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

January 30, 2025

Abstract

Non-resident equity flows into emerging markets are heavily concentrated among a few large institutional investors (*investment giants*). We investigate their behavior and impact in a model where investors consider both market fundamentals and aggregate behavior in their decision-making. In a sequential-move scenario, a single giant investor moves first, setting market direction and providing information to a continuum of typical investors. Compared to a simultaneous-move scenario, this leadership not only secures the giant's higher ex-ante payoff but also enhances the predictability and influence of its decisions on others and the market. Using monthly fund-level data, we focus on the impacts of the giants' contrarian investment (excess investment growth relative to peers or the market) to isolate their idiosyncratic influence from the macroeconomic fundamentals shared among investors. Consistent with our model, investors' and aggregate flows, and stock returns persistently increase following the contrarian flows, highlighting their predictive power. These findings suggest monitoring giants as early indicators of financial market movements in emerging economies.

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

*Department of Economics, North Carolina 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 market economies as international investors sought higher yields (Rajan 2006 and Summers 2016). These flows provide significant benefits for emerging market economies, such as enhanced opportunities for risk-sharing and external financing (Bonfiglioli 2008, Igan, Kutan and Mirzaei 2020, and Aristizabal-Ramirez, Leahy and Tesar 2023). However, they also bring notable risks: heightened exposure to global shocks, the potential for sudden reversals that intensify financial stress (Calvo and Reinhart 2002 and Gourinchas and Obstfeld 2012), and increased volatility due to investor overreaction to market fundamentals (Dornbusch and Park 1995). Financial integration further complicates these dynamics, as it increases the likelihood of crises while potentially mitigating their severity (Devereux and Yu 2019).

Despite the extensive literature on capital flows, the drivers and macro-financial consequences of cross-border portfolio flows, particularly at the fund 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 studies of U.S. and global financial markets (e.g., Corsetti, Dasgupta, Morris and Shin 2004, Buch, Koch and Koetter 2011, Ben-David, Franzoni, Moussawi and Sedunov 2021, and Coimbra, Kim and Rey 2022). This paper focuses on their strategic interactions with other investors and their broader influence on equity and currency markets in emerging economies. By doing so, we provide insights for policymakers and market participants navigating the complexities of international capital flows. In particular, our findings suggest the potential benefits of closely monitoring investment giants' activities, especially when their decisions diverge from those of other investors and market trends. Their moves may serve as early warning indicators of potential market disruptions in emerging economies.

To understand the behavior and influence of investment giants, we first construct a theoretical framework that integrates the role of a dominant player, noisy markets, and strategic complementarity. Formally, we assume that a market consists of a single dominant player (the investment giant) and a continuum of smaller investors (typical investors), in which the investment giant can

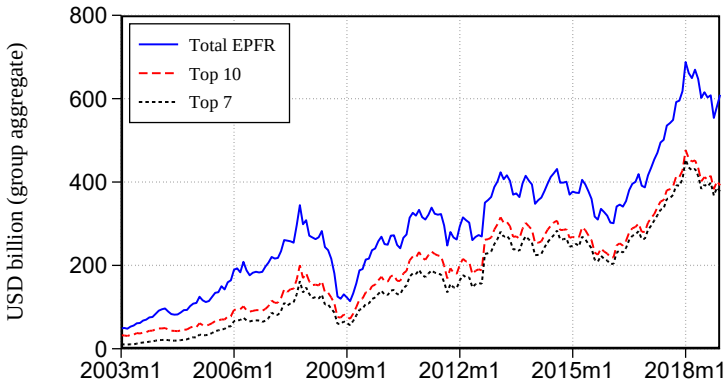


Figure 1: Equity Fund Flows to 20 Emerging Markets

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 C.1 for the details.

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

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

Our theoretical framework introduces two critical channels which enable the investment giant to lead market directions (*directional leadership channel*) and to share public information (*public information channel*). With the help of these mechanisms, the investment giant can exert a positive influence on market aggregates and other investors. Particularly, we focus on the giant's contrarian actions that deviate from other investors to insulate its idiosyncratic influences from the macroeconomic fundamentals. The influence of the investment giant's (contrarian) decisions on typical investors intensifies under two conditions: (*i*) when the giant holds a larger market share,

amplifying its impact on market aggregates, and (*ii*) when strategic complementarity is stronger, as investors place more weight on aligning their actions with others. These conditions incentivize the investment giant to adopt a sequential move strategy. Specifically, the giant's ex-ante payoffs are maximized under a sequential move, making it more preferable to a simultaneous one. Hence, the giant not only induces followers but also aligns market aggregates closer to fundamentals.

Using fund-level flow data from EPFR, we confirm our theoretical prediction that the investment giant's decisions positively influence both other investors' behaviors and market aggregates. Importantly, our empirical analyses focus on the giants' contrarian investments—measured as the growth differential between the giants' investments and those of other investors or market averages.[1] The contrarian investments not only establish a direct connection between our theoretical predictions and the data, but also facilitate a clearer identification of the giants' idiosyncratic influences by insulating the investment giants' unique contributions from common dependencies on the fundamentals. With the help of a battery of panel local projections, we test the dynamic effects (predictability) of investment giants' contrarian decisions on individual equity fund flows across 20 emerging markets. A small group of investment giants' contrarian flows consistently exhibit strong predictive power for overall equity flows into emerging markets.[2] This result highlights the investment giants' critical role in global asset reallocation.

Further, we extend the analysis to the aggregate dynamics and implications at the country-level. Capital flows and global asset allocations are pivotal in shaping financial and foreign exchange markets, particularly in emerging economies (Hau and Rey 2006, Gyntelberg, Loretan and Subhanij 2018, Wong 2017, and Goldberg and Krogstrup 2023). Surprisingly, although EPFR fund flows represent only 1–10% of market capitalization in emerging economies (Jotikasthira, Lundblad and Ramadorai 2012), our country-level analysis reveals consistent patterns with the fund-level analysis. Aggregate equity flows positively respond to investment giants' contrarian investments, with the differential between giants' and other investors' flows serving as a strong predictor of aggregate foreign equity inflows. These patterns are observed even when alternative broader datasets, such as those from the International Institute of Finance (IIF), are employed . Moreover, the positive predictability of giants' contrarian investments on stock market returns is significant,

[1] We also consider alternative measures to capture the idiosyncratic decisions of investment giants. One such measure is the giants' share of equity flows into each market (country). Additionally, following Gabaix and Koijen (2024), we use the differential between the size-weighted and unweighted averages of equity flows across all investors, termed granular instruments. All results remain robust across these three measures of contrarian investment decisions.

[2] We define the top 10 largest investors as investment giants. While there is no universally accepted threshold for identifying large investors, we also test the robustness of our findings using alternative definitions, such as the top 7 or top 15 largest investors. There are about 100 investors per month on average over the sample period.

while exchange rates exhibit depreciation in response to lower equity investments from giants relative to other investors.

The results collectively show that they are indeed "*the giants*" in emerging equity markets in that observing some of their behaviors provide enough information to predict the entire markets (Rey, Planat, Stavrakeva and Tang 2024). These findings also emphasize the importance of monitoring investment giants' activities in equity and foreign exchange markets. Such monitoring can serve as a valuable tool for forecasting foreign portfolio inflows and identifying potential financial vulnerabilities in emerging market economies.

Contribution to the literature Existing literature has examined investment decisions among institutional investors to provide valuable insights for a comprehensive understanding of financial markets. They particularly focused on the collective decision-making processes and co-movements of portfolio investments. For instance, Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992) develop a sequential decision-making model where agents imitate the actions of predecessors while ignoring their private information. This model is combined with a pricing mechanism by Avery and Zemsky (1998) to analyze collective behavior.

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

Furthermore, our model contributes to the literature by extending a framework of incomplete information and strategic complementarity to incorporate the presence of a dominant player. As highlighted by Keynes (1936), a defining characteristic of financial markets is an environment, so-called *a beauty contest*, that participants forecast both fundamental values and the behaviors of other players. This concept has been widely studied in financial markets, with significant contributions from both empirical and theoretical studies, including Chen et al. (2010), Schmidt et al. (2016), Jackson and Pernoud (2021), among others. Another essential feature of financial markets

is the presence of dominant players. By focusing on the role of investment giants and their impacts, our model advances this literature, complementing prior work such as Corsetti et al. (2004) on dominant players in currency markets and Ben-David et al. (2021) on large investors in U.S. equity markets. Through this dual focus, our study bridges two critical dimensions of financial markets: the strategic interdependence of typical investors and the outsized influence of dominant players.

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

The rest of the paper proceeds as follows: Section 2 builds a model. Section 3 presents the model properties. Section 4 provides a description of the dataset and key measurements, and bridges our theoretical framework to empirics. Section 5 tests the model prediction by employing a detailed investor-level regression analysis. In Section 6, the country-level regression analysis provides aggregate-level implications for investors and policymakers in emerging equity and currency markets. Section 7 concludes.

2 A Beauty Contest Framework with Investment Giants

2.1 Model Environments

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

As emphasized by Keynes (1936), one of key features in the financial markets is that participants

typically forecast both fundamental values and the behaviors of other players (*beauty contest*). This feature creates an environment for coordination and strategic interaction among the market players. Hence, the beauty contest concept has been extensively applied in the studies of financial markets (e.g., Chen et al. 2010, Schmidt et al. 2016, Jackson and Pernoud 2021). Building on the framework of Morris and Shin (2002), our model assumes that investor payoffs depend on market fundamentals as well as market aggregates. This strategic complementarity introduces a coordination motive in investors' actions.

Two primary assumptions underpin the model. First, as in Corsetti et al. (2004), typical investors' actions do not affect aggregate market outcomes, whereas the investment giant's decisions significantly shape market equilibrium. Second, the investment giant can choose its timing of action, either moving simultaneously with typical investors or moving first before the others. When moving first, the investment giant's actions are observable to others, consistent with the visibility typically associated with large players. The ability to choose sequential timing 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. However, typical investors collectively account for a total market share of $1 - \lambda$. Due to diversification, their idiosyncratic actions and information have no aggregate implications, in contrast to the investment giant.[3]

Beauty contest framework Each investor chooses an action a_i, representing an abstract investment decision.[4] The payoff of investor i is

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

[3] In this sense, our model can be understood as a discrete version of granular origin model (Gabaix 2011).

[4] 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.

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

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

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

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

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

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

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

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

where the respective coefficients are

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

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

- Simultaneous move ($r_1 = \text{sm}$): The investment giant and typical investors act at the same

time without observing other's actions.

- Sequential move ($r_1 = \text{sq}$): The investment giant moves first. After observing the giant's action, typical investors subsequently decide their actions.

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

In the sequential move setup, typical investors choose actions a_j (for $j \in [0, 1)$) to maximize their expected payoff 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 aggregate strategies of typical investors which react to the signal and action of the investment giant ($\bar{A}^{\text{sq}}(f, s_1, a_1)$).

On the other hand, in the simultaneous move case, each investor (both typical investors and investment giant; $i \in [0, 1]$) faces an identical payoff maximization problem. That is, each investor independently and simultaneously determines its action a_i to maximize its expected payoff ($\mathbb{E}[\pi_i | s_i]$) based only on its private signal s_i. In what follows, we elaborate on the investors' optimal strategies, given the timing of actions, in particular sequential ($r_1 = \text{sq}$).[5]

2.2 Sequential Moves: An Investment Giant Moves First

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

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

where $\bar{a}_0^{\text{sq}} \left(\equiv \int_{j \in [0,1)} a_j^{\text{sq}} \mathrm{d}j\right)$ is the average optimal action of the typical investors. This optimal strategy is a linear combination of expectations about the fundamentals (f) and the market outcome (the aggregate actions of investors, a_1 and $\bar{a}_0^{\text{sq}}$).

As shown in Morris and Shin (2002), the optimal strategy for a typical investor j under the sequential move can be expressed as a linear function of signals:[6]

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

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

[6] 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.

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

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

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

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

The average (aggregate) action of typical investors is then derived as:

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

To intuitively understand this typical investor's strategy, we consider two limiting cases: no strategic complementarity ($\omega \to 0$) and investment giant's zero market share ($\lambda \to 0$). First, in the absence of a coordination motive, the typical investor's decision problem simplifies 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.[7]

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

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

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

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

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

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

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

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

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

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

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 fundamental, the best payoff is achieved when the market aggregate aligns with the fundamentals. This implies that the most favorable direction for the market is the one that converges toward the fundamentals, which leads the investment giant' action to its belief on the fundamental. Thus, its optimal action under a sequential move is identical to that from the signal-noise extraction case, $\phi^{\text{sq}} = \theta_1$.

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 ($r_1 = \text{sq}$ and sm).

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

move structure than 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 is obvious because $\theta_0 > \gamma_0$ and ω, λ, and ϕ^{sm} are non-negative.[8]

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

Investment giant Similar to typical investors, the optimal strategy of the investment giant under a simultaneous move case is determined only by its own signal: $a_1^{\text{sm}}(s_1) = \phi^{\text{sm}} s_1$ (as in equation (A.4)). Comparing it with (12), we find the differences between the optimal strategies of investment giant under simultaneous and sequential moves in two aspects. First, the investment giant reacts less 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 investment giant with a strategic advantage and leads its action align with its belief on the fundamentals (i.e., $\phi^{\text{sq}} = \theta_1$). However, when the investment giant should move simultaneously with other investors, it looses their directional leadership. Thus, similar to typical investors, the investment giant guesses the market and adjust its action to the market direction even if it believes that the other investors' action deviates from the fundamentals. This distortion, represented by $\theta_1 - \phi^{\text{sm}}$ (or equivalently $\phi^{\text{sq}} - \phi^{\text{sm}}$), increases with a degree of strategic complementarity (ω) and the market share of typical investors ($1-\lambda$), for a given typical investor's strategy (ψ^{sm}).

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

3 Impacts of Strategic Complementarity and Investment Giants

3.1 Optimal Timing Structure of Actions

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

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

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

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

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

Here, the function $\Upsilon(x; z)$ is decreasing in $x \in (0, z)$ and $z \in (0, 1)$. Also, Υ reaches its minimum value $1 - z$ at $x = z$. Thus, $\Upsilon(\phi^{\text{sq}} = \theta_1; \theta_1) = 1 - \theta_1$. 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 signal-noise extraction problem, as shown in equation (12).

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

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

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

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

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

The first term reflects the variance of deviations from fundamentals:

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

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

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

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

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

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

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

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

The equilibrium of our model—the investment giant moves first, and then typical investors follow—is consistent with the literature. A key feature of this sequential move is the visibility of investment giant's actions (e.g., Corsetti et al. 2004). More pointedly, typical investors observe the investment 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, it 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 to 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.[9]

3.2 Impacts on Typical Investors and Market Movements

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

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

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

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

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

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

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

Furthermore, the market aggregate relies less on the fundamentals but more on the investment

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

giant as ω and λ increases:

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

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

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

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

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

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

is high:

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

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

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

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

4 Bridging Theory to Data

Motivated by the predictions of our theoretical model regarding the influence of investment giants, we will empirically examine how these giants interact with other investors and shape aggregate market dynamics. We begin by outlining 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 document the prominent role of investment giants by analyzing their flow concentration and market share, demonstrating their disproportionate influence in shaping market outcomes. These findings highlight the unique position of giants in driving equity flows, particularly in emerging markets.

Finally, we introduce the concept of *giants' contrarian investment flows*, which is central to our empirical investigation. The giants' contrarian investment is defined as the deviations between the giants' investment behavior and that of other investors or the broader market. The reason for contrarian investment is substantial and practical. It is substantial because the contrarian investment provides a critical connection between our theoretical framework and the data. By focusing on contrarian flows, we directly address the theoretical predictions regarding the giants' first-mover advantage and their ability to steer market momentum. This structure ensures a rigorous connection between theory and data, setting the stage for the empirical analyses presented in subsequent sections. It is also practical because the contrarian investment allows us to mitigate the empirical challenges, arising potentially from the shared dependencies on the fundamentals

and multicollinearity. That is, the contrarian investment isolates the giants' unique contributions from common dependencies on economic fundamentals, thereby enabling a clearer identification of giants' idiosyncratic influence.

4.1 Data and Measurements

For the empirical analyses, we primarily use data from the EPFR global funds database. This database offers relatively high-frequency (monthly) information on portfolio investment at the individual investor level, with the caveat that it exclusively encompasses institutional investors.[10] 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 Portfolio 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:

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

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 in its total investment at time t.

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 their time differences are not available in such cases, we employ the inverse hyperbolic sine (IHS) transformation ($\text{IHS}(x) = \ln[x + (x^2 + 1)^{0.5}]$) for the computation of the equity growths (flows) between t and $t + h$:

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

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

[10] As in Koepke and Paetzold (2020), we find that the aggregate of EPFR fund flows at the country level exhibits similarities to traditional IMF Balance of Payment (BoP) statistics. See Fratzscher (2012), Kim and Lee (2020), Koepke and Paetzold (2020), and Chari, Stedman and Lundblad (2022) for the discussions and details of the EPFR global funds data.

(depreciation) lead to an increase (decrease) in the investors' equity holdings. In this case, the equity growths overestimate (underestimate) investment allocation. To isolate this valuation channel, we compute the cumulative equity growth based on the adjusted equity growth with market returns:

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

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

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

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

4.2 Investment Giants and Concentrated Equity Flows

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

Specifically, we first assort equity investor sizes based on the over-time average of each investor's total equity fund investments to the 20 emerging markets between January 2010 and

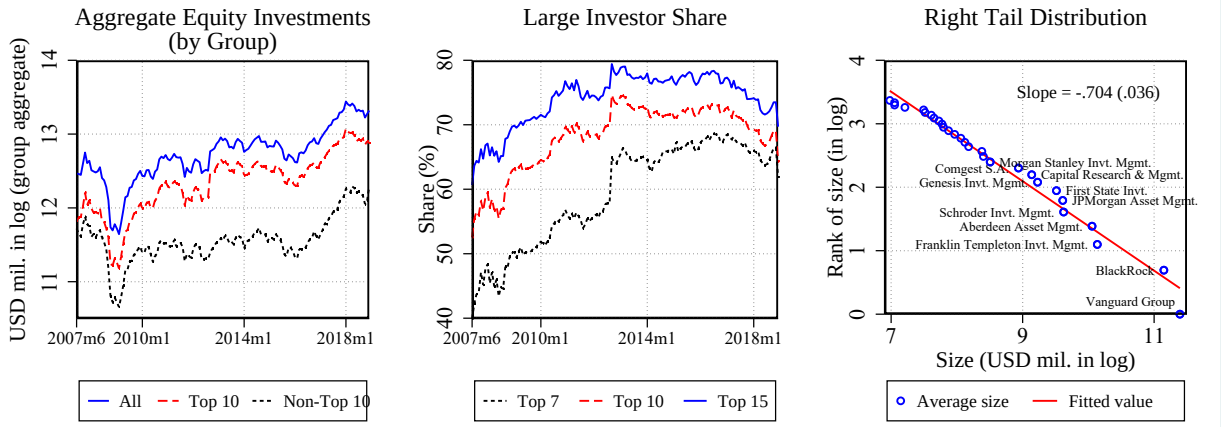


Figure 2: Trends of Equity Fund Flows to Emerging Markets

Notes: The first figure plots the equity investment made by each investor (mutual fund) group in the 20 emerging equities markets. The second figure displays the shares of the top 7, 10, and 15 largest investors in the total global equity funds allocated to the 20 emerging equity markets. The last figure plots the logged total equity investment size, averaged over the period of 2010m1–2018m12, and its logged rank in the emerging equity markets. The data includes 29 continuing investors with size exceeding one billion US dollars. The absolute value of slope of predictions (red line) implies the coefficients of power distribution with robust standard errors in parenthesis. The fund flow data are sourced from the EPFR database. See Appendix C.1 for the details.

December 2018.[11] Then, we designate the top 10 largest equity investors as the investment giants throughout the study period. 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.[12] The investors not falling within the top 10 are categorized as typical (non-large) investors. Noticeably, these investment giants have consistently held the top-ranking positions over time due to their substantial assets under management.

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

[11]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.

[12]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 funds include Deutsche Asset, Management, Invesco Asset Management, Morgan Stanley Investment Management, State Street Global Advisors, and Vontobel Asset Management, in addition to the top 10 largest investors.

(GFC) in 2008. This growth was primarily driven by investment giants. The second panel reveals that the share of equity investments attributable to large mutual funds has steadily increased since the GFC, reaching a peak around 2013, highlighting the rising dominance of these large players.

The distribution of equity investments also demonstrates pronounced concentration among a few large funds. The third panel of Figure 2 depicts a fat right tail in the size distribution of equity investments, particularly in the post-GFC period. A log-log plot of investment size against investor rank confirms a power-law relationship in the right tail, with the rank in log approximately proportional to $-\alpha \ln(\text{Size})$ for $\alpha \approx 0.7$. This pattern is consistent throughout the sample period from January 2010 to December 2018, indicating persistent granularity in emerging market equity flows.[13]

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

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

This paper focuses on the investment decisions of investment giants, their distinct behavior compared to other investors, and their broader impacts on markets. A direct regression of the giants' investment flows on other investors' flows and aggregate market investment, however, risks overstating their influence due to shared dependence on the 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. Furthermore, a strong correlation between giants' flows and fundamentals may introduce multicollinearity issues, complicating inference.

To address these challenges, we focus on the *giants' contrarian investment flows*—the differential between the giants' investment decisions and those of the market or other investors. The intuition

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

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.

To rigorously guide the empirical analysis, this subsection draws on our theoretical framework (Sections 2 and 3) to provide a micro-foundation for focusing on the giants' contrarian decisions rather than their absolute investment flows. We then develop empirically consistent measures of the giants' contrarian flows using the available data, ensuring alignment with our theoretical insights.

The model prediction In our model, the giant's contrarian action can be defined as the investment giant's deviation from the average action of typical investors:

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

The giant's contrarian action is proportional to its deviation from fundamentals, indicating advantages of using the contrarian action in our empirical analysis instead of

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

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

Equation (26) aligns closely with the main regression specification in Section 5, demonstrating that a typical investor's action is positively related to the investment giant's contrarian actions ($\beta > 0$).[14]

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

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

which aligns with the country-level regression specification in Section 6. This equation shows

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

that the market aggregate action ($\bar{A}^*$) is influenced by a combination of the investment giant's contrarian action ($a_1^* - \bar{a}_0^*$) and fundamentals (f). The model predicts that, $\tilde{\beta} > 0$, the investment giant's contrarian action positively affects market aggregates.

Measure of giants' contrarian investment The two theoretical predictions by equations (26) and (27) will be tested in Sections 5 and 6, respectively. Hence, for the empirical tests, it is important to select an appropriate measure to capture their investment behaviors, in particular when they go against other investors or prevailing market trends.

For the measurement consistent with our theoretical model, we mainly use the differential between the average equity growth of investment giants and typical investors, referring to as the investment giant's *contrarian investment*, $(a_1^* - \bar{a}_0^*)$ defined in equation (25).

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

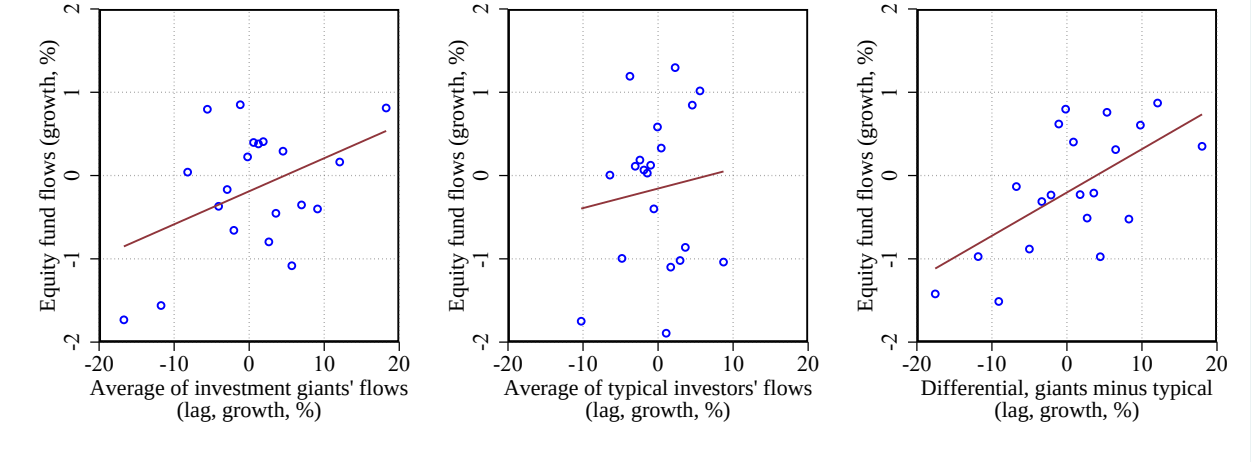
where $\bar{g}_{c,t}^{\text{giant}}$ and $\bar{g}_{c,t}^{\text{typical}}$ are the average equity growth of investors between t and $t-1$ in two groups: investment giants ($i \in \mathcal{G}$) and typical investors ($i \notin \mathcal{G}$). Additionally, $N^{\mathcal{G}}$ and N_t are the number of investment giants and the total number of investors, respectively.[15]

In a similar vein, the investment giants' share of equity flows into each market (country) serves as an alternative measure to capture their idiosyncratic investment decisions. Additionally, following Gabaix and Koijen (2024), we consider the differential between the size-weighted and unweighted averages of equity flows across all investors, which provides a choice-independent alternative to identifying giants' influence. See Section 5.3 for further details on these alternative measures.

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

[15] 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: $\tilde{\bar{g}}_{c,t}^{\text{giant}} - \tilde{\bar{g}}_{c,t}^{\text{typical}} \approx \bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}$.

(a) Around the GFC (2007m6–2009m12)



(b) After the GFC (2010m1–2018m12)

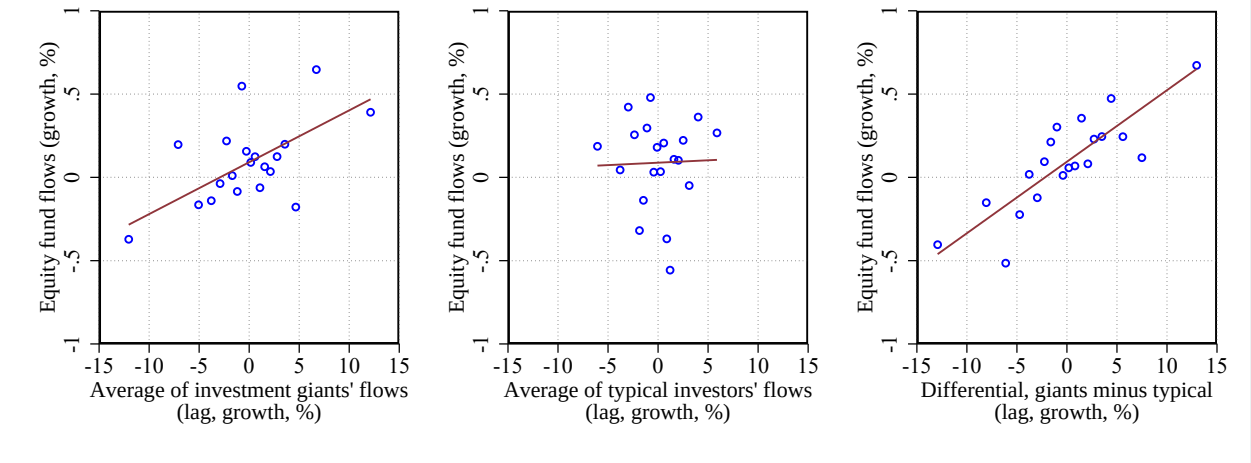


Figure 3: Equity Flows over the Lagged Investment Giants' and Typical Investors' Average Equity Flows

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

Figure 3 presents binned scatter plots that show the average increase in investor equity within each ventile of investment giants' and typical investors' prior month growth rates, along with their differential. Panels (a) and (b) display the plots for the sub-samples corresponding to the periods during and after the GFC, respectively. The results indicate that when investment giants' equity investments increase in the prior month, global investor equity flows tend to grow accordingly. However, this pattern does not hold when typical investors increase their average investments in the previous month. Furthermore, this pattern becomes clearer when examining the differential of investment giants, as shown in the third charts of each panel (a) and (b). Global investors tend to increase their equity flows in response to investment giants' growths surpassing those of typical investors. These observations suggest that the decisions made by investment giants can play an important role in emerging equity markets by influencing other investors and aggregate trends.

5 Equity Fund Flow Dynamics with Investment Giants

In this section, we implement panel local projections to the fund-level EPFR data to examine how other investors react to the investment decisions of large institutional investors in emerging equity markets. Pointedly, the regressions assess the predictive power of large investors' decisions on the subsequent equity investments made by others. Our results establish that the decisions of investment giants carry significant information, and highlight their impacts on other investors within emerging equity markets.

5.1 Empirical Specification

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

Regression specification To simplify our empirical model, we assume that each investor regards the overall stock market of each emerging economy as a representative asset. Hence, they determine their investment size in each market while considering the specific characteristics of that equity market. These characteristics systematically vary depending on the macroeconomic conditions of

each country.

Motivated from our theoretical model prediction in equation (26), we employ the investor-level demand model specified as a linear function of all covariates in equation (29). The model is estimated using panel local projection of *à la* Jordà (2005), separately for the sub-samples of the GFC and of the post-GFC periods:

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

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

Most importantly among the right-hand side variables, we include the investment giants' contrarian investment (i.e., average equity growth differential between equity investments made by the top 10 largest investors and other investors; $\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}$) as a main regressor. As demonstrated in Figure 2, the dominance of a handful of investment giants, presumably with substantial sway over other market participants, is a defining characteristic of the emerging portfolio market. As discussed in Section 4.3, this regressor isolates fundamentals shared among investors. Thus, its coefficients β^h gauge the influence of investment giants' distinct portfolio decisions on the demand of individual investors for equity flows and its dynamics.

Besides, the local projection regression accounts for overall economic conditions by incorporating standard control variables. The vector $\mathbf{Pull}_{c,t}$ and $\mathbf{Push}_t$ includes other control variables, encompassing both pull and push factors at time t along with their three lags.[16] By controlling for the factors associated with economic and financial conditions, the regression excludes the latent impacts from spurious comovements or similar reactions among investors induced by the fundamentals (Bikhchandani and Sharma 2001). It is empirically important to isolate such correlated behavior because it merely reflects an efficient asset reallocation driven by common factors. Pull factors capture domestic aspects, consisting of real interest rates (per annum), growth rates of industrial production, total reserves, exchange rates, and the stock market index for each emerging country c. On the other hand, push factors encompass external or global conditions, including the corresponding US variables, such as US real interest rates (per annum) and growth rates of the VIX, US industrial production, and stock market index (Wilshire 5000).

[16] 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).

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

Sample periods Our sample spans from June 2007 to December 2018. However, the effects of investment giants may differ across periods, in particular around the crisis. To address this concern, we divide our sample into two periods: during and after the GFC. Numerous studies, relying on gross-level data, have documented significant shifts in capital flow patterns in the aftermath of the GFC (Rey 2015). In particular, Shin (2014), Hardy and von Peter (2023), and others emphasize the importance of distinguishing between two phases of global liquidity. Following the GFC, global banks gradually ceded their dominant role to asset managers and other "buy-side" investors with global reach. Prolonged low-interest rates, primarily due to policy accommodation in the US and other advanced economies, arguably prompted global investors to take on more risk and search for higher yields.

Investor-level investigations, as well as documented shifts in aggregate net inflows, particularly in portfolio flows before and after the GFC (Ahmed and Zlate 2014 and Ahmed, Coulibaly and Zlate 2017), may provide additional insights into how interactions among individual investors contributed to the developments in capital flows during the post-GFC periods. Furthermore, during the crisis, investors in emerging markets may be suspicious of the actions taken by other investors and imitate to a lesser extent. Put differently, they tend to determine investment based on their own information, or follow other specific investors rather than the market movements (Hwang and Salmon 2004 and Ferreruela and Mallor 2021). Choe, Kho and Stulz (1999) find evidence of positive feedback trading by foreign investors in Korea before the 1997 Asian financial crisis, a pattern that dissipated during the crisis.

5.2 Regression results

Figure 4 provides the responses of equity flows to an increase in shocks of investment giant's contrarian investment. The impulse responses of equity growth are constructed based on the estimate of β^h at each horizon. The confidence intervals are drawn from the respective estimated

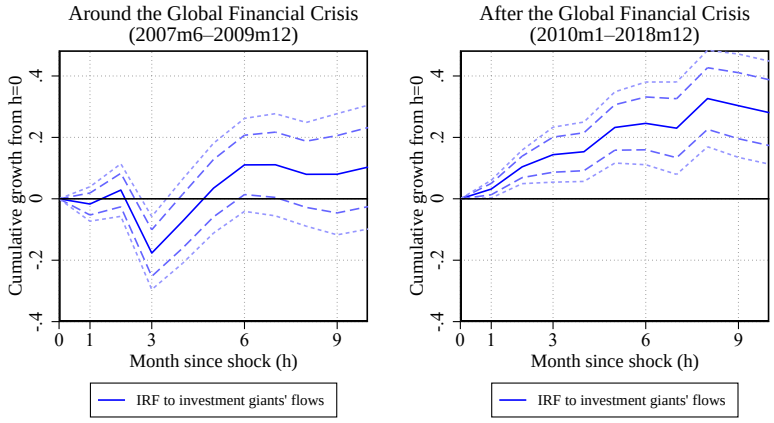


Figure 4: Investor-Level Response to the Equity Flow Differential between Investment Giants and Typical Investors

Notes: The figures depict the predictive capacity of average equity flows from the differential between investment giants' (the top 10) and typical investors' average equity growths where we use an individual investor's equity flows ($\tilde{\Delta}\text{IHS}(\text{Equity}_{ic,t})$) and the differential ($\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}$) are adjusted by stock market index and exchange rate growths to remove valuation effects. The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (29). In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. In each regression, singleton observations are dropped. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

standard errors. The results reported are based on the valuation-adjusted equity flows.[17] The figure displays impulse responses for two distinct periods: the GFC periods (from June 2007 to December 2009; left chart) and the post-crisis periods (from January 2010 to December 2018; right chart).

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

Two noteworthy findings emerge from the results. First, institutional investors tend to follow the lead of investment giants, corroborating the model prediction in equation (26). An increase in the investment giant's disproportionate equity investment compared to typical investors has a positive impact on the equity investment of individual institutional investors. The result suggests that contrarian investment made by investment giants lead the overall market participants, pre-

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

sumably providing positive signals with them. This observation is also consistent with the feature presented in Figure 3, which suggests that international investors place more weight on the leading movements of investment giants when determining global portfolio allocation.

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

5.3 Robustness Checks

To ensure the robustness of our findings, we consider alternative measures of investment giants' contrarian behavior that help isolate their idiosyncratic influence from broader market movements. Our baseline measure normalizes giants' flows by deducting those of other (typical) investors, but we introduce two alternative approaches to reinforce our identification strategy.

Alternative measure 1: Giant's market share changes The first alternative measure captures the giants' changing market share in equity market c at time t, defined as:

$$\frac{1}{N^{\mathcal{G}}} \sum_{i \in \mathcal{G}} \Delta^1 \left(\frac{\text{Equity}_{ic,t-1}}{\text{Equity}_{c,t-1}} \right) \approx \bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{agg}}_{c,t} \tag{30}$$

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. Within our theoretical framework, it can be expressed as:

$$a^*_1 - \bar{A}^* = \lambda(a^*_1 - \bar{a}^*_0) = \psi^* \lambda (a^*_1 - f), \tag{31}$$

which is proportional to our benchmark contrarian investment measure $(a^*_1 - \bar{a}^*_0)$. Deviations in the giants' market share capture their idiosyncratic investment movements, free from shared fundamentals. An increase in market share signals that giants are investing more in market c

relative to the aggregate, reinforcing their contrarian stance.

Alternative measure 2: Granular instruments As a second approach, we adopt 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:

$$\sum_i \left(\frac{\text{Equity}_{ic,t-1}}{\sum_j \text{Equity}_{jc,t-1}} \right) \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}) - \frac{1}{N_t} \sum_i \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}). \tag{32}$$

Within our model, this differential isolates idiosyncratic investment decisions from common fundamentals, as captured by:

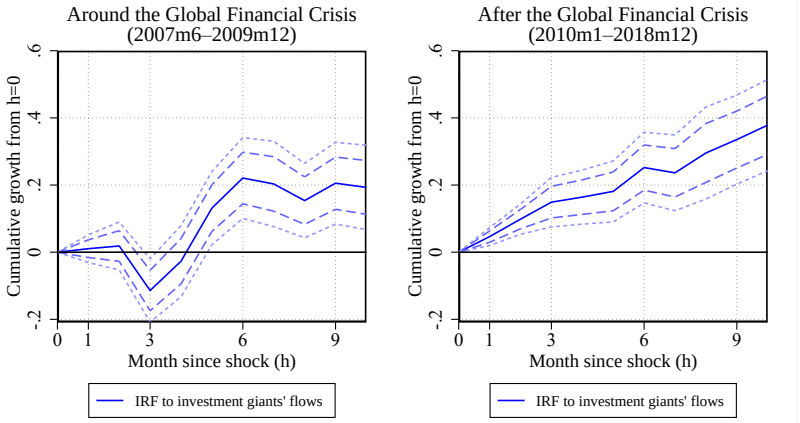
$$\int_{i\in[0,1]} \lambda_i a_i^* \mathrm{d}i - \int_{i\in[0,1]} a_i^* \mathrm{d}i = (1-\lambda)(a_1^* - \bar{a}_0^*) = \psi^*(1-\lambda)(a_1^* - f), \tag{33}$$

which is proportional to our benchmark contrarian investment measure $(a_1^* - \bar{a}_0^*)$. This differential, therefore, serves as an alternative proxy for giants' contrarian investment and should exhibit predictive power over other investors and aggregate market movements, consistent with our main results.

We estimate the local projections of equation (29), replacing our main regressor with the alternative measures defined in equations (30) and (32). Figure 5 presents the results. Subfigures (a) and (b) report investor-level equity flow responses to changes in the giants' market share and the differential between size-weighted and unweighted investment growth, respectively, for the Global Financial Crisis (GFC) period (left panel) and the post-GFC period (right panel). Our findings align with the baseline results: in the post-crisis period, individual investors' equity flows respond positively to giants' contrarian flow shocks. These patterns reinforce the robustness of our main findings in Figure 4, underscoring the influence of giants on investors and the predictive power of giants' contrarian investment decisions.

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

(a) Changes in Investment Giants Share



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

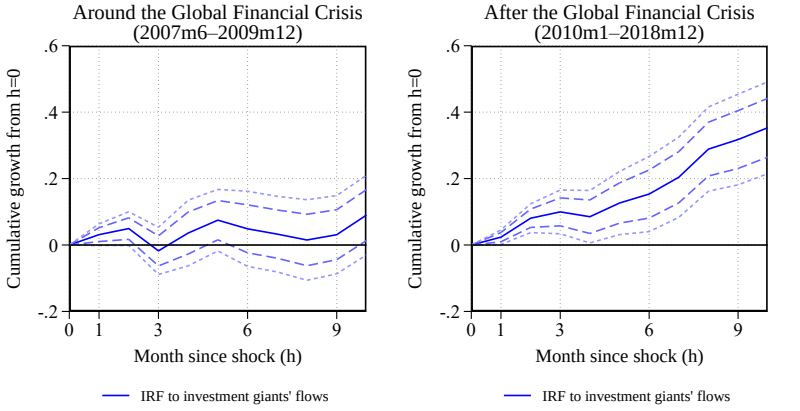


Figure 5: Investor-Level Response to Changes in Investment Giants Share: Active Fund Flows

The figures depict the predictive capacity of alternative measures of contrarian active equity investments made by the top 10 investment giants. In subfigure (a), the alternative measure is the change in share of active equity investments made by the top 10 investment giants, as defined in equation (30). In subfigure (b), the alternative measure is the difference between size-weighted and unweighted averages of investor's active flows, as defined in equation (32). 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 (29). In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

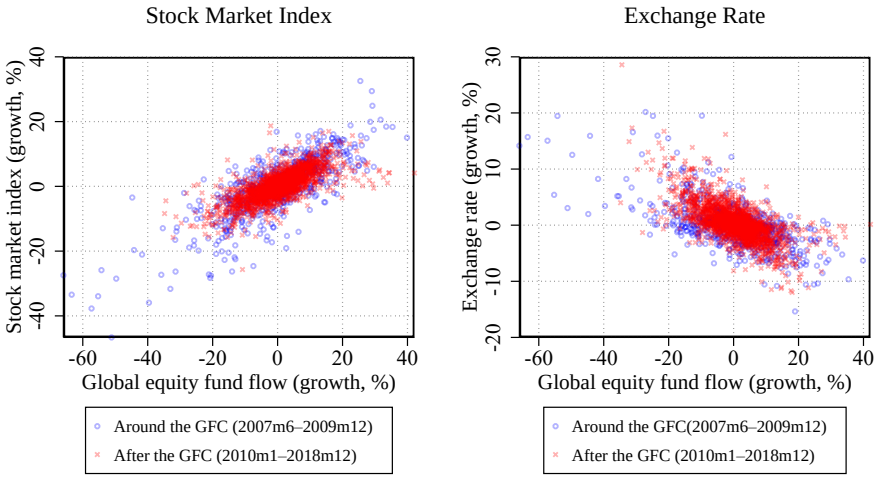


Figure 6: Global Equity Fund Flows, Stock Prices, and Exchange Rates in Emerging Economies

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.

6 Aggregate Dynamics and Implications

Capital flows and global asset allocations play crucial roles in financial and foreign exchange markets, particularly in emerging economies (e.g., Hau and Rey 2006, Gyntelberg et al. 2018, and Goldberg and Krogstrup 2023). This relationship may also be relevant from the perspective of individual global investors' portfolio choices. Figure 6 highlights the growth rates of country-level aggregated EPFR global equity fund flows, stock market indices, and exchange rates (local currency per US dollar) across 20 emerging market economies. Despite EPFR fund flows typically representing only 1–10% of the capitalization in these markets (Jotikasthira et al. 2012), an increase in global equity flows correlates strongly with stock market gains and exchange rate appreciations. These patterns underscore their influence on financial markets, well beyond their market share.

Previous research has emphasized the intricate relationships between capital flows and financial factors, both local and global, such as domestic stock indices, US equity market movements, and exchange rate fluctuations. Studies such as Warther (1995) and Edelen (1999) have demonstrated the contemporaneous impact of aggregate mutual fund flows on stock returns. Coval and Stafford (2007) revealed the price pressures exerted by large-scale fund flows in the US equity market, while Lilley, Maggiori, Neiman and Schreger (2022) found US purchases of foreign bonds to be a key driver of currency dynamics post-GFC. However, these relationships remain contested, as

evidenced by Wardlaw (2020) and Gabaix and Maggiori (2015), underscoring the need for further analysis.

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

6.1 The Impact of Investment Giants on Aggregate Flows

In the remainder of this section, we explore the extent of investment giants' impact and their ability to forecast aggregate equity flows as well as stock prices and exchange rates in emerging economies, shining a light on their implications in connection with our fund-level findings.

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

$$Y_{c,t}^h = \beta^h \left(\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}\right) + \mathbf{\Gamma}_{\text{pull}}^h \mathbf{Pull}_{c,t} + \mathbf{\Gamma}_{\text{push}}^h \mathbf{Push}_t + \delta_c^h + \delta_m^h + \varepsilon_{c,t}^h, \tag{34}$$

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

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

While the adjusted and non-adjusted aggregate equity flows are computed based on the EPFR data, the data for aggregate equity net flow is complemented with the Institute of International Finance (IIF) database from the IMF. In addition, identically to our fund-level estimations, the cumulative growth of equity flows between time t and $t+h$ is winsorized, ranging from $-h\times100\%$ to $h\times100\%$, to rule out the extreme values. Similar to previous regressions, equation (34) includes standard control variables—push and pull factors and various fixed effects. Other terms are defined comparably to those in equation (29).

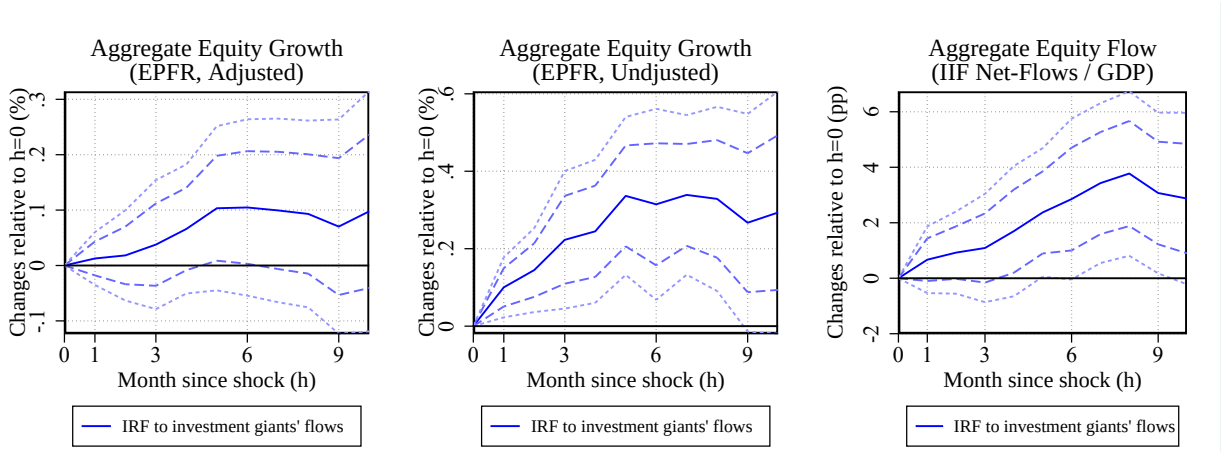


Figure 7: Aggregate Flow Responses to Investment Giants Flows

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 (34). 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 (%).

Regression results Figure 7 presents the impulse responses of the three measures of aggregate equity flows ($Y^h_{c,t}$) to shocks in the differential between investment giant and typical investor flows, respectively. Overall, the results from the country-level data are consistent with the theoretical prediction by equation (27). They also align with our earlier findings from investor-level regressions in Section 5.

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

Robustness To ensure the robustness of these findings, we conduct additional analyses using alternative specifications similar to those in Section 5: (*i*) alternative 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-weigted 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 E.1.

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

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

Emerging market economies have witnessed capital flow volatility during various crises, including the global financial crisis and the recent pandemic, which led to domestic financial distress. Further, as the impacts of global factors, dubbed as *the global financial cycle*, have substantially grown, small open economies, in particular those which experienced more credit inflow, face increasing challenges in insulating their financial markets from external shocks (*dilemma*, e.g., Rey 2015, Kalemli-Özcan 2019, and Goldberg and Krogstrup 2023).

Regression specification Against this backdrop, we investigate the responses of stock markets and foreign exchange markets to the investment giant flow shocks, using the regression (35).

$$Z_{c,t}^{h} = \beta^{h}\left(\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}\right) + \mathbf{\Gamma}_{\text{pull}}^{h}\mathbf{Pull}_{c,t} + \mathbf{\Gamma}_{\text{push}}^{h}\mathbf{Push}_{t} + \delta_{c}^{h} + \delta_{m}^{h} + \varepsilon_{c,t}^{h}, \tag{35}$$

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 (34).

Regression results Figure 8 summarizes the results, corresponding to the three measures of market returns. In the first chart, shocks in the investment giant flows have incremental effects on stock market indices in emerging markets. The response is the strongest around five months after the shock, rising around 0.14%. This finding is consistent with the literature which documents a strong positive link between capital flows and stock valuations in international financial markets

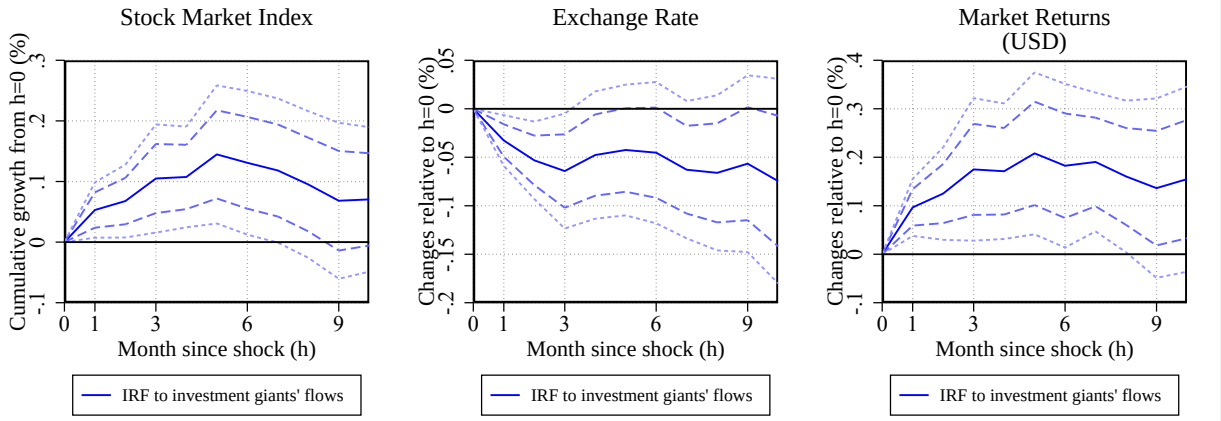


Figure 8: Stock and Currency Markets Responses to Investment Giants Flows

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 (34). 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 (%).

(Gourinchas and Rey 2014, Anaya, Hachula and Offermanns 2017, Bathia, Bouras, Demirer and Gupta 2020, and many others).

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

Last, the third chart illustrates the responses of relative stock market returns, *viz.* the differentials between domestic returns in US dollars and US returns, to the shocks in investment giants' contrarian flows. According to the uncovered equity parity hypothesis, relative market returns represent an international arbitrage opportunities in emerging equity markets. Therefore, the results suggest that shocks in giant flows generate a positive reaction in relative returns, which in turn attract other investor flows.

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

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

7 Conclusion

The global financial landscape has undergone significant shifts in recent decades, with changes in capital flows playing a critical role, particularly in emerging economies. Global factors, driven by the dominant currency US dollars and US monetary policy, shape and are shaped by capital flows, thereby impacting local financial markets. Since the GFC, cross-border capital flows have increasingly shifted toward market-based flows rather than bank-intermediated flows. More recently, the trajectory of global inflation has influenced the risk appetites of international investors as it has directly accounted for policy stances in major countries. These evolving trends call for a more comprehensive understanding on the dynamics of portfolio flows and their impacts, in particular in emerging market economies.

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

In this vein, our study lays the theoretical and empirical groundwork for in-depth investor-level analysis of global equity flows and decision-making among market players. Specifically, this paper explores the investment choices of institutional investors operating in emerging equity markets, shedding light on the pivotal roles that influential large investors play. To do so, we first construct a beauty contest model with a dominant player. The model predicts that the investment giant move first and then typical investors follow. This choice is beneficial to the giant since it can steer the market in a favorable direction, towards the market fundamentals. It is also beneficial to the typical investors since they can observe the giant's decision before their actions. The model also highlights the substantial impact of these investment giants on aggregate equity flows and their predictability for other investor flows.

Using the EPFR global fund data, we validate our theoretical predictions. Importantly, we focus on the investment giant's contrarian investments to isolate the giant's idiosyncratic contributions from common dependencies on the market fundamentals. Our findings reveal that a small group of giants contrarian flows consistently exert a strong predictive power for individual and aggregate equity flows into emerging markets. Furthermore, the contrarian investments also predict positive response of stock returns. These results are more surprising considering that EPFR fund data covers only 1-10% of market capitalization in emerging market economies.

This study enhances our understanding of investor-level flows stemming from strategic decisions made by global institutional investors. Our results underscore the importance of developing a new framework to elucidate the determinants of international portfolio flows at the investor level. From a policy perspective, our findings also emphasize the potential value in closely monitoring the actions of these investment giants as early warning indicators for emerging market downturns. In a world of dilemma where policy options are limited (Rey 2015), this insight can serve as critical guideposts for policymakers and market participants navigating the intricate realm of international portfolio flows. Moreover, by uncovering the micro-level determinants of fund flows, policymakers gain valuable implications for designing macro-prudential or foreign exchange-related policy frameworks aimed at ensuring financial stability, particularly in emerging economies deeply integrated into the global financial market.

References

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Gabaix, Xavier, "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," Technical Report, National Bureau of Economic Research 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, in Robert Thomas Crow, ed., *2014: US economic prospects: Secular stagnation, hysteresis, and the zero lower bound*, The Best of Business Economics: Highlights from the First Fifty Years, New York, NY: Palgrave Macmillan, 2016, pp. 421–435.

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

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

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

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

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

Appendix

A Simultaneous Move Case

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

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

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

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

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

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

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

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

Then, the optimal strategy can be reexpressed as:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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 investment giant's initial move, improving alignment with the market aggregate. By reducing deviations of the market aggregate from the fundamental, the public information benefits all investors, including the investment giant. This effect is particularly pronounced when the investment giant's signal precision (θ_1) is higher than that of the typical investors (θ_0).

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

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

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

C Data Appendix

C.1 Fund Flows

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 (22). 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 (23), where the cumulative growth is winsorized at both ends by $-h\times100\%$ 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 (24), 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.

C.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. macroeconomic variables.

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

Financial Database for some countries where the data is not available in the IFS dataset.[18]

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.[19] Finally, we use the Chicago Board Options Exchange Volatility Index (VIX) from Bloomberg. We calculate the month-over-month growth rates for these variables taking the first difference of logarithmic values rather than IHS because they do not contain zero value.

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

Table F.5 provides the summary statistics for the macroeconomic variables. Our final dataset includes macroeconomic variables for all 20 countries over both the mid-GFC period (31 months) 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.

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

[19] 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.

D Robustness Checks of Investor-Level Analyses

Active funds flows Next, we estimate investor's responses with a sample including active fund flows but excluding passive ones. Passive funds, also known as passive index or index-style funds, indicate the investment vehicles which replicate a stock market index in their composition of investments.[20] 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).[21]

To address this concern, we estimate regression equations (29) and (D.9) using active fund flows as the dependent and independent variables.[22] The estimation results with active funds data are broadly consistent with the full sample (active funds & passive funds) results. Specifically, as shown in Figure D.1, the results from the estimation of equation (29) using active funds flows are by and large similar to those observed in Figure 4. Active fund flows increase in reaction to a rise in investment giants' flow shocks relative to typical investors, confirming high predictability of investment giants' contrarian decisions for tailing equity flows. In addition, the significant impacts of active fund flow differential between investment giants and typical investors are more pronounced and persistent after the GFC.

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 D.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 (30) and (32), respectively. Consistent with the observations in Figures 4 and D.1, active equity flows exhibit the positive influence of investment giants on investors, in particular, after the GFC.

Investor-time fixed effects Regression equation (29) accounts for temporal fluctuations in push and pull factors by including the US and domestic country-level variables. Also, it controls for

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

[21] 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.

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

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 (29). Specifically, given that EPFR data does not provide the detailed investor characteristics, we incorporate investor-time fixed effects ($\delta^h_{i,t}$):

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

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

Figure D.3 summarizes the responses of equity flows based on the regression equation (D.8). The left chart shows the results for the GFC-period, while the right chart depicts the results for the post-GFC period. Both results are qualitatively and quantitatively similar to those of the baseline specification. In response to the shock in the giant's contrarian investment on emerging equity markets, equity flows increase, more evidently after the GFC.

Definition of investment giants Another concern that may arise is whether our baseline results are contingent on the specific definition of investment giants. In our baseline specification, investment giants (or large investors) are arbitrarily defined as the top 10 largest investors in terms of the investment size in emerging equity markets. For the check of robustness, we depart from the definition by assigning two different thresholds for investment giants—top 15 and 7 largest investors. We then re-estimate the equation (29) using the fund data sorted out according to the two different definitions of investment giants.

The results corresponding to the alternative definitions are presented in Figure D.4. 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 (29), we consider a specification that condition the response of individual institutional equity flows on the market crash events:

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

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.[23] This specification includes the same pull and push factors along with fixed effects as employed in regression equation (29).

Figure D.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).

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

[23] 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.

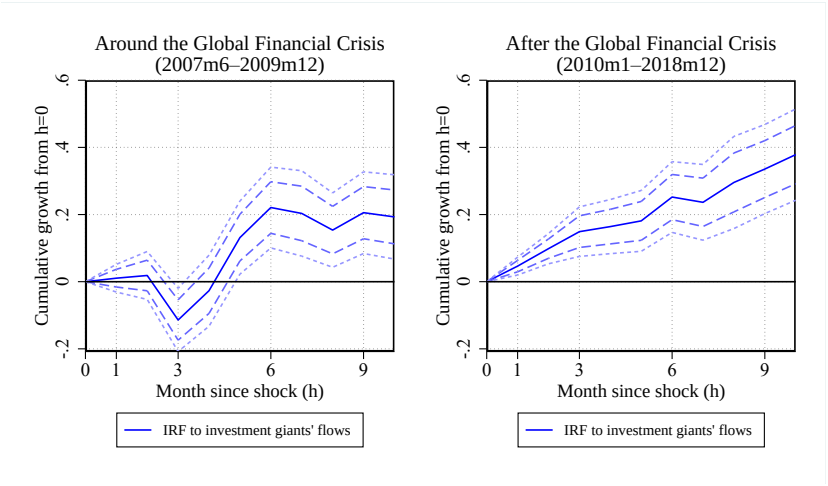
push and pull factors, the results can be interpreted as evidence of a distinct, systemic relationship at the fund level among investors which drives non-resident portfolio flows into emerging equity markets.[24]

Next, in Figure D.6, we report the results from state-dependent local projection similar to equation (D.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 (D.9), we further investigate the non-linearity of equity fund responses between crash and non-crash scenarios. Subfigures (a) and (b) in Figure D.7 summarize the results when investment giants are defined as top 15 and 7 largest investors, respectively. Consistent with the observations in Figure D.5, equity flows exhibit more pronounced responses during market collapses.

[24] 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

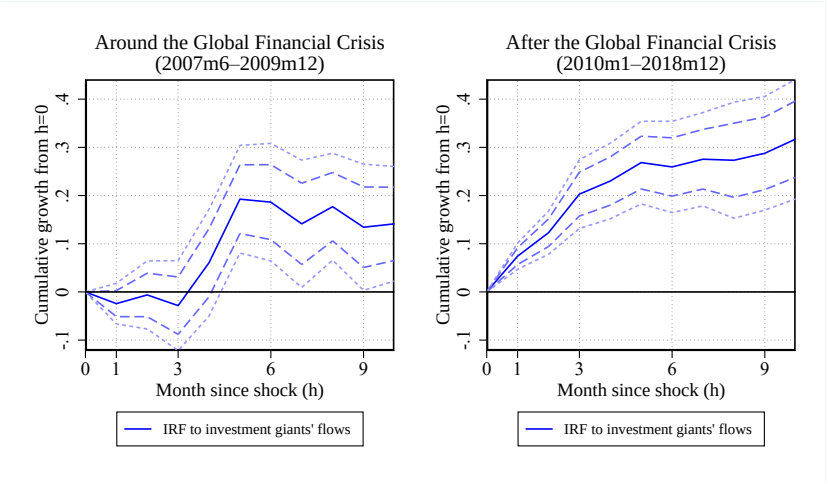
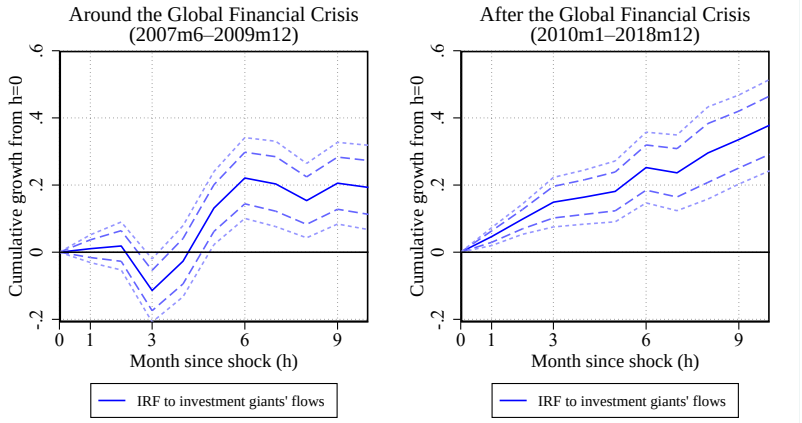


Figure D.1: Investor-Level Response to the Equity Flow Differential between Investment Giants and Typical Investors: Active Fund Flows

Notes: The figures depict the predictive capacity of average active fund flows from the differential between investment giants' (the top 10) and typical investors' average active fund growths. In 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 (29). In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

(a) Changes in Investment Giants Share



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

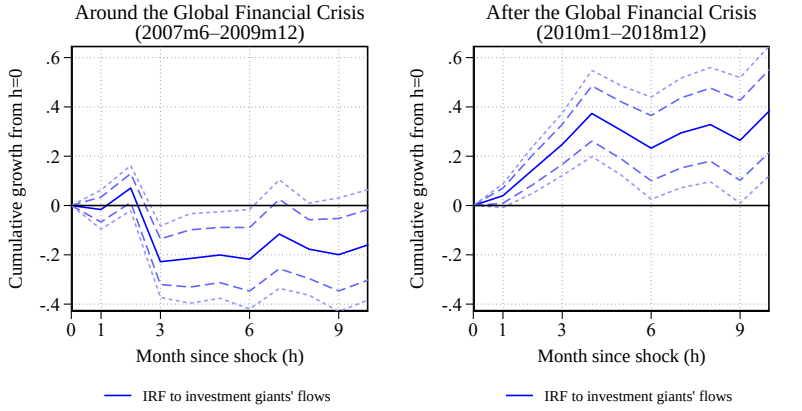


Figure D.2: Investor-Level Response to Alternative Measures of Contrarian Flows

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 (30). In subfigure (b), the alternative measure is the difference between size-weighted and unweighted averages of investor flows, as defined in equation (32). 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 (29).. In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

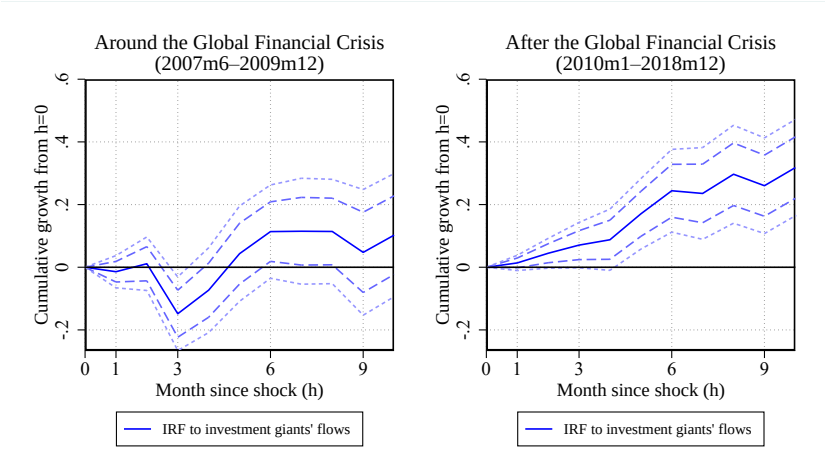
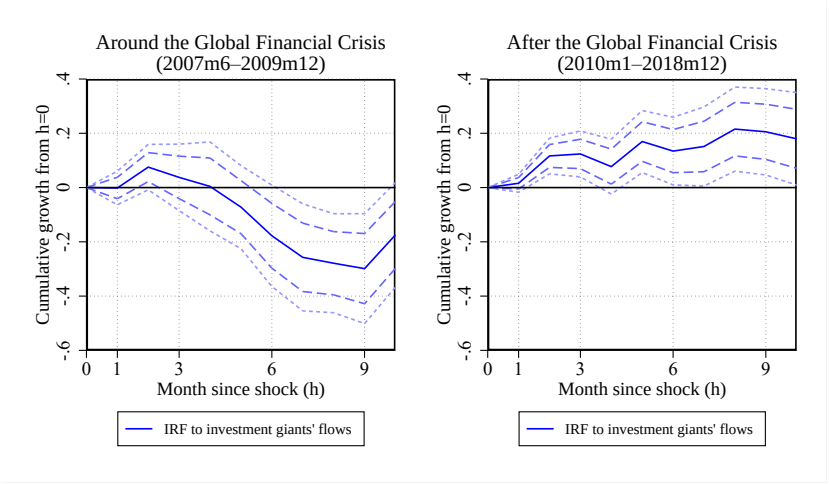


Figure D.3: Investor-Level Response to the Equity Flow Differential between Investment Giants and Typical Investors: Alternative Specification

Notes: The figures depict the predictive capacity of average equity flows from the differential between investment giants' (the top 10) and typical investors' average equity growths. The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (D.8). In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The specification controls for investor-time and country fixed effects, and contemporaneous growth of pull factors, and their three lags. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

(a) Top 15 Largest Investors



(b) Top 7 Largest Investors

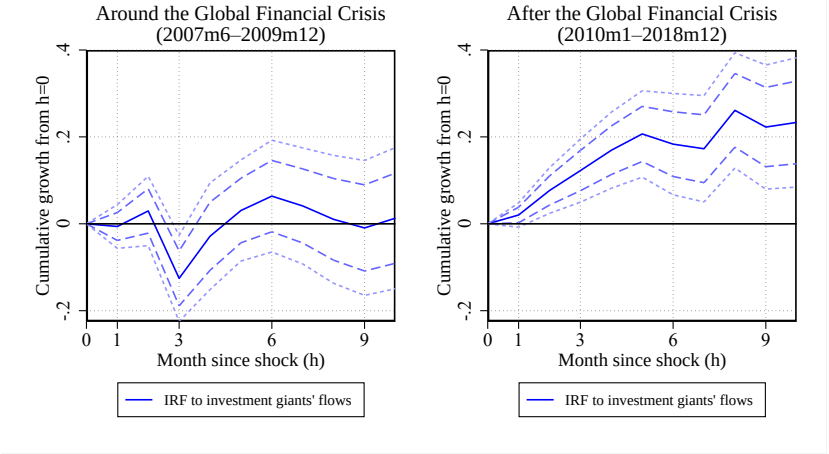


Figure D.4: Investor-Level Response to the Equity Flow Differential between Investment Giants (Top 15 or 7 Largest Investors) and Typical Investors

Notes: The 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 (29). In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

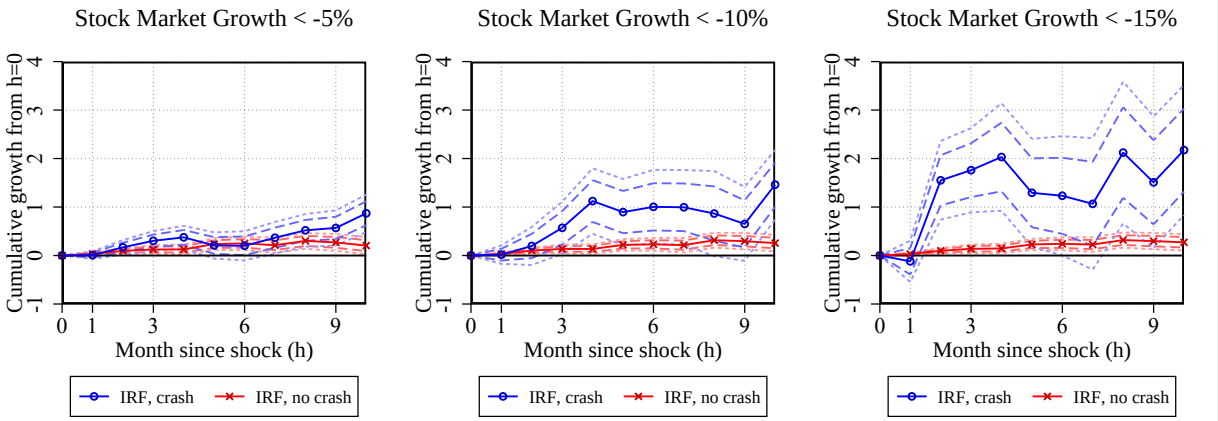


Figure D.5: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis

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 (D.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, %).

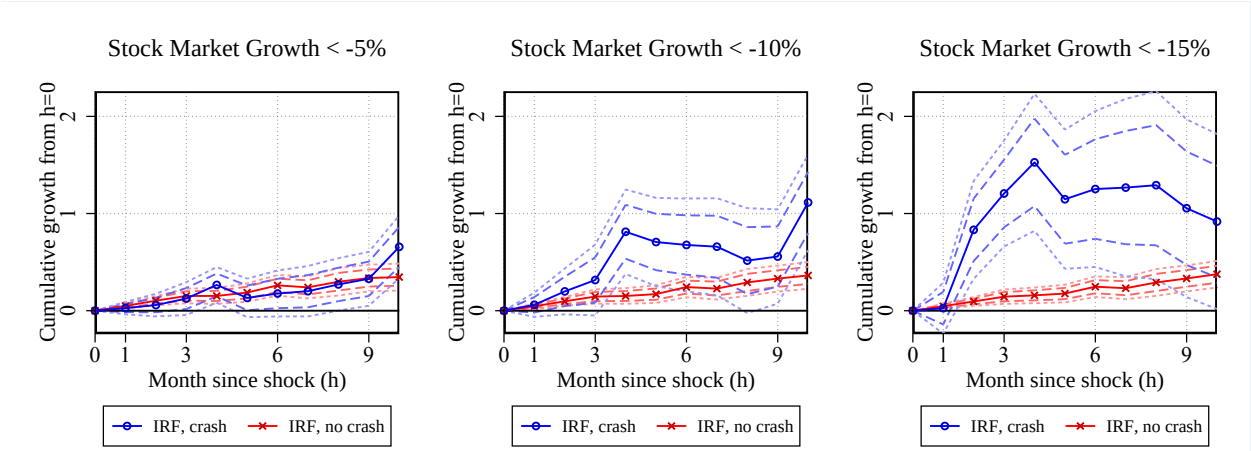
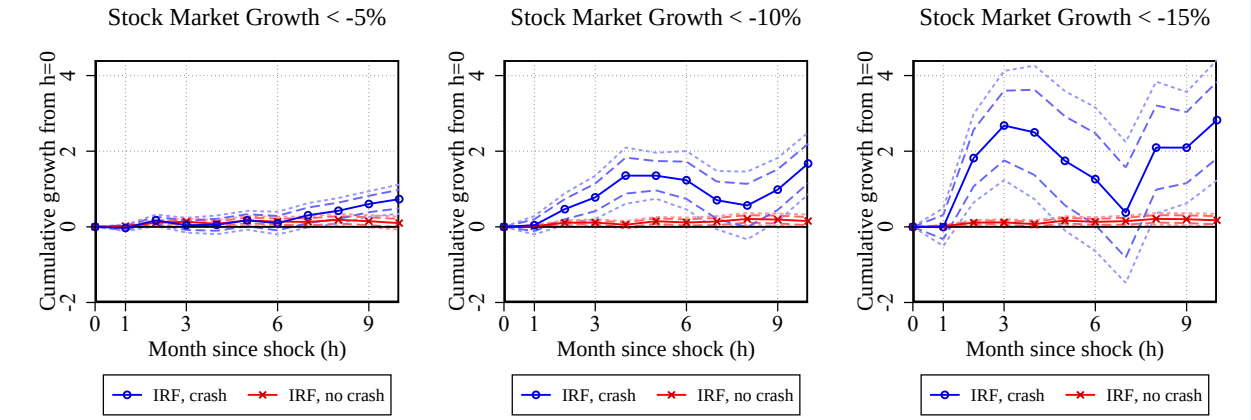


Figure D.6: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis: Active Fund Flows

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 (D.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, %).

(a) Top 15 Largest Investors



(b) Top 7 Largest Investors

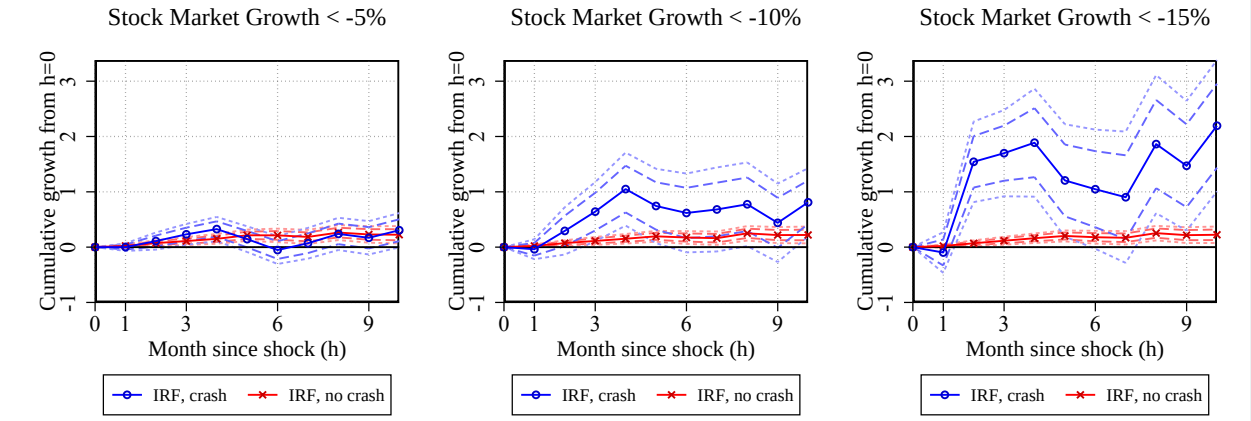


Figure D.7: Investor-Level Response with and without Stock Market Crashes After the Global Financial Crisis: Top 15 and 7 Largest Investors

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 (D.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, %).

E Robustness Checks of Country-Level Analyses

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

The results of aggregate-level regressions remain by and large robust across different data and specifications, reaffirming the substantial information embedded in the investment decisions of giants regarding the overall equity flow conditions in emerging equity markets. More specifically, we first compare our baseline results with those estimated using only active fund flows (Figure E.8). Similar to our baseline results, although aggregate equity flows computed with valuation-adjusted EPFR data exhibit to some extent weak or insignificant increase after the shock (first chart), those estimated with non-adjusted data (second chart) and IIF net flows (third chart) show significant and persistent increases.

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

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

where δ_t^h denotes the time fixed effect.[25] As summarized in Figure E.9, the responses of aggregate equity flows, based on the three measures, to the giants' contrarian investment are consistent with our baseline when the the time fixed effect is explicitly accounted for.

Third, we test the sensitivity of the results to different definitions of investment giants. Panels (a) and (b) of Figure E.10 report the impulse responses of aggregate flows to shocks in the contrarian flows of the top 15 and 7 large investors, respectively. Finally, we check the robustness of our results using an alternative main regressors—the investment giants' share and differential between size-weighted and unweighted averages, as defined in equations (30) and (32), respectively. The impulse responses of aggregate flows to the shocks are also in line with the baseline results, as presented in Figure E.11.

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

[25] Note that, similar to equation (D.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.

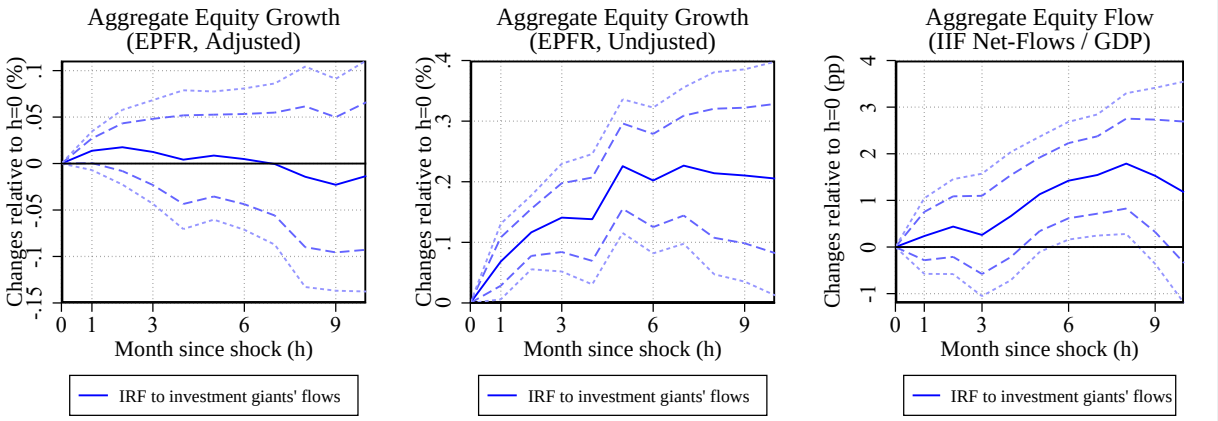


Figure E.8: Aggregate Flow Responses to Investment Giants: Active Fund Flows

Notes: The figures depict the predictive content of the differential between investment giants' (the top 10) and typical investors' average active fund equity growth for the adjusted and unadjuested EPFR aggregate active fund equity growths and and IIF aggregate equity net-flows (% of GDP). The sample periods are after the global financial crisis (2010m1–2018m12). The responses to investment giants flows are the estimates of β^h in equation (34). The specification controls for country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

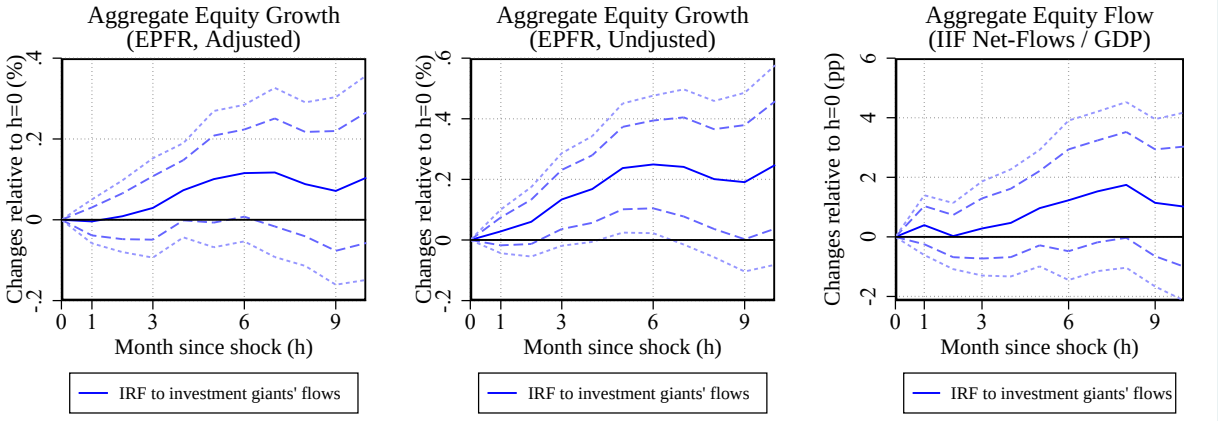
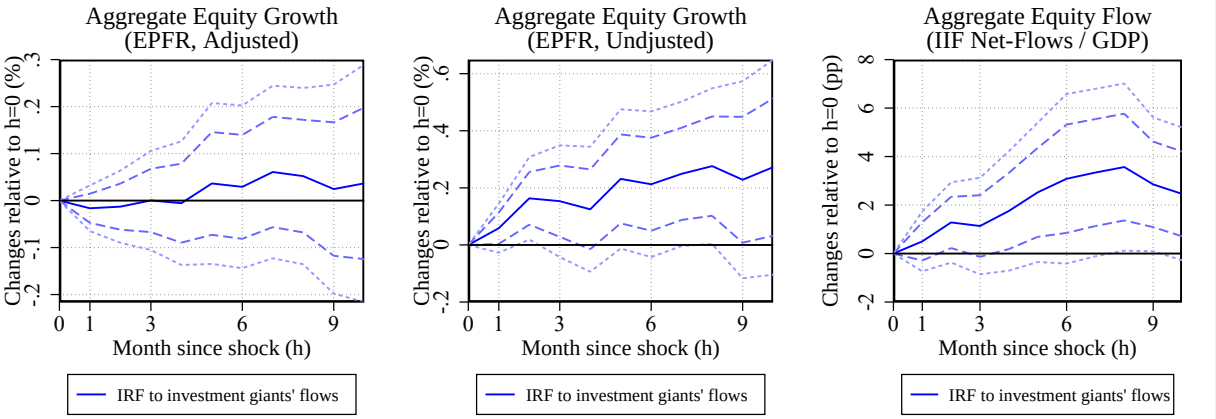


Figure E.9: Aggregate Flow Responses to Investment Giants Flows: Alternative Specification

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

(a) Top 15 Largest Investors



(b) Top 7 Largest Investors

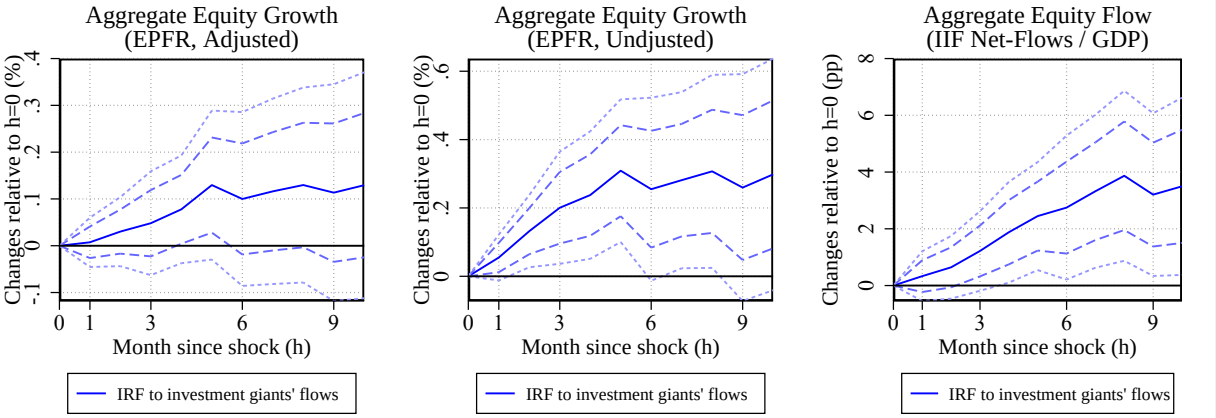
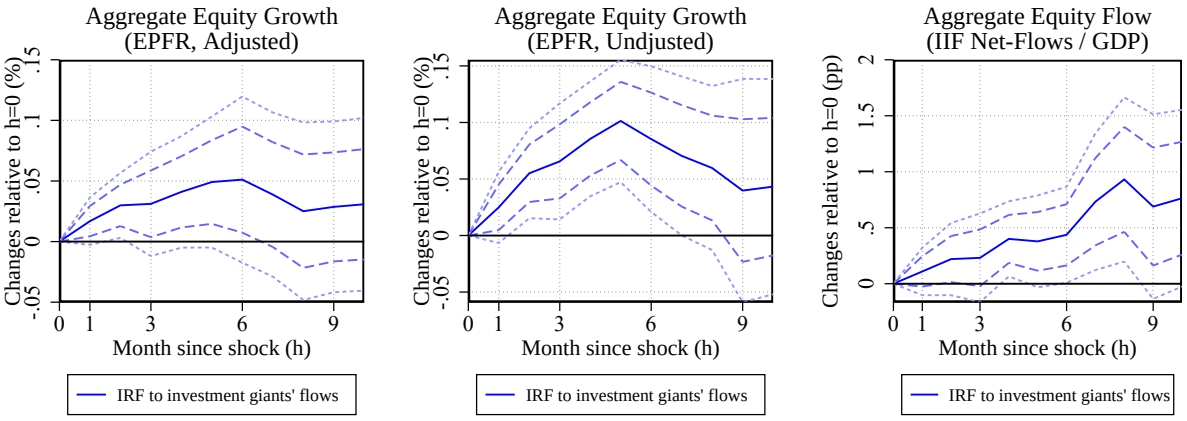


Figure E.10: Aggregate Flow Responses to Investment Giants (Top 15 and 7 Largest Investors) Flows

Notes: The panels (a) and (b) plot the predictive content of the differential between investment giants' (the top 15 and 7, respectively) and typical investors' average equity growth for the adjusted and unadjuested EPFR aggregate active fund equity growths and and IIF aggregate equity net-flows (% of GDP). The sample periods are after the global financial crisis (2010m1–2018m12), respectively. The responses to investment giants flows are the estimates of β^h in equation (35). 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

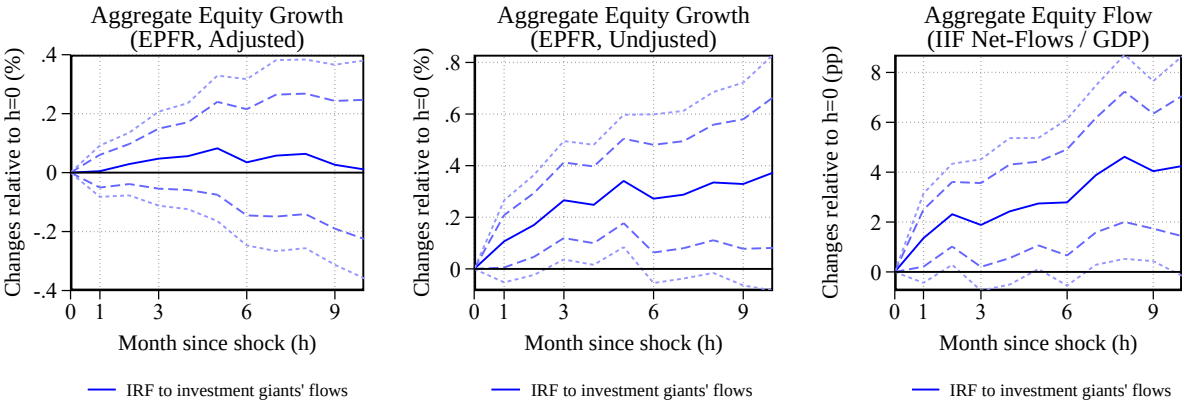


Figure E.11: Aggregate Flow Responses to Investment Giants Share

Notes: The The figures depict the predictive capacity of alternative measures of contrarian equity investments for the adjusted and unadjuested EPFR aggregate equity growths and 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 (30). In subfigure (b), the alternative measure is the difference between size-weighted and unweighted averages of investor flows, as defined in equation (32). 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 (34). The specification controls for country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

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

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

In more details, the impulse responses of the stock and currency markets to active fund flows are first reported in Figure E.12. Second, we carry out a regression similar to equation (E.10), which in particular takes into consideration time fixed effect. The estimation results are summarized in Figure E.13. Third, we reckon with different definitions of investment giant flows. Specifically, labeling the top 7 and 15 largest investors in our EPFR dataset as investment giants, we assess whether our main findings remain consistent. The corresponding results are provided in panels (a) (top 15 largest investors) and (b) (top 7 largest investors) in Figure E.14. Fourth, Figure E.15 presents the responses of stock returns and exchange rate adjustments to shocks in the alternative measure of contrarian flows of investment giants: the investment giants' share and differential between size-weighted and unweighted averages, as defined in equations (30) and (32), respectively.

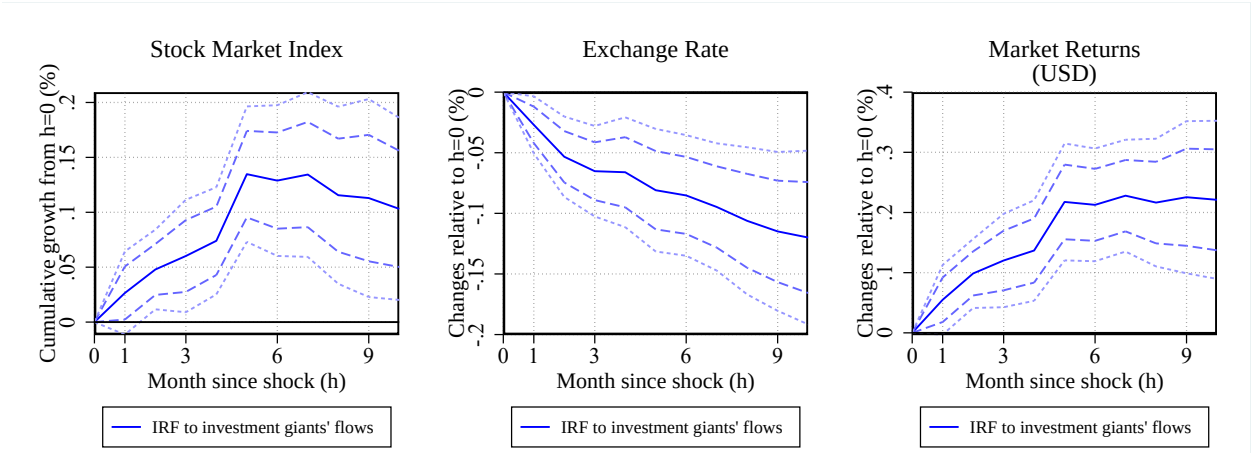


Figure E.12: Stock and Currency Markets Responses to Investment Giants: Active Fund Flows

Notes: The figures depict the predictive content of the differential between investment giants (the top 10) and typical investors' average active fund equity growth for stock price indices, exchange rates, and stock market returns (USD). The sample periods are after the global financial crisis (2010m1–2018m12). The responses to investment giants flows are the estimates of β^h in equation (35). The specification controls for country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

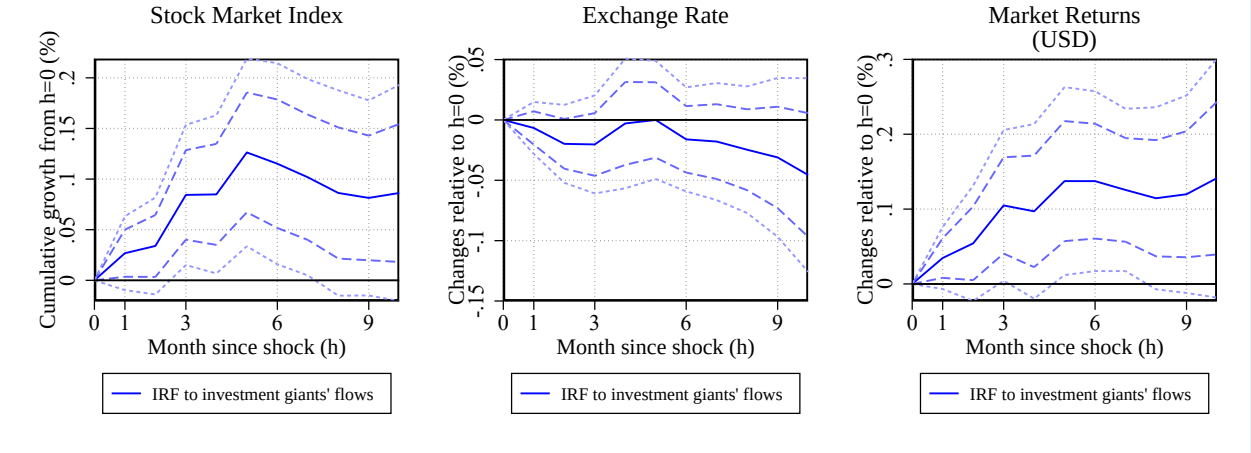


Figure E.13: Stock and Currency Markets Responses to Investment Giants Flows: Alternative Specification

Notes: The figures depict the predictive content of the differential between investment giants' (the top 10) and typical investors' average equity growth for stock price indices, exchange rates, and stock market returns (USD). The sample periods are after the global financial crisis (2010m1–2018m12). The responses to investment giants flows are the estimates of β^h in equation (35) 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 (%).

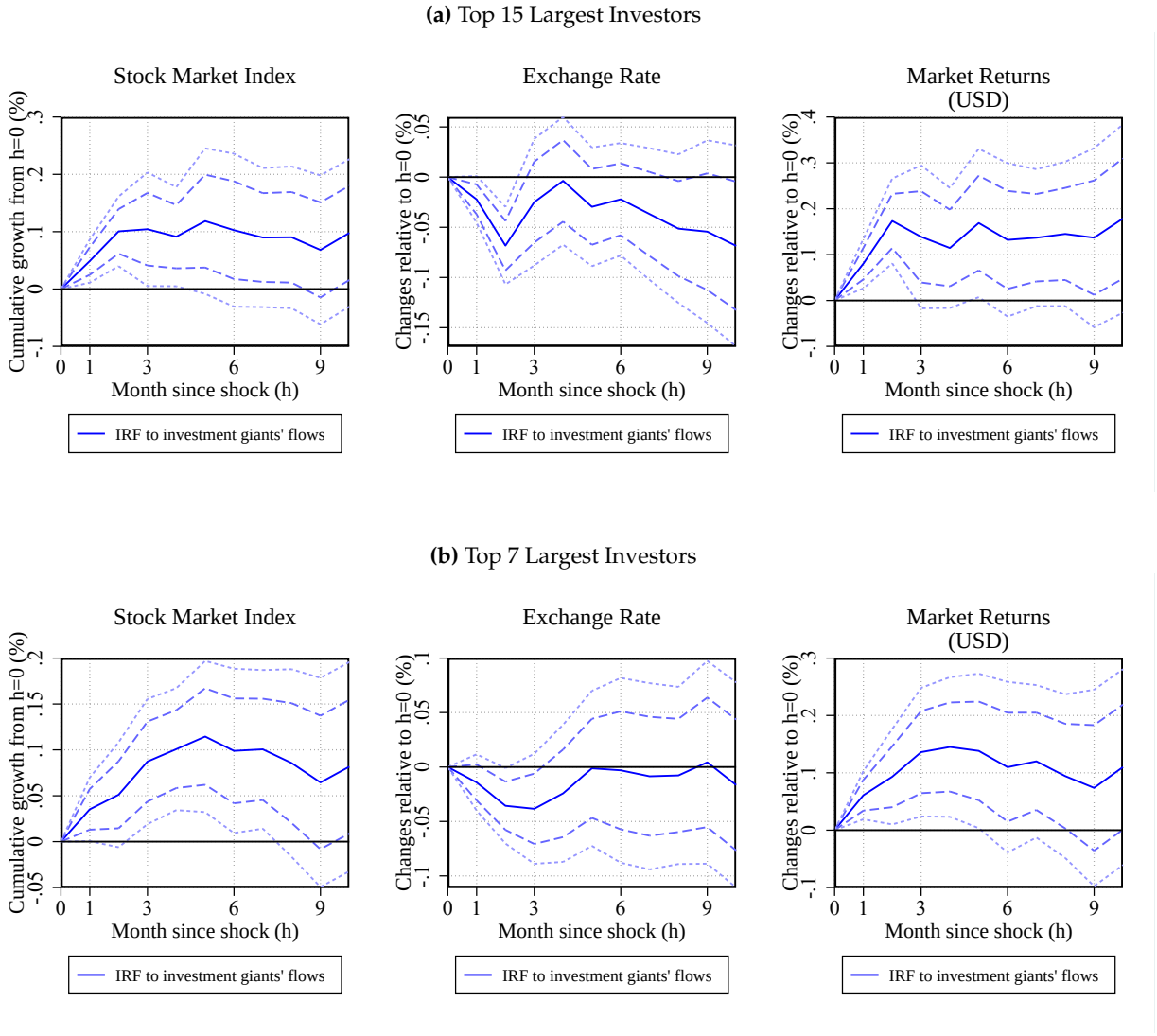
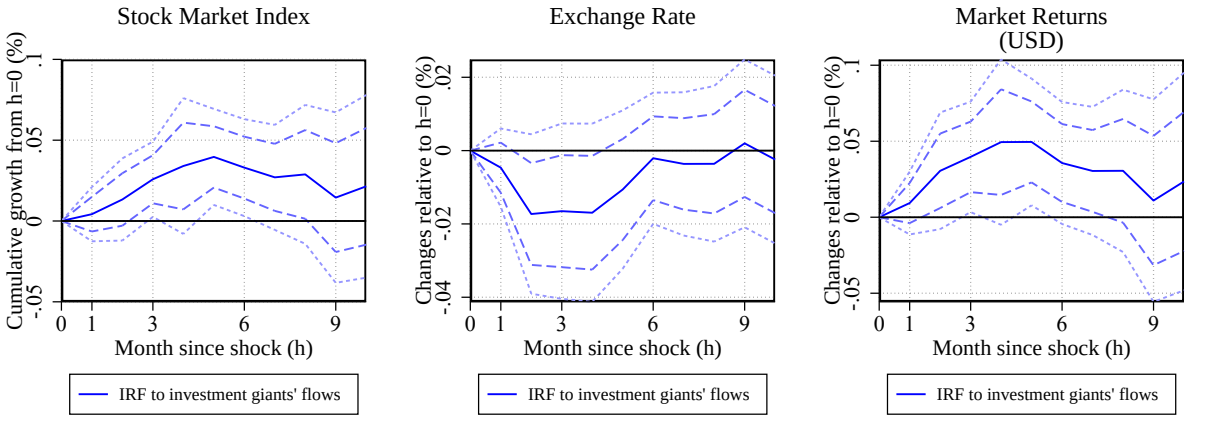


Figure E.14: Stock and Currency Markets Responses to Investment Giants (Top 15 and 7 Largest Investors) Flows

Notes: The panels (a) and (b) plot the predictive content of the differential between investment giants' (the top 15 and 7, respectively) and typical investors' average equity growth for stock price indices, exchange rates, and stock market returns (USD). The sample periods are after the global financial crisis (2010m1–2018m12). The responses to investment giants flows are the estimates of β^h in equation (34). 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

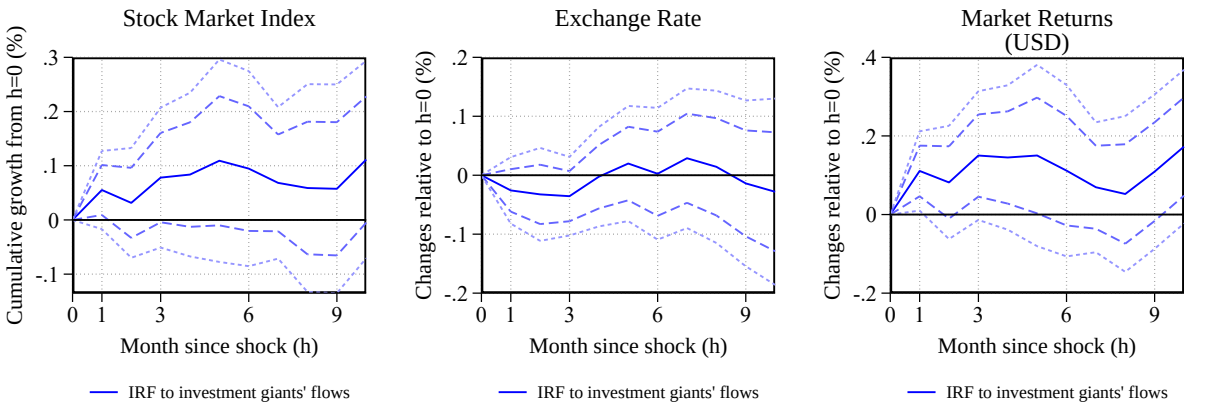


Figure E.15: Stock and Currency Markets Responses to Alternative Measures of Contrarian Flows

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 (30). In subfigure (b), the alternative measure is the difference between size-weighted and unweighted averages of investor flows, as defined in equation (32). 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 (35). The specification controls for country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes month fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

F Additional Figures and Tables

Table F.1: Summary Statistics: Equity Flows

Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Around the Global Financial Crisis (2007m6–2009m12)						
Equity flow (mil. US dollars)						
All investors	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 F.2: Summary Statistics: Average and Aggregate Equity Flows

Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Around the Global Financial Crisis (2007m6–2009m12)						
Aggregate of equity flows (monthly growth, %)						
	620	-0.15	14.14	-15.98	1.36	15.54
Aggregate of adjusted equity flows (monthly growth, %)						
	620	0.07	7.25	-9.36	0.35	8.31
Cross-sectional average of equity flow growth (monthly growth, %)						
Non-top 10 largest investors	620	-0.36	8.62	-9.76	0.18	9.53
Top 10 largest investors	620	0.49	12.69	-15.72	1.78	14.96
Cross-sectional average of adjusted equity flow growth (monthly growth, %)						
Non-top 10 largest investors	620	-0.27	4.36	-5.43	-0.37	4.92
Top 10 largest investors	620	0.66	7.93	-10.29	0.86	10.35
After the Global Financial Crisis (2010m1–2018m12)						
Aggregate of equity flows (monthly growth, %)						
	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 F.3: Summary Statistics: Active Equity Fund Flows

Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Around the Global Financial Crisis (2007m6–2009m12)						
Equity flow (mil. US dollars)						
All investors	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 F.4: Summary Statistics: Average and Aggregate Active Equity Fund Flows

Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Around the Global Financial Crisis (2007m6–2009m12)						
Aggregate of equity flows (monthly growth, %)						
	620	-0.50	14.25	-15.95	1.17	15.25
Aggregate of adjusted equity flows (monthly growth, %)						
	620	-0.27	7.75	-10.11	0.02	8.44
Cross-sectional average of equity flow growth (monthly growth, %)						
Non-top 10 largest investors	620	-0.15	11.19	-12.12	0.28	12.15
Top 10 largest investors	620	1.00	13.27	-16.05	2.45	16.97
Cross-sectional average of adjusted equity flow growth (monthly growth, %)						
Non-top 10 largest investors	620	-0.04	8.04	-10.24	-0.04	9.39
Top 10 largest investors	620	1.12	9.67	-11.90	1.08	12.26
After the Global Financial Crisis (2010m1–2018m12)						
Aggregate of equity flows (monthly growth, %)						
	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 F.5: Summary Statistics: Macroeconomic Variables

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

Notes: The monthly growth rates are the log difference.

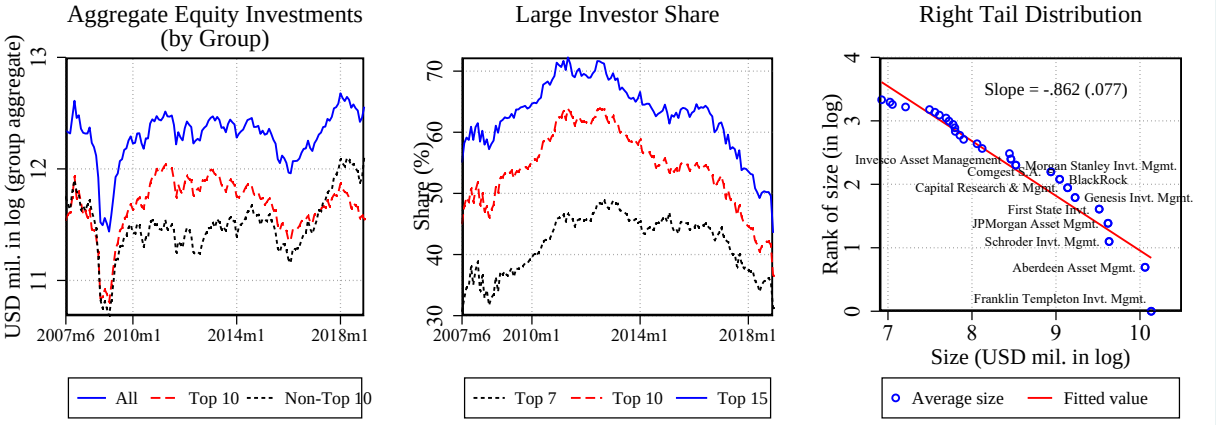


Figure F.16: Trends of Equity Fund Flows: Active Funds Only

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

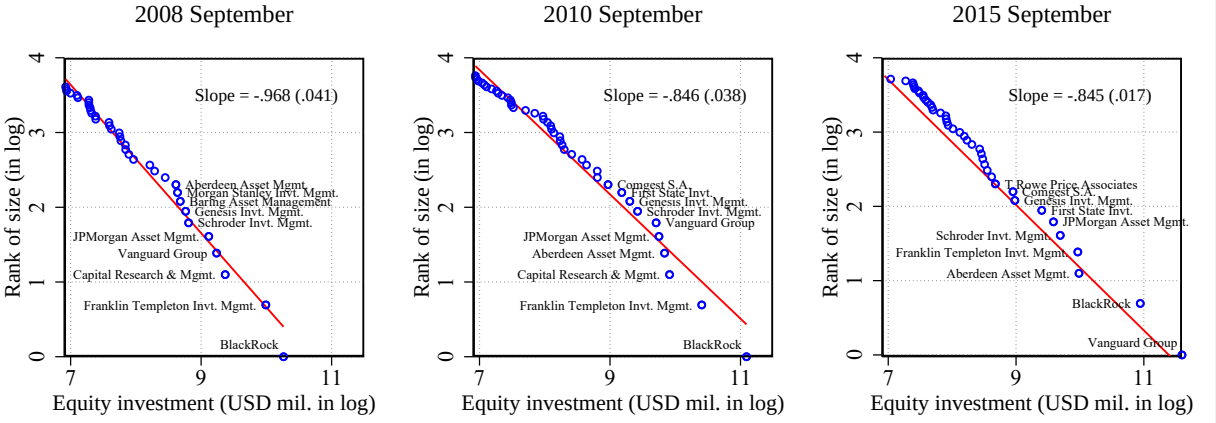


Figure F.17: The Right Tail of Investor Size

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

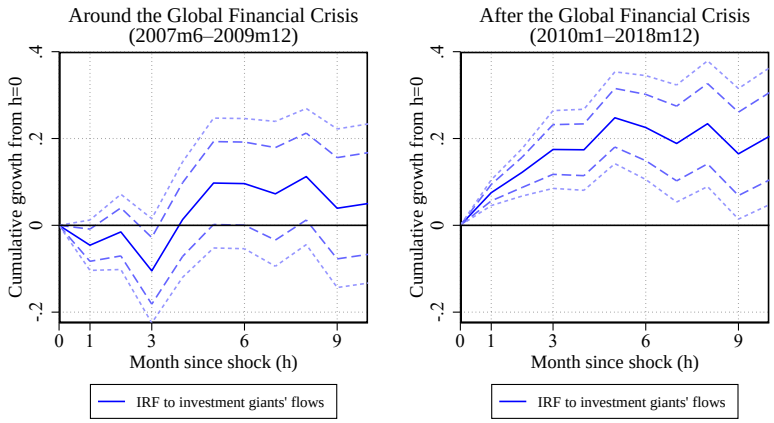


Figure F.18: Investor-Level Response to the Unadjusted Equity Flow Differential between Investment Giants and Typical Investors

Notes: The figures depict the predictive capacity of average equity flows from the differential between investment giants' (the top 10) and typical investors' average equity growths where we use non-valuation-adjusted values ($\Delta\text{IHS}(\text{Equity}_{ic,t})$). The responses to flows of investment giants relative to typical investors are the estimates of β^h in equation (29). In each panel, the sample periods are around the global financial crisis (2007m6–2009m12, left chart) and after the crisis (2010m1–2018m12, right chart), respectively. The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. In each regression, singleton observations are dropped. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).