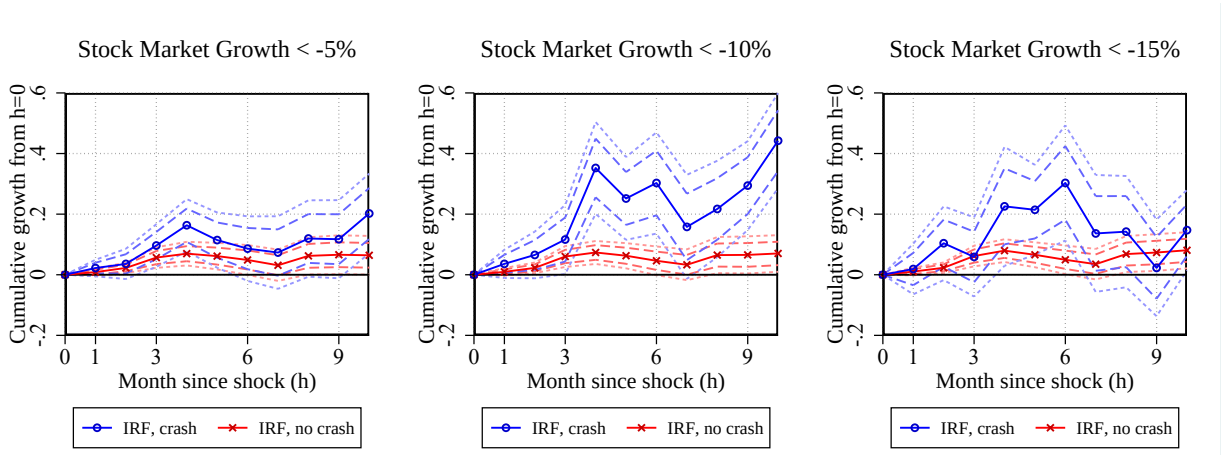


Figure 11: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis: Investment Giants' Share Changes

Notes: The figures depict the predictive capacity of average equity flows from the share of investment giants' (the top 10) equity investments with and without a stock market plunge of more than 5, 10, and 15%. The responses to flows of investment giants relative to typical investors with and without stock market crashes are the estimates of β^h_{crash} (blue circled lines) and $\beta^h_{nocrash}$ (red crossed lines), respectively, in equation (6). The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

E Robustness Checks of Country-Level Analyses

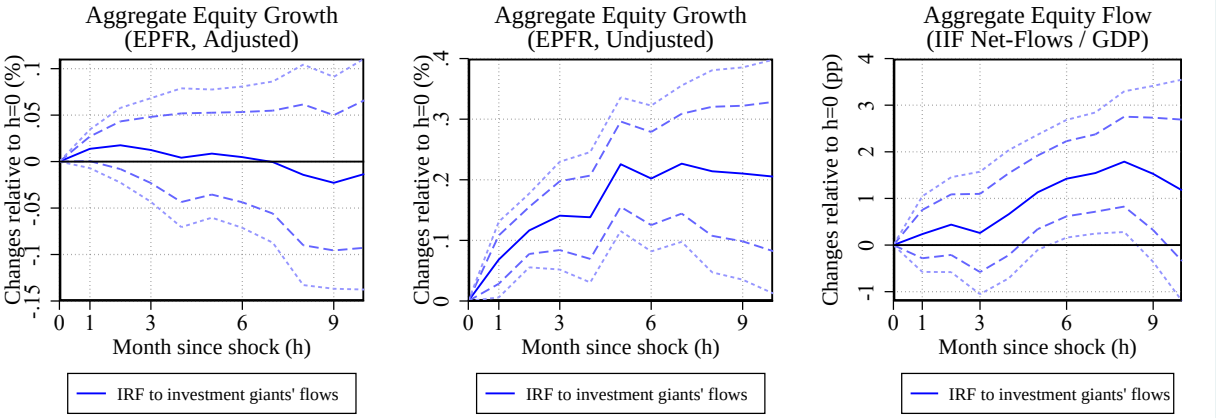


Figure 12: Aggregate Flow Responses to Investment Giants: Active Fund Flows

Notes: The figures depict the predictive content of the differential between investment giants' (the top 10) and typical investors' average active fund equity growth for the adjusted and unadjuested EPFR aggregate active fund equity growths and and IIF aggregate equity net-flows (% of GDP). The sample periods are after the global financial crisis (2010m1–2018m12). The responses to investment giants flows are the estimates of β^h in equation (9). The specification controls for country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

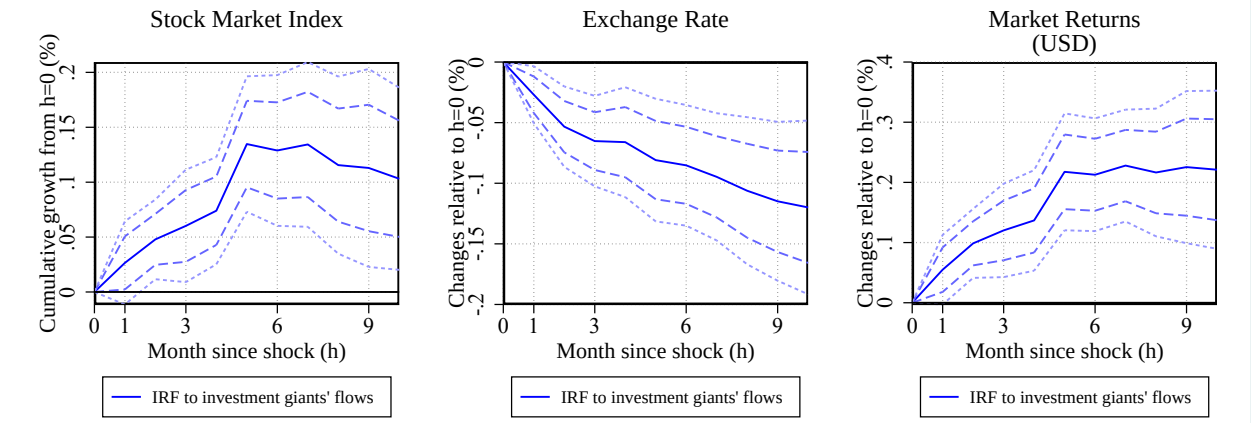


Figure 13: Stock and Currency Markets Responses to Investment Giants: Active Fund Flows

Notes: The figures depict the predictive content of the differential between investment giants (the top 10) and typical investors' average active fund equity growth for stock price indices, exchange rates, and stock market returns (USD). The sample periods are after the global financial crisis (2010m1–2018m12). The responses to investment giants flows are the estimates of β^h in equation (11). The specification controls for country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

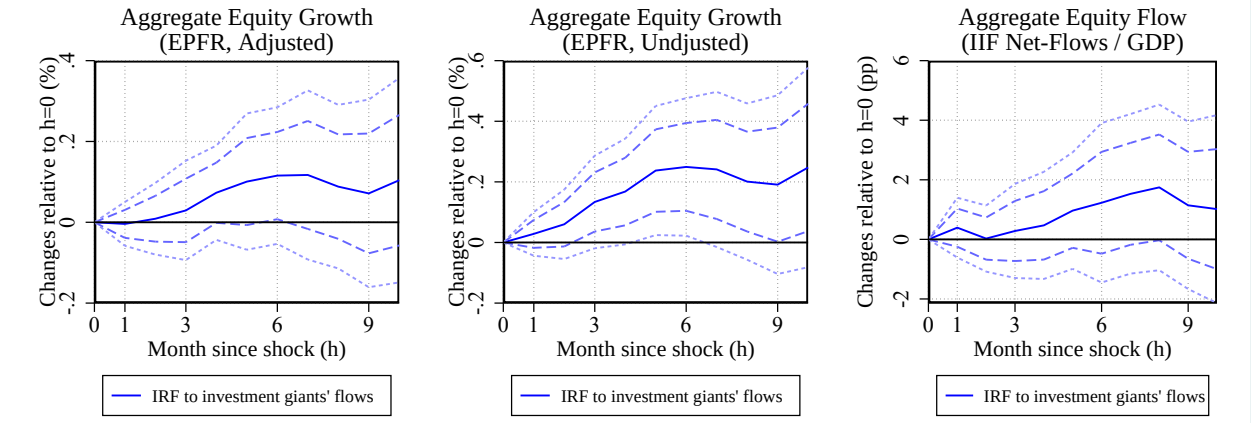


Figure 14: Aggregate Flow Responses to Investment Giants Flows: Alternative Specification

Notes: The figures depict the predictive content of the differential between investment giants' (the top 10) and typical investors' average equity growth for the adjusted and unadjuested EPFR aggregate active fund equity growths and and IIF aggregate equity net-flows (% of GDP). The sample periods are after the global financial crisis (2010m1–2018m12). The responses to investment giants flows are the estimates of β^h in equation (10). The specification controls for country and time fixed effects, and contemporaneous growth of pull factors and their three lags. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

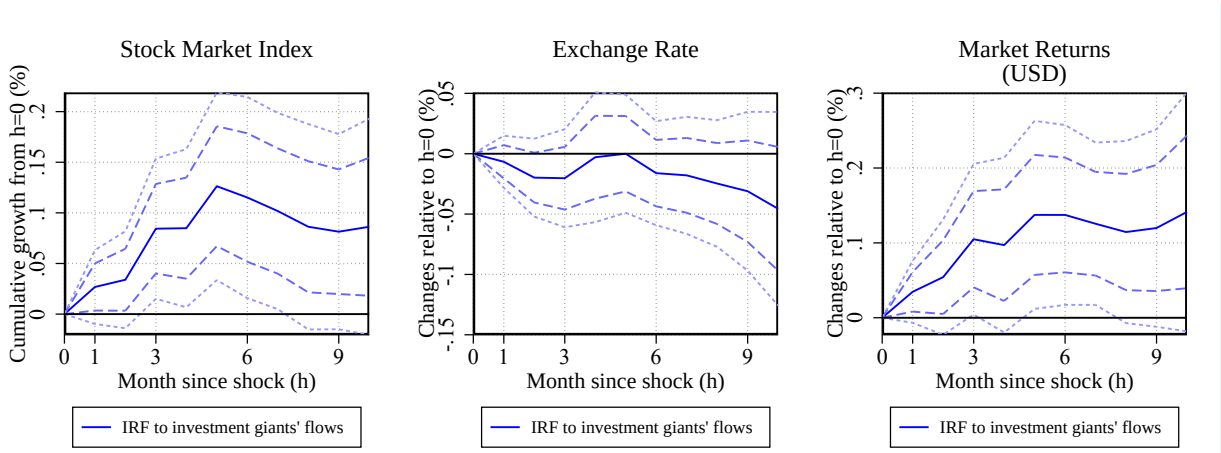
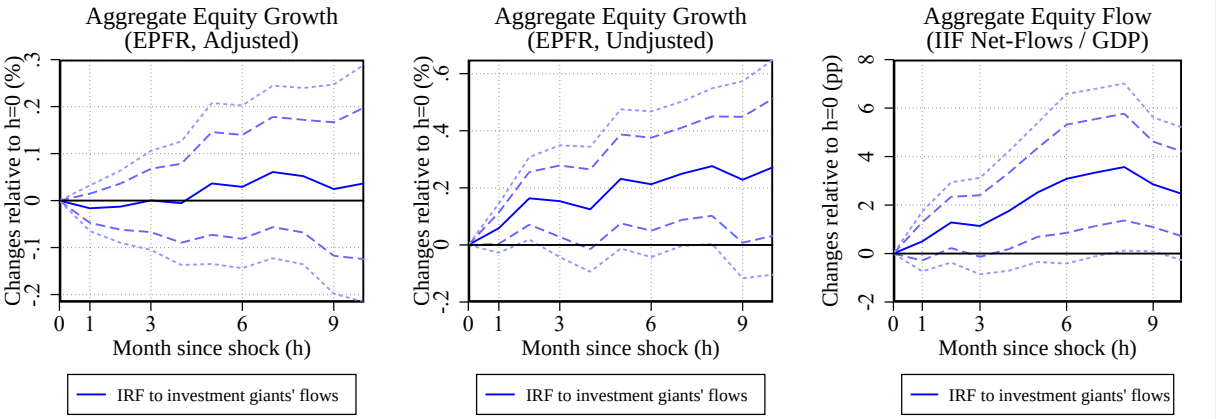


Figure 15: Stock and Currency Markets Responses to Investment Giants Flows: Alternative Specification

Notes: The figures depict the predictive content of the differential between investment giants' (the top 10) and typical investors' average equity growth for stock price indices, exchange rates, and stock market returns (USD). The sample periods are after the global financial crisis (2010m1–2018m12). The responses to investment giants flows are the estimates of β^h in equation (11) with different fixed effects. The specification controls for country and time fixed effects, and contemporaneous growth of pull factors and their three lags. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

(a) Top 15 Largest Investors



(b) Top 7 Largest Investors

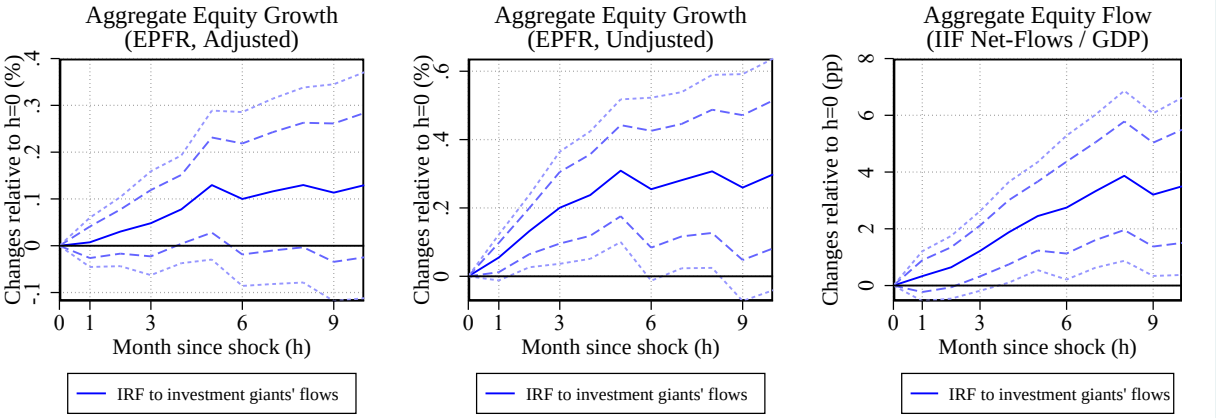


Figure 16: Aggregate Flow Responses to Investment Giants (Top 15 and 7 Largest Investors) Flows

Notes: The panels (a) and (b) plot the predictive content of the differential between investment giants' (the top 15 and 7, respectively) and typical investors' average equity growth for the adjusted and unadjuested EPFR aggregate active fund equity growths and and IIF aggregate equity net-flows (% of GDP). The sample periods are after the global financial crisis (2010m1–2018m12), respectively. The responses to investment giants flows are the estimates of β^h in equation (11). The specification controls for country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

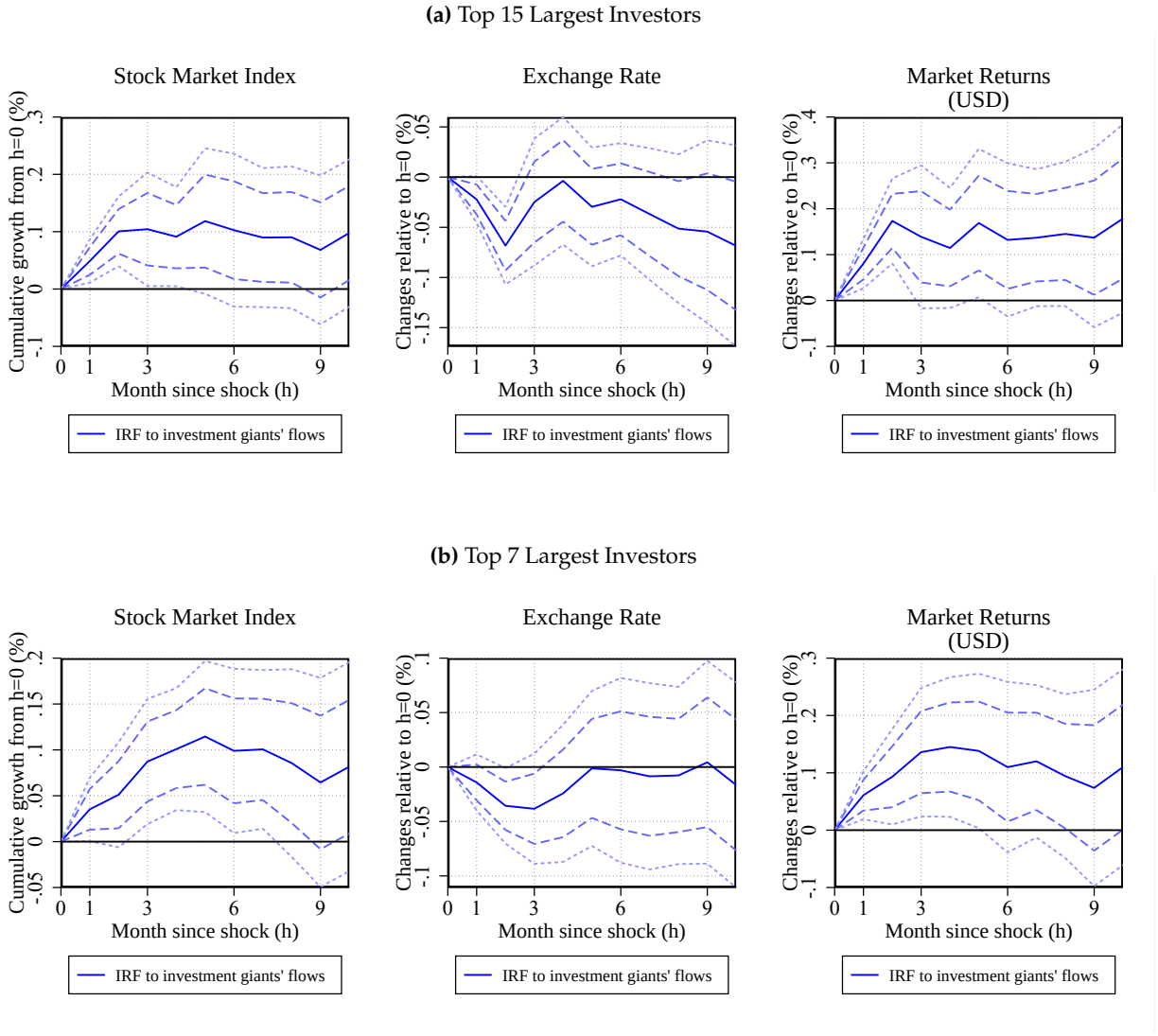


Figure 17: Stock and Currency Markets Responses to Investment Giants (Top 15 and 7 Largest Investors) Flows

Notes: The panels (a) and (b) plot the predictive content of the differential between investment giants' (the top 15 and 7, respectively) and typical investors' average equity growth for stock price indices, exchange rates, and stock market returns (USD). The sample periods are after the global financial crisis (2010m1–2018m12). The responses to investment giants flows are the estimates of β^h in equation (9). The specification controls for country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

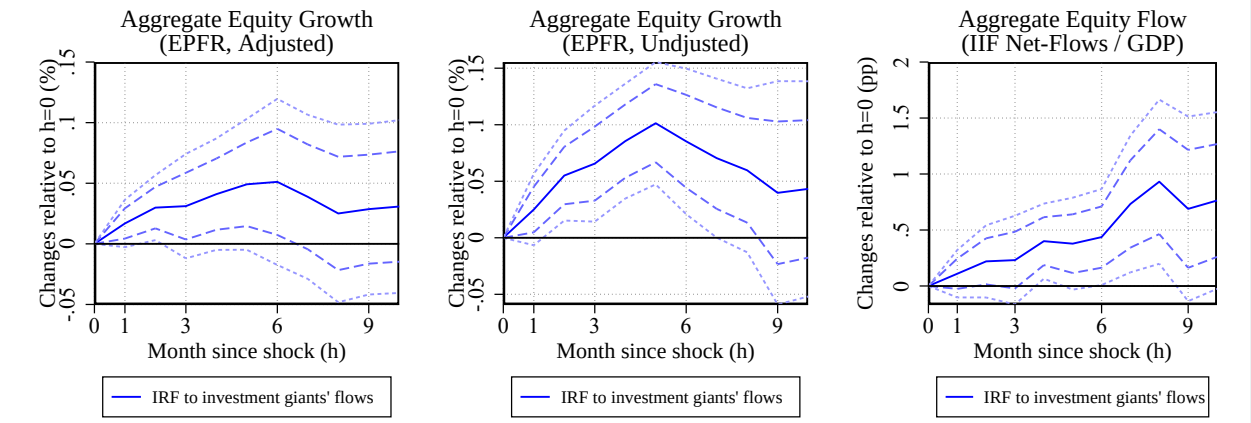


Figure 18: Aggregate Flow Responses to Investment Giants Share

Notes: The figures depict the predictive content of the share of investment giants' (the top 10) equity investments for the adjusted and unadjuested EPFR aggregate equity growths and and IIF aggregate equity net-flows (% of GDP). The sample periods are after the global financial crisis (2010m1–2018m12). The responses to investment giants flows are the estimates of β^h in equation (9). The specification controls for country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

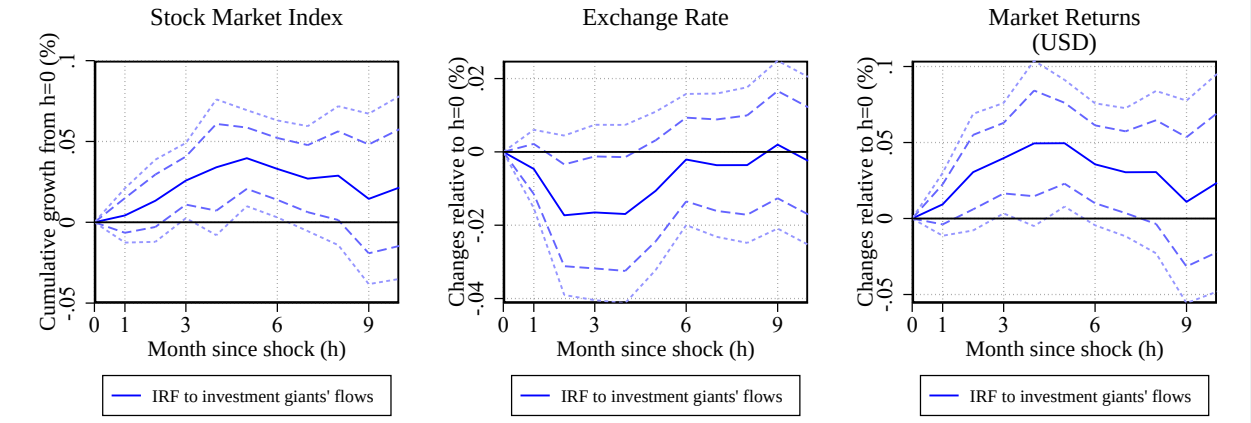


Figure 19: Stock and Currency Markets Responses to Investment Giants Share

Notes: The figures depict the predictive content of the share of investment giants' (the top 10) equity investments for stock price indices, exchange rates, and stock market returns (USD). The sample periods are after the global financial crisis (2010m1–2018m12). The responses to investment giants flows are the estimates of β^h in equation (11). The specification controls for country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

F Additional Figures and Tables

Table 1: Summary Statistics: Equity Flows

Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Around the Global Financial Crisis (2007m6–2009m12)						
Equity flow (mil. US dollars)						
All investors	56460	123.27	454.77	0.00	6.69	261.26
Non-top 10 largest investors	50260	56.08	195.06	0.00	3.67	131.75
Top 10 largest investors	6200	667.97	1114.34	6.96	248.71	1842.82
Equity flow (monthly growth, %)						
All investors	55240	-0.26	26.71	-20.84	0.00	18.60
Non-top 10 largest investors	49040	-0.36	26.93	-20.73	0.00	18.22
Top 10 largest investors	6200	0.49	24.89	-21.67	0.07	20.30
Adjusted equity flow (monthly growth, %)						
All investors	55240	-0.16	25.06	-14.69	0.00	13.62
Non-top 10 largest investors	49040	-0.27	25.36	-14.78	0.00	13.33
Top 10 largest investors	6200	0.66	22.56	-13.93	0.00	15.12
After the Global Financial Crisis (2010m1–2018m12)						
Equity flow (mil. US dollars)						
All investors	240940	176.17	1042.14	0.00	4.00	273.01
Non-top 10 largest investors	219340	57.02	187.59	0.00	2.19	142.53
Top 10 largest investors	21600	1386.12	3185.85	3.74	412.11	3297.73
Equity flow (monthly growth, %)						
All investors	234620	0.11	21.35	-11.93	0.00	11.58
Non-top 10 largest investors	213020	0.13	21.79	-11.78	0.00	11.50
Top 10 largest investors	21600	-0.07	16.46	-13.00	0.00	12.07
Adjusted equity flow (monthly growth, %)						
All investors	234620	0.10	20.77	-9.06	0.00	8.92
Non-top 10 largest investors	213020	0.12	21.24	-9.01	0.00	8.93
Top 10 largest investors	21600	-0.10	15.33	-9.25	0.00	8.88

Notes: The monthly growth rates are the first difference of IHS values.

Table 2: Summary Statistics: Average and Aggregate Equity Flows

Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Around the Global Financial Crisis (2007m6–2009m12)						
Aggregate of equity flows (monthly growth, %)						
	620	-0.15	14.14	-15.98	1.36	15.54
Aggregate of adjusted equity flows (monthly growth, %)						
	620	0.07	7.25	-9.36	0.35	8.31
Cross-sectional average of equity flow growth (monthly growth, %)						
Non-top 10 largest investors	620	-0.36	8.62	-9.76	0.18	9.53
Top 10 largest investors	620	0.49	12.69	-15.72	1.78	14.96
Cross-sectional average of adjusted equity flow growth (monthly growth, %)						
Non-top 10 largest investors	620	-0.27	4.36	-5.43	-0.37	4.92
Top 10 largest investors	620	0.66	7.93	-10.29	0.86	10.35
After the Global Financial Crisis (2010m1–2018m12)						
Aggregate of equity flows (monthly growth, %)						
	2160	0.64	8.37	-9.58	1.06	10.15
Aggregate of adjusted equity flows (monthly growth, %)						
	2160	0.60	4.77	-4.15	0.41	5.33
Cross-sectional average of equity flow growth (monthly growth, %)						
Non-top 10 largest investors	2160	0.11	4.85	-5.63	0.20	5.87
Top 10 largest investors	2160	-0.07	7.85	-10.05	0.05	9.39
Cross-sectional average of adjusted equity flow growth (monthly growth, %)						
Non-top 10 largest investors	2160	0.09	2.87	-3.40	0.11	3.68
Top 10 largest investors	2160	-0.10	5.19	-5.92	-0.11	5.75

Notes: The aggregate and cross-sectional average growth rates are the first difference of logged and IHS values, respectively.

Table 3: Summary Statistics: Active Equity Fund Flows

Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Around the Global Financial Crisis (2007m6–2009m12)						
Equity flow (mil. US dollars)						
All investors	56460	103.44	370.64	0.00	5.89	225.78
Non-top 10 largest investors	50940	56.71	197.07	0.00	3.59	131.75
Top 10 largest investors	5520	534.61	916.95	0.00	182.60	1476.44
Equity flow (monthly growth, %)						
All investors	55100	-0.16	27.28	-20.82	0.00	18.86
Non-top 10 largest investors	49640	-0.30	27.15	-20.69	0.00	18.39
Top 10 largest investors	5460	1.12	28.42	-21.85	0.00	21.76
Adjusted equity flow (monthly growth, %)						
All investors	55100	-0.08	25.70	-14.73	0.00	13.86
Non-top 10 largest investors	49640	-0.21	25.59	-14.74	0.00	13.45
Top 10 largest investors	5460	1.08	26.62	-14.72	0.00	16.48
After the Global Financial Crisis (2010m1–2018m12)						
Equity flow (mil. US dollars)						
All investors	229200	109.82	416.71	0.00	2.92	224.10
Non-top 10 largest investors	208340	54.42	187.12	0.00	1.58	132.94
Top 10 largest investors	20860	663.15	1105.20	0.00	202.93	1868.69
Equity flow (monthly growth, %)						
All investors	223320	-0.04	21.74	-12.20	0.00	11.38
Non-top 10 largest investors	202480	-0.03	22.02	-11.95	0.00	11.22
Top 10 largest investors	20840	-0.20	18.81	-13.69	0.00	12.49
Adjusted equity flow (monthly growth, %)						
All investors	223320	-0.05	21.18	-9.41	0.00	8.76
Non-top 10 largest investors	202480	-0.04	21.49	-9.29	0.00	8.65
Top 10 largest investors	20840	-0.23	17.97	-10.29	0.00	9.44

Notes: The monthly growth rates are the first difference of IHS values.

Table 4: Summary Statistics: Average and Aggregate Active Equity Fund Flows

Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Around the Global Financial Crisis (2007m6–2009m12)						
Aggregate of equity flows (monthly growth, %)						
	620	-0.50	14.25	-15.95	1.17	15.25
Aggregate of adjusted equity flows (monthly growth, %)						
	620	-0.27	7.75	-10.11	0.02	8.44
Cross-sectional average of equity flow growth (monthly growth, %)						
Non-top 10 largest investors	620	-0.15	11.19	-12.12	0.28	12.15
Top 10 largest investors	620	1.00	13.27	-16.05	2.45	16.97
Cross-sectional average of adjusted equity flow growth (monthly growth, %)						
Non-top 10 largest investors	620	-0.04	8.04	-10.24	-0.04	9.39
Top 10 largest investors	620	1.12	9.67	-11.90	1.08	12.26
After the Global Financial Crisis (2010m1–2018m12)						
Aggregate of equity flows (monthly growth, %)						
	2160	0.10	8.16	-10.24	0.29	9.56
Aggregate of adjusted equity flows (monthly growth, %)						
	2160	0.06	5.02	-5.13	-0.01	5.31
Cross-sectional average of equity flow growth (monthly growth, %)						
Non-top 10 largest investors	2160	0.37	7.01	-8.36	0.47	8.95
Top 10 largest investors	2160	0.35	5.69	-6.28	0.15	7.29
Cross-sectional average of adjusted equity flow growth (monthly growth, %)						
Non-top 10 largest investors	2160	-0.18	7.97	-10.42	0.16	9.39
Top 10 largest investors	2160	-0.22	5.98	-7.26	-0.09	6.72

Notes: The monthly growth rates are the first difference of IHS values.

Table 5: Summary Statistics: Macroeconomic Variables

Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
(a) Country-Month Level						
Around the Global Financial Crisis (2007m6–2009m12)						
Real interest rate (per annum, %)	620	1.00	4.16	-3.71	0.92	5.58
Industrial production (USD, monthly growth, %)	620	0.03	6.72	-8.01	0.17	7.46
Stock market index (monthly growth, %)	620	-0.15	9.46	-11.96	0.79	10.21
Reserve excluding gold (USD, monthly growth, %)	620	1.14	3.67	-2.37	1.24	4.62
Exchange rate (monthly growth, %)	620	0.07	4.31	-4.58	-0.18	4.80
IIF equity net-flows / GDP (ratio, %)	351	0.07	1.07	-0.88	0.08	1.13
After the Global Financial Crisis (2010m1–2018m12)						
Real interest rate (per annum, %)	2,160	0.99	2.40	-1.38	0.75	3.61
Industrial production (USD, monthly growth, %)	2,151	0.24	7.38	-8.25	0.41	9.11
Stock market index (monthly growth, %)	2,160	0.35	4.55	-5.26	0.56	5.86
Reserve excluding gold (USD, monthly growth, %)	2,160	0.36	2.32	-1.92	0.28	2.86
Exchange rate (monthly growth, %)	2,160	0.31	3.13	-3.00	0.04	3.91
IIF equity net-flows / GDP (ratio, %)	1,593	0.10	0.69	-0.51	0.06	0.78
(b) Month Level						
Around the Global Financial Crisis (2007m6–2009m12)						
US real interest rate (per annum, %)	31	-0.52	2.00	-3.13	-0.05	1.94
US industrial production (monthly growth, %)	31	-0.45	2.00	-2.81	-0.45	2.65
US stock market index (monthly growth, %)	31	-0.94	6.48	-8.81	0.21	5.42
VIX (monthly growth, %)	31	1.64	21.61	-22.49	-1.63	29.51
After the Global Financial Crisis (2010m1–2018m12)						
US real interest rate (per annum, %)	108	-1.37	0.95	-2.79	-1.27	-0.14
US industrial production (monthly growth, %)	108	0.18	1.41	-1.39	-0.04	2.56
US stock market index (monthly growth, %)	108	0.74	3.68	-4.21	0.99	5.12
VIX (monthly growth, %)	108	0.15	22.11	-27.38	-0.61	30.65

Notes: The monthly growth rates are the log difference.

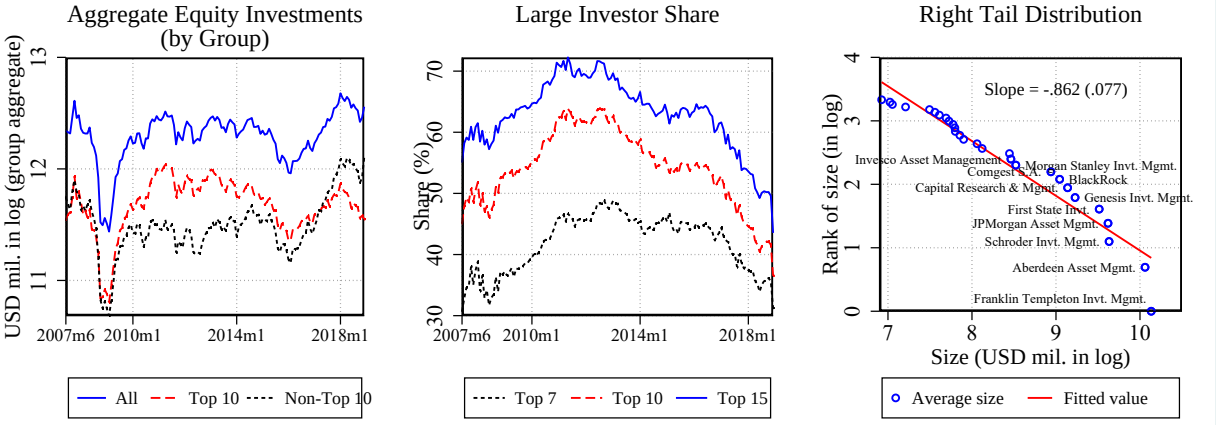


Figure 20: Trends of Equity Fund Flows: Active Funds Only

Notes: The first figure plots the total active fund equity investment made by each investor group in the 20 emerging equities markets. The second figure displays the shares of the top 7, 10, and 15 largest aggregated global active fund equity flows in the 20 emerging equity markets. The last figure plots the logged total active fund equity investment size, averaged over the period of 2010m1–2018m12, and its logged rank in the emerging equity markets. The data includes 29 continuing investors with size more than one billion US dollars. The robust standard error of slope estimate is in parenthesis. The absolute value of slope of predictions (red line) implies the coefficients of power distribution. See Figure 2 for the results from all funds (active & passive).

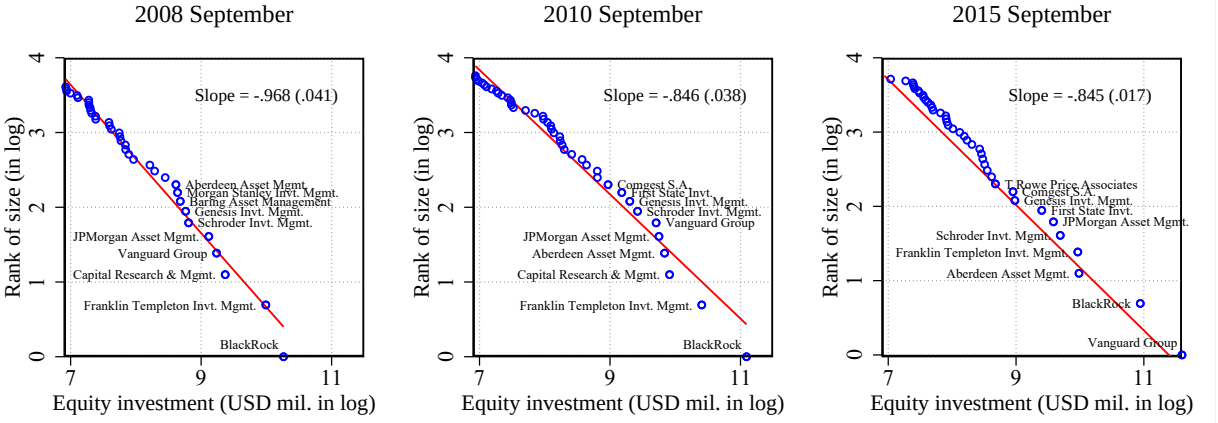


Figure 21: The Right Tail of Investor Size

Notes: The figures separately plot the logged rank of total equity investment (y-axis) and logged total equity investment size (x-axis) in the 20 emerging equity markets in September 2008, 2010, and 2015. The data includes investors with more than one billion US dollars in the emerging equity markets. There are approximately 40 investors on each figure. The robust standard errors of slope estimates are in parenthesis. The absolute value of slope of predictions (red line) implies the coefficients of power distribution.