Investment Giants and Their Impacts in Emerging Markets

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Abstract

Non-resident equity flows into emerging markets are heavily concentrated among a few large institutional investors, termed "*investment giants*." We investigate the behavior and impact of these giants in a model where investors consider both market fundamentals and aggregates in their decision-making. In a sequential move case, a single giant investor sets a market direction and provides information to a continuum of typical investors by moving first. This leadership and information dissemination secure the giant's higher ex-ante payoff compared to a simultaneous-move scenario and create a positive influence of its (contrarian) decisions on both other investors and market aggregates. Monthly fund-level data confirm our model predictions. Equity flows into emerging markets persistently increase following giants' contrarian flows—measured by excess growth relative to peers or the market—highlighting their predictive power. Furthermore, aggregate equity flows and stock indexes rise, and exchange rates appreciate in response to these investments. These findings suggest the potential value of monitoring investment giants as early indicators of market movements and financial instability in emerging economies.

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1 Introduction

The increasing integration of international financial markets has fueled a steady rise in cross-border portfolio flows, reshaping global financial environments. Following the global financial crisis (GFC), low interest rates in advanced economies spurred substantial portfolio flows into emerging market economies as international investors sought higher yields (Rajan 2006 and Summers 2016). These flows provide significant benefits for emerging market economies, such as enhanced opportunities for risk-sharing and external financing (Bonfiglioli 2008, Igan, Kutan and Mirzaei 2020, and Aristizabal-Ramirez, Leahy and Tesar 2023). However, they also bring notable risks: heightened exposure to global shocks, the potential for sudden reversals that intensify financial stress (Calvo and Reinhart 2002 and Gourinchas and Obstfeld 2012), and increased volatility due to investor overreaction to market fundamentals (Dornbusch and Park 1995). Financial integration further complicates these dynamics, as it increases the likelihood of crises while potentially mitigating their severity (Devereux and Yu 2019).

Despite the extensive literature on capital flows, the drivers and macro-financial consequences of cross-border portfolio flows, particularly at the fund investor level, remain underexplored. This paper aims to address this gap by theoretically and empirically analyzing the strategic behavior of institutional investors in emerging equity markets. One of the most pronounced characteristics of global equity allocations to emerging markets is their high concentration among a small group of dominant institutional investors, referred to as "*investment giants*" (Figure 1). These giants wield disproportionate influence, echoing patterns observed in studies of U.S. and global financial markets (e.g., Corsetti, Dasgupta, Morris and Shin 2004, Buch, Koch and Koetter 2011, Ben-David, Franzoni, Moussawi and Sedunov 2021, and Coimbra, Kim and Rey 2022). This paper focuses on their interactions with other investors and their broader influence on equity and currency markets. By doing so, we provide insights for policymakers and market participants navigating the complexities of international capital flows in emerging markets. In particular, our findings suggest the potential benefits of closely monitoring investment giants' activities, especially when their decisions diverge from those of other investors and market trends. Their moves may serve as early warning indicators of potential market disruptions in emerging economies.

To understand the behavior and influence of investment giants, we first construct a theoretical framework that integrates noisy markets, strategic complementarity, and the role of a dominant player. Formally, we assume that a market consists of a single dominant player (the investment

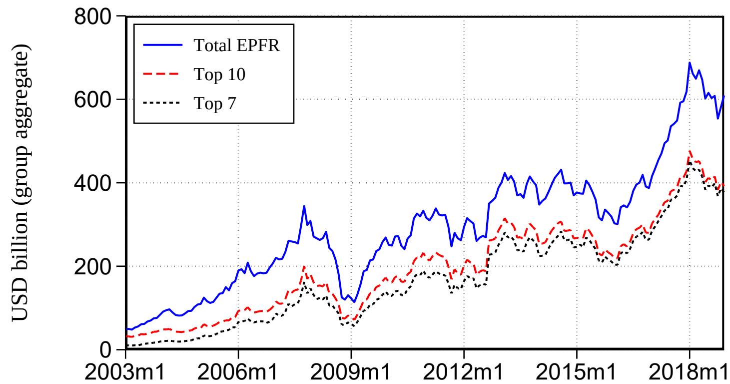


Figure 1: Equity Fund Flows to 20 Emerging Markets

Notes: The figure plots the aggregate equity investment made by each investor (mutual fund) group (all, top 7 and 10) in the 20 emerging equities markets. The fund flows are sourced from the EPFR database. See Appendix C.1 for the details.

giant) and a continuum of smaller investors (typical investors), in which the investment giant can choose its timing for moving—either simultaneously with others or sequentially. Similar to Corsetti et al. (2004), the market is characterized by the visibility and influence of the investment giant, whose actions shape market equilibrium.

To capture the key features of financial markets, as conceptualized in the beauty contest analogy (Keynes 1936; see also Chen, Goldstein and Jiang 2010 and Schmidt, Timmermann and Wermers 2016), we adopt the incomplete information and strategic complementarity framework of Morris and Shin (2002). In this setup, investors' payoffs depend on their proximity to both market fundamentals and the aggregate behavior of others. The investment giant gains a strategic advantage as a first-mover to set a market direction that other investors are incentivized to follow—effectively locking in momentum. This first-mover advantage is particularly pronounced when the giant commands a significant market share. For typical investors, acting after the giant allows them to refine their strategies by observing its actions and to reduce reliance on private signals.

Our theoretical framework introduces two critical channels which enable the investment giant to lead market directions (*directional leadership channel*) and to share public information (*public information channel*). With the help of these mechanisms, the investment giant, particularly through contrarian actions that deviate from other investors, can exert a positive influence on market aggregates and other investors. The influence of the investment giant's (contrarian) decisions on typical investors intensifies under two conditions: *(i)* when the giant holds a larger market share, amplifying its impact on market aggregates, and *(ii)* when strategic complementarity is stronger, as investors place more weight on aligning their actions with others. These conditions incentivize the investment giant to adopt a sequential move strategy, which maximizes its ex-ante payoffs, thereby making sequential moves preferable to simultaneous ones. Put another way, by leading the market, the giant not only induces followers but also aligns market aggregates closer to fundamentals.

Using fund-level flow data from EPFR, we confirm our theoretical prediction that the investment giant's contrarian decisions positively influence both other investors' behaviors and market aggregates. Specifically, we employ a battery of panel local projections to examine how individual investors react to the decisions of investment giants. By doing so, we test the dynamic effects (predictability) of the giants' contrarian investments—measured as the growth differential between the giants' flows and those of other investors or market averages—on individual equity fund flows across 20 emerging markets.[1] Our findings reveal that equity flows into emerging markets exhibit a persistent increase following shocks to investment giants' flows (i.e., the differential between giants' average flows and those of other investors). This result strong predictive power of large investor flows for overall institutional equity flows highlights their critical role in global asset reallocation.

We extend the analysis to the aggregate dynamics and implications at the country-level. Capital flows and global asset allocations are pivotal in shaping financial and foreign exchange markets, particularly in emerging economies (Hau and Rey 2006, Gyntelberg, Loretan and Subhanij 2018, Wong 2017, and Goldberg and Krogstrup 2023). Although EPFR fund flows represent only 1–10% of market capitalization in emerging economies (Jotikasthira, Lundblad and Ramadorai 2012), their movements show strong correlations with macro-financial variables, such as stock returns and exchange rates. Our country-level analysis reveals consistent patterns with the fund-level analysis. Aggregate equity flows positively respond to investment giants' contrarian investments, with the differential between giants' and other investors' flows serving as a strong predictor of aggregate foreign equity inflows. These patterns are observed using both EPFR aggregate data and alternative datasets such as the International Institute of Finance (IIF). Moreover, the positive predictability of giants' contrarian investments on stock market returns is significant, while exchange rates exhibit depreciation in response to lower equity investments from giants relative to other investors.

These findings emphasize the importance of monitoring investment giants' activities in equity and foreign exchange markets. Such monitoring can serve as a valuable tool for forecasting foreign portfolio inflows and identifying potential financial vulnerabilities in emerging market economies.

[1]We define the top 10 largest investors as investment giants. While there is no universally accepted threshold for identifying large investors, we also test the robustness of our findings using alternative definitions, such as the top 7 or top 15 largest investors.

Contribution to the literature Existing literature has examined investment decisions among institutional investors to provide valuable insights for a comprehensive understanding of financial markets. They particularly focused 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.

However, there are still unexplored dimensions in this research landscape that our paper seeks to contribute. Most of the existing studies focus on domestic markets, 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, our model contributes to the literature by extending a framework of incomplete information and strategic complementarity to incorporate the presence of a dominant player. As highlighted by Keynes (1936), a defining characteristic of financial markets is an environment, so-called *a beauty contest*, that participants forecast both fundamental values and the behaviors of other players. This concept has been widely studied in financial markets, with significant contributions from both empirical and theoretical studies, including Chen et al. (2010), Schmidt et al. (2016), Jackson and Pernoud (2021), among others. Another essential feature of financial markets is the presence of dominant players. By focusing on the role of investment giants and their impacts, our model advances this literature, complementing prior work such as Corsetti et al. (2004) on dominant players in currency markets and Ben-David et al. (2021) on large investors in U.S. equity markets. Through this dual focus, our study bridges two critical dimensions of financial markets: the strategic interdependence of typical investors and the outsized influence of dominant players.

In addition, most of the empirical studies lack 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, 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 builds a model. Section 3 presents the model properties. Section 4 provides a description of the dataset and key measurements, and bridges our theoretical framework to empirics. Section 5 tests the model prediction by employing a detailed investor-level regression analysis. In Section 6, the country-level regression analysis provides aggregate-level implications for investors and policymakers in emerging equity and currency markets. Section 7 concludes.

2 A Beauty Contest Framework with Investment Giants

2.1 Model Environments

How do investment giants influence other investors and shape equity markets in emerging economies? To address this question, we construct a model that incorporates three core elements: a beauty contest framework (strategic complementarity), a dominant player (the investment giant), and sequential decision-making.

A key feature of financial markets is that participants must forecast both fundamental values and the behaviors of other players (*beauty contest*). This feature creates an environment for coordination and strategic interaction among the market players. Dating back to Keynes (1936), the beauty contest concept has been extensively studied in the context of financial markets (e.g., Chen et al. 2010, Schmidt et al. 2016, Jackson and Pernoud 2021). Building on the framework of Morris and Shin (2002), our model assumes that investor payoffs depend on market fundamentals as well as market aggregates. Such strategic complementarity generates a coordination motive in investors' actions.

Two primary assumptions underpin the model. First, as in Corsetti et al. (2004), typical investors' actions do not affect aggregate market outcomes, whereas the investment giant's decisions significantly shape market equilibrium. Second, the investment giant can choose its timing of action, either moving simultaneously with typical investors or moving first before the others. When moving first, the investment giant's actions are observable to others, consistent with the visibility typically associated with large players. The ability to choose sequential timing rationalizes the investment giant's preference for preemptive moves.

Investors and size There exists a continuum of investors indexed by $i \in [0,1]$, each with a market share λ_i. The investment giant ($i = 1$) has a substantial market share $\lambda_1 (\equiv \lambda \in [0,1])$, while typical investors j ($i = j \in [0,1)$) have negligible market shares $\lambda_j \simeq 0$ and are ex-ante identical. Collectively, typical investors hold a market share of $1-\lambda$. Due to diversification, their idiosyncratic actions and information have no aggregate implications, in contrast to the investment giant.

Beauty contest framework Each investor chooses an action a_i, representing an abstract investment decision.[2] The payoff of investor i is

$$\pi_i(a_i, \bar{A}, f) = -(1-\omega) \times (a_i - f)^2 - \omega \times (a_i - \bar{A})^2, \tag{1}$$

where f represents the fundamentals and $\bar{A}$ is the aggregate action, defined as a weighted sum of the investment giant's action a_1 and the average action of typical investors $\bar{a}_0$:

$$\bar{A} \equiv \lambda a_1 + (1-\lambda)\bar{a}_0 \quad \text{and} \quad \bar{a}_0 \equiv \int_{j\in[0,1)} a_j \mathrm{d}j$$

The first term of the payoff function, $(a_i - f)^2$, captures the loss from deviating from fundamentals The second term, $(a_i - \bar{A})^2$, is an investor's deviation from aggregate market actions, which reflects a strategic complementarity causing a coordination motive among investors. The parameter $\omega(\in [0,1])$, referred to as the strategic complementarity parameter, governs the importance of coordination to the market aggregates relative to fundamentals. When $\omega = 0$, investors focus solely on fundamentals, ignoring others' actions, and thus solve a signal-noise extraction problem.

Information and beliefs The fundamentals f are unobservable but are known to follow a normal distribution. Each investor receives a noisy private signal s_i about f:

$$s_i = f + \epsilon_i, \qquad \text{where} \quad f \sim \mathcal{N}(0, \sigma_f^2) \quad \text{and} \quad \epsilon_i \sim \mathcal{N}(0, \sigma_{\epsilon,i}^2) \tag{2}$$

[2]As noted in Bao, Hommes and Makarewicz (2017), an asset market with a price adjustment mechanism as in Beja and Goldman (1980) translates forecasting problems into investment quantity decisions.

Here, ϵ_i is idiosyncratic noise, independent across investors ($\epsilon_i \perp \epsilon_j$ for all $i \neq j$). By the law of large numbers, the average signal of typical investors equals the fundamental: $\bar{s}_0 \equiv \int_{j\in[0,1)} s_j \mathrm{d}j = f$. The signal precision is identical across the typical investors but differs between the investment giant and typical investors: $\sigma_{\epsilon,1}^{-2} \neq \sigma_{\epsilon,0}^{-2} (= \sigma_{\epsilon,j}^{-2})$ for all $j \in [0,1)$.

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

$$\mathbb{E}[f|s_1] = \theta_1 s_1, \quad \mathbb{E}[f|s_{j\neq 1}] = \theta_0 s_{j\neq 1}, \quad \text{and} \quad \mathbb{E}[f|s_{j\neq 1}, s_1] = \gamma_0 s_{j\neq 1} + \gamma_1 s_1, \tag{3}$$

where the respective coefficients are

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

Timing of actions At the beginning (before observing signals), the investment giant can choose its timing of action:

- Simultaneous moves ($r_1 = \text{sm}$): The investment giant and typical investors act at the same time without observing other's actions.
- Sequential moves ($r_1 = \text{sq}$): The investment giant moves first. Typical investors observe the giant's action, and then subsequently decide their actions.

The investment giant's choice between $r_1 = \text{sm}$ and sq depends on a comparison of its expected payoffs ($\mathbb{E}[\pi_1^{\text{sm}}]$ vs. $\mathbb{E}[\pi_1^{\text{sq}}]$) under each timing structure.

In the sequential move setup, typical investors choose actions a_j (for $j \in [0,1)$) to maximize their expected payoff ($\mathbb{E}[\pi_j|s_j, s_1, a_1]$) given the signal and action of the investment giant. The investment giant maximizes its expected payoff based on the optimal strategies of typical investors ($\bar{A}^{\text{sq}}(f, s_1, a_1)$) which react to the investment giant's action.

On the other hand, in the simultaneous move case, each investor (both typical investors and investment giant; $i \in [0,1]$) faces an identical payoff maximization problem. That is, each investor independently and simultaneously determines its action a_i to maximize its expected payoff ($\mathbb{E}[\pi_i|s_i]$) based only on its private signal s_i. In what follows, we elaborate on the investors' optimal strategies, given the timing of actions, in particular sequential ($r_1 = \text{sq}$).[3]

[3] Appendix A provides details on the case of simultaneous move ($r_1 = \text{sm}$).

2.2 Sequential Moves: An Investment Giant Moves First

Typical investors Each typical investor chooses an action a_j (for $j \neq 1$) to maximize their expected payoff in equation (1) given the investment giant's signal and action. The first-order condition yields:

$$a_j^{\text{sq}} = (1-\omega)\mathbb{E}[f|s_j, s_1] + \omega\big\{\lambda a_1 + (1-\lambda)\mathbb{E}[\bar{a}_0^{\text{sq}}|s_j, s_1, a_1]\big\}, \tag{4}$$

where $\bar{a}_0^{\text{sq}}\left(\equiv \int_{j\in[0,1)} a_j^{\text{sq}}\mathrm{d}j\right)$ 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, a_1 and $\bar{a}_0^{\text{sq}}$).

As shown in Morris and Shin (2002), the optimal strategy for a typical investor j under the sequential move can be expressed as a linear function of signals:[4]

$$a_j^{\text{sq}}(s_j, s_1, a_1) \equiv \psi^{\text{sq}} s_j + \eta_s^{\text{sq}} s_1 + \eta_a^{\text{sq}} a_1. \tag{5}$$

By substituting the typical investor's belief about the average investment of others ($\mathbb{E}[\bar{a}_0^{\text{sq}}|s_j, s_1, a_1] = \psi^{\text{sq}}\mathbb{E}[f|s_j, s_1] + \eta_s^{\text{sq}} s_1 + \eta_a^{\text{sq}} a_1$) into the first-order condition equation (4), we derive the optimal responses to the private signal, the investment giant's signal, and the investment giant's action as follows:

$$\psi^{\text{sq}} = \left[\frac{1-\omega}{1-\omega(1-\lambda)\gamma_0}\right]\gamma_0, \tag{6}$$

$$\eta_s^{\text{sq}} = \left\{\frac{1-\omega}{[1-\omega(1-\lambda)][1-\omega(1-\lambda)\gamma_0]}\right\}\gamma_1 = \left[\frac{\psi^{\text{sq}}}{1-\omega(1-\lambda)}\right]\frac{\gamma_1}{\gamma_0}, \tag{7}$$

$$\eta_a^{\text{sq}} = \frac{\lambda\omega}{1-\omega(1-\lambda)} = 1 - \psi^{\text{sq}} - \frac{\eta_s^{\text{sq}}}{\theta_1}. \tag{8}$$

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

$$\bar{a}_0^{\text{sq}}(f, s_1, a_1) \equiv \int_{j\in[0,1)} a_j^{\text{sq}}\mathrm{d}j = \psi^{\text{sq}} f + \eta_s^{\text{sq}} s_1 + \eta_a^{\text{sq}} a_1. \tag{9}$$

To understand this typical investor's strategy intuitively, we consider two limiting cases: no strategic complementarity ($\omega \to 0$) and investment giant's zero market share ($\lambda \to 0$). First,

[4] 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 action of the investment giant a_1. Here, a_1 is distinguished from the public signal s_1 in that a_1 is the posterior outcome based on the prior information s_1.

when there is no coordination motive, the typical investor's problem reduces to a conventional signal-extraction problem:

$$\lim_{\omega\to 0}\psi^{\mathrm{sq}}=\gamma_0,\quad \lim_{\omega\to 0}\eta_s^{\mathrm{sq}}=\gamma_1,\quad \text{and}\quad \lim_{\omega\to 0}\eta_a^{\mathrm{sq}}=0.$$

In this limiting case, the investment giant's market share (λ) has no influence on typical investors' decisions as their actions are solely guided by their private signals. Second, when the investment giant has zero market share, it acts purely as a provider of public information.[5]

Investment giant Investment giant chooses an action a_1 to minimize its deviation from the fundamental and typical investors' action. Specifically, given typical investors' average action (9), the giant's profit maximization problem can be modified as follows:

$$\max_{a_1}\mathbb{E}\big[-(1-\omega)(a_1-f)^2-\omega(1-\lambda)^2[a_1-\bar{a}_0^{\mathrm{sq}}(f,s_1,a_1)]^2\big|s_1\big],$$

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

$$a_1^{\mathrm{sq}}=(1-\omega)\mathbb{E}[f|s_1]+\omega\big\{\lambda a_1+(1-\lambda)\mathbb{E}[\bar{a}_0^{\mathrm{sq}}(f,s_1,a_1)|s_1]\big\}(1-\lambda)\left\{1-\frac{\partial\mathbb{E}[\bar{a}_0^{\mathrm{sq}}(f,s_1,a_1)|s_1]}{\partial a_1}\right\},\tag{10}$$

where the investment giant's expectation on the typical investors' average action is a convex combination of its belief about the fundamental $\mathbb{E}[f|s_1]$ and its own action a_1:

$$\mathbb{E}[\bar{a}_0^{\mathrm{sq}}(f,s_1,a_1)|s_1]=(1-\eta_a^{\mathrm{sq}})\mathbb{E}[f|s_1]+\eta_a^{\mathrm{sq}}a_1,\quad \text{where}\quad \mathbb{E}[f|s_1]=\theta_1 s_1.\tag{11}$$

Additionally, $\partial\mathbb{E}[\bar{a}_0^{\mathrm{sq}}|s_1]/\partial a_1=\eta_a^{\mathrm{sq}}$.

Taking these all together, we obtain the giant's optimal action as:

$$a_1^{\mathrm{sq}}(s_1)=\underbrace{\left\{\frac{(1-\omega)+\omega(1-\lambda)^2(1-\eta_a^{\mathrm{sq}})\left(\psi^{\mathrm{sq}}+\eta_s^{\mathrm{sq}}\frac{s_1}{\mathbb{E}[f|s_1]}\right)}{(1-\omega)+\omega(1-\lambda)^2(1-\eta_a^{\mathrm{sq}})^2}\right\}}_{=1\quad\because\,\mathbb{E}[f|s_1]=\theta_1 s_1\text{ and }\psi^{\mathrm{sq}}+\eta_s^{\mathrm{sq}}/\theta_1+\eta_a^{\mathrm{sq}}=1}\mathbb{E}[f|s_1]=\phi^{\mathrm{sq}}s_1,\tag{12}$$

where $\phi^{\mathrm{sq}}=\theta_1$. In the sequential move structure, the investment giant can set the market to a

[5]This limiting case is considered in Morris and Shin (2002).

favorable direction. Since its payoff decreases as its action deviates from the market aggregate and the fundamental, the best payoff is achieved when the market aggregate aligns with the fundamentals. This implies that the most favorable direction for the market is toward the fundamentals, which leads the investment giant' action to its belief on the fundamental. Thus, its optimal action is identical to that from the signal-noise extraction case, $\phi^{\mathrm{sq}} = \theta_1$.

2.3 Comparison between Sequential and Simultaneous Moves

We now compare optimal strategies of investors between the two different timings of action: sequential and simultaneous moves ($r_1 = \mathrm{sq}$ and sm).

Typical investors As delineated in Appendix A, the optimal action of typical investor under simultaneous move structure is a linear function of its own private signal: $a_j^{\mathrm{sm}}(s_j) = \psi^{\mathrm{sm}} s_j$ (as in equation (A.2)). Hence, optimal strategies of typical investors in the two timing structure differ in two aspects. First, typical investors react more actively to their own signal under the simultaneous move structure than the sequential move structure:

$$\psi^{\mathrm{sq}} < \psi^{\mathrm{sm}} = \left[\frac{(1-\omega) + \omega\lambda\phi^{\mathrm{sm}}}{1-\omega(1-\lambda)\theta_0}\right]\theta_0.$$

This inequality is obvious because $\theta_0 > \gamma_0$ and ω, λ, and ϕ^{sm} are non-negative.[6]

Furthermore, typical investors' reliance on own signal is smaller under the simultaneous move structure than the sequential move structure. Formally, typical investors make their decision solely based on their own signal (s_j) in the simultaneous move structure. However, when taking an optimal action under the sequential move structure, they also consider the public information (investment giant's signal; s_1), and investment giant's action (a_1). The latter is locked in the portion (λ) of market aggregate, thereby enforcing typical investors to follow it to minimize their deviation from the market aggregate.

Investment giant Similar to typical investors, the optimal strategy of the investment giant under a simultaneous move case is determined only by its own signal: $a_1^{\mathrm{sm}}(s_1) = \phi^{\mathrm{sm}} s_1$ (as in equation (A.4)). Comparing it with (12), we find the differences between the optimal strategies of investment giant under simultaneous and sequential moves in two aspects. First, the investment giant reacts less

[6]Here, ϕ^{sm} denotes the investment giant's optimal response to its own signal in a simultaneous move case, i.e., $a_1^{\mathrm{sm}}(s_1) = \phi^{\mathrm{sm}} s_1$.

actively to its own signal under the simultaneous move structure than under the sequential move structure:

$$\phi^{\mathrm{sq}} < \phi^{\mathrm{sm}} = \left[\frac{(1-\omega)+\omega(1-\lambda)^2\psi^{\mathrm{sm}}}{(1-\omega)+\omega(1-\lambda)^2}\right]\theta_1.$$

This inequality holds because ψ^{sm} is non-negative.

Second, as discussed above, the sequential move provides the investment giant with a strategic advantage and leads its action align with its belief on the fundamentals (i.e., $\phi^{\mathrm{sq}} = \theta_1$). However, when the investment giant should move simultaneously with other investors, it looses their directional leadership. Thus, as typical investors, the investment giant guesses the market and adjust its action to the market direction even if it believes that the other investors' action deviates from the fundamentals. This distortion, represented by $\theta_1 - \phi^{\mathrm{sm}}$ (or equivalently $\phi^{\mathrm{sq}} - \phi^{\mathrm{sm}}$), increases with a degree of strategic complementarity (ω) and the market share of typical investors ($1-\lambda$), for a given typical investor's strategy (ψ^{sm}).

3 Impacts of Strategic Complementarity and Investment Giants

3.1 Optimal Timing Structure of Actions

In our model, the critical role of the investment giant is determined by its choice of whether to move first or simultaneously with typical investors. The investment giant chooses the timing structure by comparing its expected payoffs under each timing structure; that is, $r_1^* = \operatorname{argmax}_{r_1 \in \{\mathrm{sm},\mathrm{sq}\}}\{\mathbb{E}[\pi_1^{\mathrm{sm}}],\ \mathbb{E}[\pi_1^{\mathrm{sq}}]\}$.

Ex-ante payoffs Under the sequential move, the giant's ex-ante payoff is:

$$\mathbb{E}[\pi_1^{\mathrm{sq}}] \equiv -(1-\omega)\mathrm{var}(a_1^{\mathrm{sq}} - f) - \omega\mathrm{var}(a_1^{\mathrm{sq}} - \bar{A}^{\mathrm{sq}}). \tag{13}$$

As in the right-hand side, the payoff comprises two components. The first term represents the ex-ante variance of the investment giant's deviation from the fundamentals:

$$\mathrm{var}(a_1^{\mathrm{sq}} - f) = \sigma_f^2 \Upsilon(\phi^{\mathrm{sq}}; \theta_1), \quad \text{where} \quad \Upsilon(x; z) \equiv \frac{x^2}{z} - 2x + 1. \tag{14}$$

Here, the function $\Upsilon(x; z)$ is decreasing in $x \in (0, z)$ and $z \in (0, 1)$. Also, Υ reaches its minimum value $1-z$ at $x = z$. Thus, $\Upsilon(\phi^{\text{sq}} = \theta_1; \theta_1) = 1-\theta_1$. This highlights that $\text{var}(a_1^{\text{sq}}-f)$ depends only on the fundamental variance (σ_f^2) and the quality of the investment giant's signal (θ_1). Importantly, it is because the investment giant's optimal action is identical to the solution of signal-noise extraction problem, as shown in equation (12).

The second term in the payoff equation captures the ex-ante variance of the investment giant's deviation from the market aggregate:

$$\text{var}(a_1^{\text{sq}} - \bar{A}^{\text{sq}}) = \sigma_f^2(1-\lambda)^2(\psi^{\text{sq}})^2\Upsilon(\phi^{\text{sq}}; \theta_1). \tag{15}$$

The giant's dominant market share (high λ) mechanically ensures small deviations from the market aggregate ($\bar{A}^{\text{sq}} = \lambda a_1^{\text{sq}} + (1-\lambda)\bar{a}_0^{\text{sq}}$). In addition, the strategic interaction mechanisms are succinctly captured by the term $(\psi^{\text{sq}})^2$. That is, in the sequential move case, the investment giant can set the market direction, thereby reducing its deviations from the market. This strategic advantage is amplified by a stronger coordination motive (ω) and its greater market dominance (λ).

Similarly, under the simultaneous move, the giant's ex-ante payoff is given by:

$$\mathbb{E}[\pi_1^{\text{sm}}] \equiv -(1-\omega)\text{var}(a_1^{\text{sm}} - f) - \omega\text{var}(a_1^{\text{sm}} - \bar{A}^{\text{sm}}). \tag{16}$$

The first term reflects the variance of deviations from fundamentals:

$$\text{var}(a_1^{\text{sm}} - f) = \sigma_f^2\Upsilon(\phi^{\text{sm}}; \theta_1), \tag{17}$$

and the second term captures the variance of deviations from the market outcome:

$$\text{var}(a_1^{\text{sm}} - \bar{A}^{\text{sm}}) = \sigma_f^2(1-\lambda)^2(\psi^{\text{sm}})^2\Upsilon(\phi^{\text{sm}}/\psi^{\text{sm}}; \theta_1). \tag{18}$$

Investment giant's optimal choice: simultaneous move Comparing the ex-ante payoffs from sequential and simultaneous move structures reveals the investment giant's preference for moving first. Because $\Upsilon(\cdot; \theta_1) \geq 1-\theta_1 = \Upsilon(\phi^{\text{sq}}; \theta_1)$ and $\psi^{\text{sm}} > \psi^{\text{sq}}$, the variances of both deviations from fundamentals and the market outcome are larger under the simultaneous move case.

$$\begin{aligned}\text{var}(a_1^{\text{sq}} - f) &< \text{var}(a_1^{\text{sm}} - f) = \sigma_f^2 \Upsilon(\phi^{\text{sm}}; \theta_1) \\ \text{var}(a_1^{\text{sq}} - \bar{A}^{\text{sq}}) &< \text{var}(a_1^{\text{sm}} - \bar{A}^{\text{sm}}) = \sigma_f^2 (1-\lambda)^2 (\psi^{\text{sm}})^2 \Upsilon(\phi^{\text{sm}}/\psi^{\text{sm}}; \theta_1)\end{aligned}$$

Thus, the investment giant's ex-ante payoff is maximized in the sequential move structure:

$$\mathbb{E}[\pi_1^*] \equiv \max\left\{\mathbb{E}[\pi_1^{\text{sq}}], \mathbb{E}[\pi_1^{\text{sm}}]\right\} = \mathbb{E}[\pi_1^{\text{sq}}], \tag{19}$$

where the asterisk (*) denotes the equilibrium outcomes: $r_1^* = \text{sq}$, $a_1^* = a_1^{\text{sq}}$, and $a_j^* = a_j^{\text{sq}}$ with $\{\phi^*, \psi^*, \eta_s^*, \eta_a^*\} = \{\phi^{\text{sq}}, \psi^{\text{sq}}, \eta_s^{\text{sq}}, \eta_a^{\text{sq}}\}$.

In equilibrium, the investment giant makes a choice to move first, and then typical investors follow, consistent with the literature. In this sequential move, an important feature is the investment giant's visibility in financial market (e.g., Corsetti et al. 2004). Specifically, typical investors observe the investment giant's decision, treating it as public information that implicitly signals market fundamentals (*public information channel*). This structure grants an informational advantage to typical investors. That is, it helps typical investors reduce uncertainty by making their decisions based on both private signals and the giant's revealed action. Therefore, typical investors can move in the same directions of both the fundamentals and the market. Our beauty contest framework also highlights a strategic advantage for the giant as a first-mover because it can lead the market aggregate to a favorable direction, close to both the fundamental and its own action (*directional leadership channel*). Consequently, the investment giant has a strong incentive to lead the market by moving first.[7]

3.2 Impacts on Typical Investors and Market Movements

Typical investors' optimal choices In equilibrium, the investment giant's signal s_1 not only determines its optimal action a_1^* (equation (12)), but also influences the optimal decisions of typical investors both individually (a_j^*) and as a group ($\bar{a}_0^*$) (each shown in (5) and (9), respectively). By substituting s_1 with a_1^* in these equations, we derive:

$$a_j^* = \psi^* s_j + (1-\psi^*) a_1^* \quad \text{and} \quad \bar{a}_0^* = \psi^* f + (1-\psi^*) a_1^*. \tag{20}$$

[7] These two channels will be discussed further from the typical investors' perspective in the following section.

These expressions imply that typical investors' optimal actions represent a weighted average of their private signals (s_j) or the fundamentals (f) and the investment giant's action (a_1^*), with the weights determined by ψ^*. Similarly, the market's aggregate action can be expressed as a function of the fundamentals and the investment giant's action:

$$\bar{A}^* = (1-\lambda)\psi^* f + [1-(1-\lambda)\psi^*]a_1^*. \tag{21}$$

Hence, the influence of investment giant's decision on the market aggregate increases with its market share (λ) and with typical investors' reliance on the investment giant's action ($1-\psi^*$).

The above equations reveal how strategic complementarity (ω) and the investment giant's market share (λ) shape typical investors' behavior. Specifically, as either the investment giant's market share (λ) or strategic complementarity (ω) increases, typical investors place less weight on their private signals ($\partial a_j^*/\partial s_j = \psi^*$) and rely more heavily on the investment giant's action ($\partial a_j^*/\partial a_1^* = 1-\psi^*$) in equation (20) :

$$\frac{\partial}{\partial \lambda}\left(\frac{\partial a_j^*}{\partial s_j}\right), \quad \frac{\partial}{\partial \omega}\left(\frac{\partial a_j^*}{\partial s_j}\right) < 0 \quad \text{and} \quad \frac{\partial}{\partial \lambda}\left(\frac{\partial a_j^*}{\partial a_1^*}\right), \quad \frac{\partial}{\partial \omega}\left(\frac{\partial a_j^*}{\partial a_1^*}\right) > 0.$$

Furthermore, the market aggregate relies less on the fundamentals but more on the investment giant as ω and λ increases:

$$\frac{\partial}{\partial \lambda}\left(\frac{\partial \bar{A}^*}{\partial f}\right), \quad \frac{\partial}{\partial \omega}\left(\frac{\partial \bar{A}^*}{\partial f}\right) < 0 \quad \text{and} \quad \frac{\partial}{\partial \lambda}\left(\frac{\partial \bar{A}^*}{\partial a_1^*}\right), \quad \frac{\partial}{\partial \omega}\left(\frac{\partial \bar{A}^*}{\partial a_1^*}\right) > 0,$$

where the market reliance on the fundamentals and the investment giant's action are $\partial \bar{A}^*/\partial f = (1-\lambda)\psi^*$ and $\partial \bar{A}^*/\partial a_1^* = 1-(1-\lambda)\psi^*$, respectively, as shown in equation (21).

These model mechanisms also underscore the dual role of the investment giant: as a leader in shaping market direction (*directional leadership channel*) and as a provider of public information that mitigates uncertainty for other market participants (*public information channel*). By committing to an earlier decision, the investment giant can steer the market towards its preferred direction. When the investment giant has a substantial market share (high λ), typical investors are discouraged from deviating, aligning their actions more closely with the giant's decision. Additionally, stronger strategic complementarity (high ω) amplifies the motivation to follow the investment giant's revealed action, as investors' choices become increasingly interdependent, leading the market to rely more on the giant's action and signal. Together, these channels highlight the centrality of investment giants in driving market dynamics and coordinating investor behavior.

Impacts on typical investors' payoffs In addition to their influence on typical investor's decision and market behaviors, the investment giant's market share (λ) and strategic complementarity (ω) also systemically shape a typical investor's ex-ante payoff. While the investment giant's first-move decision provides valuable public information that enhances forecasts of the fundamental, it also fosters coordination effects that restrict typical investors' independent actions. Strong strategic complementarity (high ω) or substantial market dominance by the investment giant (high λ) widens the deviation of typical investors' actions from the fundamental, thereby reducing their ex-ante payoffs:

$$\frac{\partial}{\partial \lambda}\mathrm{var}(a_j - f) > 0 \quad \text{and} \quad \frac{\partial}{\partial \omega}\mathrm{var}(a_j - f) > 0.$$

Conversely, the investment giant's directional leadership reduces the variance of deviation in typical investors' actions from the market aggregate. By establishing a market direction, the giant discourages the deviations, especially when its market share is large or strategic complementarity is high:

$$\frac{\partial}{\partial \lambda}\mathrm{var}(a_j - \bar{A}) < 0 \quad \text{and} \quad \frac{\partial}{\partial \omega}\mathrm{var}(a_j - \bar{A}) < 0.$$

In equilibrium, the investment giant secures a higher ex-ante payoff than typical investors as its variances of deviation from both the market aggregate and the fundamental are smaller than those of typical investors:

$$\mathrm{var}(a_1^* - f) < \mathrm{var}(a_j^* - f) \quad \text{and} \quad \mathrm{var}(a_1^* - \bar{A}^*) \le \mathrm{var}(a_j^* - \bar{A}^*) \quad \Rightarrow \quad \mathbb{E}[\pi_1^*] > \mathbb{E}[\pi_j^*].$$

This advantage stems from its dual role as a market leader and a source of public information. Further details and discussions can be found in Appendix B.

4 Bridging Theory to Data

Motivated by the predictions of our model regarding the influence of investment giants, we now empirically examine the interactions among investors and their aggregate impact on the market.

To this end, this section first outlines details the construction of our dataset and the measurement of key variables. Subsequently, the interface between our model and empirics—the giants and their contrarian investment—is further discussed.

4.1 Data and Measurements

For the empirical analyses, 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.[8] The EPFR database provides detailed information for each mutual fund's name, total net assets, country allocation weights as a percentage of fund assets, investment destination countries/target regions, and investment type (passive or active).

Mutual Funds Portfolio Flows To track how each fund adjusts its investment behavior, we calculate the size of the fund i's equity investment, $\text{Equity}_{ic,t}$, to a particular country c at time (month) t, as:

$$\text{Equity}_{ic,t} = \sum_{a \in \text{AssetClass}} \text{EquityShare}_{aic,t} \times \text{TotalNetAssets}_{ai,t}, \tag{22}$$

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.

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 $t+h$:

$$\Delta^h \text{IHS}(\text{Equity}_{ic,t}) = \text{IHS}(\text{Equity}_{ic,t+h}) - \text{IHS}(\text{Equity}_{ic,t}), \tag{23}$$

which includes valuations resulting from equity returns and exchange rates. Hence, even when investors do not adjust their investment, high (low) equity returns and currency appreciation

[8] 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.

(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:

$$\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = \text{IHS}\left(\text{Equity}_{ic,t+h} \times \frac{\text{StockIndex}_{c,t}}{\text{StockIndex}_{c,t+h}} \frac{\text{FX}_{c,t+h}}{\text{FX}_{c,t}}\right) - \text{IHS}(\text{Equity}_{ic,t}), \tag{24}$$

which controls the growths of stock market index and exchange rate growths for the fund i in country c at time $t+h$.

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 and summary statistics Further details regarding data collection and variable construction are available in Appendix C.1. Tables F.1–F.5 report summary statistics.

4.2 Investment Giants and Concentrated Equity Flows

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, $i \notin \mathcal{G}$). 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.[9] Then, we

[9]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.

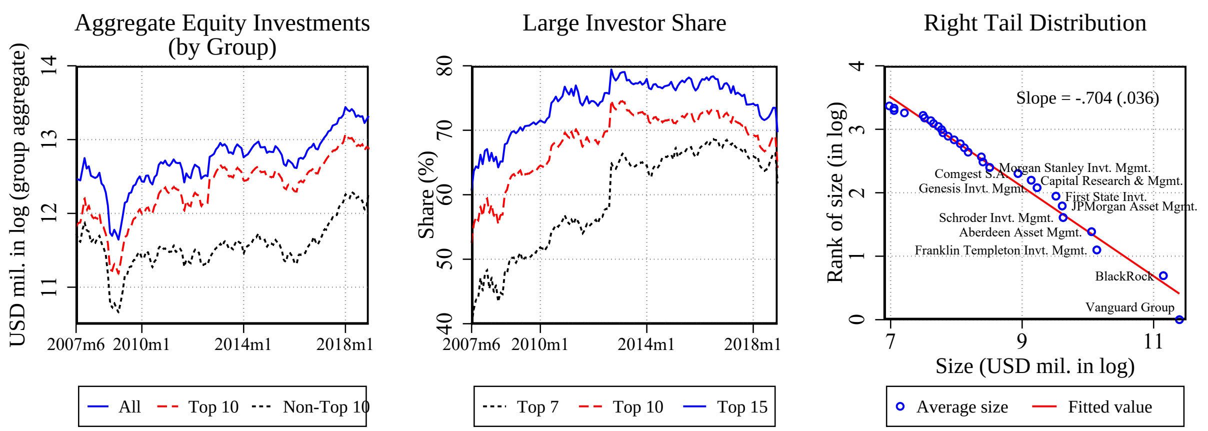


Figure 2: Trends of Equity Fund Flows to Emerging Markets

Notes: The first figure plots the equity investment made by each investor (mutual fund) 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 with robust standard errors in parenthesis. The fund flow data are sourced from the EPFR database. See Appendix C.1 for the details.

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 Group.[10] 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.

Evidence from fund-level equity flow data points on the critical role of investment giants in the equity markets of emerging economies. These dominant players significantly influence both the volume and direction of portfolio flows. Figure 2 illustrates key patterns in equity investments by funds focused on emerging markets. The first panel shows that, over the sample period, total equity allocations to emerging markets (measured in logarithmic terms) grew significantly, from approximately 200 billion to 600 billion USD, with a sharp decline during the Global Financial Crisis (GFC) in 2008. This growth was primarily driven by investment giants. The second panel reveals

[10] 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.

that the share of equity investments attributable to large mutual funds has steadily increased since the GFC, reaching a peak around 2013, highlighting the rising dominance of these large players.

The distribution of equity investments also demonstrates pronounced concentration among a few large funds. The third panel of Figure 2 depicts a fat right tail in the size distribution of equity investments, particularly in the post-GFC period. A log-log plot of investment size against investor rank confirms a power-law relationship in the right tail, with the rank in log approximately proportional to $-\alpha \ln(\text{Size})$ for $\alpha \approx 0.7$. This pattern is consistent throughout the sample period from January 2010 to December 2018, indicating persistent granularity in emerging market equity flows.[11]

In summary, fund-level data reveals important facts: emerging equity markets are increasingly reliant on capital inflows from investment giants, and these investments are concentrated among a small number of dominant funds. These observations are in line with the model environments, and thus motivate a closer empirical investigation into the strategic interactions between investment giants and typical investors.

4.3 Giant's Contrarian Investment: Key Interface between Theory to Empirics

The model prediction Our primary focus in this paper is on the investment decisions of the giants, distinguished from the other investors, and their impacts on the markets. To guide the empirical analysis in the following sections from our theoretical framework in Sections 2 and 3, we pay attention to the investment giant's contrarian action. Specifically, we define it as the investment giant's deviation from the average action of typical investors. This can be expressed as:

$$a_1^* - \bar{a}_0^* = \psi^*(a_1^* - f). \tag{25}$$

The giant's contrarian action is proportional to its deviation from fundamentals.

Integrating these relationships, we derive a key equation that connects the investment giant's contrarian action, fundamentals, and noise to the optimal action of a typical investor:

$$a_j^* = \beta(a_1^* - \bar{a}_0^*) + f + \psi^* \epsilon_j, \quad \text{where} \quad \beta \equiv \frac{1}{\psi^*} - 1 > 0. \tag{26}$$

[11] For additional insights, Figure F.16 presents similar patterns for active fund flows, excluding passive funds. These results corroborate the heavy reliance of emerging equity markets on investment giants. In Figure F.17, right-tail distributions for specific periods, such as September 2008, September 2010, and September 2015, further confirm robust granularity. Notably, the absolute values of these slopes are below two, signifying that idiosyncratic shocks to large funds are not diversified away and can materially affect aggregate market outcomes.

Equation (26) aligns closely with the main regression specification in Section 5, demonstrating that a typical investor's action is positively related to the investment giant's contrarian actions ($\beta > 0$).[12]

The investor-level relationships extend naturally to market aggregates. Specifically, the investment giant's contrarian action positively influences the market's aggregate action. Using linear algebra to modify equations (25) and (21), the market aggregate action can be expressed as:

$$\bar{A}^* = \tilde{\beta}(a_1^* - \bar{a}_0^*) + f, \quad \text{where} \quad \tilde{\beta} \equiv \frac{1}{\psi^*} - (1-\lambda) > 0, \tag{27}$$

which aligns with the country-level regression specification in Section 6. This equation shows that the market aggregate action ($\bar{A}^*$) is influenced by a combination of the investment giant's contrarian action ($a_1^* - \bar{a}_0^*$) and fundamentals (f). The model predicts that, $\tilde{\beta} > 0$, the investment giant's contrarian action positively affects market aggregates.

Measure of giants' contrarian investment The two theoretical predictions by equations (26) and (27) will be tested in Sections 5 and 6, respectively. Hence, for the empirical tests, 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 consistent with our theoretical model, 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*, ($a_1^* - \bar{a}_0^*$) defined in equation (25).[13]

$$\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}} = \frac{1}{N^{\mathcal{G}}} \sum_{i \in \mathcal{G}} \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}) - \frac{1}{N_t - N^{\mathcal{G}}} \sum_{i \notin \mathcal{G}} \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}), \tag{28}$$

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.[14]

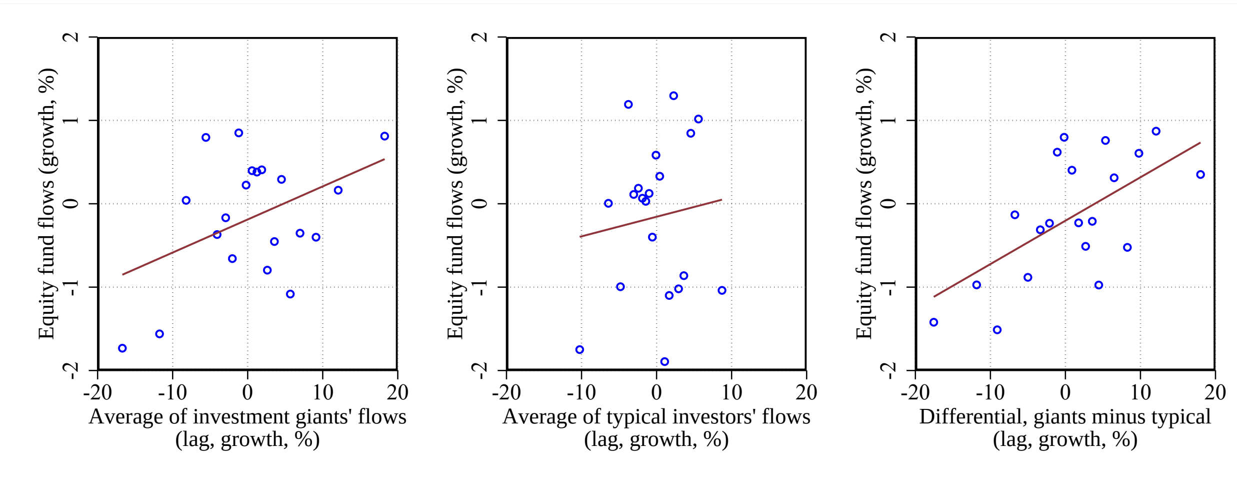
The investment giant's contrarian investment gauges the extent to which their investment size outpaces in emerging equity markets compared to that of typical investors. A positive differential,

[12] Alternatively, the coefficient β can be derived from the model's covariance and variance conditional on fundamentals: $\beta = \text{cov}(a_j^*, a_1^* - \bar{a}_0^* | f)/\text{var}(a_1^* - \bar{a}_0^* | f) = 1/\psi^* - 1$.

[13] In a similar vein, investment giants share of equity flows into each market (country) is also considered as an alternative measure. See Section 5.3 and Appendix D for the details.

[14] 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)

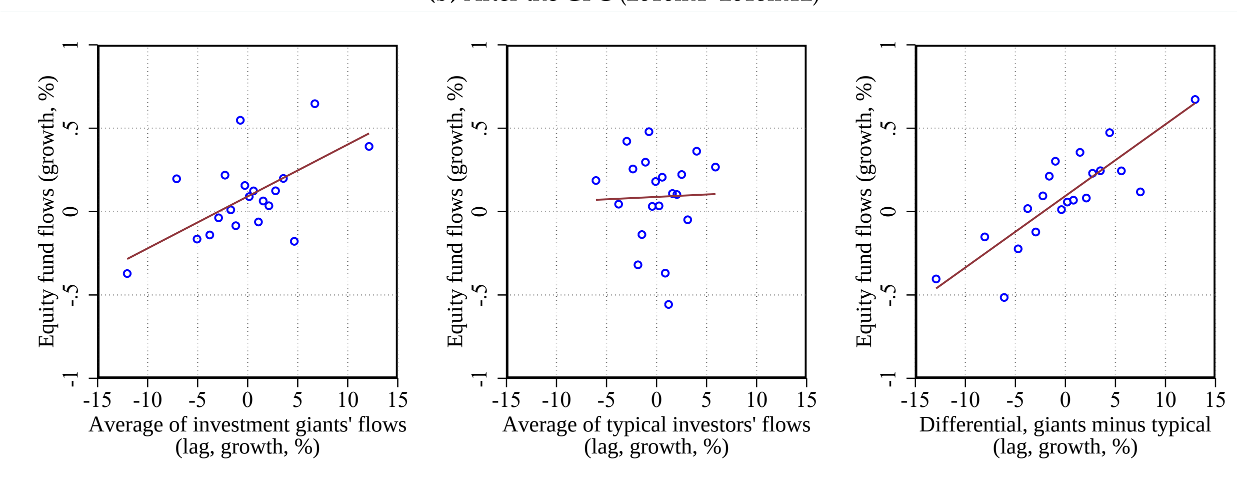


Figure 3: Equity Flows over the Lagged Investment Giants' and Typical Investors' Average Equity Flows

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.

$\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}} > 0$, 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 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.

5 Equity Fund Flow Dynamics with Investment Giants

In this section, we implement panel local projections to the fund-level EPFR data to examine how other investors react to the investment decisions of large institutional investors in emerging equity markets. Pointedly, the regressions 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.

5.1 Empirical Specification

Our formal regression analyses assess the predictability of investment giants' contrarian equity flow growth for subsequent other equity flow growth and its time-varying nature. This is done by testing the hypothesis from our model prediction in equation (26) of Section 4.3. The main hypothesis posits that individual fund flows were influenced by the investment giants' contrarian investments in emerging markets.

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.

Motivated from our theoretical model prediction in equation (26), we employ the investor-level demand model specified as a linear function of all covariates in equation (29). 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:

$$\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = \beta^h \left(\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}\right) + \mathbf{\Gamma}_{\text{pull}}^h \mathbf{Pull}_{c,t} + \mathbf{\Gamma}_{\text{push}}^h \mathbf{Push}_t + \delta_i^h + \delta_c^h + \delta_m^h + \varepsilon_{ic,t}^h, \quad (29)$$

for the time horizon considered $h = 1, 2, \cdots, 10$, and where the dependent variable is the adjusted cumulative equity growth in equation (24).

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 Figure 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.[15] 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

[15]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). For more comprehensive discussions and surveys on the influence of the cyclical common factors, refer to Hannan (2017), Hannan and Cubeddu (2018) and Koepke (2019).

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.

Sample periods Our sample spans from June 2007 to December 2018. However, the effects of investment giants may differ across periods, in particular around the crisis. To address this concern, we divide our sample into two periods: during and 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, Coulibaly and Zlate 2017), may provide additional insights into how interactions among individual investors contributed to the developments in capital flows during the post-GFC periods. Furthermore, 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). Choe, Kho and Stulz (1999) find evidence of positive feedback trading by foreign investors in Korea before the 1997 Asian financial crisis, a pattern that dissipated during the crisis.

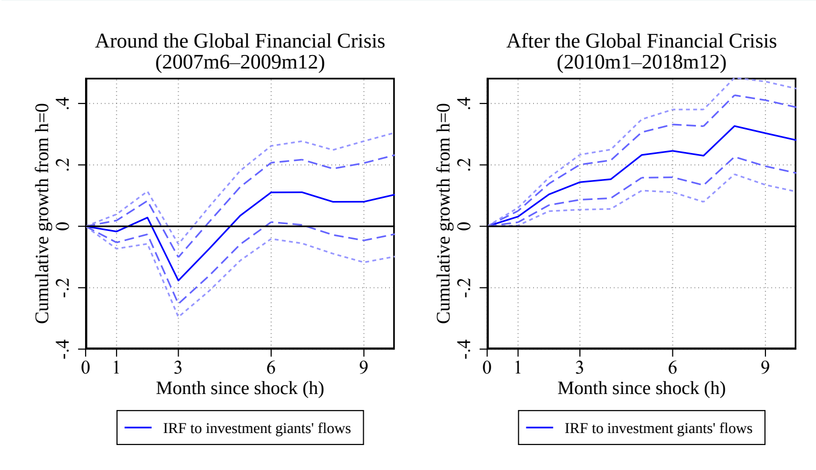


Figure 4: Investor-Level Response to the Equity Flow Differential between Investment Giants and Typical Investors

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 ($\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}$) 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 (29). 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, %).

5.2 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.[16] 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).

The 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.

[16]For comparison, we also provided the results with non-adjusted equity flows in Figure F.18.

Two noteworthy findings emerge from the results. First, institutional investors tend to follow the lead of investment giants, corroborating the model prediction in equation (26). 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 observation 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.

5.3 Robustness Checks

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. In addition to the baseline regression of equation (29), we consider a specification that condition the response of individual institutional equity flows on the market crash events:

$$\begin{aligned}\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) =& \beta^h_{nocrash}\left(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\right) \times \mathbb{1}_{\{\Delta^1 \ln \text{StockIndex}_{c,t} > -5\%\}} \\ &+ \beta^h_{crash}\left(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\right) \times \mathbb{1}_{\{\Delta^1 \ln \text{StockIndex}_{c,t} \leq -5\%\}} \\ &+ \mathbf{\Gamma}^h_{\text{pull}}\mathbf{Pull}_{c,t} + \mathbf{\Gamma}^h_{\text{push}}\mathbf{Push}_t + \delta^h_i + \delta^h_c + \delta^h_{m,t} + \varepsilon^h_{ic,t}, \end{aligned} \tag{30}$$

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%-

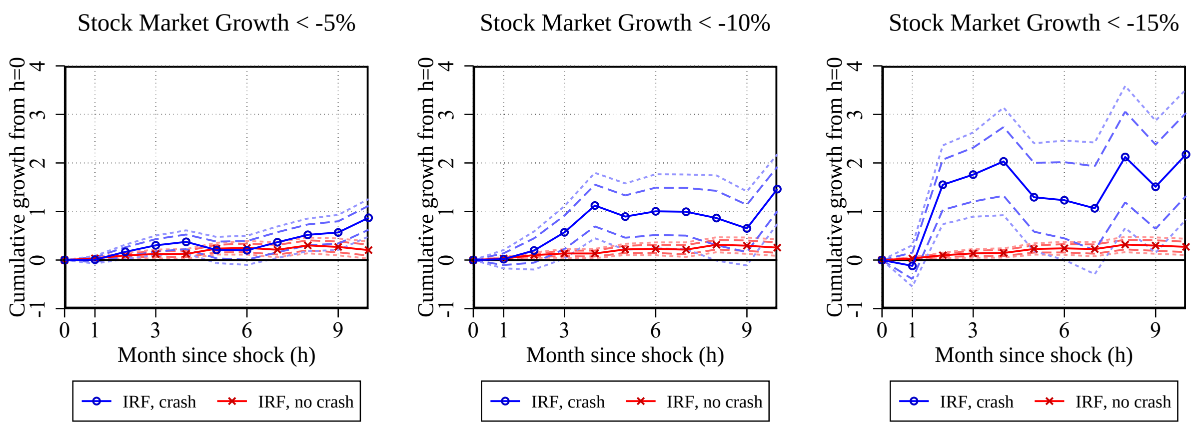


Figure 5: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis

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 (30). 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, %).

and 15%-stock market crashes for comparison.[17] This specification includes the same pull and push factors along with fixed effects as employed in regression equation (29).

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).[18]

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. Also, 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.

[17]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.

[18]See Appendix Figure F.19 for the responses around the global financial crisis (2007m6–2009m12).

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.[19]

Further robustness checks In Appendix D, 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).

6 Aggregate Dynamics and Implications

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 et al. 2018, and Goldberg and Krogstrup 2023). This relationship may also be relevant from the perspective of individual global investors' portfolio choices. Figure 6 highlights the growth rates of country-level aggregated EPFR global equity fund flows, stock market indices, and exchange rates (local currency per US dollar) across 20 emerging market economies. Despite EPFR fund flows typically representing only 1–10% of the capitalization in these markets (Jotikasthira et al. 2012), an increase in global equity flows correlates strongly with stock market gains and exchange rate appreciations. These patterns underscore their influence on financial markets, well beyond their market share.

Previous research has emphasized the intricate relationships between capital flows and financial factors, both local and global, such as domestic stock indices, US equity market movements, and exchange rate fluctuations. Studies such as Warther (1995) and Edelen (1999) have demonstrated the contemporaneous impact of aggregate mutual fund flows on stock returns. Coval and Stafford (2007) revealed the price pressures exerted by large-scale fund flows in the US equity market,

[19] 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.

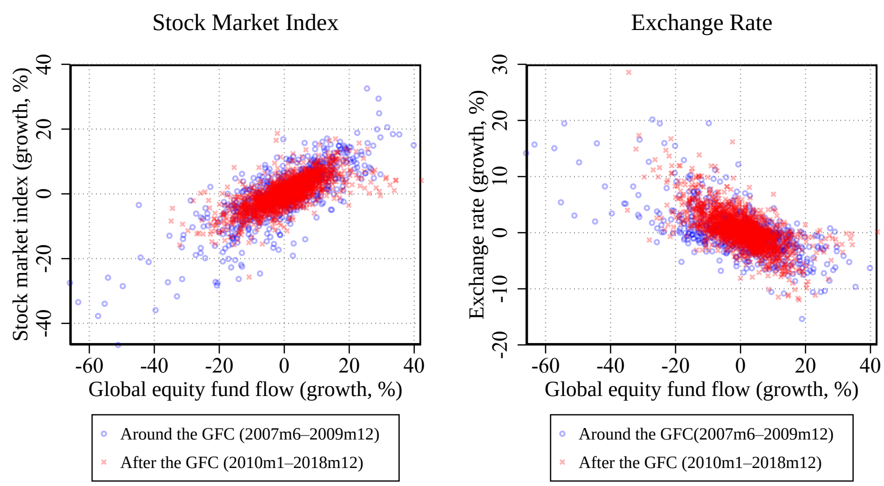


Figure 6: Global Equity Fund Flows, Stock Prices, and Exchange Rates in Emerging Economies

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.

while Lilley, Maggiori, Neiman and Schreger (2022) found US purchases of foreign bonds to be a key driver of currency dynamics post-GFC. However, these relationships remain contested, as evidenced by Wardlaw (2020) and Gabaix and Maggiori (2015), underscoring the need for further analysis.

Guided by these insights and the rationales from our theoretical model, our study extends the fund-level findings to the aggregate level, examining the broader drivers of capital flow dynamics and market conditions. Our findings consistently reveal a significant pattern: reductions in investments by these giants often precede major capital outflows and subsequent financial downturns in emerging markets. These results highlight the predictive power of investment giant flows and their pivotal role in shaping aggregate market dynamics.

6.1 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 aggregate equity flows as well as stock prices and exchange rates in emerging economies, shining a light on their implications in connection with our fund-level findings.

Regression specification Mapping our theoretical model prediction in equation (27) of Section 4.3 to the data, we begin by estimating country-month panel local projections for the aggregate flows using the equation, given as:

$$Y_{c,t}^{h} = \beta^{h}\left(\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}\right) + \mathbf{\Gamma}_{\text{pull}}^{h}\mathbf{Pull}_{c,t} + \mathbf{\Gamma}_{\text{push}}^{h}\mathbf{Push}_{t} + \delta_{c}^{h} + \delta_{m}^{h} + \varepsilon_{c,t}^{h}, \tag{31}$$

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 (31) includes standard control variables—push and pull factors and various fixed effects. Other terms are defined comparably to those in equation (29).

Regression results Figure 7 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 are consistent with the theoretical prediction by equation (27). They also align with our earlier findings from investor-level regressions in Section 5.

Both the valuation-adjusted (first chart) and non-adjusted average equity flow growths (second chart) react positively to changes in the investment 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.

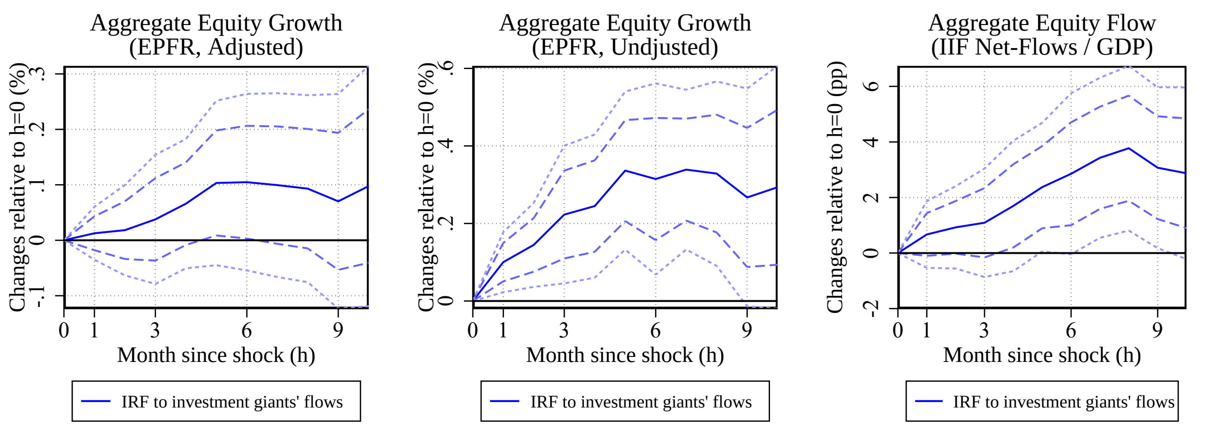


Figure 7: Aggregate Flow Responses to Investment Giants Flows

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 (31). 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 (%).

Robustness To ensure the robustness of these findings, we conduct additional analyses using alternative specifications similar to those in Section 5: (*i*) alternative dataset, (*ii*) different fixed effects, (*iii*) different definitions of investment giants, and (*iv*) alternative main regressor (changes in investment giants' share). The results of aggregate-level regressions remain by and large robust across different data and specifications. We present the results for our robustness checks in Appendix E.1.

6.2 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 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 (32).

$$Z^h_{c,t} = \beta^h \left(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\right) + \mathbf{\Gamma}^h_{\text{pull}}\mathbf{Pull}_{c,t} + \mathbf{\Gamma}^h_{\text{push}}\mathbf{Push}_t + \delta^h_c + \delta^h_m + \varepsilon^h_{c,t}, \tag{32}$$

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 (31).

Regression results Figure 8 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 (Gourinchas and Rey 2014, Anaya, Hachula and Offermanns 2017, Bathia, Bouras, Demirer and Gupta 2020, 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 results suggest that shocks in giant flows generate a positive reaction in relative returns, which in

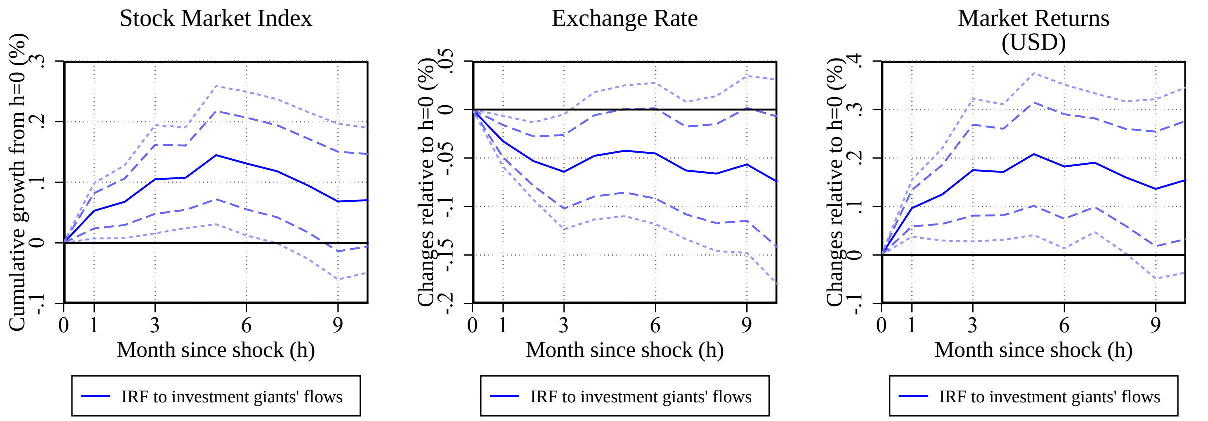


Figure 8: Stock and Currency Markets Responses to Investment Giants Flows

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 (31). 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 (%).

turn attract other investor flows.

Robustness To ensure the robustness of these findings, we conduct additional analyses using alternative specifications: (*i*) alternative dataset, (*ii*) different fixed effects, (*iii*) different definitions of investment giants, and (*iv*) alternative main regressor (changes in investment giants' share). The results of aggregate-level regressions remain by and large robust across different data and specifications. Appendix E.2 presents the results for our robustness checks.

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.

7 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.

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 for in-depth fund-level analysis of global equity flows and decision-making among market players. Specifically, this paper explores the investment choices of institutional investors operating in emerging equity markets, shedding light on the pivotal roles that influential large investors play. The results highlight the substantial impact of these investment giants on aggregate equity flows and their predictability for other investor flows.

This study enhances our understanding of fund-level flows stemming from strategic decisions made by global institutional investors. Our results underscore 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 also 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.

References

Ahmed, Shaghil and Andrei Zlate, "Capital flows to emerging market economies: A brave new world?," *Journal of International Money and Finance*, 2014, *48*, 221–248.

_ , Brahima Coulibaly, and Andrei Zlate, "International financial spillovers to emerging market economies: How important are economic fundamentals?," *Journal of International Money and Finance*, 2017, *76*, 133–152.

Anaya, Pablo, Michael Hachula, and Christian J Offermanns, "Spillovers of US unconventional monetary policy to emerging markets: The role of capital flows," *Journal of International Money and Finance*, 2017, *73*, 275–295.

Aristizabal-Ramirez, Maria, John Leahy, and Linda L. Tesar, "A north-south model of structural change and growth," *Journal of Monetary Economics*, 2023, *133*, 77–102.

Avery, Christopher and Peter Zemsky, "Multidimensional uncertainty and herd behavior in financial markets," *The American Economic Review*, 1998, *88* (4), 724–748.

Banerjee, Abhijit V., "A simple model of herd behavior," *The Quarterly Journal of Economics*, 08 1992, *107* (3), 797–817.

Bao, Te, Cars Hommes, and Tomasz Makarewicz, "Bubble Formation and (In)Efficient Markets in Learning-to-Forecast and optimise Experiments," *The Economic Journal*, 10 2017, *127* (605), F581–F609.

Bathia, Deven, Christos Bouras, Riza Demirer, and Rangan Gupta, "Cross-border capital flows and return dynamics in emerging stock markets: Relative roles of equity and debt flows," *Journal of International Money and Finance*, 2020, *109*, 102258.

Beja, Avraham and M. Barry Goldman, "On The Dynamic Behavior of Prices in Disequilibrium," *The Journal of Finance*, 1980, *35* (2), 235–248.

Ben-David, Itzhak, Francesco Franzoni, Rabih Moussawi, and John Sedunov, "The granular nature of large institutional investors," *Management Science*, 2021, *67* (11), 6629–6659.

Bikhchandani, Sushil and Sunil Sharma, "Herd behavior in financial markets," *IMF Staff Papers*, July 2001, *47* (3), 279–310.

_ , David Hirshleifer, and Ivo Welch, "A theory of fads, fashion, custom, and cultural change as informational cascades," *Journal of Political Economy*, 1992, *100* (5), 992–1026.

Bonfiglioli, Alessandra, "Financial integration, productivity and capital accumulation," *Journal of International Economics*, 2008, *76* (2), 337–355.

Borio, C, "Monetary policy frameworks in EMEs: inflation targeting, the exchange rate and financial stability," *BIS Annual Economic Report*, 2019.

Buch, Claudia M., Cathérine T. Koch, and Michael Koetter, "Size, productivity, and international banking," *Journal of International Economics*, 2011, *85* (2), 329–334.

Calvo, Guillermo A and Carmen M Reinhart, "Fear of floating," *The Quarterly Journal of Economics*, 2002, *117* (2), 379–408.

—, Leonardo Leiderman, and Carmen M Reinhart, "Capital inflows and real exchange rate appreciation in Latin America: the role of external factors," *IMF Staff Papers*, 1993, *40* (1), 108–151.

—, —, and —, "Inflows of capital to developing countries in the 1990s," *Journal of Economic Perspectives*, 1996, *10* (2), 123–139.

Carney, Mark, "Pull, push, pipes: Sustainable capital flows for a new world order," *Speech given at the June 2019 Institute of International Finance Spring Membership Meeting, Tokyo.*, 2019.

Chari, Anusha, "Global risk, Non-bank financial intermediation, and emerging market vulnerabilities," *Annual Review of Economics*, 2023, *15* (1), 549–572.

—, Karlye Dilts Stedman, and Christian Lundblad, "Global fund flows and emerging market tail risk," Working Paper, University of North Carolina May 2022.

Chen, Qi, Itay Goldstein, and Wei Jiang, "Payoff complementarities and financial fragility: Evidence from mutual fund outflows," *Journal of Financial Economics*, 2010, *97* (2), 239–262.

Choe, Hyuk, Bong-Chan Kho, and René M Stulz, "Do foreign investors destabilize stock markets? The Korean experience in 1997," *Journal of Financial Economics*, 1999, *54* (2), 227–264.

Coimbra, Nuno, Daisoon Kim, and Hélène Rey, "Central bank policy and the concentration of risk: Empirical estimates," *Journal of Monetary Economics*, 2022, *125*, 182–198.

Corsetti, Giancarlo, Amil Dasgupta, Stephen Morris, and Hyun Song Shin, "Does one Soros make a difference? A theory of currency crises with large and small traders," *The Review of Economic Studies*, 2004, *71* (1), 87–113.

Coval, Joshua and Erik Stafford, "Asset fire sales (and purchases) in equity markets," *Journal of Financial Economics*, 2007, *86* (2), 479–512.

Devereux, Michael B and Changhua Yu, "International financial integration and crisis contagion," *The Review of Economic Studies*, 10 2019, *87* (3), 1174–1212.

Dornbusch, Rudiger and Yung Chul Park, in Rudiger Dornbusch and Yung Chul Park, eds., *Financial integration in a second-best world: Are we still sure about our classical prejudices?*, Financial Opening: Policy Lessons for Korea, Seoul, The Republic of Korea: Korea Institute of Finance and International Center for Economic Growth, 1995.

Edelen, Roger M, "Investor flows and the assessed performance of open-end mutual funds," *Journal of Financial Economics*, 1999, *53* (3), 439–466.

Fernandez-Arias, Eduardo, "The new wave of private capital inflows: Push or pull?," *Journal of Development Economics*, 1996, *48* (2), 389–418.

Ferreruela, Sandra and Tania Mallor, "Herding in the bad times: The 2008 and COVID-19 crises," *The North American Journal of Economics and Finance*, 2021, *58*, 101531.

Forbes, Kristin J. and Francis E. Warnock, "Capital flow waves: Surges, stops, flight, and retrenchment," *Journal of International Economics*, 2012, *88* (2), 235–251.

Fratzscher, Marcel, "Capital flows, push versus pull factors and the global financial crisis," *Journal of International Economics*, 2012, *88* (2), 341–356.

Gabaix, Xavier and Matteo Maggiori, "International liquidity and exchange rate dynamics," *The Quarterly Journal of Economics*, 2015, *130* (3), 1369–1420.

Goldberg, Linda S. and Signe Krogstrup, "International capital flow pressures and global factors," *Journal of International Economics*, 2023, p. 103749.

Gourinchas, Pierre-Olivier and Hélène Rey, "Chapter 10 – External adjustment, global imbalances, valuation Effects," in Gita Gopinath, Elhanan Helpman, and Kenneth Rogoff, eds., *Handbook of International Economics*, Vol. 4 of *Handbook of International Economics*, Elsevier, 2014, pp. 585–645.

_ and Maurice Obstfeld, "Stories of the twentieth century for the twenty-first," *American Economic Journal: Macroeconomics*, 2012, *4* (1), 226–265.

Gyntelberg, Jacob, Mico Loretan, and Tientip Subhanij, "Private information, capital flows, and exchange rates," *Journal of International Money and Finance*, 2018, *81*, 40–55.

Hannan, Swarnali Ahmed, "The drivers of capital flows in emerging markets post global financial crisis," *Journal of International Commerce, Economics and Policy*, 2017, *08* (02), 1750009.

_ and Luis M. Cubeddu, "Revisiting the determinants of capital flows to emerging markets–A survey of the evolving literature," *IMF Working Papers*, 2018, *2018* (214).

Hardy, Bryan and Goetz von Peter, "Global liquidity: a new phase?," *BIS Quarterly Review*, December 2023, pp. 21–31.

Hau, Harald and Hélène Rey, "Exchange rates, equity prices, and capital flows," *The Review of Financial Studies*, 2006, *19* (1), 273–317.

Hwang, Soosung and Mark Salmon, "Market stress and herding," *Journal of Empirical Finance*, 2004, *11* (4), 585–616.

Igan, Deniz, Ali M Kutan, and Ali Mirzaei, "The real effects of capital inflows in emerging markets," *Journal of Banking & Finance*, 2020, *119*, 105933.

Jackson, Matthew O. and Agathe Pernoud, "Systemic risk in financial networks: A survey," *Annual Review of Economics*, 2021, *13* (Volume 13, 2021), 171–202.

Jotikasthira, Chotibhak, Christian Lundblad, and Tarun Ramadorai, "Asset fire sales and purchases and the international transmission of funding shocks," *The Journal of Finance*, 2012, *67* (6), 2015–2050.

Kalemli-Özcan, Sebnem, "U.S. Monetary Policy and International Risk Spillovers," Working Paper 26297, National Bureau of Economic Research September 2019.

Keynes, John Maynard, *The general theory of employment, interest, and money*, London, UK: Macmillan, November 1936.

Kim, Kyungkeun and Dongwon Lee, "Equity market integration and portfolio rebalancing," *Journal of Banking & Finance*, 2020, *113*, 105775.

Koepke, Robin, "What drivers capital flows to emerging markets? A survey of the empirical literature," *Journal of Economic Surveys*, 2019, *33* (2), 516–540.

— and Simon Paetzold, "Capital flow data – A guide for empirical analysis and real-time tracking," *IMF Working Papers*, 2020, *2020* (171), A001.

Lilley, Andrew, Matteo Maggiori, Brent Neiman, and Jesse Schreger, "Exchange rate reconnect," *Review of Economics and Statistics*, 2022, *104* (4), 845–855.

Morris, Stephen and Hyun Song Shin, "Social value of public information," *The American Economic Review*, 2002, *92* (5), pp. 1521–1534.

Raddatz, Claudio and Sergio L Schmukler, "On the international transmission of shocks: Micro-evidence from mutual fund portfolios," *Journal of International Economics*, 2012, *88* (2), 357–374.

Rajan, Raghuram G., "Has finance made the world riskier?," *European Financial Management*, 2006, *12* (4), 499–533.

Rey, Hélène, "Dilemma not trilemma: The global financial cycle and monetary policy independence," Working Paper 21162, National Bureau of Economic Research May 2015.

Schmidt, Lawrence, Allan Timmermann, and Russ Wermers, "Runs on money market mutual funds," *American Economic Review*, September 2016, *106* (9), 2625–57.

Shin, Hyun Song, "The Second Phase of Global Liquidity and Its Impact on Emerging Economies," in Kyuil Chung, Soyoung Kim, Hail Park, Changho Choi, and Hyun Song Shin, eds., *Volatile Capital Flows in Korea: Current Policies and Future Responses*, New York: Palgrave Macmillan US, 2014, pp. 247–257.

Summers, Lawrence H, in Robert Thomas Crow, ed., *2014: US economic prospects: Secular stagnation, hysteresis, and the zero lower bound*, The Best of Business Economics: Highlights from the First Fifty Years, New York, NY: Palgrave Macmillan, 2016, pp. 421–435.

Taylor, Mark P. and Lucio Sarno, "Capital flows to developing countries: Long- and short-term determinants," *The World Bank Economic Review*, 09 1997, *11* (3), 451–470.

Wardlaw, Malcolm, "Measuring mutual fund flow pressure as shock to stock returns," *The Journal of Finance*, 2020, *75* (6), 3221–3243.

Warther, Vincent A, "Aggregate mutual fund flows and security returns," *Journal of financial economics*, 1995, *39* (2-3), 209–235.

Wong, Hock Tsen, "Real exchange rate returns and real stock price returns," *International Review of Economics & Finance*, 2017, *49*, 340–352.

Òscar Jordà, "Estimation and inference of impulse responses by local projections," *American Economic Review*, 3 2005, *95* (1), 161–182.

Appendix

A Simultaneous Move Case

All investors, both typical investors and investment giant ($i \in [0,1]$), independently and simultaneously make an investment decision a_i to maximize their expected payoff, $\mathbb{E}[\pi_i|s_i]$, based on their own private signal, s_i.

Typical investor's optimal strategy The first-order condition of typical investors yields:

$$a_j^{\text{sm}}(s_j) = (1-\omega)\mathbb{E}[f|s_j] + \omega\big\{\lambda\mathbb{E}[a_1^{\text{sm}}|s_j] + (1-\lambda)\mathbb{E}[\bar{a}_0^{\text{sm}}|s_j]\big\}, \tag{A.1}$$

which represents a convex combination of the expectations of fundamentals and the aggregated market outcomes (i.e., the actions of other investors). Again, following the approach in Morris and Shin (2002), the optimal strategy can be expressed as a linear function of each investor's private signal. Then, the optimal action of typical investor j under the simultaneous move structure is reformulated as:

$$a_j^{\text{sm}}(s_j) = \psi^{\text{sm}} s_j \quad \text{where} \quad \psi^{\text{sm}} \equiv \left[\frac{(1-\omega)+\omega\lambda\phi^{\text{sm}}}{1-\omega(1-\lambda)\theta_0}\right]\theta_0. \tag{A.2}$$

Here, ϕ^{sm} is the investment giant's optimal response to its own signal, i.e., $a_1^{\text{sm}}(s_1) = \phi^{\text{sm}} s_1$. The payoff of typical investors depends on the aggregate market action. Therefore, the greater their optimal response to own signal (ψ^{sm}), the more sensitive the investment giant becomes to its own signal (i.e., ϕ^{sm} is larger). This channel is further amplified when the investment giant's influence (λ) and the strategic interaction motive (ω) increase.

Investment giant's optimal strategy Like typical investors, the investment giant's first-order condition is:

$$a_1^{\text{sm}}(s_1) = \frac{(1-\omega)\mathbb{E}[f|s_1] + \omega(1-\lambda)\big\{\lambda a_1^{\text{sm}} + (1-\lambda)\mathbb{E}[\bar{a}_0^{\text{sm}}|s_1]\big\}}{(1-\omega)+\omega(1-\lambda)}. \tag{A.3}$$

Then, the optimal strategy can be reexpressed as:

$$a_1^{\text{sm}}(s_1) = \phi^{\text{sm}} s_1 \quad \text{where} \quad \phi^{\text{sm}} \equiv \left[\frac{(1-\omega)+\omega(1-\lambda)^2\psi^{\text{sm}}}{(1-\omega)+\omega(1-\lambda)^2}\right]\theta_1, \tag{A.4}$$

where ψ^{sm} denotes the coefficient of typical investor's optimal response to own signal as given in equation (A.2).

B Impacts of Strategic Complementarity and Investment Giants on Typical Investor Payoffs

Impacts on typical investor's ex-ante payoffs To discuss the impact of the investment giant and strategic complementarity, we explore the ex-ante payoff of a typical investor j given by:

$$\mathbb{E}[\pi_j^*] \equiv -(1-\omega)\text{var}(a_j^* - f) - \omega\text{var}(a_j^* - \bar{A}^*), \tag{B.5}$$

where the respective two terms in the right-hand side represent the variances of j's action relative to the fundamental (f) and the market aggregate ($\bar{A}^*$), weighted by the degree of strategic complementarity (ω).

Variance of deviations from the fundamental In equilibrium, the variance in a deviation of a typical investor's action from the fundamental can be rewritten as:

$$\text{var}(a_j^* - f) = \sigma_f^2 \Upsilon(\psi^*; \theta_0), \tag{B.6}$$

where $\Upsilon(\psi^*; \theta_0)$ decreases with the precision of the private signal (θ_0), enabling the investor to forecast the fundamental more accurately.

While the investment giant's early move provides typical investors valuable public information, helping them forecast the fundamental, it also introduces a coordination effect that limits their ability to act independently. Under a condition of strong strategic complementarity (ω) or substantial market dominance by the investment giant (λ), typical investor's action increasingly deviates from their optimal signal-extraction forecast, resulting in higher variance:

$$\frac{\partial}{\partial \lambda}\text{var}(a_j^* - f) > 0 \quad \text{and} \quad \frac{\partial}{\partial \omega}\text{var}(a_j^* - f) > 0.$$

Therefore, both strategic complementarity and the investment giant's market dominance bring about a negative impact on the typical investor's ex-ante payoff.

Variance of deviations from the market aggregate The ex-ante variance of a typical investor's action deviation from the market aggregate is:

$$\mathrm{var}(a_j^* - \bar{A}^*) = \sigma_f^2 \psi^{*2} \left\{ \frac{1}{\theta_0} - 1 + \lambda^2 \Upsilon(\theta_1; \theta_1) \right\}. \tag{B.7}$$

By committing to an early decision, the investment giant establishes a market direction that followers are likely to align with. This *directional leadership channel* reduces the ex-ante variance of deviations from the market aggregate, particularly when: *(i)* the investment giant's market share is substantial, discouraging deviation from its lead, and *(ii)* the degree of strategic complementarity is high, as actions become increasingly interdependent. Thus, the variance is decreasing in both λ and ω:

$$\frac{\partial}{\partial \lambda} \mathrm{var}(a_j^* - \bar{A}^*) < 0 \quad \text{and} \quad \frac{\partial}{\partial \omega} \mathrm{var}(a_j^* - \bar{A}^*) < 0,$$

Higher precision of private or public signals (θ_0 or θ_1) further reduces the variance. The *public information channel* allows typical investors to refine their strategies based on the investment giant's initial move, improving alignment with the market aggregate. By reducing deviations of the market aggregate from the fundamental, the public information benefits all investors, including the investment giant. This effect is particularly pronounced when the investment giant's signal precision (θ_1) is higher than that of the typical investors (θ_0).

Comparison of payoffs: Typical investors vs. investment giant The *public information* and *directional leadership* channels ensure that the investment giant's actions deviate less from both the fundamental and the market aggregate compared to those of typical investors. As a result, the investment giant achieves a higher ex-ante payoff in the sequential move equilibrium:

$$\mathrm{var}(a_1^* - f) < \mathrm{var}(a_j^* - f) \quad \text{and} \quad \mathrm{var}(a_1^* - \bar{A}^*) \leq \mathrm{var}(a_j^* - \bar{A}^*) \quad \Rightarrow \quad \mathbb{E}[\pi_1^*] > \mathbb{E}[\pi_j^*].$$

This reflects the dual advantage of the investment giant. The giant shapes market direction through leadership, thereby enhancing coordination. Also, the giant leverages the public information, which it generates, to improve other investors' information, benefiting itself and other market participants.

C Data Appendix

C.1 Fund Flows

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.[20]

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.[21] 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 F.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)

[20] 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.

[21] 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.

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.

C.2 Macroeconomic Variables

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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.[23] 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.

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D Robustness Checks of Investor-Level Analyses

Active funds flows Next, 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.[24] 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 push factors, in comparison to passive funds (Chari et al. 2022 and Chari 2023).[25]

To address this concern, we estimate regression equations (29) and (30) using active fund flows as the dependent and independent variables.[26] The estimation results with active funds data are broadly consistent with the full sample (active funds & passive funds) results. Specifically, as shown in Figure D.1, the results from the estimation of equation (29) 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 D.2, we report the results from state-dependent local projection similar to equation (30), 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 (29) 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

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

[25]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.

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

specification fails to capture heterogeneity in investor-level dynamics.

To address this potential issue, we carry out an additional regression by adjusting the equation (29). Specifically, given that EPFR data does not provide the detailed investor characteristics, we incorporate investor-time fixed effects ($\delta^h_{i,t}$):

$$\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = \beta^h \left(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\right) + \mathbf{\Gamma}^h_{\text{pull}} \mathbf{Pull}_{c,t} + \delta^h_{i,t} + \delta^h_c + \varepsilon^h_{ic,t}, \tag{D.8}$$

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 D.3 summarizes the responses of equity flows based on the regression equation (D.8). The 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 (29) 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 D.4. 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 (30), we further investigate the non-linearity of equity fund responses between crash and non-crash scenarios. Panels (a) and

(b) in Figure D.5 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:

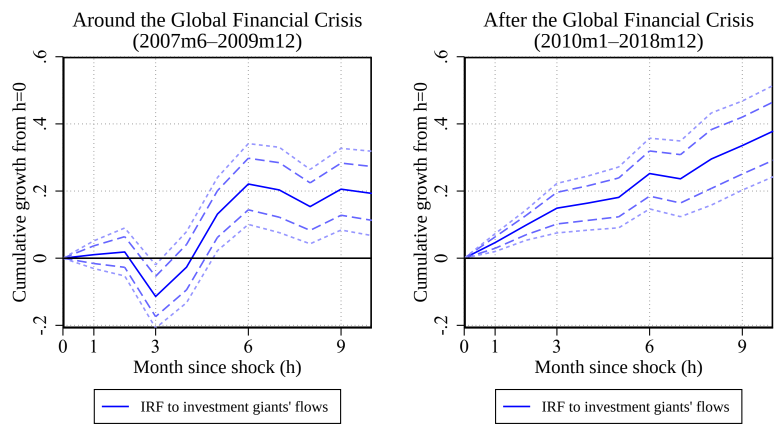
$$\frac{1}{N^{\mathcal{G}}}\sum_{i\in\mathcal{G}}\Delta^1\left(\frac{\text{Equity}_{ic,t-1}}{\text{Equity}_{c,t-1}}\right)\approx\bar{g}^{\text{giant}}_{c,t}-\bar{g}^{\text{agg}}_{c,t} \tag{D.9}$$

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 (29) and (30) by substituting the main regressor with the average change of investment giants' market share in equation (D.9). Figure D.6 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 D.7 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.

(a) Valuation-adjusted Active Fund Equity flows



(b) Unadjusted Active Fund Equity Flows

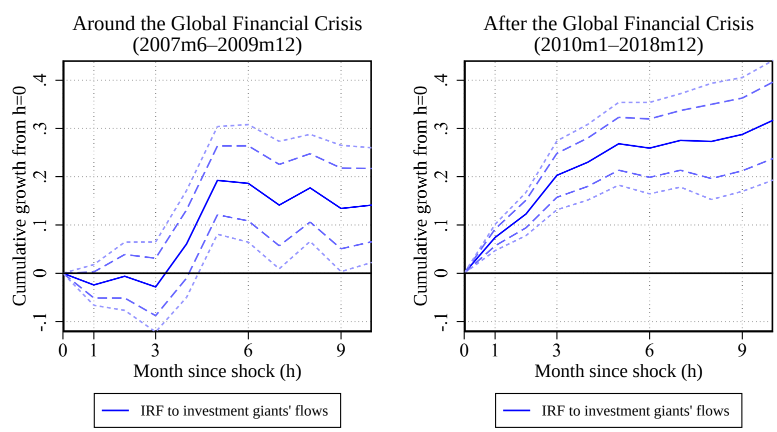


Figure D.1: Investor-Level Response to the Equity Flow Differential between Investment Giants and Typical Investors: Active Fund Flows

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 ($\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}$) 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 $\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}$). The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (29). 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, %).

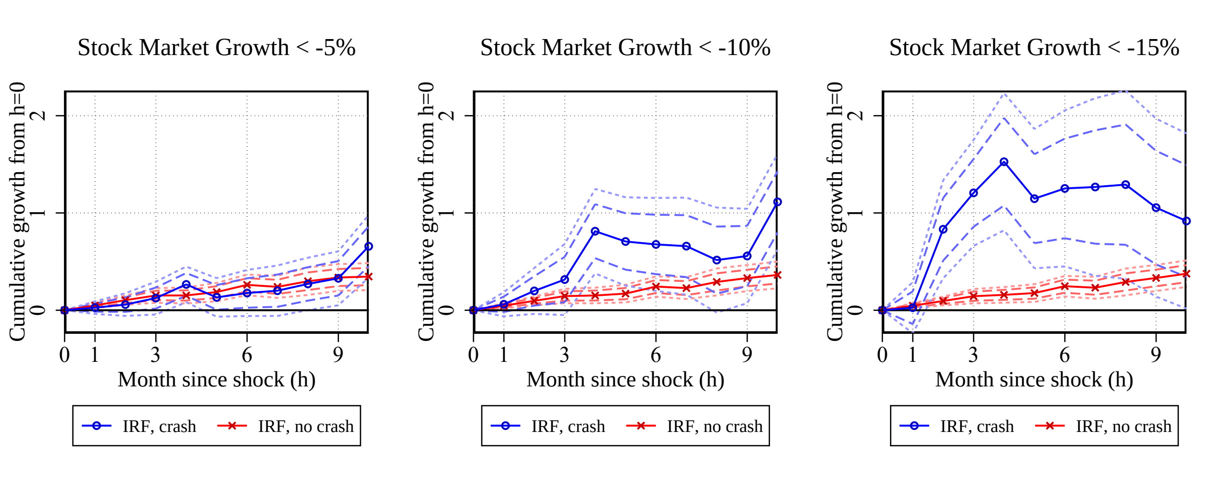


Figure D.2: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis: Active Fund Flows

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 (30). 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, %).

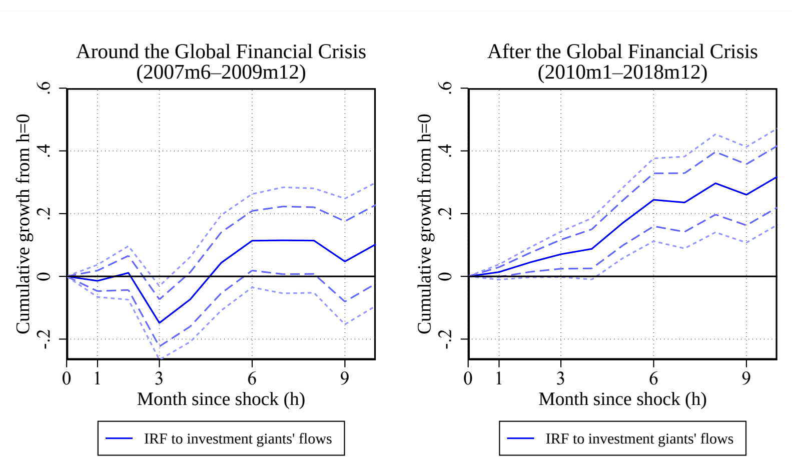
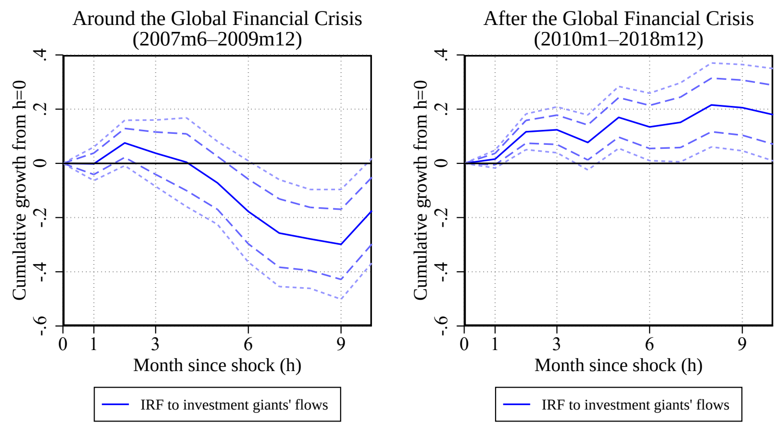


Figure D.3: Investor-Level Response to the Equity Flow Differential between Investment Giants and Typical Investors: Alternative Specification

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 (D.8). 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

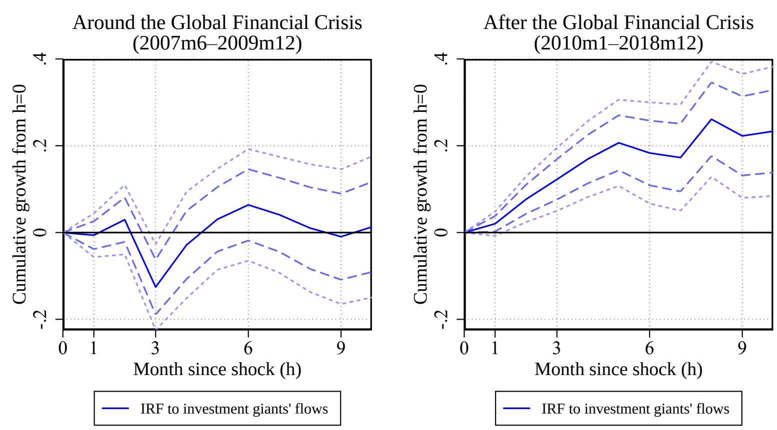
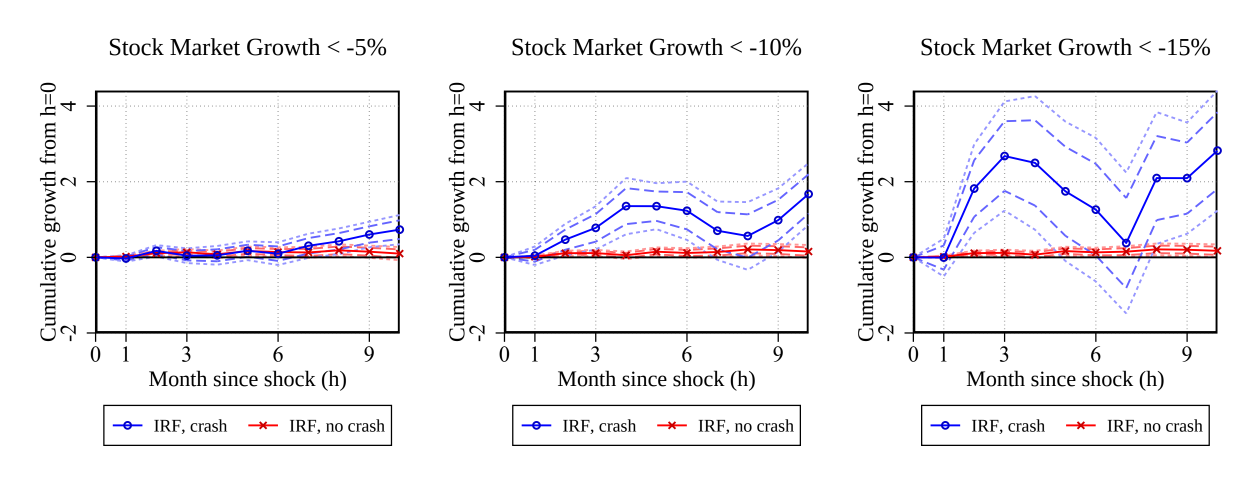


Figure D.4: Investor-Level Response to the Equity Flow Differential between Investment Giants (Top 15 or 7 Largest Investors) and Typical Investors

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 (29). 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

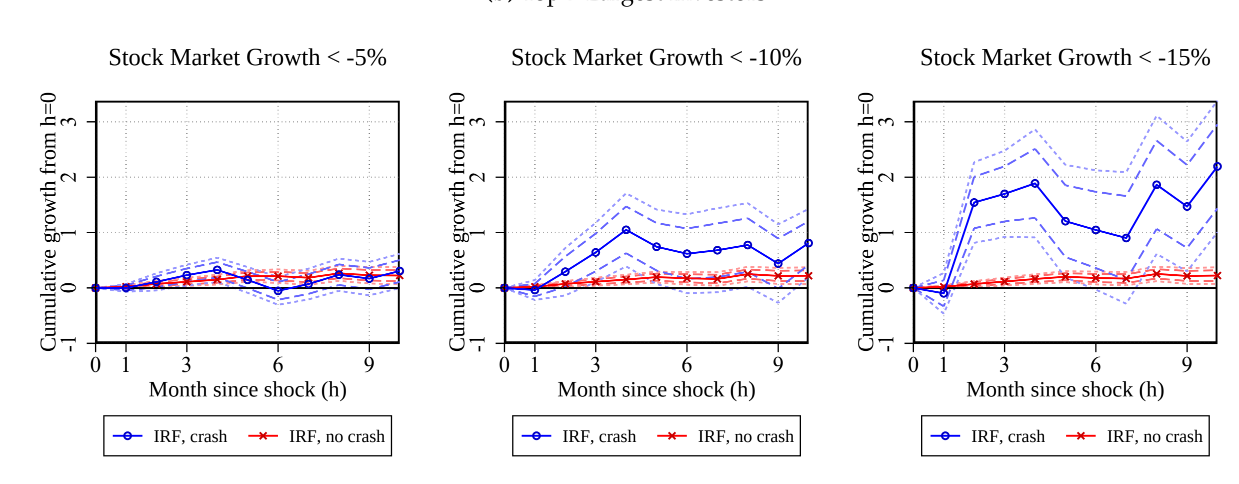


Figure D.5: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis: Top 15 and 7 Largest Investors

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 (30). 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, %).

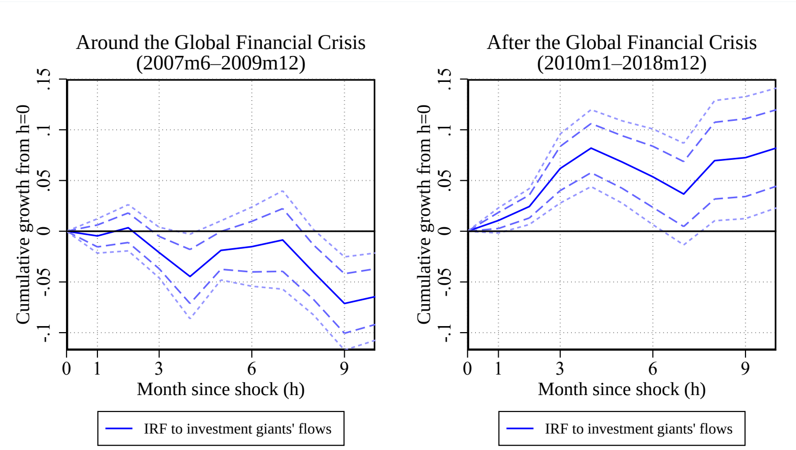


Figure D.6: Investor-Level Response to Changes in Investment Giants Share

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 (29). 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, %).

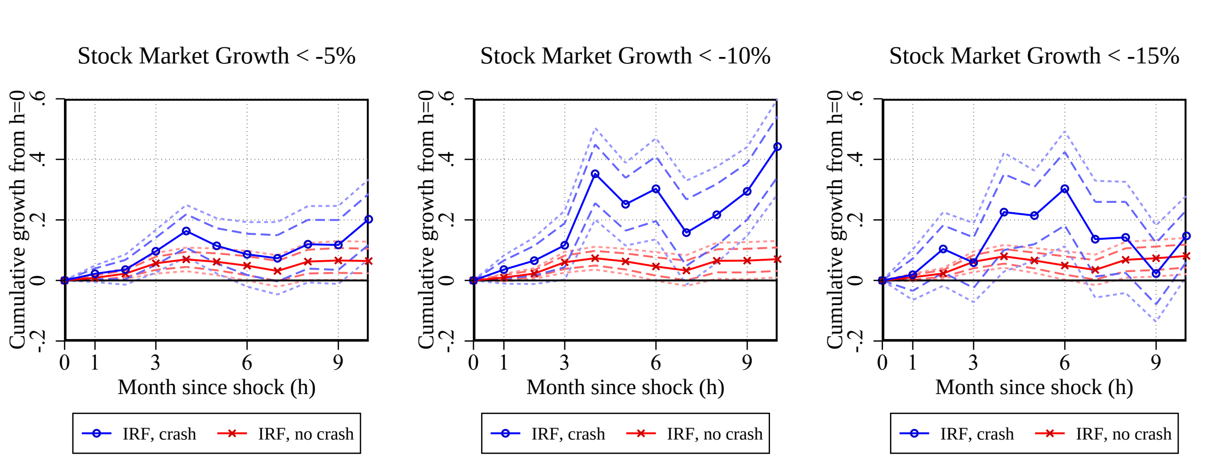


Figure D.7: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis: Investment Giants' Share Changes

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 (30). 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

E.1 Robustness Check: The Impact of Investment Giants on Aggregate Flows

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 E.8). 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:

$$Y^h_{c,t} = \beta^h \left(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\right) + \mathbf{\Gamma}^h_{\text{pull}}\mathbf{Pull}_{c,t} + \delta^h_c + \delta^h_t + \varepsilon^h_{c,t}, \tag{E.10}$$

where δ^h_t denotes the time fixed effect.[27] As summarized in Figure E.9, 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 E.10 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 (D.9). The impulse responses of aggregate flows to the shocks are also in line with the baseline results, as presented in Figure E.11.

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 highlights 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.

[27] Note that, similar to equation (D.8), push factor ($\mathbf{Push}_t$) and month fixed effect (δ^h_m) are excluded from the regression as the time fixed effect is included.

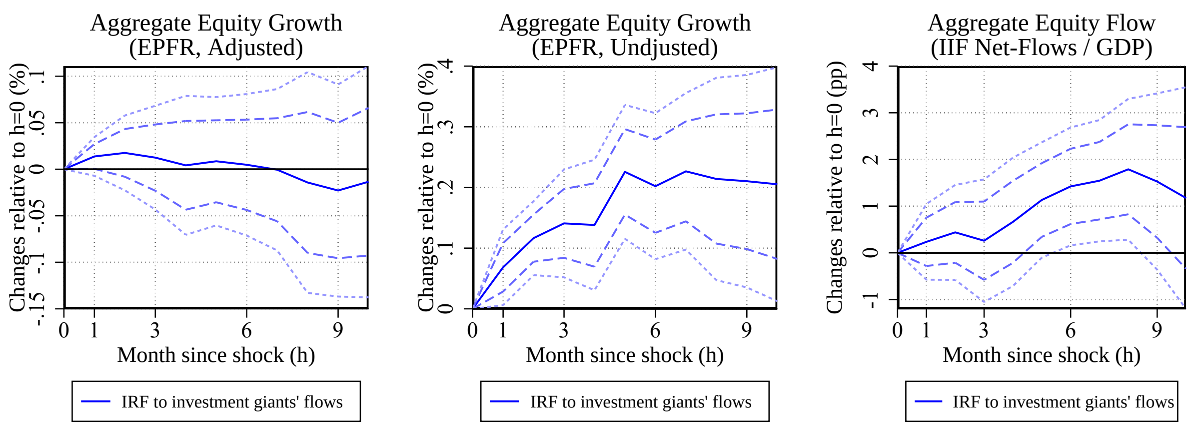


Figure E.8: Aggregate Flow Responses to Investment Giants: Active Fund Flows

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 (31). 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 (%).

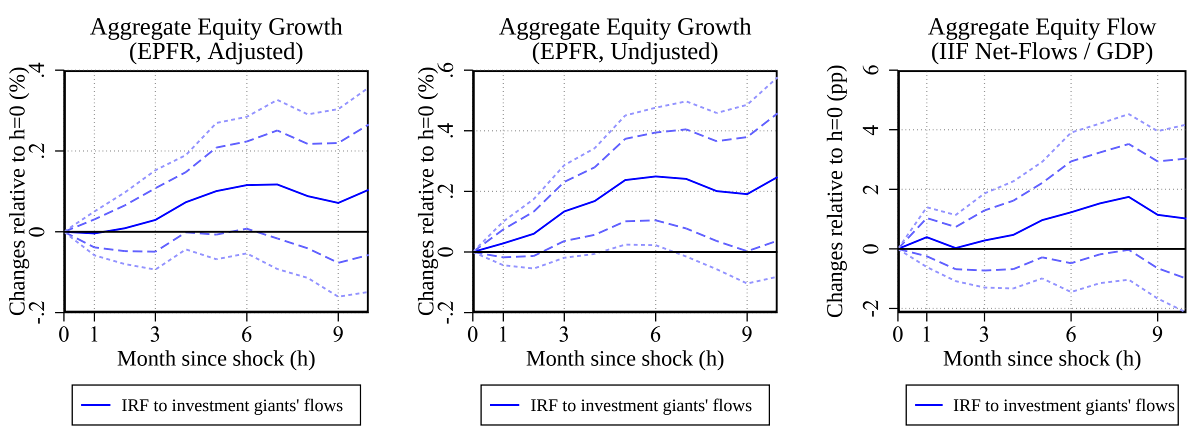
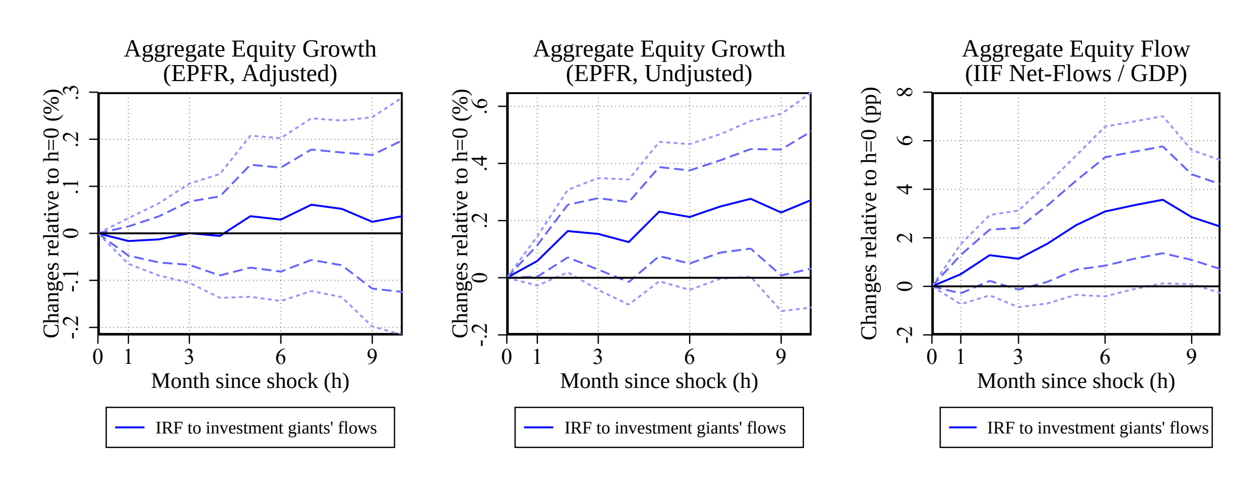


Figure E.9: Aggregate Flow Responses to Investment Giants Flows: Alternative Specification

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 (E.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 (%).

(a) Top 15 Largest Investors



(b) Top 7 Largest Investors

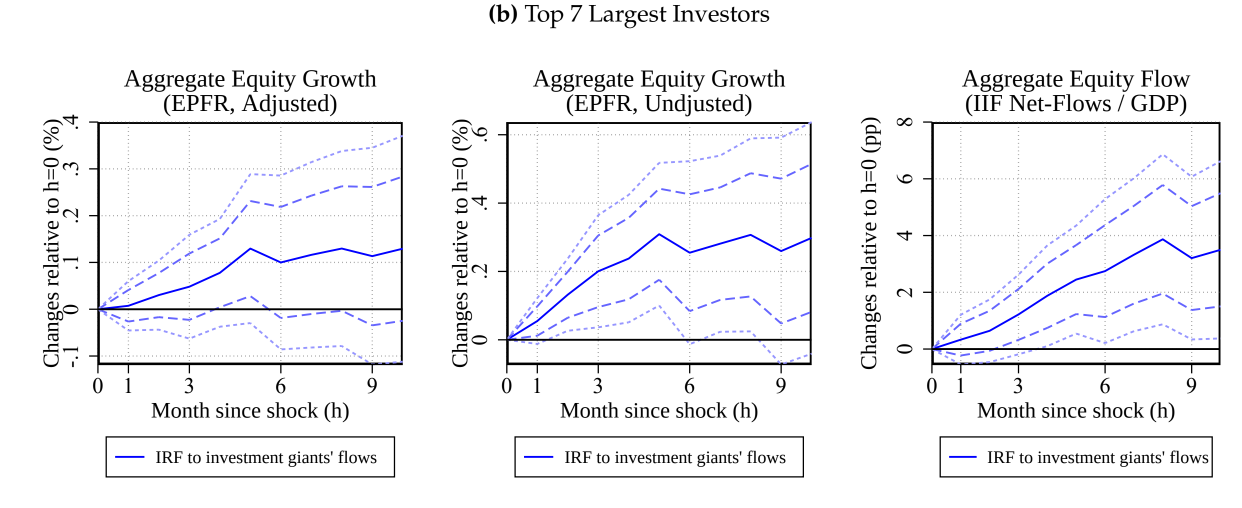


Figure E.10: Aggregate Flow Responses to Investment Giants (Top 15 and 7 Largest Investors) Flows

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 (32). 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 (%).

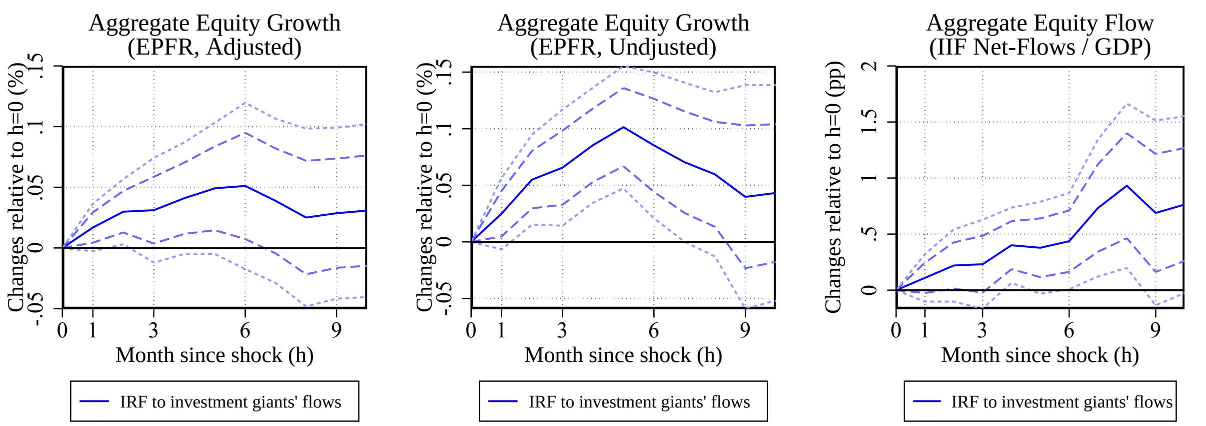


Figure E.11: Aggregate Flow Responses to Investment Giants Share

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 (31). 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 (%).

E.2 Robustness Check: Investment Giants, Future Exchange Rate, Stock Price and Returns

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 details, the impulse responses of the stock and currency markets to active fund flows are first reported in Figure E.12. Second, we carry out a regression similar to equation (E.10), which in particular takes into consideration time fixed effect. The estimation results are summarized in Figure E.13. 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 E.14. Fourth, Figure E.15 presents the responses of stock returns and exchange rate adjustments to shocks in the investment giants' share, as defined in equation (D.9).

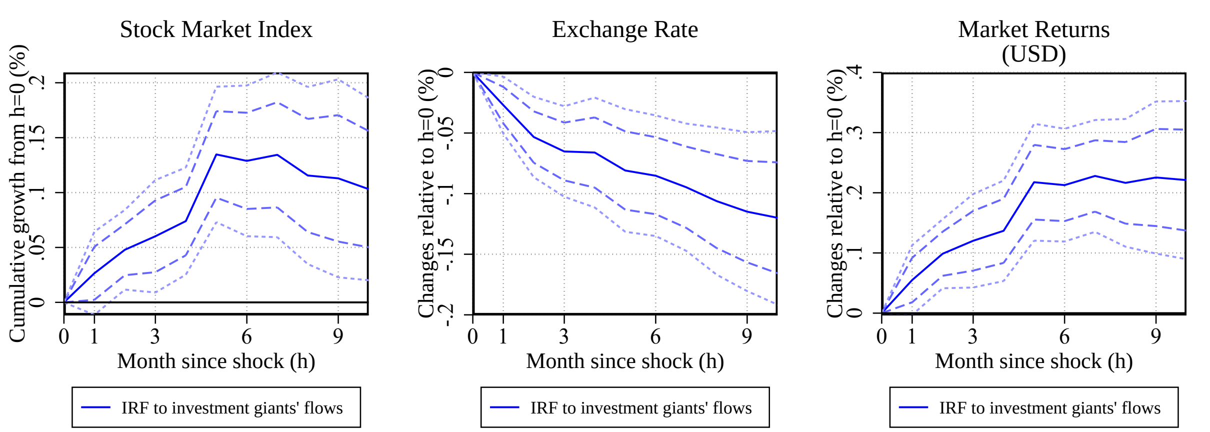


Figure E.12: Stock and Currency Markets Responses to Investment Giants: Active Fund Flows

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 (32). 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 (%).

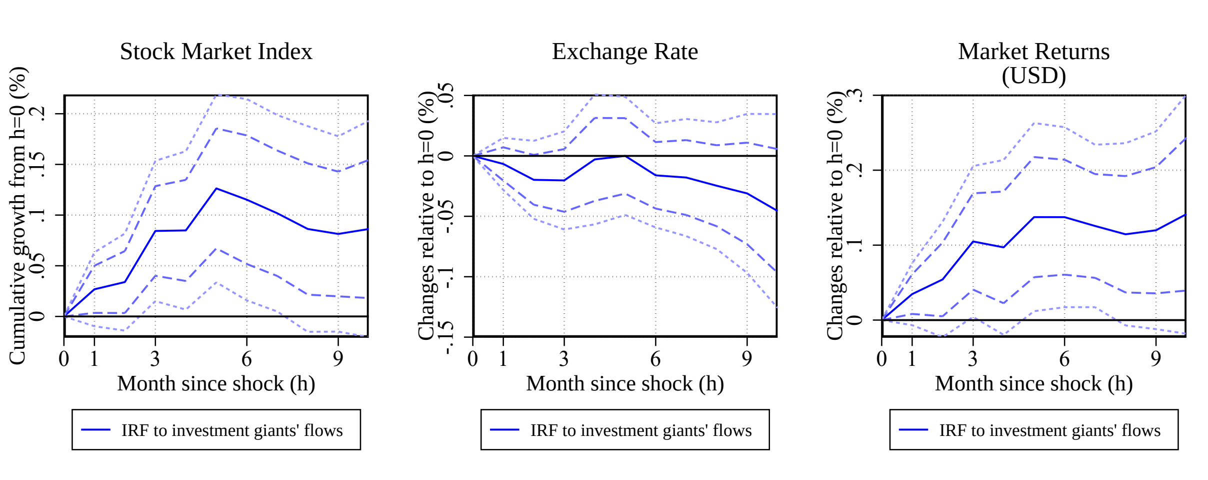
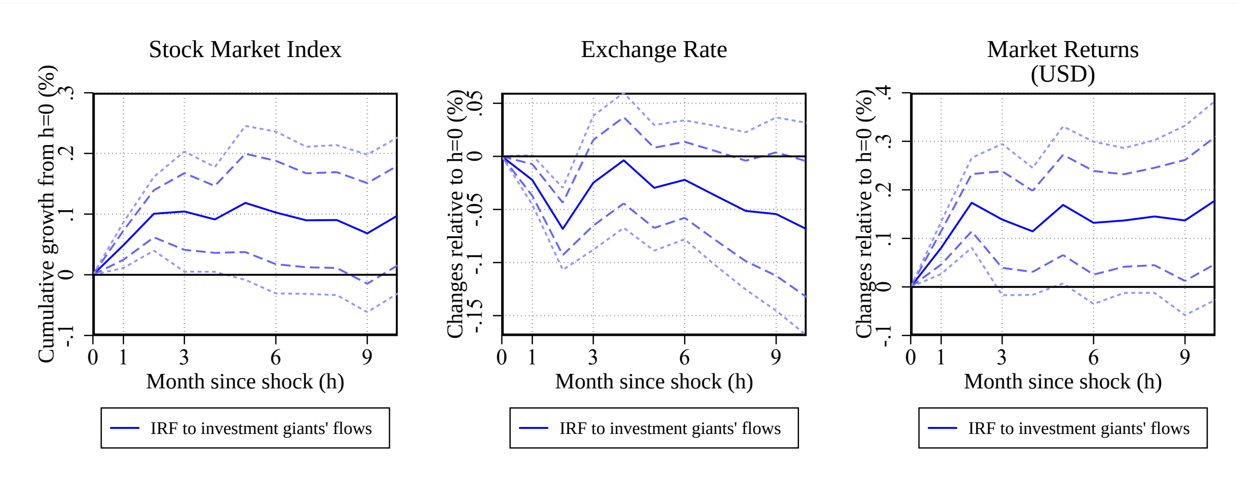


Figure E.13: Stock and Currency Markets Responses to Investment Giants Flows: Alternative Specification

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 (32) 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

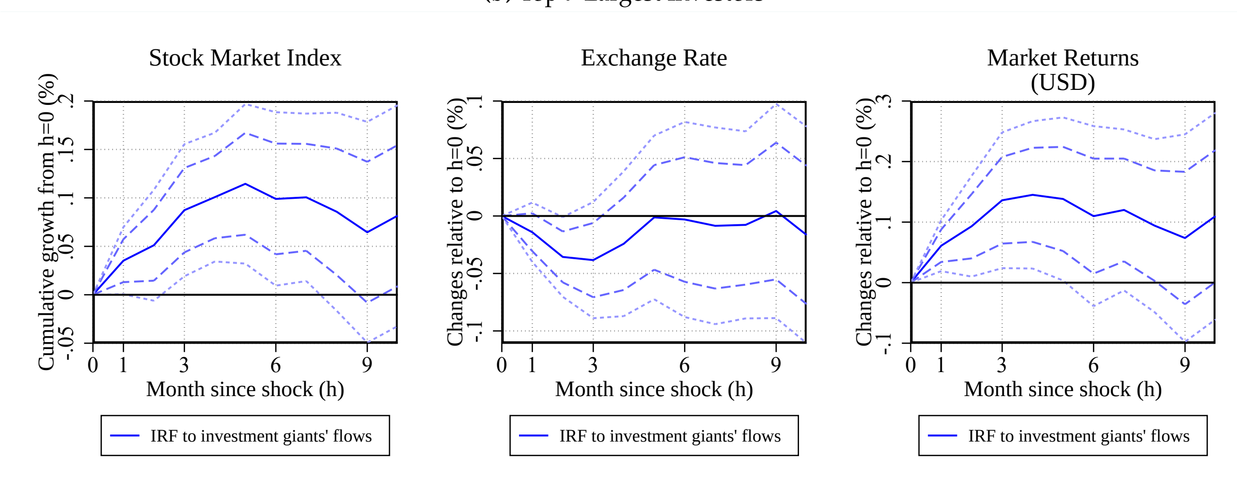


Figure E.14: Stock and Currency Markets Responses to Investment Giants (Top 15 and 7 Largest Investors) Flows

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 (31). 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 (%).

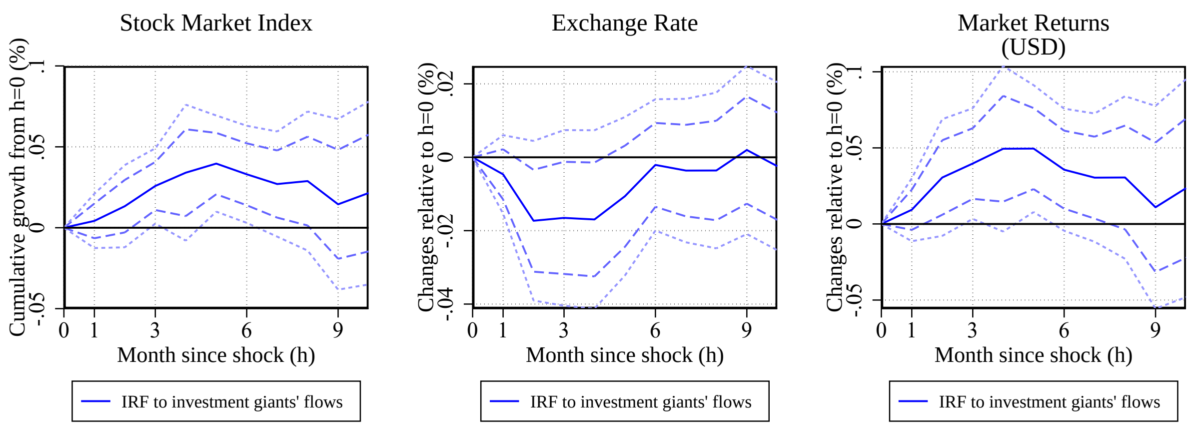


Figure E.15: Stock and Currency Markets Responses to Investment Giants Share

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 (32). 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 F.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 F.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 F.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 F.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 F.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.

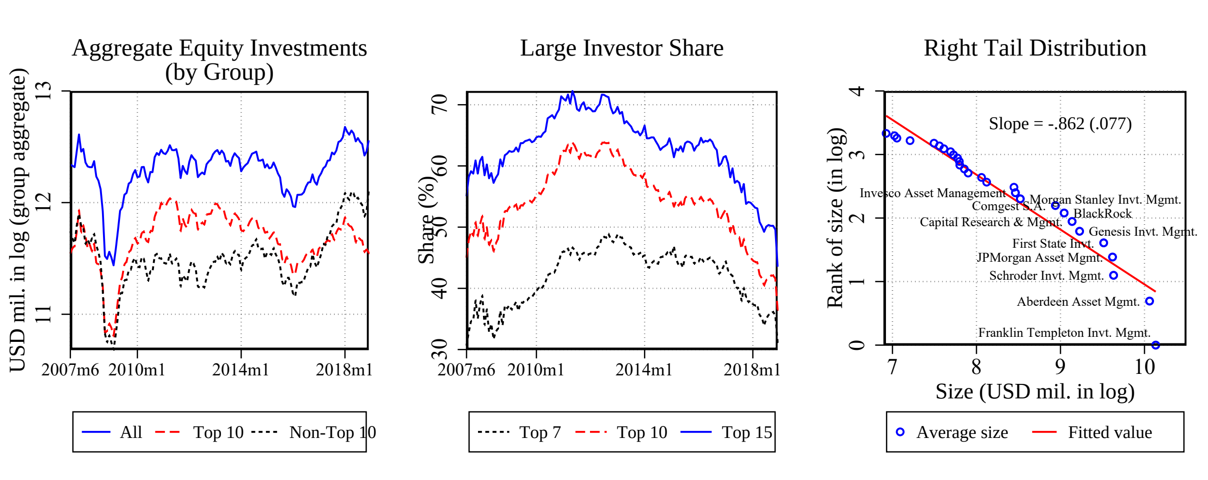


Figure F.16: Trends of Equity Fund Flows: Active Funds Only

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).

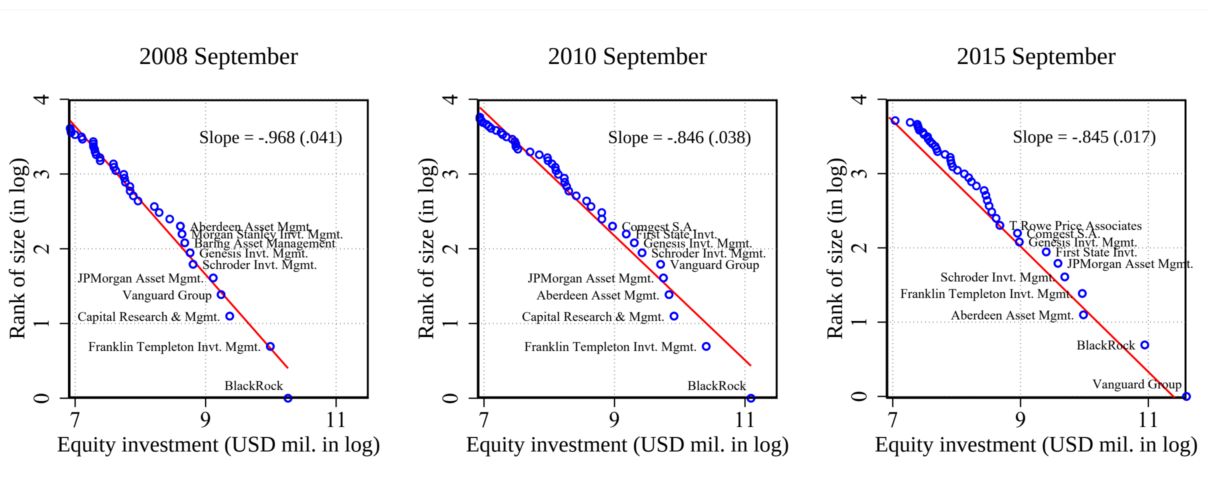


Figure F.17: The Right Tail of Investor Size

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.

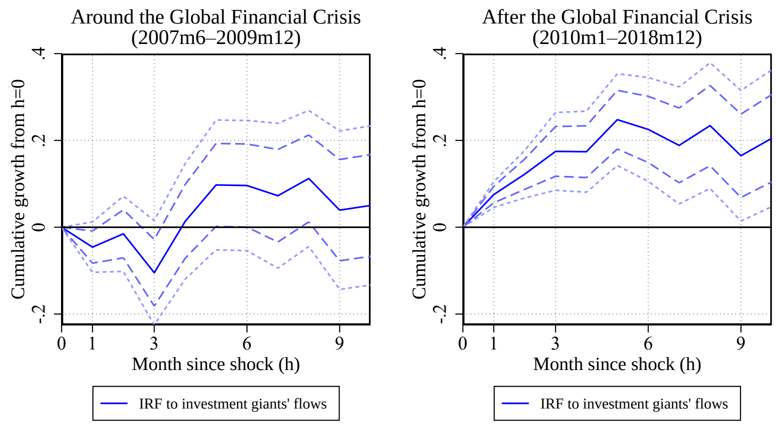


Figure F.18: Investor-Level Response to the Unadjusted Equity Flow Differential between Investment Giants and Typical Investors

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 (ΔIHS(Equity$_{ic,t}$)). The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (29). 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, %).

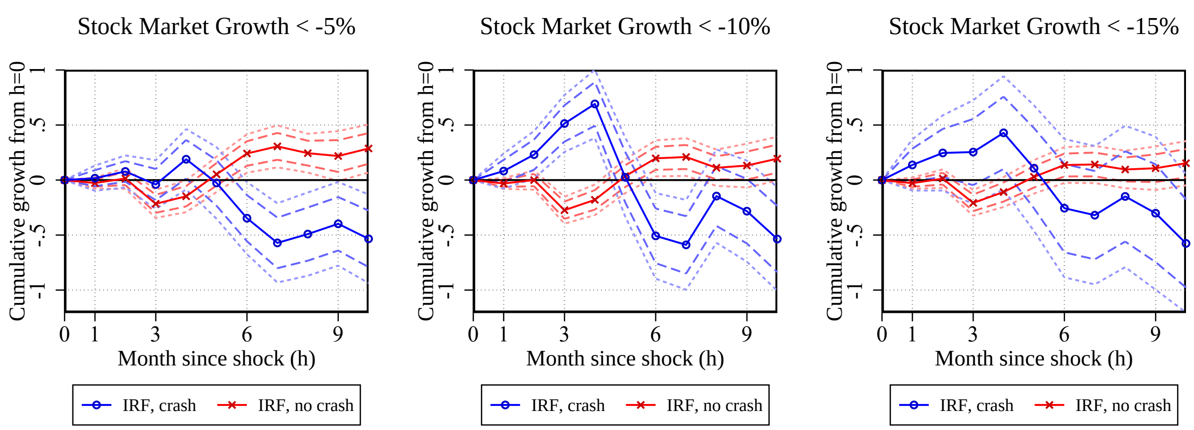


Figure F.19: Investor-Level Response with and without Stock Market Crashes: 2007m6–2009m12

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 (30). 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, %).