Investment Giants and Their Impacts in Emerging Markets

Daisoon Kim*
North Carolina State University

Jee Won Park†
Ministry of Economy and Finance of Korea

Inhwan So‡
Bank of Korea

February 25, 2025

Abstract

A small group of large institutional investors (*investment giants*) takes the lion's share of cross-border equity flows into emerging markets. This paper examines their behavior and market impact through a theoretical framework in which investors consider both market fundamentals and aggregate behavior. In equilibrium, a single investment giant moves first, setting market direction and providing information to a continuum of typical investors. Compared to a simultaneous-move strategy, this directional leadership increases the giant's ex-ante payoff while establishing the predictability and outsized influence of its decisions. Empirically, we introduce *contrarian investment* (excess investment growth relative to peers or the market) to isolate the giants' idiosyncratic influence from the shared macroeconomic fundamentals. Using fund-level data, we find that investor flows, aggregate flows, stock returns, and exchange rates persistently increase following giants' contrarian flows, demonstrating their predictive power. These findings suggest monitoring giants as early indicators of financial market movements in emerging economies.

JEL Classification: F32, G11, G15, G23.
Keywords: Emerging market, Fund-level data, Global equity flows, Large player, Portfolio management.

*Department of Economics, NC State University, Raleigh, NC, US. E-mail: dkim29@ncsu.edu.
†Ministry of Economy and Finance, Sejong, Korea. E-mail: jwpark72@korea.kr.
‡Bank of Korea, Seoul, Korea. E-mail: ihsoh@bok.or.kr.

The authors would like to thank Anusha Chari, Jon A. Garfinkel, Fabio Ghironi, Thomas Gilbert, Jongrim Ha, Dongwon Lee, John Kim, Kyungkeun Kim, Jun Hee Kwak, Sangyup Choi, Felipe Saffie, Hélène Rey, and Huanhuan Zheng as well as all participants at the 3rd ASB-CEPR-ERSA-ADB-CAMA-BNM and WB Workshop on Macroeconomic Policy in Emerging Markets, the 2024 RCEA International Conference in Economics, Econometrics, and Finance, and the 2022 Annual Meeting of Southern Economic Association, and the seminar participants at the University of Washington, Indian School of Business, Bank of Korea, and Yonsei University for useful comments.

The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Bank of Korea or the Ministry of Economy and Finance of the Republic of Korea.

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 markets as international investors sought higher yields (Rajan 2006, Summers 2016). These flows provide significant benefits, such as better opportunities for risk-sharing and external financing (Bonfiglioli 2008, Igan, Kutan and Mirzaei 2020, Aristizabal-Ramirez, Leahy and Tesar 2023). However, they also carry notable risks: heightened exposure to global shocks, the potential for sudden reversals that intensify financial stress (Calvo and Reinhart 2002, 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 or investor level, remain underexplored. One of the most pronounced characteristics of global equity allocations to emerging markets is their high concentration led by only a small group of dominant institutional investors, referred to as "*investment giants*" (Figure 1). These giants may wield disproportionate influence, echoing patterns observed in 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, Coimbra, Kim and Rey 2022).

This paper examines their strategic interactions with other investors and their broader influence on equity and currency markets in emerging economies. Our findings offer insights for policymakers and market participants navigating the complexities of international capital flows. In particular, we highlight the value of monitoring investment giants' actions, especially when their decisions diverge from market trends. Their moves may serve as early indicators of potential market disruptions in emerging market economies.

To analyze the behavior and influence of investment giants, we first develop a theoretical framework incorporating a dominant player, noisy markets, and strategic comple-

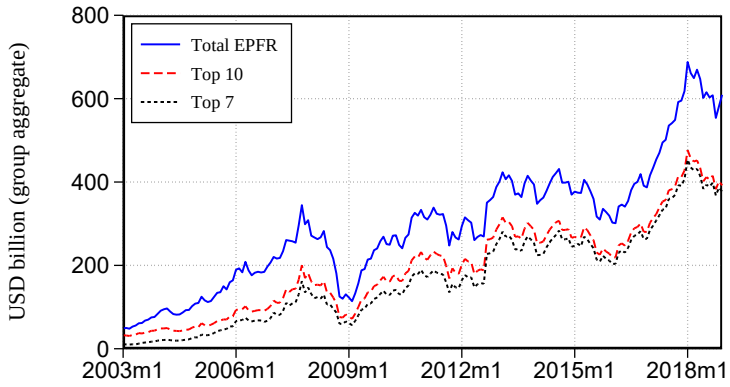


Figure 1: Equity Fund Flows to 20 Emerging Markets

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

mentarity. Formally, we model a market with a single dominant player (investment giant) and a continuum of smaller investors (typical investors), allowing the giant to choose its timing—either moving simultaneously with others or sequentially before them. To reflect the key features of financial markets, as conceptualized in the beauty contest analogy (Keynes 1936; see also Chen, Goldstein and Jiang 2010, Schmidt, Timmermann and Wermers 2016), we adopt the framework of Morris and Shin (2002) with incomplete information and strategic complementarity, where investors' payoffs depend on their proximity to both market fundamentals and the aggregate behavior of others.

Market equilibrium is characterized by the visibility and outsized influence of the investment giant, whose actions guide other investors and overall market behaviors. As a first-mover, the giant gains a strategic advantage by setting market direction, effectively locking market momentum. Observing the giant's actions enables typical investors to refine their strategies and rely less on private information.

The giant exerts disproportionate influence beyond its market share through two key channels: *the public information channel*, where its actions serve as a public signal that reduces uncertainty for other investors, and *the directional leadership channel*, where it actively steers market aggregates. This influence intensifies when (*i*) the giant holds a larger market share, increasing its weight in market aggregates, and (*ii*) strategic complementarity

is stronger, leading investors to prioritize coordination. These conditions incentivize the investment giant to adopt a sequential-move strategy, as its ex-ante payoffs are higher than those under a simultaneous-move strategy. Consequently, the giant not only induces follower behavior but also steers market aggregates closer to fundamentals.

We then empirically validate our theoretical prediction that investment giants' decisions persistently shape both investor behavior and market aggregates. To that end, we focus on their *contrarian investments*—measured as the growth differential between their investments and those of other investors or market averages.[1] By isolating the giants' unique contributions from common dependencies on fundamentals, contrarian investments allow for a clearer identification of their idiosyncratic influence.

Using panel local projections with EPFR fund-level flow data, we examine the dynamic effects (predictability) of a small group of investment giants' contrarian decisions on individual equity funds across 20 emerging markets.[2] The giants' contrarian flows consistently exhibit strong predictive power for global investor equity flows into emerging markets, highlighting their pivotal role in global asset reallocation.

Further, we extend the analyses to country-level aggregate dynamics. Capital flows and global asset allocations play a pivotal role in shaping financial and foreign exchange markets, particularly in emerging economies (e.g., Hau and Rey 2006, Gyntelberg, Loretan and Subhanij 2018, Wong 2017, Goldberg and Krogstrup 2023). Although EPFR fund flows represent only 1–10% of market capitalization in emerging markets (Jotikasthira, Lundblad and Ramadorai 2012), our country-level analysis consistently reveals that EPFR aggregate flows respond positively to giants' contrarian investments. This pattern remain robust even when using broader datasets such as those from the International Institute of Finance (IIF). The results suggest that investment giants' contrarian flows are a strong predictor of aggregate foreign equity inflows.

Moreover, the predictive power of giants' contrarian investments extends to stock

[1]We also consider two alternative measures to capture the idiosyncratic decisions of giants: (*i*) their share of equity flows into each market (country) and (*ii*) the differential between size-weighted and unweighted averages of equity flows across all investors, following Gabaix and Koijen (2024), termed granular instruments.

[2]We define the top 10 largest investors as giants. Since there is no universally accepted threshold for defining large investors, we test the robustness of our findings using alternative definitions (e.g., the top 7 or top 15 largest investors). The sample includes approximately 100 investors per month on average.

market returns, which show significant positive responses, while exchange rates tend to appreciate following higher equity investments from giants relative to other investors.

Overall, our findings demonstrate that investment giants are indeed the giants in emerging equity markets—observing their behavior provides substantial information for predicting broader market movements (Rey, Planat, Stavrakeva and Tang 2024). These results emphasize the importance of closely monitoring giants' activities in equity and foreign exchange markets, which can serve as an early warning indicator for forecasting foreign portfolio inflows and identifying potential financial vulnerabilities in emerging market economies.

Contribution to the literature Existing literature has examined investment decisions among institutional investors to provide valuable insights for a comprehensive understanding of financial markets. It particularly focused on the collective decision-making processes and co-movements of portfolio investments. 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).

However, there are still unexplored dimensions in this research landscape to which 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 from domestic investors, there is a need for a more international perspective on these issues (Jotikasthira et al. 2012, Raddatz and Schmukler 2012). Our paper takes this perspective into account, thereby providing a better understanding of portfolio allocations by nonresident fund investors. This broader view can be useful for ensuring financial stability in emerging economies increasingly 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 the so-called *a beauty contest* environment, in which participants forecast the behaviors of other players. This concept has been widely studied in financial markets, with significant contributions from both empirical and theoretical studies (e.g., Chen et al. 2010, Schmidt et al. 2016, Jackson and Pernoud 2021). Another essential feature of financial markets is the presence of dominant players. For instance, prior works investigate their prominent role and impacts in the markets; e.g., Corsetti et al. (2004) on dominant players in currency markets and Ben-David et al. (2021) on large investors in U.S. equity markets. Our study bridges the two critical dimensions of financial markets: the strategic interdependence of typical investors and the outsized influence of dominant players.

In addition, most empirical studies pay little attention to the determinants of international portfolio flows at the fund or investor level. While prior studies have predominantly concentrated on aggregate-level flows and the impact of external ("*push*") conditions (e.g., Calvo, Leiderman and Reinhart 1993, 1996, Fernandez-Arias 1996, Taylor and Sarno 1997, Forbes and Warnock 2012), our research enhances this understanding by investigating both new and unexplored determinants at the investor (fund company) 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, Goldberg and Krogstrup 2023). Our paper fills this research void by providing insights into how these factors interact with the investment decisions of institutional investors in emerging equity markets. Probing portfolio choices at the micro level offers a more comprehensive understanding of the dynamics of entire market (Rey et al. 2024).

The remainder of the paper is structured as follows. Section 2 develops the theoretical model, and Section 3 explores its key properties. Section 4 describes the dataset and measurements. Section 5 introduces giants' contrarian flows. Section 6 empirically tests the model's predictions using investor-level regression analysis, while Section 7 extends the analysis to the country level, providing implications for equity and currency markets. Section 8 concludes.

2 A Beauty Contest Framework with Investment Giants

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, and sequential decision-making.

2.1 Model Environments

As emphasized by Keynes (1936), a key feature of financial markets is that participants consider the behaviors of other players (*beauty contest*). This creates an environment for strategic complementarity and coordination among market participants. The beauty contest concept has been widely applied in financial market studies (e.g., Chen et al. 2010, Schmidt et al. 2016, Jackson and Pernoud 2021). Building on the model of Morris and Shin (2002), we assume that investor payoffs depend on market fundamentals and aggregates, thereby introducing coordination motives.

Another feature typically observed in financial markets is the existence of dominant players. Relatedly, two additional assumptions underpin our model. First, typical investors' actions do not affect aggregate market outcomes, whereas the investment giant's decisions shape market equilibrium, as in Corsetti et al. (2004). Second, the giant can choose its timing of action, either moving simultaneously with typical investors or moving first before the others. When moving first, the giant's actions are observable to others (visibility), which is typically associated with large players in financial markets. The ability to choose sequential timing also 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 holding 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 individual market shares $\lambda_j \simeq 0$ and are ex-ante identical. Typical investors collectively account for a total market share of $1 - \lambda$. Due to diversification, their idiosyncratic shocks and information have no aggregate implications, unlike those of the investment giant. In this sense, our

model can be understood as a discrete version of the granular origin model (Gabaix 2011).

Beauty contest framework Each investor chooses an action a_i, representing an abstract investment decision.[3] 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 loss from deviating from aggregate market actions. The latter reflects a strategic complementarity, introducing a coordination motive among investors. The parameter $\omega(\in [0,1])$ governs the importance of coordination 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:

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

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 the 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,

[3] 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.

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

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

The investment giant's timing 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 what follows, we elaborate on the investors' optimal strategies, given the timing of actions, in particular sequential-move ($r_1 = \text{sq}$).[4]

[4]Appendix A.1 provides details on the case of simultaneous-move ($r_1 = \text{sm}$).

2.2 Sequential-move: The Investment Giant Moves First

Typical investors In the sequential-move case, each typical investor chooses an action a_j (for $j \neq 1$) to maximize their expected payoff in equation (1) where the investment giant's signal and action serve as the public information. The first-order condition yields:

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

where $\mathbb{E}[\bar{A}^{\text{sq}}|s_j, s_1, a_1] \equiv \lambda a_1 + (1-\lambda)\mathbb{E}[\bar{a}_0^{\text{sq}}|s_j, s_1, a_1]$ is its belief on the market aggregate action. This optimal strategy is a linear combination of beliefs on the fundamentals (f) and the other investors' actions (the aggregate actions of investors, $\bar{A}^{\text{sq}}$).

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:[5]

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

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 in 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 action of typical investors is then derived as:

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

[5] 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.

To intuitively understand this typical investor's strategy, we consider two limiting cases: (*i*) no strategic complementarity ($\omega \to 0$) and (*ii*) the investment giant's zero market share ($\lambda \to 0$). First, in the absence of a coordination motive, the typical investor's decision problem reduces to a conventional signal-extraction problem:

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

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

Investment giant In the sequential-move case, the investment giant chooses its action a_1 to minimize its deviation from the fundamentals and typical investors' average action. Specifically, given typical investors' average action in equation (9), the giant's profit maximization problem can be modified as follows:

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

where $(1-\lambda)^2$ in the second term reflects the investment giant's advantage arisen from its market dominance. That is, as the giant's market share increases, the loss from deviating from the aggregate market action diminishes. Then, the first-order condition yields:

$$a_1^{\text{sq}} = (1-\omega)\mathbb{E}[f|s_1] + \omega \mathbb{E}[\bar{A}^{\text{sq}}(f, s_1, a_1)|s_1] \underbrace{(1-\lambda)}_{\substack{\text{mkt share} \\ \text{advantage}}} \underbrace{\left\{ 1 - \frac{\partial \mathbb{E}[\bar{a}_0^{\text{sq}}(f, s_1, a_1)|s_1]}{\partial a_1} \right\}}_{\text{first-move advantage}}, \tag{10}$$

where $\mathbb{E}[\bar{A}^{\text{sq}}(f, s_1, a_1)|s_1] = \lambda a_1 + (1-\lambda)\mathbb{E}[\bar{a}_0^{\text{sq}}(f, s_1, a_1)|s_1]$ is the giant's belief on the aggregate. The expectation of the typical investors' average action is represented as a convex combination of its belief about the fundamental and its own action:

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

The giant's optimal decision rule in equation (10) reflects its directional leadership and advantage: its dominant market share (λ) and influence over typical investors ($\partial \mathbb{E}[\bar{a}_0^{\text{sq}}|s_1]/\partial a_1 = \eta_a^{\text{sq}}$) allow it to steer the market, placing less weights on the aggregate market ($\bar{A}^{\text{sq}}$).

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

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

where $\phi^{\text{sq}} = \theta_1$. In the sequential-move structure, the investment giant can steer the market in a favorable direction. Since its payoff decreases as its action deviates from the market aggregate and the fundamentals, the best payoff is achieved when the market aggregate aligns with the fundamentals. Put differently, the most favorable direction for the market is the one that converges toward the fundamentals, which leads the investment giant's action to its belief about the fundamentals. Consequently, the giant's action in the sequential-move setting is identical to that in a signal-extraction scenario, $\phi^{\text{sq}} = \theta_1$.

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 ($r_1 =$ sq and sm).

Simultaneous-move case The optimal action of an investor $i \in [0,1]$ satisfies

$$a_i^{\text{sm}} = (1-\omega)\mathbb{E}[f|s_i] + \omega \mathbb{E}[\bar{A}^{\text{sm}}(a_1^{\text{sm}}, \bar{a}_0^{\text{sm}})|s_i](1-\lambda_i). \tag{13}$$

Unlike in the sequential-move case in equation (4), where investors consider the investment giant's signal (s_1) and action (a_1), typical investors here rely only on their own private signal s_j. In addition, although the investment giant still benefits from its market dominance (represented by $1-\lambda$), it loses a first-move advantage, $\partial \mathbb{E}[\bar{a}_0^{\text{sm}}|s_1]/\partial a_1 = 0$, compared to the sequential case. See A.1 for the details.

Typical investors As delineated in equation (A.2), the optimal action of a typical investor under the simultaneous-move structure is a linear function of its own private signal: $a_j^{\text{sm}}(s_j) = \psi^{\text{sm}} s_j$. Hence, compared to simultaneous-move case, optimal strategies of typical investors in the sequential-move structure differ in two aspects: (*i*) weaker reaction to private signals and (*ii*) stronger dependence on the giant.

Typical investors react less actively to their own signal under the sequential-move structure than under the simultaneous-move structure:

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

This inequality follows from $\theta_0 > \gamma_0$ and ω, λ, and ϕ^{sm} are non-negative.[6] In the simultaneous-move structure, typical investors make their decision solely based on their own signal (s_j). However, when taking an optimal action under the sequential-move structure, they also consider the public information (investment giant's signal; s_1) and the investment giant's action (a_1). The latter is locked in the portion (λ) of the market aggregate, thereby compelling typical investors to follow it to minimize their deviation from the aggregate.

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

First, the investment giant reacts less actively to its own signal under the sequential-move structure than under the simultaneous-move structure:

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

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

Second, as discussed above, the sequential-move provides the giant with a strategic advantage and leads its action to align with its belief about the fundamentals (i.e., $\phi^{\text{sq}} = \theta_1$).

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

However, when the investment giant moves simultaneously with other investors, it loses its directional leadership. Thus, similar to typical investors, the investment giant guesses the market and adjusts its action to the market direction even if it believes that the other investors' actions deviate from the fundamentals. This distortion, represented by $\theta_1 - \phi^{\text{sm}}$ (or equivalently $\phi^{\text{sq}} - \phi^{\text{sm}}$), increases with the degree of strategic complementarity (ω) and the market share of typical investors ($1 - \lambda$), for a given typical investor's strategy (ψ^{sm}).

3 The Role of the Investment Giant: Lead and Influence

The investment giant's role is determined by its decision on whether to move first or simultaneously with typical investors. This choice is guided by a comparison of expected payoffs under each scenario:; $r_1^* = \text{argmax}_{r_1 \in \{\text{sm,sq}\}} \{\mathbb{E}[\pi_1^{\text{sm}}],\ \mathbb{E}[\pi_1^{\text{sq}}]\}$. A sequential move is preferred because the first-move advantage establishes market leadership and amplifies its influence over other investors beyond what its market share alone would suggest.

3.1 Optimal Timing Structure of Actions

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

$$\mathbb{E}[\pi_1^{\text{sq}}] \equiv -(1-\omega)\text{var}(a_1^{\text{sq}} - f) - \omega\text{var}(a_1^{\text{sq}} - \bar{A}^{\text{sq}}). \tag{14}$$

As shown on 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:

$$\text{var}(a_1^{\text{sq}} - f) = \sigma_f^2 \Upsilon(\phi^{\text{sq}}; \theta_1), \quad \text{where} \quad \Upsilon(x; z) \equiv \frac{x^2}{z} - 2x + 1. \tag{15}$$

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, $\Upsilon(\phi^{\text{sq}} = \theta_1; \theta_1) = 1 - \theta_1$. Therefore, $\text{var}(a_1^{\text{sq}} - f)$ depends only on the fundamental variance (σ_f^2) and the quality of the investment giant's signal (θ_1). Importantly, this is because the investment giant's optimal action is identical to

the solution of the 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:

$$\text{var}(a_1^{\text{sq}} - \bar{A}^{\text{sq}}) = \sigma_f^2(1-\lambda)^2(\psi^{\text{sq}})^2\Upsilon(\phi^{\text{sq}};\theta_1). \tag{16}$$

A higher market share of the giant (λ) mechanically reduces its deviations from the market aggregate, as the aggregate action is a weighted combination of the giant's and typical investors' actions ($\bar{A}^{\text{sq}} = \lambda a_1^{\text{sq}} + (1-\lambda)\bar{a}_0^{\text{sq}}$). Beyond this mechanical effect, strategic interaction plays a key role, captured by the term $(\psi^{\text{sq}})^2$. In the sequential-move case, the investment giant's first-move advantage allows it to steer the market. Typical investors, anticipating this, rely less on their own private signals (low ψ^{sq}) and instead follow the giant's lead. This herding behavior reduces the giant's deviation from the market, reinforcing its influence. This strategic advantage is further amplified when the coordination motive is strong (high ω) and when the giant holds a dominant market position (high λ).

The giant's optimal choice: Sequential-move Comparing the ex-ante payoffs under sequential- and simultaneous-move structures reveals that the giant prefers to move first.

When the giant moves simultaneously, its ex-ante payoff is:

$$\mathbb{E}[\pi_1^{\text{sm}}] \equiv -(1-\omega)\text{var}(a_1^{\text{sm}} - f) - \omega\text{var}(a_1^{\text{sm}} - \bar{A}^{\text{sm}}). \tag{17}$$

The first term captures the variance of the giant's deviation from fundamentals:

$$\text{var}(a_1^{\text{sm}} - f) = \sigma_f^2\Upsilon(\phi^{\text{sm}};\theta_1) > \text{var}(a_1^{\text{sq}} - f). \tag{18}$$

Because $\Upsilon(\cdot;\theta_1) \geq 1-\theta_1 = \Upsilon(\phi^{\text{sq}};\theta_1)$, the variance of deviations from fundamentals is always higher in the simultaneous-move case. In our setting, the giant has an incentive to align its action with its belief about typical investors' actions, leading it to deviate from its belief about the fundamental value. However, under the sequential-move structure, market leadership allows the giant's action to align only with its belief about fundamentals,

reducing this variance.

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

$$\text{var}(a_1^{\text{sm}} - \bar{A}^{\text{sm}}) = \sigma_f^2(1-\lambda)^2(\psi^{\text{sm}})^2\Upsilon(\phi^{\text{sm}}/\psi^{\text{sm}};\theta_1) > \text{var}(a_1^{\text{sq}} - \bar{A}^{\text{sq}}), \tag{19}$$

The inequality holds because $\psi^{\text{sm}} > \psi^{\text{sq}}$. The investment giant can steer typical investors more effectively in the sequential-move case than in the simultaneous-move case, reducing the variance of its deviation from the market.

Overall, the giant's ex-ante payoff is maximized under the sequential-move structure:

$$\mathbb{E}[\pi_1^*] \equiv \max\left\{\mathbb{E}[\pi_1^{\text{sq}}], \mathbb{E}[\pi_1^{\text{sm}}]\right\} = \mathbb{E}[\pi_1^{\text{sq}}], \tag{20}$$

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 $\{\phi^*, \psi^*, \eta_s^*, \eta_a^*\} = \{\phi^{\text{sq}}, \psi^{\text{sq}}, \eta_s^{\text{sq}}, \eta_a^{\text{sq}}\}$.

The equilibrium of our model—the investment giant moves first, and then typical investors follow—is consistent with the literature. A key feature of the equilibrium is the visibility of the giant's actions (e.g., Corsetti et al. 2004). More pointedly, typical investors observe the giant's decision, treating it as public information that implicitly signals market fundamentals (*public information channel*). This channel grants an informational advantage to typical investors. That is, the public information helps typical investors reduce uncertainty as they can base their decisions not only on their private signals but also on the giant's revealed action. Therefore, typical investors align their actions with both the fundamentals and the market. Moreover, our beauty contest framework highlights a strategic advantage for the giant as a first-mover. By acting first, the giant can lead the market aggregate in a favorable direction, bringing it closer to both the fundamentals and its own action (*directional leadership channel*). Consequently, the investment giant has a strong incentive to lead the market by taking the first move. These two channels will be discussed further from the typical investors' perspective in the following subsection.

3.2 Influences on Typical Investors and Market Movements

Typical investor's optimal choices In equilibrium, the investment giant's signal s_1 not only determines its optimal action a_1^* in 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 equations (5) and (9), respectively. By substituting s_1 with a_1^* in these equations, we derive:

$$a_j^* = \psi^* s_j + (1-\psi^*)a_1^* = \psi^* f + (1-\psi^*)a_1^* + \psi^* \epsilon_j, \tag{21}$$

where typical investors' optimal actions represent a weighted average of their private signals (s_j) and the investment giant's action (a_1^*), with the weights determined by $\psi^* \in [0,1]$. This aligns closely with the main regression specification in Section 6, demonstrating that a typical investor's action is positively related to the investment giant's action.

Similarly, the market's aggregate action can be reformulated as a function of the fundamentals and the investment giant's action:

$$\bar{A}^* = (1-\lambda)\psi^* f + [1-(1-\lambda)\psi^*]a_1^*. \tag{22}$$

Hence, the influence of the giant's decision on the market aggregate increases with its market share (λ) and with typical investors' reliance on the giant's action ($1-\psi^*$). This corresponds to the country-level regression specification in Section 7, showing the model prediction that the giant's action positively affects market aggregates. Therefore, these predictions from equations (21) and (22) guide our empirical investigation into how giants influence other investors' decisions and aggregate market dynamics.

The above two equations also reveal how strategic complementarity and the investment giant's market share shape typical investors' behavior. Specifically, as either the 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 giant's action ($\partial a_j^*/\partial a_1^* = 1-\psi^*$) in equation (21):

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

Furthermore, as ω and λ increase, the market aggregate relies less on the fundamentals but more on the giant's action:

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

where $\partial\bar{A}^*/\partial f$ and $\partial\bar{A}^*/\partial a_1^*$ denote the market reliance on the fundamentals and the giant's action, each derived from equation (22) as $(1-\lambda)\psi^*$ and $1-(1-\lambda)\psi^*$, respectively.

These results underscore the investment giant's dual role: 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 giant can steer the market towards its preferred direction. When the giant holds a substantial market share (high λ), typical investors are discouraged from deviating, and instead align their actions more closely with the giant's decision. Also, stronger strategic complementarity (high ω) amplifies the motivation to follow the 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 giants in driving market dynamics and coordinating investor behavior.

Typical investor's payoffs In equilibrium, a typical investor's ex-ante payoff systematically depends on the investment giant's market share (λ) and the degree of strategic complementarity (ω). A larger market share of the giant (high λ) strengthens its ability to influence market direction (*directional leadership*), prompting typical investors to follow the giant more closely. As a result, their deviation from the market aggregate decreases, whereas their deviation from the fundamentals increases:

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

Similarly, stronger strategic complementarity (high ω) amplifies coordination motives, further widening the deviation from the fundamentals while narrowing the deviation from

the market aggregate:

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

The above results imply that the giant's directional leadership reduces cross-sectional variation in investment decisions among typical investors but also contributes to market disconnection from fundamentals, i.e, excess volatility. In equilibrium, the ex-ante variance of the market-wide deviation from the fundamentals is given by:

$$\text{var}(\bar{A}^* - f) = [1 - (1 - \lambda)\psi^*]^2(1 - \theta_1) \times \sigma_f^2, \tag{23}$$

where ψ^* represents a typical investor's reliance on their private signal, which decreases with both the giant's market share and the degree of strategic complementarity. Consequently, when the giant has strong market leadership and typical investors rely more on its actions (high λ and ω), the market's deviation from the fundamentals increases:

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

Next, we compare the payoffs of the investment giant and typical investors. The investment giant's first-move advantage is always beneficial for the giant itself. However, its impact on typical investors is to some extent nuanced. On the one hand, the giant's early action provides valuable public information, helping typical investors form more accurate forecasts of the fundamentals. On the other hand, the giant's strong market influence can reduce typical investors' payoffs by reinforcing coordination effect, which constrains independent decision-making. Ultimately, the giant always secures a higher ex-ante payoff than typical investors, as its deviations from both the market aggregate and the fundamentals are smaller:

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

Further details and discussions can be found in Appendix A.2.

4 Data and Measurements

Motivated by the predictions of our theoretical model regarding the influence of investment giants, we will empirically examine how these giants interact with other investors and shape aggregate market dynamics. As a preliminary step before the empirical analysis, this section first outlines the data sources and the construction of key variables. This provides the foundation for measuring investor behavior at a granular level, enabling a systematic investigation of equity market dynamics. Next, we visually explore the data to highlight investment giants based on flow concentration and market share.

4.1 Mutual Funds and Macro Data

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.[7] The EPFR database provides detailed information for each fund company'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 Equity Flows To track how each institutional investor (fund company) adjusts its investment behavior, we calculate the size of the investor i's equity investment, $\text{Equity}_{ic,t}$, to a particular country c at time (month) t, as:

$$\text{Equity}_{ic,t} = \sum_{a \in \text{AssetClass}} \text{EquityShare}_{aic,t} \times \text{TotalNetAssets}_{ai,t}, \tag{24}$$

where $\text{TotalNetAssets}_{ai,t}$ is the total (equity) investment of investor i's asset class a across all host countries, and $\text{EquityShare}_{aic,t}$ is the equity investment share of investor i's asset class a in country c out of its total investment at time t.

[7] 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.

There are instances where an institutional investor does not invest in equities in a particular market or country. Since both the logarithmic value of equity investment and its 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 $t + h$:

$$\Delta^h \text{IHS}(\text{Equity}_{ic,t}) = \text{IHS}(\text{Equity}_{ic,t+h}) - \text{IHS}(\text{Equity}_{ic,t}). \tag{25}$$

However, equity growth in equation (25) includes valuations resulting from equity returns and exchange rates. Hence, even when investors do not adjust their investments, high (low) equity returns and currency appreciation (depreciation) lead to an increase (decrease) in the investors' equity holdings. In this case, the equity growths overestimate (underestimate) investment allocation. To isolate the valuation effect, we compute the cumulative equity growth based on the adjusted equity growth accounting for market returns:

$$\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = \text{IHS}\left(\text{Equity}_{ic,t+h} \times \frac{\text{StockIndex}_{c,t}}{\text{StockIndex}_{c,t+h}} \frac{\text{FX}_{c,t+h}}{\text{FX}_{c,t}}\right) - \text{IHS}(\text{Equity}_{ic,t}), \tag{26}$$

which controls for the stock market index and exchange rate growths in country c.

Macroeconomic variables In addition to fund-level data, we incorporate country-level macroeconomic variables, which 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, a pull factor pertains to domestic features that reflect a country's macroeconomic fundamentals such as GDP, reserves, interest rates, and the stock market index. A 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 the pull and push factors, along with their three lags.

Further details and summary statistics Further details on data collection and variable construction are available in Appendix B. Tables A.1–A.5 report summary statistics.

4.2 Investment Giants and Concentrated Equity Flows

For our analysis of the interplay among investor flows of different sizes, we should first set a criterion for categorizing individual flows 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 investors from non-large ones. To address this issue, we establish a reasonable rule of thumb by analyzing the size distribution of investor flows in relation to their equity investments in 20 emerging markets.[8]

Specifically, we first sort equity investor sizes based on the over-time average of each investor's total equity fund investments in the 20 emerging markets between January 2010 and December 2018.[9] Then, we designate the top 10 largest equity investors as the investment giants throughout the sample period.[10] The investors not falling within the top 10 are categorized as typical (non-large) investors. Notably, these investment giants have consistently held the top-ranking positions over time due to their substantial assets under management.

Investor-level equity flow data points to the critical role of investment giants in global capital flows to emerging markets. These dominant players significantly shape both the volume and direction of portfolio flows. Figure 2 illustrates key patterns in equity investments by investors 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 over the sample period, rising from approximately USD 200 billion to USD 600 billion, with a sharp decline during the GFC in 2008. This growth was primarily driven by investment giants. The second panel reveals a steady increase in the

[8]They include Brazil, Chile, China, Colombia, Czech Republic, Hungary, Indonesia, India, Israel, South Korea, Mexico, Malaysia, Peru, the Philippines, Poland, Russia, Thailand, Turkey, Taiwan, and South Africa.

[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.

[10]These 10 investors 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.

Alternatively, we also consider the top 7 and 15 largest investors as investment giants. The top 7 largest investors are identical to the top 10 largest investors but excluding Capital Research & Management, Comgest S.A., and Genesis Investment Management. The top 15 largest investors 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 investors.

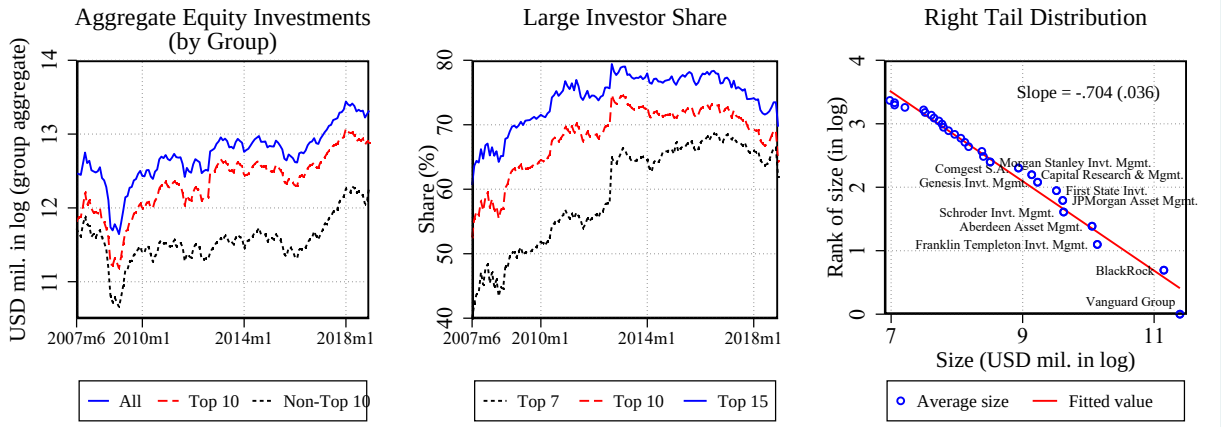


Figure 2: Trends of Equity Flows to Emerging Markets

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 flows 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 investor-level equity flow data are sourced from the EPFR database. See Appendix B.1 for the details.

share of equity investments attributable to large mutual funds since the GFC, peaking around 2013, highlighting the growing dominance of these major players.

The distribution of global equity investments also demonstrates pronounced concentration among a few large investors. 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 the size in log: $\ln(\text{Rank}) \approx -0.7 \ln(\text{Size})$. This pattern is consistent throughout the sample period from January 2010 to December 2018, indicating persistent granularity in non-resident equity flows into emerging market.[11]

In summary, fund-level data reveal 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

[11]Figure A.16 presents similar patterns for active fund flows, excluding passive funds. These results corroborate the heavy reliance of emerging equity markets on giants. In Figure A.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.

with the model environment, and thus motivate a closer empirical investigation into the strategic interactions between investment giants and typical investors.

5 Investment Giant's Contrarian Equity Flow

Before our regression analyses, we introduce the concept of *giants' contrarian investment flows*, defined as the deviation of giants' investments from those of other investors or market. This measure is central for identifying giants' influence, as it mitigates empirical challenges arising from shared dependencies on fundamentals in investment decisions.

5.1 Measure for the Giant's Idiosyncratic Decisions

Our primary empirical interest lies in the investment decisions of giants and their influence. However, a direct regression of giants' investment flows on other investors' flows or aggregate market variables risks overstating their influence due to shared dependence on underlying economic fundamentals. Since both giants and other investors make their investment decisions based on the fundamentals, the observed relationships may reflect spurious correlations. While panel regressions account for fixed effects as well as push and pull factors, they may still suffer from unobserved fundamentals. Consequently, the estimated influence of giants' flows can be largely derived from their correlation with these shared fundamentals. Moreover, strong correlations between giants' flows and fundamentals may introduce multicollinearity, complicating inference.

To address these challenges, we focus on the giants' contrarian investment flows. The intuition is straightforward: since both the giants' and other investors' decisions reflect common economic fundamentals, these fundamentals can be effectively canceled out in the differential. Moreover, the idiosyncratic components of other investors' decisions are largely diversified away at the aggregate/average level. As a result, the giants' contrarian flows isolate their unique idiosyncratic investment behavior while excluding the confounding effects of shared fundamentals.

5.2 Benchmark Measure

As a proxy for the giant's idiosyncratic investment decisions (*contrarian investment*), we primarily use the difference between the average equity growth of giants and that of typical investors.

$$\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}} = \frac{1}{N^{\mathcal{G}}} \sum_{i \in \mathcal{G}} \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}) - \frac{1}{N_t - N^{\mathcal{G}}} \sum_{i \notin \mathcal{G}} \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}), \quad (27)$$

where $\bar{g}_{c,t}^{\text{giant}}$ and $\bar{g}_{c,t}^{\text{typical}}$ are the average equity growth between t and $t-1$ for investors in two groups: investment giants ($i \in \mathcal{G}$) and typical investors ($i \notin \mathcal{G}$). $N^{\mathcal{G}}$ and N_t denote the number of investment giants and the total number of investors, respectively.[12]

The investment giants' contrarian investment measures the extent to which their investment growth surpasses that of typical investors. A positive differential, $\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}} > 0$, indicates that giants increased their equity investments in country c more than typical investors. This suggests that giants are more aggressive or optimistic in their investment decisions compared to typical 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. Global investor equity flows increase following a rise in giants' investments in the prior month, whereas no such pattern emerges for typical investors' flows. This pattern becomes even more pronounced when examining the differential between investment giants and typical investors, as shown in the third chart of each panel. Global investors tend to increase their equity flows when giants' growth rates exceed those of typical investors. These observations suggest that giants' decisions may substantially influence other investors and shape aggregate trends in emerging equity markets.

[12] Here, we use the valuation-adjusted equity growths. Similarly, the investment giants' and typical investors' averages of valuation-adjusted equity growth ($\tilde{\bar{g}}_{c,t}^{\text{giant}}$ and $\tilde{\bar{g}}_{c,t}^{\text{typical}}$) 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: $\tilde{\bar{g}}_{c,t}^{\text{giant}} - \tilde{\bar{g}}_{c,t}^{\text{typical}} \approx \bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}$.

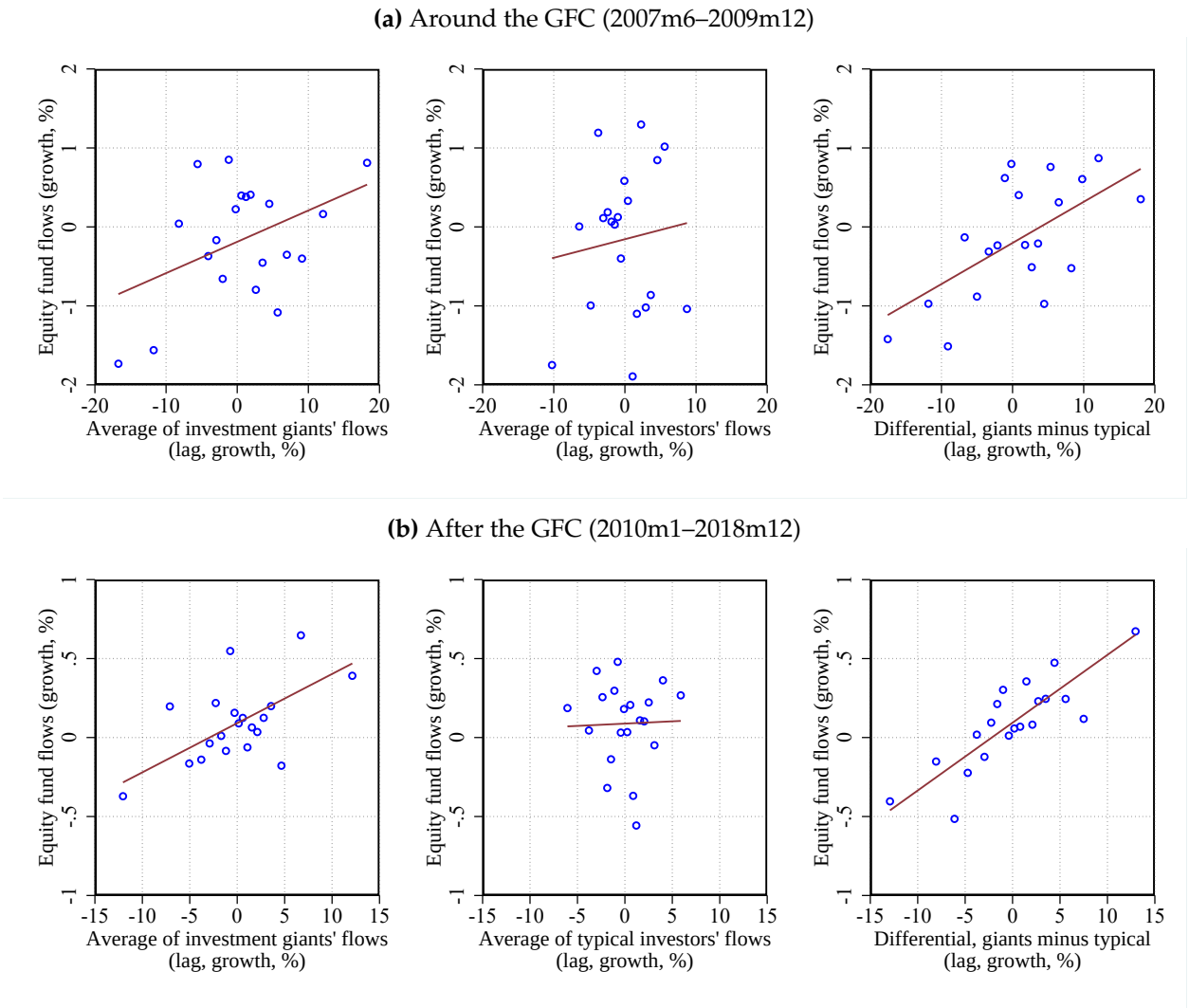


Figure 3: Equity Flows over the Lagged Investment Giants' and Typical Investors' Average Equity Flows

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 charts of each panel, investors are divided into 20 bins on the x-axis based on their average one-month lagged equity investment growths as investment giants (top 10 largest investors; $\bar{\tilde{g}}^{\text{giant}}_{c,t-1}$) and typical investors (non-investment giants; $\bar{\tilde{g}}^{\text{typical}}_{c,t-1}$), 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.

5.3 Alternative Measures

In a similar vein, two alternative measures are taken into account to capture the giants' contrarian investment. The first alternative measure captures the giants' changing market share in the equity market c at time t, defined as:

$$\frac{1}{N^{\mathcal{G}}}\sum_{i\in\mathcal{G}}\Delta^1\left(\frac{\text{Equity}_{ic,t-1}}{\text{Equity}_{c,t-1}}\right)\approx \bar{g}^{\text{giant}}_{c,t}-\bar{g}^{\text{agg}}_{c,t} \tag{28}$$

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 growth of aggregate equity between t and $t-1$ in country c. This measure approximates the giants' average investment growth relative to the aggregate market.

The second approach adopts a continuous-type measure that does not depend on a predefined set of giants. Inspired by Gabaix and Koijen (2024), we construct a granular instrument that extracts idiosyncratic giants' flows by comparing the size-weighted and unweighted investment growth of all investors:

$$\sum_i\left(\frac{\text{Equity}_{ic,t-1}}{\sum_j\text{Equity}_{jc,t-1}}\right)\Delta^1\text{IHS}(\text{Equity}_{ic,t-1})-\frac{1}{N_t}\sum_i\Delta^1\text{IHS}(\text{Equity}_{ic,t-1}). \tag{29}$$

The benchmark and alternative measures are positively correlated as shown in Figure A.18. After the GFC (2007m6–2009m12), the correlation coefficients between the benchmark measure and the two alternative measures are 40.76% (with the giants' changing market share) and 65.68% (with the differential between size-weighted and unweighted investment growth). Additionally, the correlation between the two alternative measures is 37.47%.[13] Such strong correlations predict that the three measures capture similar dynamics of giants' idiosyncratic behavior, and all empirical results remain robust across the different measurements, reinforcing the consistency of our findings.

[13]The corresponding correlation coefficients during the GFC period (2010m1–2018m12) are 54.61%, 64.73%, and 45.28%, respectively.

6 Equity Flow Dynamics with Investment Giants

This section implements panel local projections on the investor-level data to examine how other investors react to the decisions of investment giants in emerging equity markets. Our micro-level results establish that the giants' decisions carry significant information and highlight their influence on other investors, in line with the model prediction.

6.1 Empirical Specification

Our regression analyses examine the predictability of investment giants' contrarian equity flow growth for subsequent equity flow growth of other investors and its time-varying nature. The main hypothesis, derived from our model predictions in Section 3, posits that individual fund flows in emerging markets are influenced by the giants' investments. To simplify our empirical framework, we assume that each investor perceives the overall stock market of an emerging economy as a representative asset and determines their investment considering the specific characteristics of the market. These characteristics systematically vary with the macroeconomic conditions in each country. Since investment giants are also affected by the conditions, we rely on their contrarian (idiosyncratic) investment decisions, as discussed in Section 5, to isolate their distinct influence.

Regression specification Motivated by our theoretical model as in equation (21), we employ the investor-level demand model specified as a linear function of all covariates. The regression of (30) is estimated using panel local projection *à la* Jordà (2005), separately for the sub-samples during the GFC and of the post-GFC periods.

$$\begin{aligned}\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = \beta^h \big(\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}\big) \\ + \mathbf{\Gamma}^h_{\text{pull}} \mathbf{Pull}_{c,t} + \mathbf{\Gamma}^h_{\text{push}} \mathbf{Push}_t + \delta_i^h + \delta_c^h + \delta_m^h + \varepsilon_{ic,t}^h, \end{aligned} \tag{30}$$

for the time horizon considered $h = 1, 2, \cdots, 10$. The dependent variable is the adjusted cumulative equity growth given in equation (26).

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; $\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}$ in equation (27)) as a main regressor. As discussed in Section 5, it is constructed to exclude the effects of fundamentals shared among investors. Thus, its coefficients β^h gauge the influence of giants' distinct portfolio decisions on the demand of individual investors for equity flows and their dynamics.

The regression further accounts for overall economic conditions by incorporating standard control variables. The vector $\mathbf{Pull}_{c,t}$ and $\mathbf{Push}_t$ include other control variables, encompassing both pull and push factors at time t along with their three lags.[14] 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, growth rates of industrial production, total reserves, exchange rates, and the stock market index for each emerging country c. Push factors encompass external or global conditions, including the corresponding US variables, such as US real interest rates and growth rates of the VIX, US industrial production and stock market index.

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

Sample periods Our sample period is June 2007 to December 2018. However, the effects of investment giants may differ across periods, particularly around the GFC. To address

[14] 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).

this concern, we divide our sample into two periods: during the GFC (from June 2007 to December 2009) and after the GFC (from January 2010 to December 2018).

Numerous studies, relying on gross-level data, have documented significant shifts in capital flow patterns in the aftermath of the GFC (Rey 2015). Shin (2014), Hardy and von Peter (2023), and other studies emphasize the importance of distinguishing between two phases of global liquidity. Ahmed and Zlate (2014), Ahmed, Coulibaly and Zlate (2017) report shifts in aggregate net inflows, particularly in portfolio flows before and after the GFC. 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 may provide additional insights into how interactions among individual investors contributed to the developments in capital flows during the post-GFC periods. For instance, during the crisis, investors in emerging markets may become suspicious of the actions taken by other investors and imitate them 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, 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.

6.2 Regression results

Figure 4 provides the impulse responses (β^h) of valuation-adjusted equity flows to an increase in shocks to investment giants' contrarian investment for the GFC period (left chart) and the post-crisis period (right chart).[15] The impulse responses provide information on the predictability of average growth rate differentials between giants and typical investor flows for subsequent equity flows among other individual investors. The confidence intervals are drawn from the clustered standard errors at the investor-level.

[15]For comparison, we also provide the results with non-adjusted equity flows in Figure A.19.

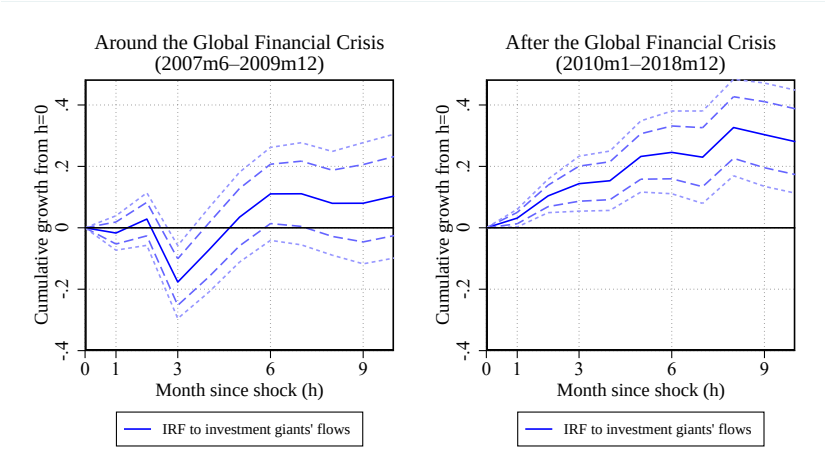


Figure 4: Investor-Level Response to the Equity Flow Differential between Investment Giants and Typical Investors

Notes: The figures depict the predictive capacity of average equity flows from the differential between investment giants' (the top 10) and typical investors' average equity growths where we use an individual investor's equity flows ($\tilde{\Delta}\text{IHS}(\text{Equity}_{ic,t})$) and the differential ($\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}$) are adjusted by stock market index and exchange rate growths to remove valuation effects. The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (30). 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, %).

Two noteworthy findings emerge from the results. First, institutional investors tend to follow the lead of investment giants, corroborating the model prediction. An increase in the giants' 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 giants leads the overall market participants, presumably providing positive signals to 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 giants when determining global portfolio allocation.

Second, the pattern of individual equity flows following giants' contrarian decisions 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 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 $h = 8$. The finding indicates that the post-GFC period provides an environment more conducive to the behaviors predicted by our theoretical framework. This likely reflects the structural shifts in global capital flows and investor behavior after the crisis, marked by the rise of investment funds searching for yields—conditions that align more closely with our model's predictions.

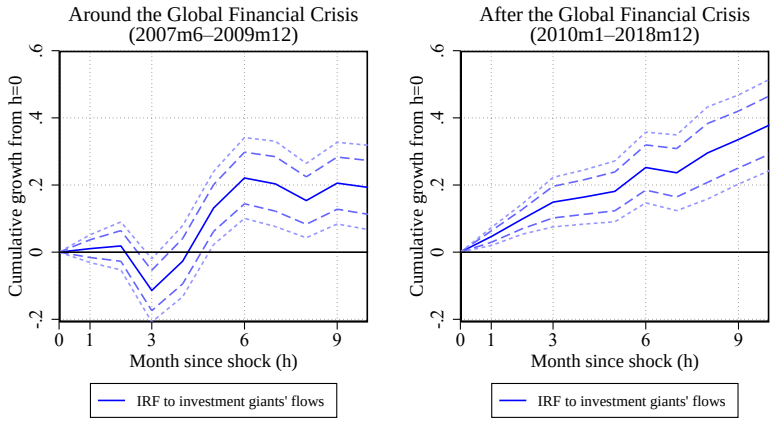
6.3 Robustness Checks

To ensure the robustness of our findings, we consider the alternative measures of investment giants' contrarian behavior, presented in Section 5, that help isolate their idiosyncratic influence from broader market movements. Specifically, we estimate the local projections of equation (30), replacing our main regressor with the two alternative measures: (*i*) the investment giants' share of equity flows into each market (country), defined in equation (28), and (*ii*) the differential between the size-weighted and unweighted averages of equity flows across all investors in equation (29).

Figure 5 presents the results. Panels (a) and (b) report investor-level equity flow responses to changes in the two measures, respectively, for the GFC period (left charts) and the post-GFC period (right charts). The results largely align with the baseline: in the post-crisis period, individual investors' equity flows respond positively to giants' contrarian flow shocks. These patterns reinforce the robustness of our findings in Figure 4, underscoring the influence of giants on other investors and the predictive power of giants' contrarian investment decisions.

Further robustness checks In Appendix C, we summarize the results from a battery of robustness checks. The strong predictability of investment giants' flows for the equity market is greatly robust to (*i*) dataset with active flows, (*ii*) different fixed effects, and (*iii*) different definitions of giants, and (*iv*) regression during (local) stock market crashes.

(a) Changes in Investment Giants Share



(b) Equity Flow Differential between Size-weighted and Unweighted Averages

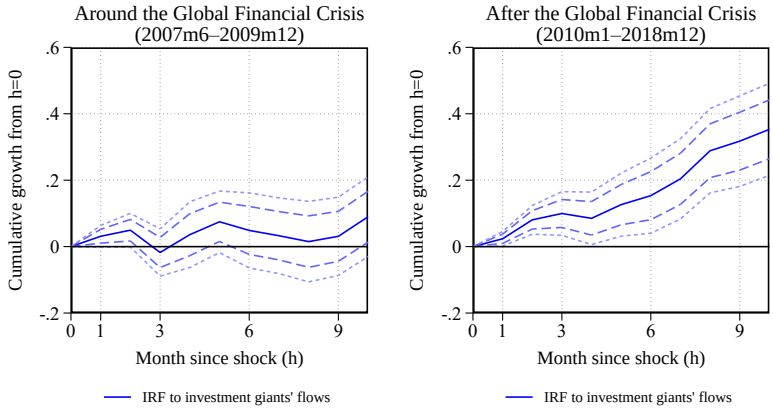


Figure 5: Investor-Level Response to Changes in Alternative Measures of Contrarian Investments

Notes: The figures depict the predictive capacity of alternative measures of contrarian active equity investments made by the top 10 investment giants. In panel (a), the alternative measure is the change in the share of active equity investments made by the top 10 investment giants, as defined in equation (28). In panel (b), the alternative measure is the difference between size-weighted and unweighted averages of investors' active flows, as defined in equation (29). They are adjusted by stock market index and exchange rate growths to remove valuation effects. The responses to contrarian active flows are the estimates of β^h in equation (30). 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, %).

7 Aggregate Dynamics and Implications

This section investigates the influence and predictive power of these giants on aggregate capital flows, stock returns, and exchange rates in emerging markets. Aggregate-level analysis goes beyond simply validating our theoretical predictions; it also provides practical policy implications for emerging economies. Emerging market economies have steadily grappled with the challenge of predicting and mitigating global financial shocks while coping with volatile cross-border capital flows—key drivers of financial instability. Investment giants may serve as the nexus between these global factors and capital movements. That is, with their substantial market share and strategic behavior, investment giants may play a systemically important role by extending their influence beyond individual investor decisions to broader macroeconomic and financial market dynamics.

7.1 Connecting the Dots: From Investor-level to Aggregate-level

One of the fundamental questions in international finance is how cross-border capital flows influence financial and foreign exchange markets, particularly in emerging economies (e.g., Hau and Rey 2006, Gyntelberg et al. 2018, Goldberg and Krogstrup 2023). While prior studies have examined aggregate capital flows, less attention has been given to the role of individual global investors, including investment giants, in driving these dynamics. However, investors' decisions at the micro level account for stock prices and exchange rates remarkably well in emerging markets.

Figure 6 indeed exhibits a strong correlation between global equity fund flows (aggregated EPFR), stock prices, and exchange rates (local currency per USD) across 20 emerging markets. Despite accounting for only 1–10% of market capitalization, EPFR fund flows exhibit strong co-movement with aggregate flows (Jotikasthira et al. 2012) and market returns (Rey et al. 2024). This suggests that even relatively small cross-border equity flows can exert outsized influence, and also raises an important empirical question: do investment giants, through their contrarian flows, systematically impact country-level equity flows and financial conditions in emerging markets?

Prior research has documented the link between capital flows and financial factors,

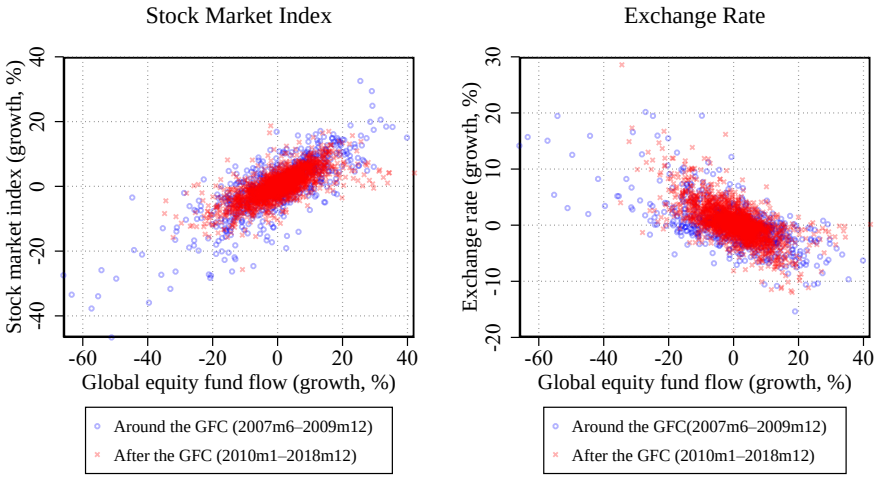


Figure 6: Global Equity Fund Flows, Stock Prices, and Exchange Rates in Emerging Economies

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.

both local and global, such as domestic stock indices, US equity market movements, and exchange rate fluctuations. Among them, Warther (1995) and Edelen (1999) highlight the contemporaneous impact of aggregate mutual fund flows on stock returns, while Coval and Stafford (2007) documents the price pressures exerted by large-scale fund flows in the US equity market. Additionally, Lilley, Maggiori, Neiman and Schreger (2022) finds that US purchases of foreign bonds have been a key driver of currency dynamics post-GFC. However, these relationships remain debatable (Wardlaw 2020, Gabaix and Maggiori 2015).

The rest of this section empirically examines the predictive role of investment giants in shaping aggregate market outcomes, addressing whether their contrarian flows can serve as early indicators of financial stress in emerging equity and currency markets.

7.2 Investment Giants and Aggregate Equity Flows

We initiate aggregate-level examination by assessing the investment giants' role in the dynamics of aggregate equity flows. Given their limited market coverage, the predictive power of giants' contrarian flows within the investor-level EPFR universe does not necessarily imply their predictability for the entire equity flows (e.g., those in the Institute of

International Finance (IIF) database). Hence, beyond testing the theoretical predictions, this exercise also addresses an important empirical question that remains open.

Regression specification Mapping our theoretical model prediction in equation (22) of Section 5 to the data, we estimate country-month panel local projections for the aggregate flows using the following equation:

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

where $Y_{c,t}^h$ represents (either valuation-adjusted or non-adjusted) aggregate equity growth or the change in the ratio of aggregate net flows to GDP 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 flows are supplemented by the IIF database from the IMF. In addition, identically to our investor-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 extreme values. Similar to previous regressions, equation (31) includes standard control variables—push and pull factors and various fixed effects—defined comparably to those in equation (30).

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 of equation (22). They also align with our earlier findings from investor-level regressions in Section 6.

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

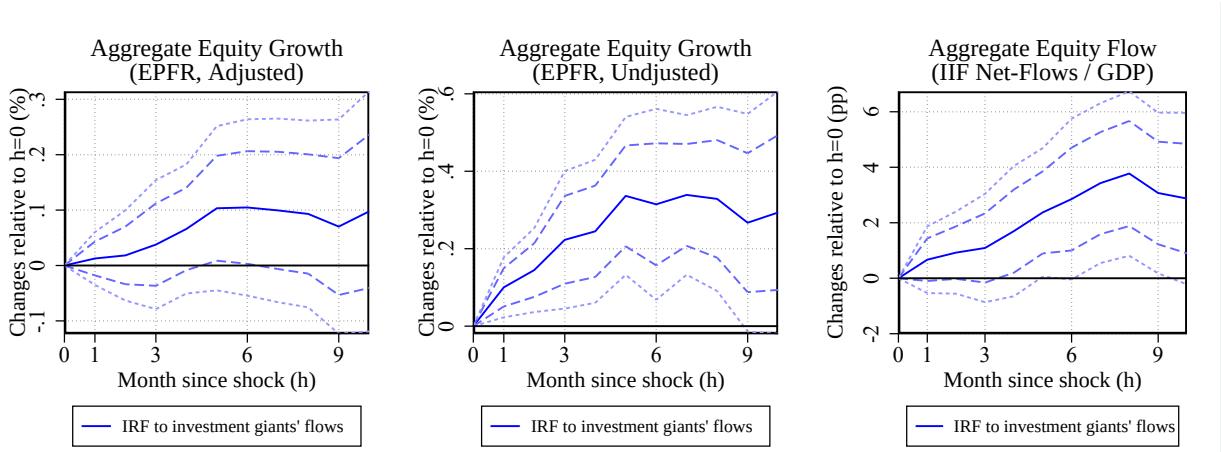


Figure 7: Aggregate Flow Responses to Investment Giants Flows

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 (%).

results from aggregate funds data corroborate the predictability of giants' idiosyncratic flows for other equity flows, consistent with the findings from the investor-level data. Put another way, the results collectively indicate that preceding contrarian movements by investment giants have strong predictive power for investor flows not only at the investor level but also at the entire aggregate level.

Robustness checks To ensure the robustness of these findings, we conduct additional analyses using alternative specifications similar to those in Section 6: (*i*) dataset with active flows, (*ii*) different fixed effects, (*iii*) different definitions of investment giants, and (*iv*) alternative main regressors (changes in investment giants' share and differential between size-weighted and unweighted average of equity flows). 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 D.1.

7.3 Investment Giants, Future Stock Returns and Exchange Rates

Having explored the impact of investment giants on aggregate capital flows, we now examine the relationship between their contrarian flows and financial conditions in emerging markets, focusing on stock returns and exchange rates. This analysis contributes to the ongoing debate on global financial cycles and their consequences by identifying investment giants as a robust predictor and a potential transmission channel for global factors into emerging markets.

Regression specification We estimate the responses of stock markets and foreign exchange markets to the giant flow shocks (contrarian flows), using the regression:

$$Z_{c,t}^h = \beta^h \left(\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}} \right) + \mathbf{\Gamma}_{\text{pull}}^h \mathbf{Pull}_{c,t} + \mathbf{\Gamma}_{\text{push}}^h \mathbf{Push}_t + \delta_c^h + \delta_m^h + \varepsilon_{c,t}^h, \tag{32}$$

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

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

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, the investment giant idiosyncratic flows have incremental effects on stock market indices in emerging markets. The response is the strongest around five months after the shock, rising by around 0.14%. This finding is consistent with the literature that 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 advanced economies (Hau and Rey 2006) and emerging economies (Borio 2019). In

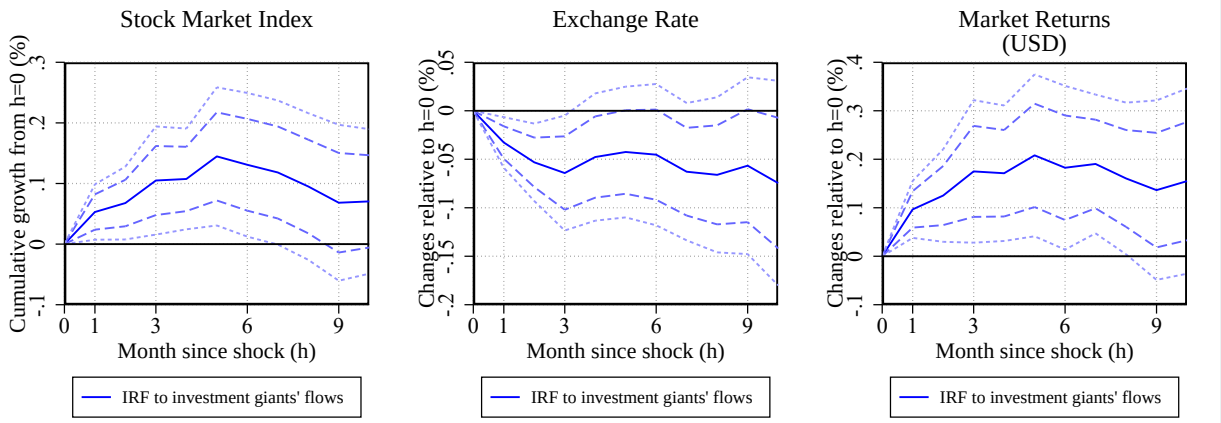


Figure 8: Stock and Currency Markets Responses to Investment Giants Flows

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 (%).

conjunction with our previous finding—the positive predictability of investment giant flows on aggregate equity flows—the relationship between giant flows and exchange rates supports the earlier findings and further identifies giants as an important driving force.

Lastly, 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 giants' contrarian flows. According to the uncovered equity parity hypothesis, relative market returns represent international arbitrage opportunities in emerging equity markets. Therefore, the results suggest that idiosyncratic flows of giants generate a positive reaction in relative returns, which in turn attracts other investor flows.

Policy implications Our findings have significant policy implications, particularly for emerging markets. As the influence of global factors, often referred to as *the global financial cycle*, has substantially grown, small open economies—especially those that have experienced large credit inflows—face increasing challenges in shielding their financial markets from external shocks (*dilemma*, e.g., Rey 2015, Kalemli-Özcan 2019, Goldberg and

Krogstrup 2023). In light of this, economies highly exposed to cross-border portfolio flows must refine their policy frameworks to better monitor capital flow shocks.

Given the giants' predictive power, central banks and regulators could track the contrarian flows as early warning indicators of market shifts. Furthermore, policies aimed at mitigating hot money risks (e.g., macroprudential regulations, capital controls) should account for the outsized influence of investment giants. As capital flows impact (or predict) currency valuations, foreign exchange market interventions and reserve accumulation strategies should factor in the behavior of the dominant investors.

Robustness checks To ensure the robustness of these findings, we conduct additional analyses using alternative specifications: (*i*) dataset with active flows, (*ii*) different fixed effects, (*iii*) different definitions of investment giants, and (*iv*) alternative main regressors (the change in giants' share and the differential between size-weighted and unweighted averages). The aggregate-level results remain by and large robust across different data and specifications. Appendix D.2 presents the results for our robustness checks.

8 Conclusion

The global financial landscape has undergone significant shifts in recent decades, with changes in capital flows playing a crucial role, particularly in emerging economies. Global factors—primarily the dominance of the US dollar and US monetary policy—not only shape capital flows but are also influenced by them, with profound implications for local financial markets. Since the Global Financial Crisis, cross-border capital flows have increasingly shifted from bank-intermediated to market-based channels, underscoring the need for a deeper understanding of portfolio flow dynamics and their macro-financial consequences, especially in emerging markets.

Despite its critical importance, however, our understanding of global portfolio allocations remains limited, with much of the focus centered on the aggregate-level interplay among the flows and macroeconomic factors. Studies at the fund or investor level, which explore the interactions among investors, their effects on aggregate flows, and the under-

lying mechanisms, are still scarce. This knowledge gap is particularly concerning in an environment where the composition of investors and investment strategies has become increasingly complex. A lack of granular insights not only constrains our understanding of capital flow dynamics but also limits policymakers' ability to respond proactively to shifts in global capital flows.

This paper addresses this void by providing both theoretical and empirical frameworks for understanding the role of influential institutional investors—*investment giants*—in shaping equity flows to emerging markets. We develop a beauty contest model with a dominant player. The model predicts that the investment giant moves first, setting the market direction and establishing its broader influence beyond its market share. Our investor-level empirical analysis focuses on *contrarian investment* as a means to isolate the idiosyncratic influence of these giants from common macroeconomic fundamentals. The results reveal that a small group of investment giants' contrarian flows consistently predict both individual and aggregate equity flows into emerging markets. Furthermore, these flows also forecast positive movements in stock returns and exchange rates. These results are more surprising considering that EPFR fund data covers only 1–10% of market capitalization in emerging market economies.

By shedding light on the investor-level determinants of portfolio flows, this study contributes to a more nuanced understanding of global capital markets. Our findings highlight the necessity of developing a new analytical framework that captures the strategic decision-making processes of global institutional investors. From a policy perspective, closely monitoring investment giants could provide valuable early warning signals for emerging market vulnerabilities. In a world where policy options are constrained by the global financial cycle (Rey 2015), such insights offer critical guidance for policymakers and market participants navigating the complexities of international capital flows. Moreover, by uncovering the micro-level determinants of fund flows, policymakers gain valuable insights for designing macro-prudential or foreign exchange-related policy frameworks aimed at ensuring financial stability, particularly in emerging market 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, "Financial integration in a second-best world: Are we still sure about our classical prejudices?," in Rudiger Dornbusch and Yung Chul Park, eds., *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, "The granular origins of aggregate fluctuations," *Econometrica*, 2011, *79* (3), 733–772.

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

_ and Ralph S. J. Koijen, "Granular instrumental variables," *Journal of Political Economy*, 2024, *132* (7), 2274–2303.

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, Adrien Rousset Planat, Vania Stavrakeva, and Jenny Tang, "Elephants in equity markets," Working Paper 32756, National Bureau of Economic Research July 2024.

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, "2014: US economic prospects: Secular stagnation, hysteresis, and the zero lower bound," in Robert Thomas Crow, ed., *The best of business economics: Highlights from the first fifty years*, 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 Model Appendix

A.1 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 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 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 The 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).

A.2 Typical Investor Payoffs

To discuss the impact of the giant and strategic complementarity, we explore the ex-ante payoff of a typical investor j given by:

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

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:

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

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:

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

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:

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

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 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 giant. This effect is particularly pronounced when the 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 in-

vestors. As a result, the giant achieves a higher ex-ante payoff in the sequential move equilibrium:

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

This reflects the dual advantage of the 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.

B Data Appendix

B.1 Fund Flows

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

Emerging market-dedicated funds are categorized into specific target regions, including Asia ex-Japan, Emerging Europe, Europe, Middle East & Africa, Global Emerging, Latin America, and Middle East. Within these regions, we have selected funds that include a total of 20 host countries, namely Brazil, Chile, China, Colombia, Czech Republic, Hungary, Indonesia, India, Israel, South Korea, Mexico, Malaysia, Peru, the Philippines, Poland, Russia, Thailand, Turkey, Taiwan, and South Africa. These 20 countries are chosen, considering that their equity fund investment accounts for a significant share of total emerging economy investment and their monthly macroeconomic indicators are available for the sample period.

For our analysis, we chose two distinct periods: the period from June 2007 to December 2009 and the period from January 2010 to December 2018, which follows the global financial crisis (GFC). We conducted a preliminary screening of the EPFR data by excluding funds

with less than 12 months of observations or those with an average total investment of less than 100 million US dollars over the observed time series. After applying these filters, our dataset comprises approximately 100 mutual funds per month, with a range of 86 to 126 funds during the study period (June 2007–December 2018).

To track how each institutional investor (fund company) adjusts its investment behavior, we calculate the size of the investor i's equity investment or its estimated allocation to a particular country c at time (month) t, $\text{Equity}_{ic,t}$, using the information available in the EPFR database as $\text{Equity}_{ic,t} = \sum_{a \in \text{AssetClass}} \text{EquityShare}_{aic,t} \times \text{TotalNetAssets}_{ai,t}$ in equation (24). Here, $\text{TotalNetAssets}_{ai,t}$ is the total (equity) investment of investor i's asset class a across all host countries, and $\text{EquityShare}_{aic,t}$ is the equity investment share of investor i's asset class a in country c in its total investment at time t. Each investor includes 12 class of assets, indexed by a. The list of the 12 asset classes is Global Emerging Markets-GEM-CA-Equity, Emerging Europe Regional-EMEA-CA-Equity, Asia ex-Japan Regional-Asia Ex-Japan-CA-Equity, Latin America Regional-LatAm-CA-Equity, Global-Global-CA-Equity, Middle East Regional-EMEA-CA-Equity, Global ex-US-Global-CA-Equity, Europe, Middle East & Africa Regional-EMEA-CA-Equity, Greater China-Asia Ex-Japan-CA-Equity, BRIC-GEM-CA-Equity, Africa Regional-EMEA-CA-Equity, and Middle East & Africa Regional-EMEA-CA-Equity.

For instance, in December 2011, J.P. Morgan Asset Management held total net assets of 8,825.83 million US dollars under the asset class of Global Emerging Markets, with South Korea accounting for 10.1% of that total allocation. Similarly, the company held 2,085.92 million US dollars in the Asia ex-Japan Regional, with South Korea accounting for 16.8% of the country weight. Hence, J.P. Morgan's equity investment in South Korea for that particular month amounted to 1,241.84 million US dollars (= 8,825.83×0.101 + 2,085.92×0.168). The same procedure is applied consistently across all funds and host countries.

There are instances where an investor does not invest in equities in a particular market or country. Thus, 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 $t + h$ as in equation (25), where the cumulative growth is winsorized at both ends by –h×100%

and $h\times100\%$ (i.e., 100% monthly growth rate), to prevent our regression results from being potentially influenced by a few extreme flows. This is similar to one that winsorizes the top and bottom 1% of observations in the case of $h = 1$. To exclude this valuation channel, we compute the cumulative equity growth based on the adjusted equity growth with market returns as in equation (26), which is also winsorized at both ends by $-h\times100\%$ and $h\times100\%$. We checked the estimation results without winsorization, and found that the main results remain robust.

B.2 Macroeconomic Variables

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. 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. More pointedly, we take nominal interest rates from three sources as follows.

- For Brazil, Hungary, Israel, Mexico, South Africa, and Thailand, we use the treasury bill rate sourced from the IFS dataset.
- 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.
- 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.

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. 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.

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

C Robustness Checks of Investor-Level Analyses

Active funds flows 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.[16] 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).[17]

To address this concern, we estimate regression equations (30) and (A.9) using active fund flows as the dependent and independent variables.[18] The estimation results with active funds data are broadly consistent with the full sample (active funds & passive funds) results. Specifically, as shown in Figure A.1, the results from the estimation of equation (30) 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.

Taking the two alternative measures of investment giants' contrarian active equity flows, we further check robustness of our main results. Subfigures (a) and (b) in Figure A.2 summarize the results when we use the change in share of equity investments made by the top 10 investment giants and the difference between size-weighted and unweighted averages of investor flows, as defined in equations (28) and (29), respectively. Consistent with the observations in Figures 4 and A.1, active equity flows exhibit the positive influence

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

[17] 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.

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

of investment giants on investors, in particular, after the GFC.

Investor-time fixed effects Regression equation (30) accounts for temporal fluctuations in push and pull factors by including the US and domestic country-level variables. Also, it controls for both firm and country fixed effects. However, there could remain the limitation that the baseline specification fails to capture heterogeneity in investor-level dynamics.

To address this potential issue, we carry out an additional regression by adjusting the equation (30). Specifically, given that EPFR data does not provide the detailed investor characteristics, we incorporate investor-time fixed effects ($\delta^h_{i,t}$):

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

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 A.3 summarizes the responses of equity flows based on the regression equation (A.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 (30) 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 A.4.

Subfigures (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.

Stock market crashes Shedding more lights on the role of investment giants in times of tail risks, we conduct an additional local projection estimation which takes into account stock market crashes. In addition to the baseline regression of equation (30), we consider a specification that condition the response of equity flows on the market crash events:

$$\begin{aligned}\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) =& \beta^h_{nocrash}\left(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\right) \times \mathbb{1}_{\{\Delta^1 \ln \text{StockIndex}_{c,t} > -5\%\}} \\ &+ \beta^h_{crash}\left(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\right) \times \mathbb{1}_{\{\Delta^1 \ln \text{StockIndex}_{c,t} \leq -5\%\}} \\ &+ \mathbf{\Gamma}^h_{\text{pull}}\mathbf{Pull}_{c,t} + \mathbf{\Gamma}^h_{\text{push}}\mathbf{Push}_t + \delta^h_i + \delta^h_c + \delta^h_{m,t} + \varepsilon^h_{ic,t}, \end{aligned} \tag{A.9}$$

where $\mathbb{1}_{\{\Delta^1 \ln \text{StockIndex}_{c,t} > -5\%\}}$ and $\mathbb{1}_{\{\Delta^1 \ln \text{StockIndex}_{c,t} \leq -5\%\}}$ are indicator functions for stock market crashes (i.e., when the stock market index, $\text{StockIndex}_{c,t}$, declines by more than –5% on a monthly basis) and tranquil market conditions (no crashes), respectively. Similarly, we also consider 10%- and 15%-stock market crashes for comparison.[19] This specification includes the same pull and push factors along with fixed effects as employed in regression equation (30).

Figure A.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).

[19] 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.

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.

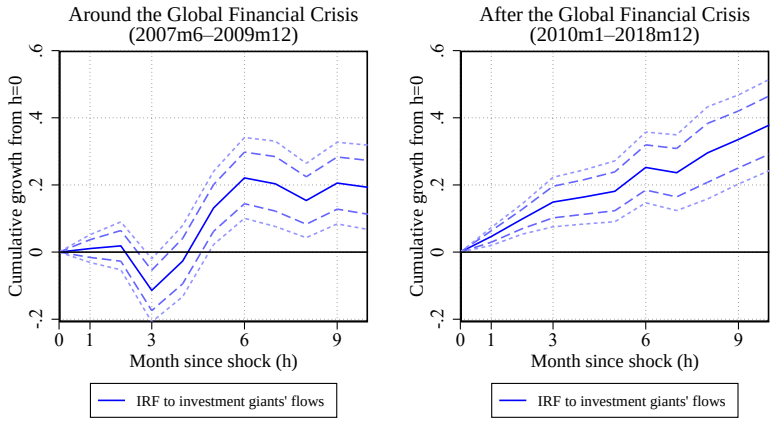
These results highlight the dynamic and complex interplay at the fund level among institutional equity flows driven by investment giants and its state-dependence on market conditions in emerging economies. From a viewpoint of international financial architecture, fund-level interactions among market 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.[20]

Next, in Figure A.6, we report the results from state-dependent local projection similar to equation (A.9), 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.

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

[20]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.

(a) Valuation-adjusted Active Fund Equity flows



(b) Unadjusted Active Fund Equity Flows

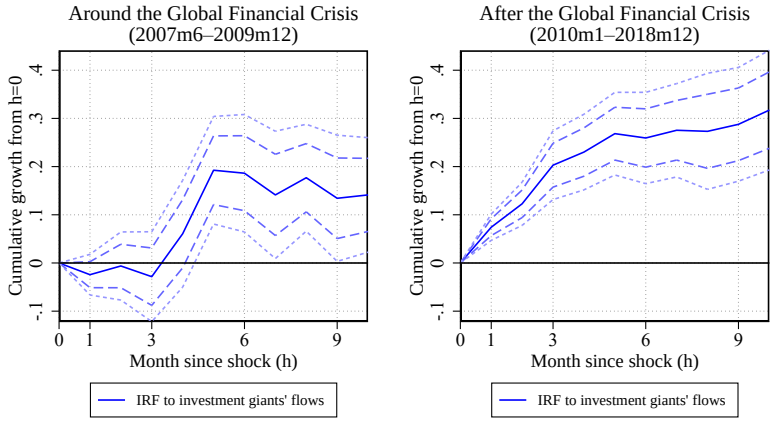
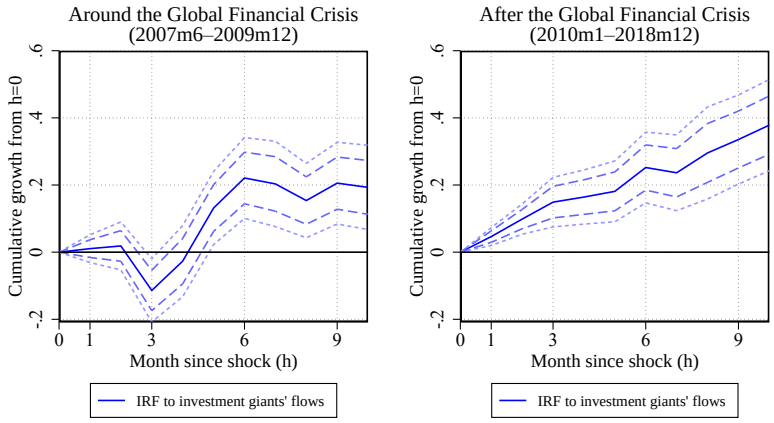


Figure A.1: Investor-Level Response to the Equity Flow Differential between Investment Giants and Typical Investors: Active Fund Flows

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 subfigure (a), an individual investor's active fund flows ($\tilde{\Delta}\text{IHS}(\text{Equity}_{ic,t})$) and the differential ($\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}$) are adjusted by stock market index and exchange rate growths to remove valuation effects. Subfigure (b) uses unadjusted values ($\Delta\text{IHS}(\text{Equity}_{ic,t})$ and $\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}$). The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (30). 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) Changes in Investment Giants Share



(b) Equity Flow Differential between Size-weighted and Unweighted Averages

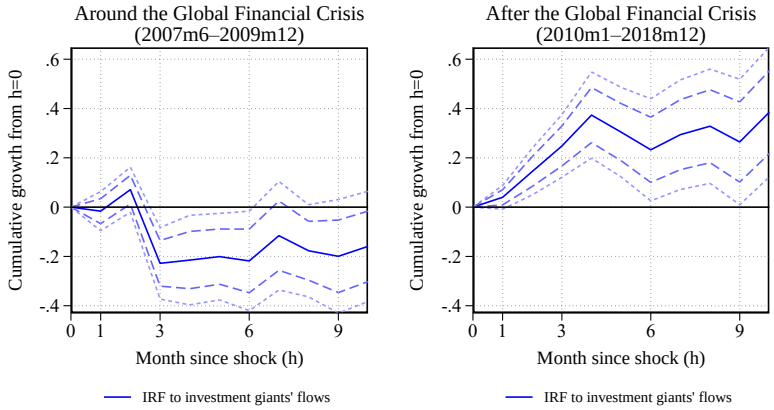


Figure A.2: Investor-Level Response to Alternative Measures of Contrarian Flows

The figures depict the predictive capacity of alternative measures of contrarian equity investments made by the top 10 investment giants. In subfigure (a), the alternative measure is the change in share of equity investments made by the top 10 investment giants, as defined in equation (28). In subfigure (b), the alternative measure is the difference between size-weighted and unweighted averages of investor flows, as defined in equation (29). They are adjusted by stock market index and exchange rate growths to remove valuation effects. The responses to contrarian flows are the estimates of β^h in equation (30). 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, %).

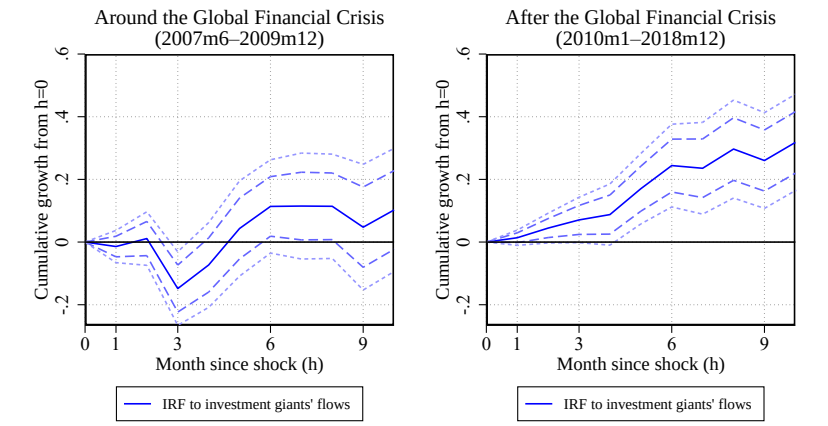
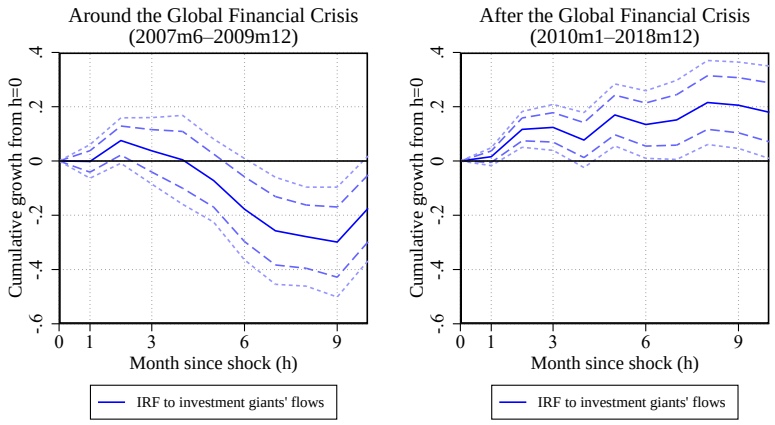


Figure A.3: Investor-Level Response to the Equity Flow Differential between Investment Giants and Typical Investors: Alternative Specification

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 (A.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

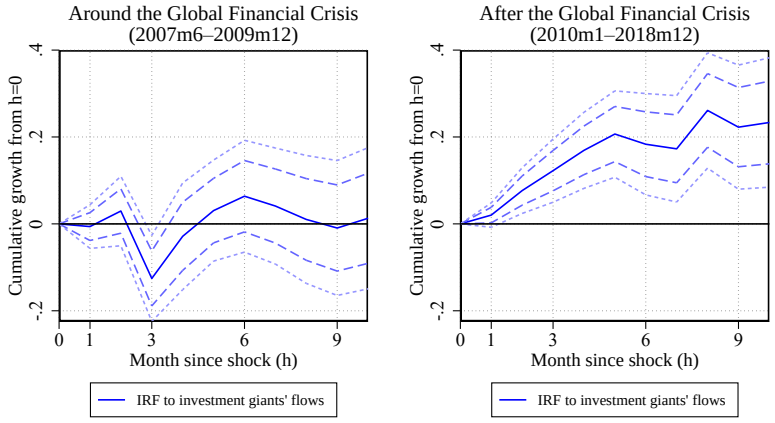


Figure A.4: Investor-Level Response to the Equity Flow Differential between Investment Giants (Top 15 or 7 Largest Investors) and Typical Investors

Notes: The subfigures (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 (30). 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, %).

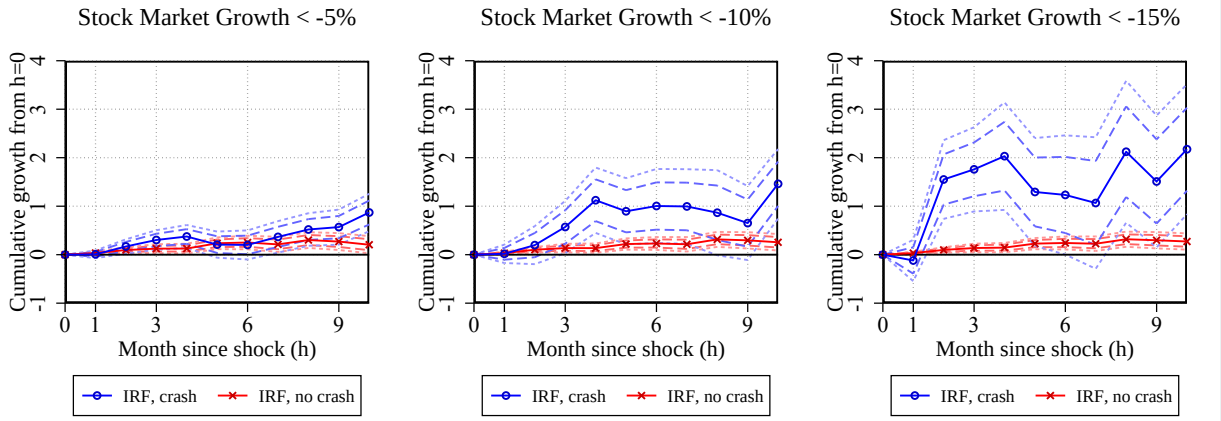


Figure A.5: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis

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 (A.9). 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, %).

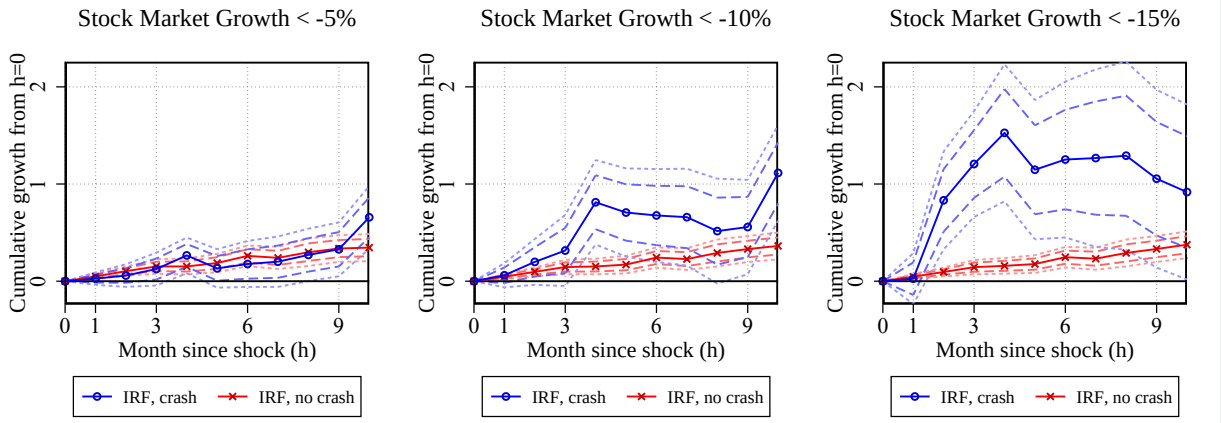


Figure A.6: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis: Active Fund Flows

Notes: The figures depict the predictive capacity of average active fund flows from the differential between investment giants' (the top 10) and typical investors' average active fund growths with and without a stock market plunge of more than 5, 10, and 15%. The sample periods are after the crisis (2010m1–2018m12). The responses to flows of investment giants relative to typical investors with and without stock market crashes are the estimates of β^h_{crash} (circled lines) and $\beta^h_{nocrash}$ (crossed lines), respectively, in equation (A.9). 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, %).

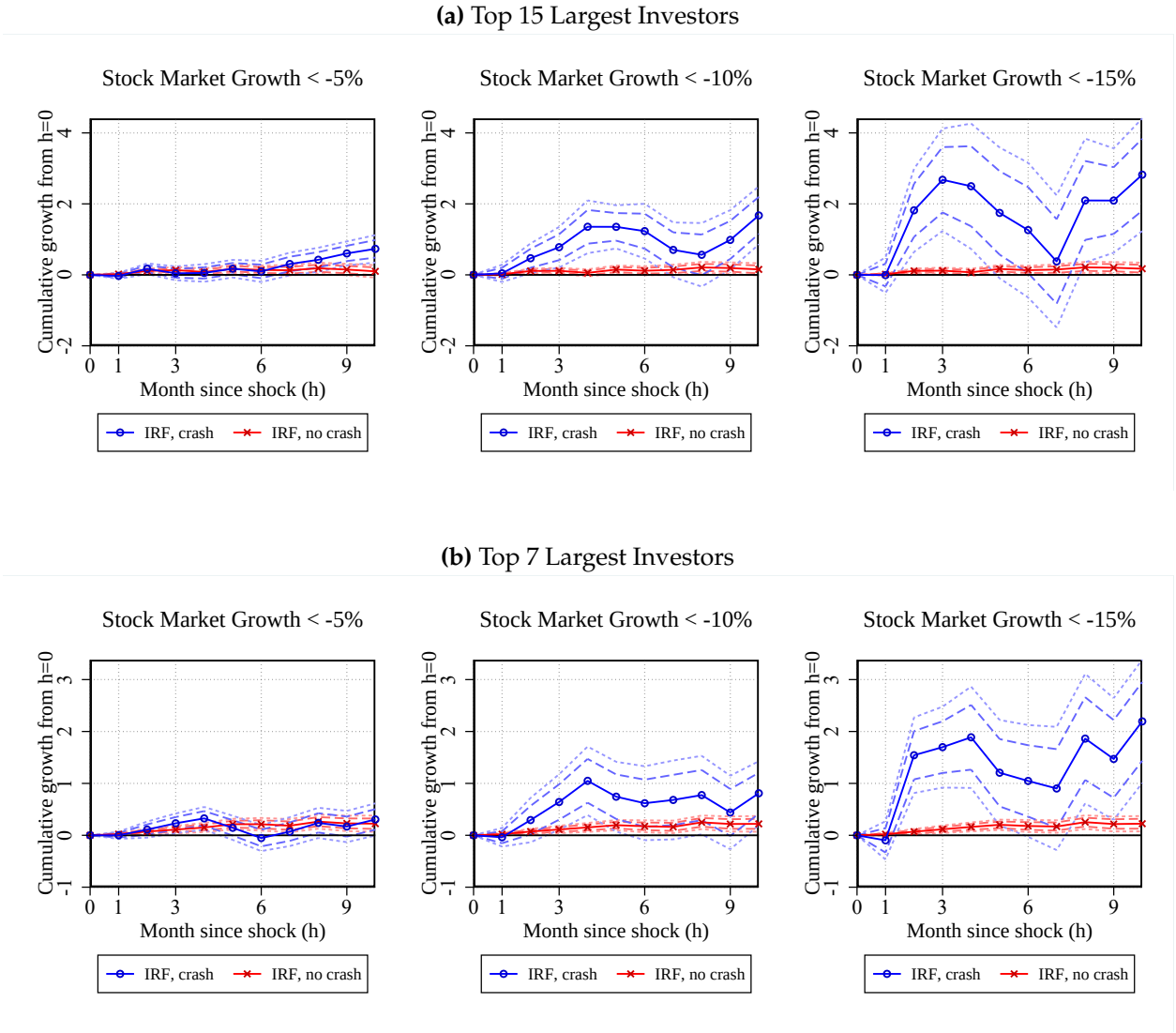


Figure A.7: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis: Top 15 and 7 Largest Investors

Notes: The subfigures (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 (A.9). 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, %).

D Robustness Checks of Country-Level Analyses

D.1 Robustness: Impact of 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 A.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:

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

where δ_t^h denotes the time fixed effect.[21] As summarized in Figure A.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 A.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 regressors—the investment giants' share and differential between size-weighted and unweighted averages, as defined in equations (28) and (29), respectively. The impulse responses of aggregate flows to the shocks are also in line with the baseline results, as presented in Figure A.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

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

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.

D.2 Robustness: Giants, Future Stock Returns and Exchange Rates

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 A.12. Second, we carry out a regression similar to equation (A.10), which in particular takes into consideration time fixed effect. The estimation results are summarized in Figure A.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 A.14. Fourth, Figure A.15 presents the responses of stock returns and exchange rate adjustments to shocks in the alternative measure of contrarian flows of investment giants: the investment giants' share and differential between size-weighted and unweighted averages, as defined in equations (28) and (29), respectively.

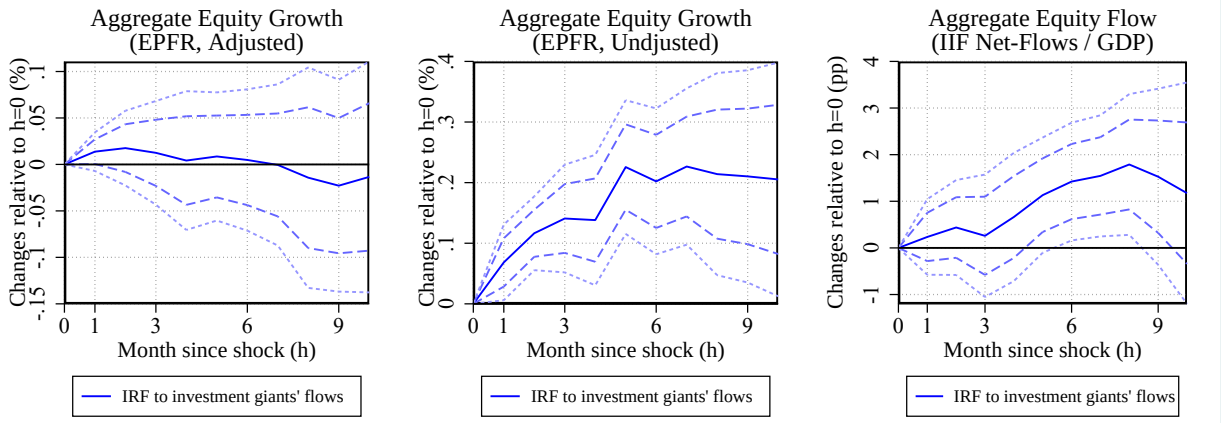


Figure A.8: Aggregate Flow Responses to Investment Giants: Active Fund Flows

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 (%).

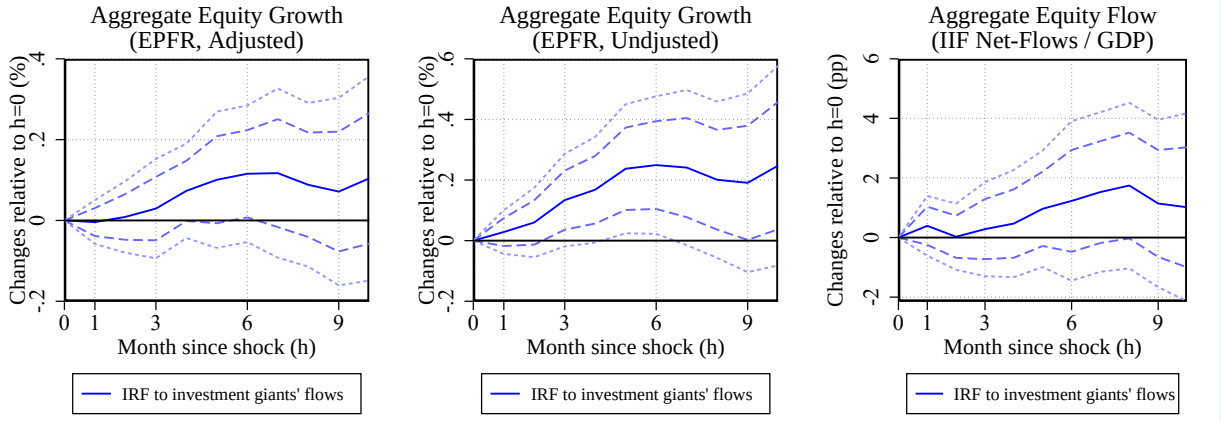
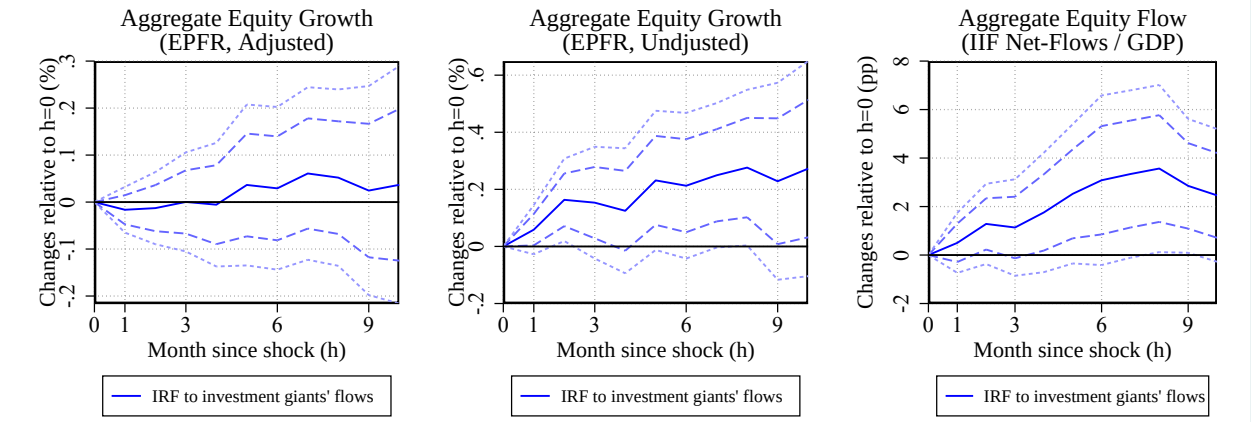


Figure A.9: Aggregate Flow Responses to Investment Giants Flows: Alternative Specification

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 (A.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

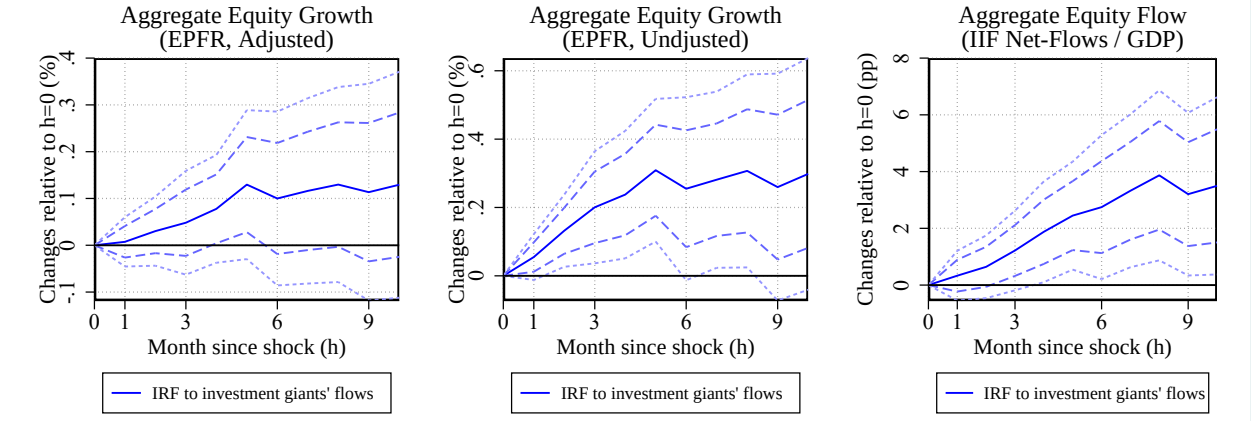
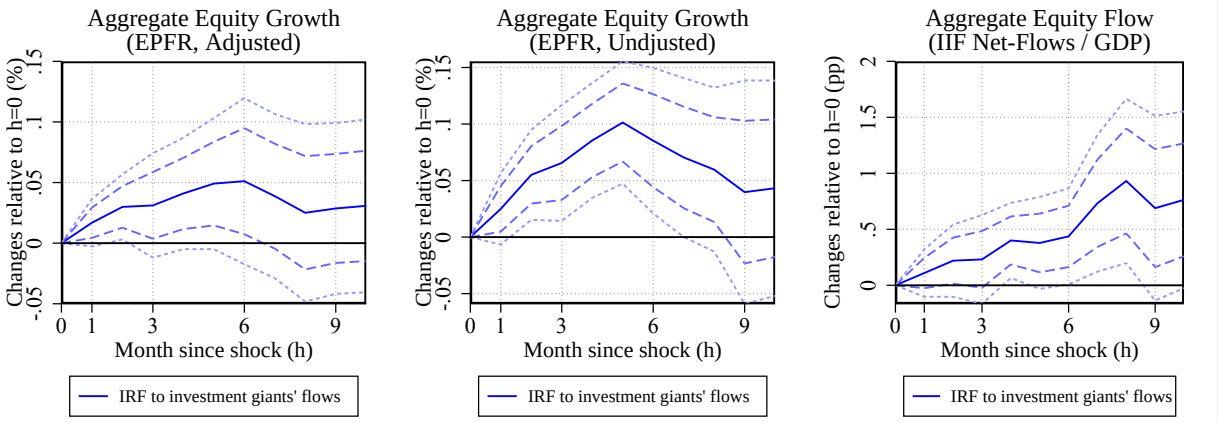


Figure A.10: Aggregate Flow Responses to Investment Giants (Top 15 and 7 Largest Investors) Flows

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 (%).

(a) Changes in Investment Giants Share



(b) Equity Flow Differential between Size-weighted and Unweighted Averages

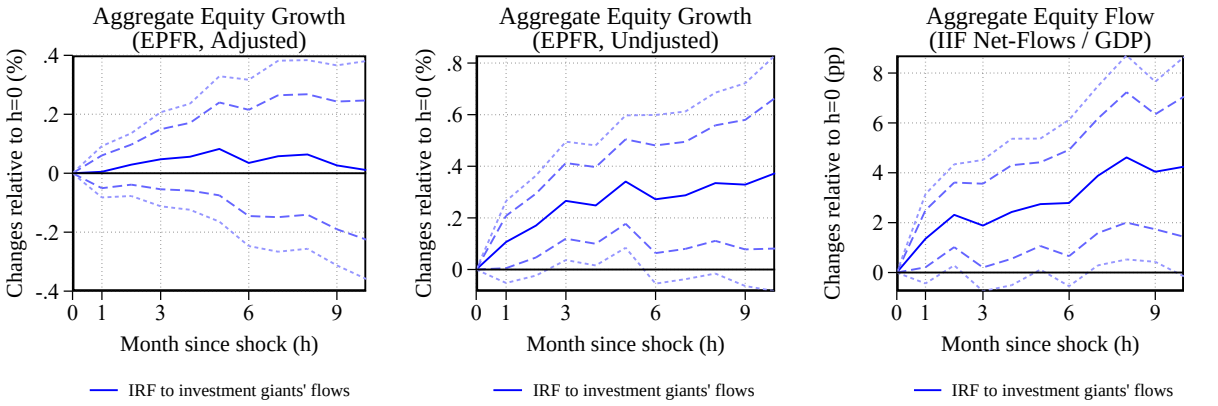


Figure A.11: Aggregate Flow Responses to Investment Giants Share

Notes: The figures depict the predictive capacity of alternative measures of contrarian equity investments for the adjusted and unadjuested EPFR aggregate equity growths and IIF aggregate equity net-flows (% of GDP). In subfigure (a), the alternative measure is the change in share of equity investments made by the top 10 investment giants, as defined in equation (28). In subfigure (b), the alternative measure is the difference between size-weighted and unweighted averages of investor flows, as defined in equation (29). They are adjusted by stock market index and exchange rate growths to remove valuation effects. 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 (%).

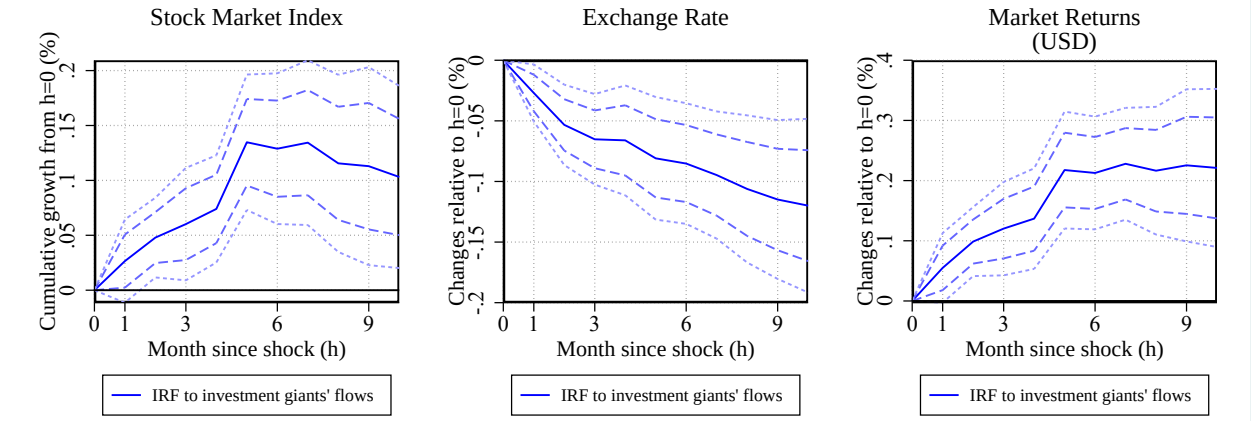


Figure A.12: Stock and Currency Markets Responses to Investment Giants: Active Fund Flows

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 (%).

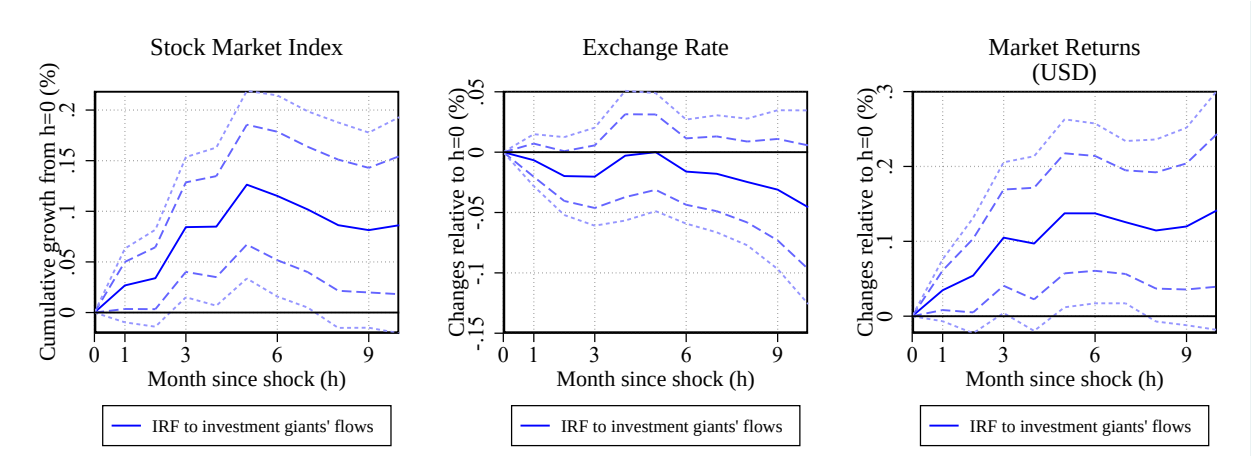


Figure A.13: Stock and Currency Markets Responses to Investment Giants Flows: Alternative Specification

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 (%).

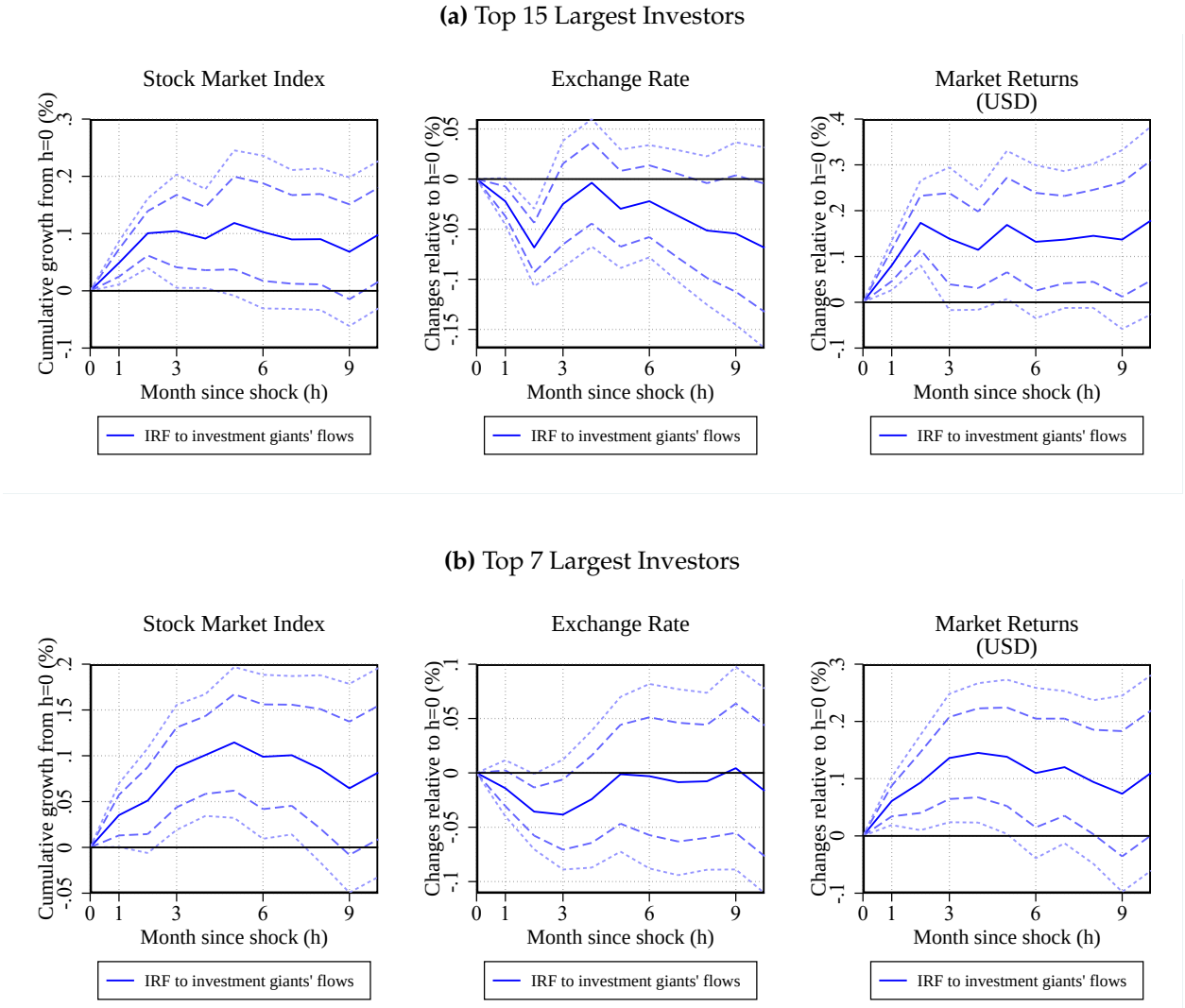
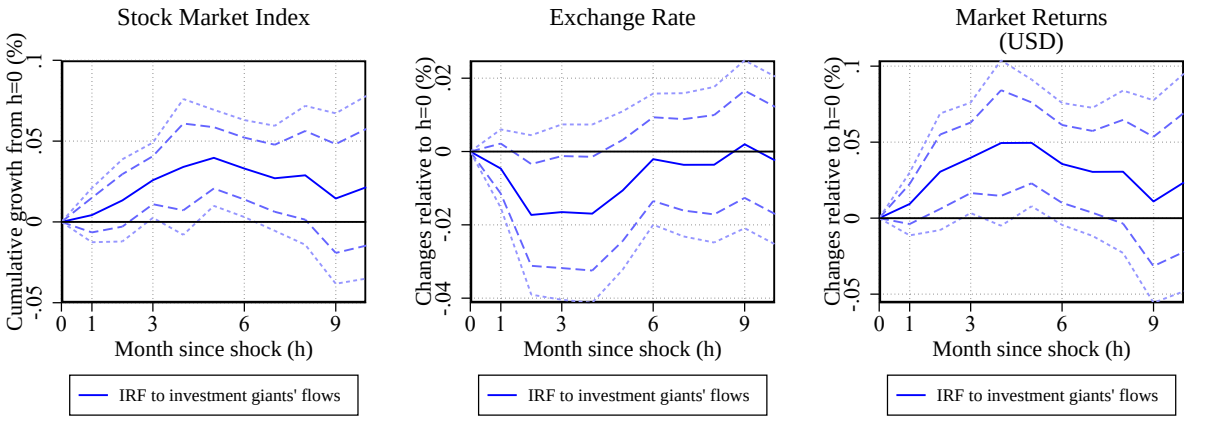


Figure A.14: Stock and Currency Markets Responses to Investment Giants (Top 15 and 7 Largest Investors) Flows

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 (%).

(a) Changes in Investment Giants Share



(b) Equity Flow Differential between Size-weighted and Unweighted Averages

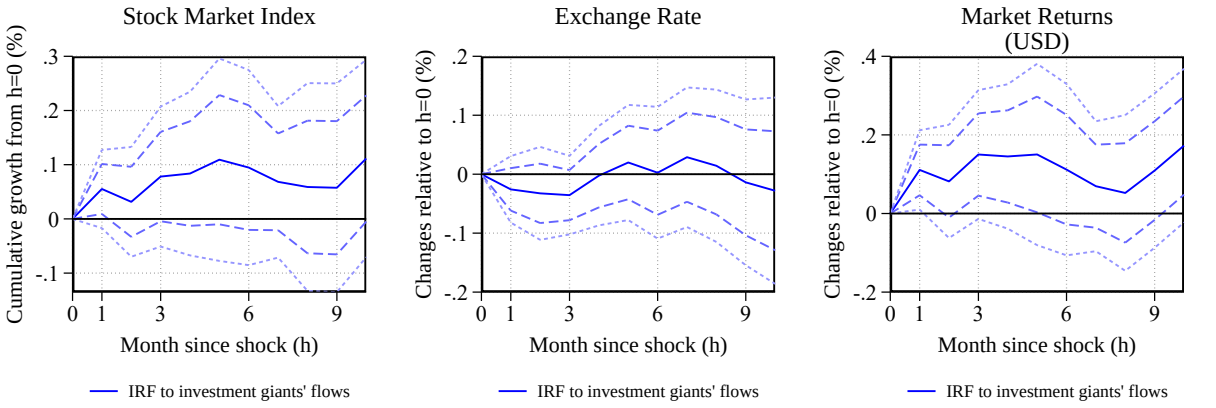


Figure A.15: Stock and Currency Markets Responses to Alternative Measures of Contrarian Flows

Notes: The figures depict the predictive capacity of alternative measures of contrarian equity investments for stock price indices, exchange rates, and stock market returns (USD). In subfigure (a), the alternative measure is the change in share of equity investments made by the top 10 investment giants, as defined in equation (28). In subfigure (b), the alternative measure is the difference between size-weighted and unweighted averages of investor flows, as defined in equation (29). They are adjusted by stock market index and exchange rate growths to remove valuation effects. 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 (%).

E Additional Figures and Tables

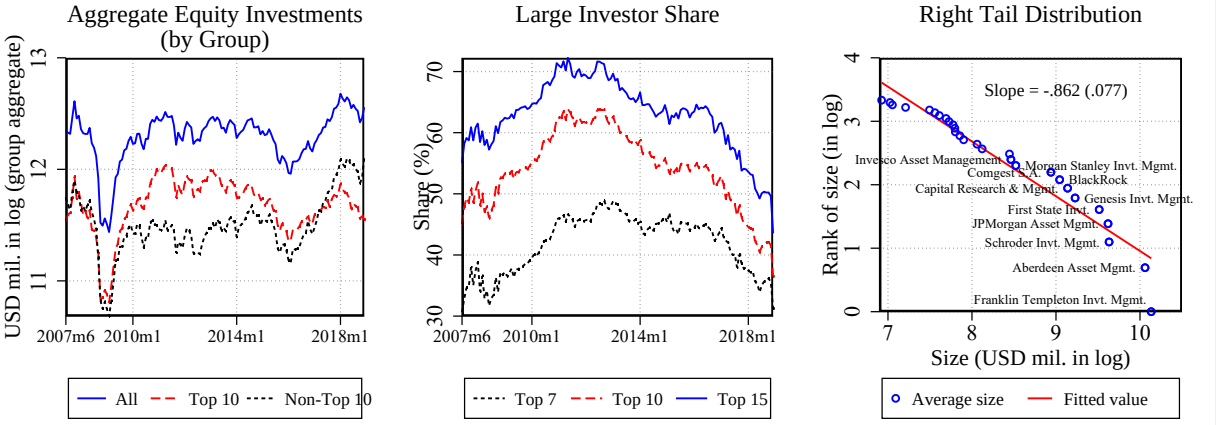


Figure A.16: Trends of Equity Fund Flows: Active Funds Only

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).

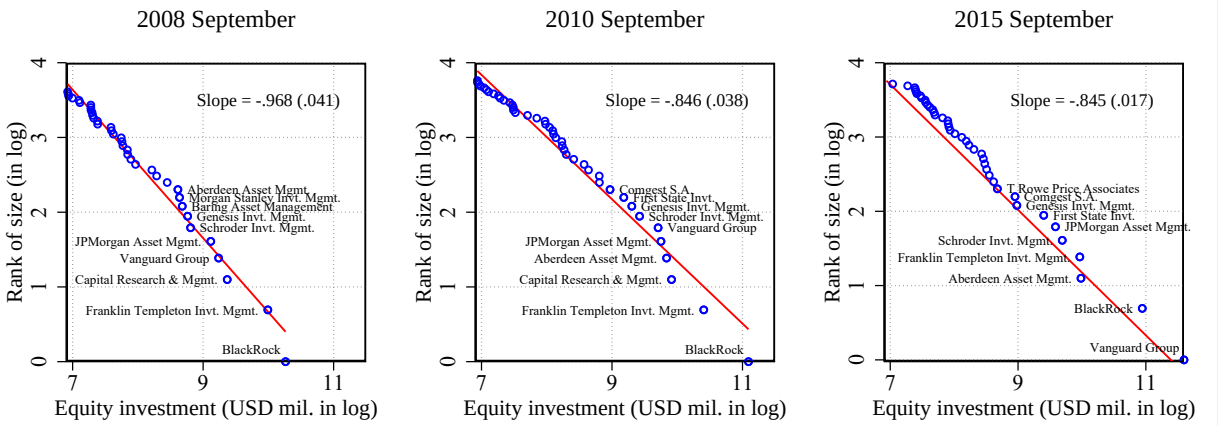


Figure A.17: The Right Tail of Investor Size

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.

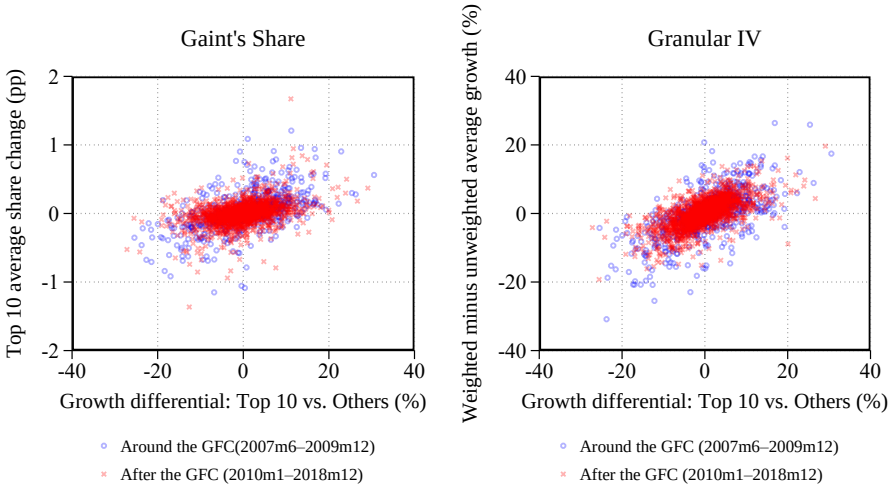


Figure A.18: Investment Giant's Contrarian Investment: Benchmark and Alternative Measures

Notes: The figures illustrate the relationship between the benchmark and alternative measures of investment giants' contrarian investment. In both panels, the x-axis represents our benchmark measure, defined in equation (27), which captures the differential between the average equity growth of investment giants and that of typical investors. The y-axis in the left and right panels corresponds to the alternative measures from equations (28) and (29), respectively: the giants' changing market share in each equity market and the differential between size-weighted and unweighted investment growth of all investors, referred to as granular instruments. The blue circles and red crosses are observations around the global financial crisis (2007m6–2009m12) and after the crisis (2010m1–2018m12), respectively.

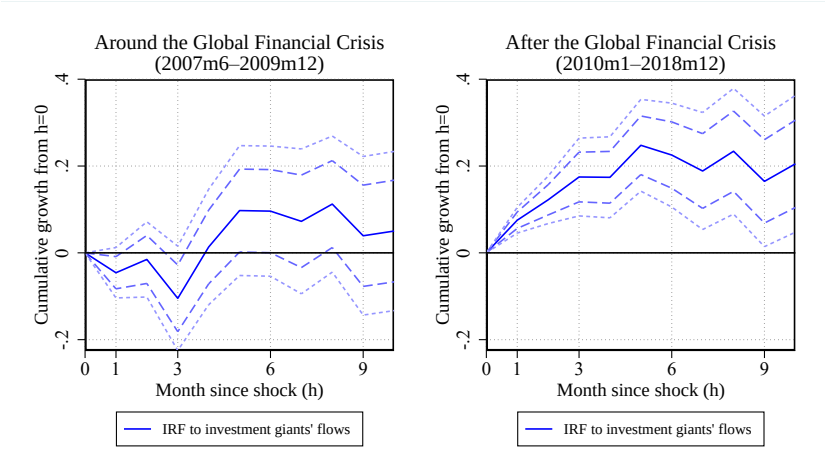


Figure A.19: Investor-Level Response to the Unadjusted Equity Flow Differential between Investment Giants and Typical Investors

Notes: The figures depict the predictive capacity of average equity flows from the differential between investment giants' (the top 10) and typical investors' average equity growths where we use non-valuation-adjusted values ($\Delta\text{IHS}(\text{Equity}_{ic,t})$). The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (30). 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, %).

Table A.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	56,460	123.27	454.77	0.00	6.69	261.26
Non-top 10 largest investors	50,260	56.08	195.06	0.00	3.67	131.75
Top 10 largest investors	6,200	667.97	1,114.34	6.96	248.71	1,842.82
Equity flow (monthly growth, %)						
All investors	55,240	-0.26	26.71	-20.84	0.00	18.60
Non-top 10 largest investors	49,040	-0.36	26.93	-20.73	0.00	18.22
Top 10 largest investors	6,200	0.49	24.89	-21.67	0.07	20.30
Adjusted equity flow (monthly growth, %)						
All investors	55,240	-0.16	25.06	-14.69	0.00	13.62
Non-top 10 largest investors	49,040	-0.27	25.36	-14.78	0.00	13.33
Top 10 largest investors	6,200	0.66	22.56	-13.93	0.00	15.12
After the Global Financial Crisis (2010m1–2018m12)						
Equity flow (mil. US dollars)						
All investors	240,940	176.17	1,042.14	0.00	4.00	273.01
Non-top 10 largest investors	219,340	57.02	187.59	0.00	2.19	142.53
Top 10 largest investors	21,600	1,386.12	3,185.85	3.74	412.11	3,297.73
Equity flow (monthly growth, %)						
All investors	234,620	0.11	21.35	-11.93	0.00	11.58
Non-top 10 largest investors	213,020	0.13	21.79	-11.78	0.00	11.50
Top 10 largest investors	21,600	-0.07	16.46	-13.00	0.00	12.07
Adjusted equity flow (monthly growth, %)						
All investors	234,620	0.10	20.77	-9.06	0.00	8.92
Non-top 10 largest investors	213,020	0.12	21.24	-9.01	0.00	8.93
Top 10 largest investors	21,600	-0.10	15.33	-9.25	0.00	8.88

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

Table A.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, %)						
	2,160	0.64	8.37	-9.58	1.06	10.15
Aggregate of adjusted equity flows (monthly growth, %)						
	2,160	0.60	4.77	-4.15	0.41	5.33
Cross-sectional average of equity flow growth (monthly growth, %)						
Non-top 10 largest investors	2,160	0.11	4.85	-5.63	0.20	5.87
Top 10 largest investors	2,160	-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	2,160	0.09	2.87	-3.40	0.11	3.68
Top 10 largest investors	2,160	-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 A.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	56,460	103.44	370.64	0.00	5.89	225.78
Non-top 10 largest investors	50,940	56.71	197.07	0.00	3.59	131.75
Top 10 largest investors	5,520	534.61	916.95	0.00	182.60	1,476.44
Equity flow (monthly growth, %)						
All investors	55,100	-0.16	27.28	-20.82	0.00	18.86
Non-top 10 largest investors	49,640	-0.30	27.15	-20.69	0.00	18.39
Top 10 largest investors	5,460	1.12	28.42	-21.85	0.00	21.76
Adjusted equity flow (monthly growth, %)						
All investors	55,100	-0.08	25.70	-14.73	0.00	13.86
Non-top 10 largest investors	49,640	-0.21	25.59	-14.74	0.00	13.45
Top 10 largest investors	5,460	1.08	26.62	-14.72	0.00	16.48
After the Global Financial Crisis (2010m1–2018m12)						
Equity flow (mil. US dollars)						
All investors	229,200	109.82	416.71	0.00	2.92	224.10
Non-top 10 largest investors	208,340	54.42	187.12	0.00	1.58	132.94
Top 10 largest investors	20,860	663.15	1,105.20	0.00	202.93	1,868.69
Equity flow (monthly growth, %)						
All investors	223,320	-0.04	21.74	-12.20	0.00	11.38
Non-top 10 largest investors	202,480	-0.03	22.02	-11.95	0.00	11.22
Top 10 largest investors	20,840	-0.20	18.81	-13.69	0.00	12.49
Adjusted equity flow (monthly growth, %)						
All investors	223,320	-0.05	21.18	-9.41	0.00	8.76
Non-top 10 largest investors	202,480	-0.04	21.49	-9.29	0.00	8.65
Top 10 largest investors	20,840	-0.23	17.97	-10.29	0.00	9.44

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

Table A.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, %)						
	2,160	0.10	8.16	-10.24	0.29	9.56
Aggregate of adjusted equity flows (monthly growth, %)						
	2,160	0.06	5.02	-5.13	-0.01	5.31
Cross-sectional average of equity flow growth (monthly growth, %)						
Non-top 10 largest investors	2,160	0.37	7.01	-8.36	0.47	8.95
Top 10 largest investors	2,160	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	2,160	-0.18	7.97	-10.42	0.16	9.39
Top 10 largest investors	2,160	-0.22	5.98	-7.26	-0.09	6.72

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

Table A.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 (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 excl. 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 (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 excl. 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.