Investment Giants in Emerging Markets

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April 2026

Abstract

Cross-border equity flows to emerging markets are highly concentrated among a few large institutional investors ("*investment giants*"). We study their strategic behavior and market impact through a model of incomplete information with strategic complementarity. In equilibrium, concentration generates directional leadership: a first-mover advantage induces a dominant investor to act first, revealing information that steers the subsequent decisions of a continuum of smaller investors. Compared to a simultaneous-move benchmark, this sequential structure raises the giant's ex-ante payoff, amplifies market influence, and generates predictability. Empirically, we isolate idiosyncratic influence using "*contrarian investment*" (excess investment growth relative to peers or the market) to filter out shared macroeconomic factors. Using fund-level data across emerging economies, we find that shocks to giants' contrarian flows trigger persistent increases in investor flows, aggregate capital inflows, stock returns, and currency values. Our findings illustrate how concentration shapes strategic timing and global portfolio allocation dynamics.

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

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The authors would like to thank Anusha Chari, Sangyup Choi, Jon A. Garfinkel, Fabio Ghironi, Thomas Gilbert, Jongrim Ha, John Kim, Kyungkeun Kim, Jun Hee Kwak, Dongwon Lee, Jae Won Lee, Lubos Pastor, Hélène Rey, Felipe Saffie, and Huanhuan Zheng as well as all participants at the 2026 ASSA/AEA Annual Meeting, the 2025 World Congress of the Econometric Society, the PKU 9th International Macroeconomics and Finance Conference, 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, the 2022 Annual Meeting of the Southern Economic Association, KIFA-KIEP-KIF conference: Interactions of International Finance and Trade in the Modern Era, and the seminar participants at the University of Washington, Indian School of Business, Bank of Korea, Yonsei University, Korea Institute for International Economic Policy, and Korea Institute of Public Finance for useful comments.

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, low interest rates in advanced economies spurred substantial portfolio flows into emerging markets as international investors sought higher yields (Rajan 2006; Summers 2016). These flows provide significant benefits, such as better opportunities for risk-sharing and external financing (Bonfiglioli 2008; Igan, Kutan and Mirzaei 2020; Aristizabal-Ramirez, Leahy and Tesar 2023). However, they also carry notable risks: heightened exposure to global shocks, the potential for sudden reversals that intensify financial stress (Calvo and Reinhart 2002; Gourinchas and Obstfeld 2012), and increased volatility due to investors' 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, with only a small group of dominant institutional investors, referred to as "*investment giants*," accounting for a disproportionate share of cross-border flows. These giants may wield outsized influence, echoing patterns documented in U.S. and global financial markets (e.g., Corsetti, Dasgupta, Morris and Shin 2004; Buch, Koch and Koetter 2011; Ben-David, Franzoni, Moussawi and Sedunov 2021; Coimbra, Kim and Rey 2022).

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

To analyze the behavior and influence of investment giants, we first develop a theoretical framework incorporating a dominant player, noisy markets, and strategic complementarity. Formally, we model a market with a single dominant player (investment giant) and a continuum of smaller investors (typical investors), allowing the giant to choose its timing—either moving simultaneously with others or sequentially before them. To reflect the key features of financial markets, as conceptualized in the beauty contest analogy (Keynes 1936; see also Chen, Goldstein and Jiang 2010; Schmidt, Timmermann and Wermers 2016), we adopt the framework of Morris and Shin (2002) with incomplete information and strategic complementarity, where investors' payoffs depend on their proximity to both market fundamentals and the aggregate behavior of others.[1]

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

The giant exerts disproportionate influence beyond its market share through two key channels: *the public information channel*, where its actions serve as a public signal that reduces uncertainty for other investors, and *the directional leadership channel*, where it actively steers market aggregates. This influence intensifies when (*i*) the giant holds a larger market share, increasing its weight in market aggregates, and (*ii*) strategic complementarity is stronger, leading investors to prioritize coordination. These conditions incentivize the investment giant to adopt a sequential-move strategy, as its ex-ante payoffs are higher than those under a simultaneous-move strategy. Consequently, the giant not only induces follower behavior but also steers market aggregates closer to its belief about fundamentals.

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

[1] An alternative interpretation or rationalization of the payoff term of proximity to the aggregate is in terms of decreasing returns to scale in investment, as in Perold and Salomon Jr. (1991); Berk and Green (2004); Pástor and Stambaugh (2012).

for a clearer identification of their idiosyncratic influence.[2]

Using panel local projections with EPFR (Emerging Portfolio Fund Research) fund-level monthly flow data (2010–2018), we examine the dynamic effects (predictability) of a small group of investment giants' contrarian decisions on individual equity funds across 20 emerging markets. The giants' contrarian flows consistently exhibit strong predictive power for global investor equity flows into emerging markets, highlighting their pivotal role in global asset reallocation.

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

Beyond aggregate capital inflows, the predictive power of giants' contrarian investments extends to stock market returns, which show significant positive responses, while exchange rates tend to appreciate following higher equity investments from giants relative to other investors.

Our paper complements the literature on '*granular*' macroeconomics and the '*inelastic markets hypothesis*' (Gabaix 2011; Gabaix and Koijen 2024). While this literature primarily emphasizes the mechanical price impacts of large institutional investors—positing that markets are inelastic and therefore large trades move prices via multipliers—we introduce a strategic behavioral layer to the granular framework.

In contrast to the focus on purely mechanical demand shocks, we show that the influence of investment giants is amplified through a strategic coordination channel.

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

By embedding an incomplete information *'beauty contest'* (Morris and Shin 2002) into a granular setting, we provide a microfoundation for why smaller investors follow the lead of larger ones. In our model, the giant's move is not just a large demand shock; it is a directional signal that resolves uncertainty and coordinates the expectations of a continuum of smaller investors. This shift from mechanical multipliers to strategic leadership explains the persistent predictability we observe in emerging market capital flows—a phenomenon that is difficult to reconcile with purely inelastic demand but consistent with sequential information revelation and strategic timing.

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

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

However, there are still unexplored dimensions in this research landscape to which our paper seeks to contribute. Most of the existing studies focus on domestic markets, which may not fully capture the international nature of investment strategies. As global investors may employ different decision strategies from domestic investors, there is a need for a more international perspective on these issues (Jotikasthira et al. 2012; Raddatz and Schmukler 2012). Our paper takes this perspective into account, thereby providing a better understanding of portfolio allocations by nonresident fund investors. This broader view can be useful for ensuring financial stability in emerging economies increasingly integrated into the international financial markets, for example, through the design of 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 a so-called *beauty contest* environment, in which participants forecast the behavior of other players. This concept has been widely studied in financial markets, with significant contributions from both empirical and theoretical studies (e.g., Chen et al. 2010; Schmidt et al. 2016; Jackson and Pernoud 2021). Another essential feature of financial markets is the presence of dominant players. For instance, prior works investigate their prominent role and impacts in the markets; e.g., Corsetti et al. (2004) on dominant players in currency markets and Ben-David et al. (2021) on large investors in U.S. equity markets. Our study bridges the two critical dimensions of financial markets: the strategic interdependence of typical investors and the outsized influence of dominant players.

In addition, most empirical studies pay little attention to the determinants of international portfolio flows at the fund or investor level. While prior studies have predominantly concentrated on aggregate-level flows and the impact of external ("*push*") conditions (e.g., Calvo, Leiderman and Reinhart 1993, 1996; Fernandez-Arias 1996; Taylor and Sarno 1997; Forbes and Warnock 2012), our research enhances this understanding by investigating both new and unexplored determinants at the investor (fund company) level. This aspect is particularly notable because global factors, including U.S. monetary policy, significantly influence *inter alia* the global financial cycle (e.g., Rey 2015; Kalemli-Özcan 2019; Goldberg and Krogstrup 2023). Our paper fills this research void by providing insights into how these factors interact with the investment decisions of institutional investors in emerging equity markets. Probing portfolio choices at the micro level offers a more comprehensive understanding of the dynamics of the entire market (Rey et al. 2024).

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

2 Investment Giants and Concentrated Equity Flows

As a preliminary step before the theoretical and empirical analysis, this section first provides the foundation for measuring investor behavior at a granular level, enabling a systematic investigation of equity dynamics. Next, we document some stylized facts in global equity flow data, highlighting a fat-tailed size distribution with investment giants.

Mutual Funds Data We compile data on global mutual funds' equity flows to 20 emerging markets from the Emerging Portfolio Fund Research (EPFR) database.[3] 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.[4] 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).

To track how each institutional investor (fund company) adjusts its investment behavior, we calculate the investor i's equity investment to country c at time (month) t, as:

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

where $\text{TotalNetAssets}_{ai,t}$ is the total assets under management of investor i's asset class a across all host countries, and $\text{EquityShare}_{aic,t}$ is the equity investment share of investor i's asset class a in country c out of its total investment at time t. Further details on data collection and variable construction are available in Appendix C.1. Appendix Tables A.1–A.3 report summary statistics.

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

[4]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 also Fratzscher (2012), Kim and Lee (2020), and Chari, Stedman and Lundblad (2022) for the discussions and details of the EPFR data.

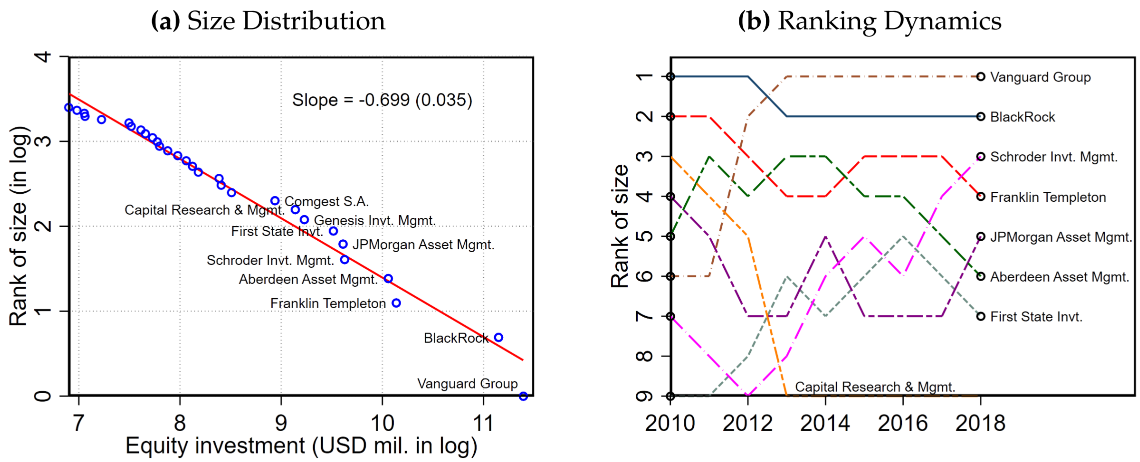

Figure 1: Global Investor Size Distribution and Ranking Dynamics

Notes: The left panel plots logged total equity investment size, averaged over 2010m1–2018m12, against logged rank in 20 emerging equity markets. The sample includes the 30 largest investors with full observations. The right panel shows the evolution of rankings based on annual investment sizes.

Investment Giants To analyze the interaction between investors of different sizes, we first establish a criterion to classify individual equity flows as originating from either *investment giants* (large investors, indexed by $i \in \mathcal{G}$) or *typical investors* (non-large investors, $i \notin \mathcal{G}$). Because there is no natural threshold separating large from non-large institutions, we adopt a data-driven rule based on the cross-sectional distribution of investor size, measured by their equity investments in the 20 emerging markets.

The distribution of global equity investments demonstrates pronounced concentration among a few large investors. The left panel of Figure 1 depicts a fat right tail in the size distribution of equity investments. A log-log plot of investment size against investor rank confirms a power-law relationship in the right tail, with log rank approximately proportional to log size: $\ln(\text{Rank}) \approx -0.7\ln(\text{Size})$. Furthermore, the right panel shows that, although there is some ranking dynamics among the largest investors, these changes are limited within this group rather than reflecting entry and exit. Accordingly, we fix the set of large investors throughout the sample period.

Specifically, we rank investors according to the time-series average of their total equity fund investments in the 20 emerging markets over the period January 2010 to December 2018. We then define the top 10 investors in this ranking as investment giants throughout the sample period.[5] All remaining investors are categorized as typical investors. Importantly, these institutions persistently occupy the upper tail of the size distribution, reflecting their substantial and stable assets under management.

These observations suggest that emerging equity markets are increasingly reliant on capital inflows from a limited number of dominant funds. This empirical regularity closely aligns with the structure of our theoretical framework and motivates a focused investigation of the strategic interactions between investment giants and typical investors.

3 A Beauty Contest Framework with Investment Giants

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

3.1 Model Environments

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

Another feature typically observed in financial markets is the existence of dominant players. Relatedly, two additional assumptions underpin our model. First, typical investors' actions do not affect aggregate market outcomes, whereas the investment giant's decisions

[5] These 10 investors are 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. The top 7 exclude Capital Research & Management, Comgest S.A., and Genesis Investment Management from the top 10 group. The top 15 additionally include Deutsche Asset Management, Invesco Asset Management, Morgan Stanley Investment Management, State Street Global Advisors, and Vontobel Asset Management.

shape market equilibrium, as in Corsetti et al. (2004). Second, the giant can choose its timing of action, either moving simultaneously with typical investors or moving first before the others. When moving first, the giant's actions are observable to others (visibility), which is typically associated with large players in financial markets. The ability to choose sequential timing also rationalizes the giant's preference for preemptive moves.

Investors and Size There exists a continuum of investors indexed by $i \in [0,1]$, each holding market share λ_i. The investment giant ($i = 1$) has a substantial market share $\lambda_1 (\equiv \lambda \in [0,1])$, while typical investors j $(i = j \in [0,1))$ have negligible individual market shares $\lambda_j \simeq 0$ and are ex-ante identical. Typical investors collectively account for a total market share of $1-\lambda$. Due to diversification, their idiosyncratic shocks and information have no aggregate implications, unlike those of the giant. In this sense, our model can be understood as a discrete version of the granular origin model (Gabaix 2011).

Beauty Contest Framework The payoff of investor i is given by

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

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

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

The first term of the payoff function, $(a_i - f)^2$, captures the loss from deviating from fundamentals. The second term, $(a_i - \bar{A})^2$, is an investor's loss from deviating from aggregate market actions. The latter reflects a strategic complementarity, introducing a coordination/herding motive among investors. The parameter $\omega (\in [0,1])$ governs the importance of coordination relative to fundamentals. When $\omega = 0$, the problem collapses to standard signal extraction. This coordination motive can alternatively be interpreted as reflecting decreasing returns to scale in investment (e.g., Perold and Salomon Jr. 1991; Berk and Green 2004; Pástor and Stambaugh 2012), whereby marginal returns decline in an investor's position relative to the market, with the marginal effect given by $-2\omega(a_i - \bar{A})$.

The choice of action a_i can be interpreted as an abstract investment decision. As discussed in Bao, Hommes and Makarewicz (2017), asset pricing models with price adjustment mechanisms, such as in Beja and Goldman (1980), allow forecasting problems to be recast as quantity (investment) decisions. Consistent with this approach, the payoff structure in our model implies that the optimal action is a linear function of the investor's expectations about fundamentals and aggregate market behavior.

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:

$$s_i = f + \epsilon_i, \qquad \text{where} \quad f \sim \mathcal{N}(0, \sigma_f^2) \quad \text{and} \quad \epsilon_i \sim \mathcal{N}(0, \sigma_{\epsilon,i}^2). \tag{3}$$

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 giant and the typical investors: $\sigma_{\epsilon,1}^{-2} \neq \sigma_{\epsilon,0}^{-2} (= \sigma_{\epsilon,j}^{-2})$ for all $j \in [0,1)$. Applying the conditional expectation formula for normally distributed variables, the beliefs about the fundamentals given the signals are:

$$\mathbb{E}[f|s_1] = \theta_1 s_1, \quad \mathbb{E}[f|s_{j\neq 1}] = \theta_0 s_{j\neq 1}, \quad \text{and} \quad \mathbb{E}[f|s_{j\neq 1}, s_1] = \gamma_0 s_{j\neq 1} + \gamma_1 s_1, \tag{4}$$

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 giant and typical investors act at the same time without observing others' actions.

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

In the sequential-move setup, typical investors choose actions a_j (for $j \in [0,1)$) to maximize their expected payoff given the signal and action of the giant: $\mathbb{E}[\pi_j|s_j, s_1, a_1]$. The investment giant maximizes its expected payoff based on the optimal strategy ($a_j^{\text{sq}}(s_j, s_1, a_1)$) of typical investors which react to the signal and action of the giant. On the other hand, in the simultaneous-move case, each investor (both typical investors and investment giant; $i \in [0,1]$) faces an identical payoff maximization problem. That is, each investor independently and simultaneously determines its action a_i to maximize its expected payoff ($\mathbb{E}[\pi_i|s_i]$) based only on its private signal s_i.

The giant's timing choice between $r_1 = \text{sm}$ and sq depends on a comparison of its expected payoffs ($\mathbb{E}[\pi_1^{\text{sm}}]$ vs. $\mathbb{E}[\pi_1^{\text{sq}}]$) under each timing structure. In what follows, we elaborate on the investors' optimal strategies, given the timing of actions, in particular sequential-move ($r_1 = \text{sq}$).

3.2 Sequential-move: The Investment Giant Moves First

Typical Investors In the sequential-move case, each typical investor chooses an action a_j (for $j \neq 1$) to maximize their expected payoff in equation (2) where the giant's signal and action serve as the public information. The first-order condition yields:

$$a_j^{\text{sq}} = (1-\omega)\mathbb{E}[f|s_j, s_1] + \omega\mathbb{E}[\bar{A}^{\text{sq}}|s_j, s_1, a_1], \tag{5}$$

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

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

$$a_j^{\text{sq}}(s_j, s_1, a_1) \equiv \psi^{\text{sq}} s_j + \eta_s^{\text{sq}} s_1 + \eta_a^{\text{sq}} a_1. \tag{6}$$

The average action of typical investors is then:

$$\bar{a}_0^{\text{sq}}(f, s_1, a_1) \equiv \int_{j\in[0,1)} a_j^{\text{sq}} \mathrm{d}j = \psi^{\text{sq}} f + \eta_s^{\text{sq}} s_1 + \eta_a^{\text{sq}} a_1. \tag{7}$$

By substituting the typical investor's belief about the average investment of others, $(\mathbb{E}[\bar{a}_0^{\text{sq}}|s_j, s_1, a_1] = \psi^{\text{sq}}\mathbb{E}[f|s_j, s_1] + \eta_s^{\text{sq}} s_1 + \eta_a^{\text{sq}} a_1)$, into the first-order condition in equation (5), we derive the optimal responses to the private signal, the giant's signal, and the giant's action as follows:

$$\psi^{\text{sq}} = \left[\frac{1-\omega}{1-\omega(1-\lambda)\gamma_0}\right]\gamma_0, \tag{8}$$

$$\eta_s^{\text{sq}} = \left\{\frac{1-\omega}{[1-\omega(1-\lambda)][1-\omega(1-\lambda)\gamma_0]}\right\}\gamma_1 = \left[\frac{\psi^{\text{sq}}}{1-\omega(1-\lambda)}\right]\frac{\gamma_1}{\gamma_0}, \tag{9}$$

$$\eta_a^{\text{sq}} = \frac{\lambda\omega}{1-\omega(1-\lambda)} = 1 - \psi^{\text{sq}} - \frac{\eta_s^{\text{sq}}}{\theta_1}. \tag{10}$$

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

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

In this limiting case, the 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 giant has zero market share, it acts purely as a provider of public information. This limiting case is considered in Morris and Shin (2002).

Investment Giant In the sequential-move case, the investment giant chooses its action a_1 to minimize its deviation from the fundamentals and typical investors' average action. Specifically, given typical investors' average action in equation (7), the giant's profit maximization problem can be modified as follows:

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

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

$$a_1^{\text{sq}} = (1-\omega)\mathbb{E}[f|s_1] + \omega\mathbb{E}[\bar{A}^{\text{sq}}(f,s_1,a_1)|s_1]\underbrace{(1-\lambda)}_{\substack{\text{mkt share}\\ \text{advantage}}}\underbrace{\left\{1-\frac{\partial\mathbb{E}[\bar{a}_0^{\text{sq}}(f,s_1,a_1)|s_1]}{\partial a_1}\right\}}_{\text{first-move advantage}}, \tag{11}$$

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

$$\mathbb{E}[\bar{a}_0^{\text{sq}}(f,s_1,a_1)|s_1] = (1-\eta_a^{\text{sq}})\mathbb{E}[f|s_1]+\eta_a^{\text{sq}}a_1, \quad \text{where} \quad \mathbb{E}[f|s_1]=\theta_1 s_1. \tag{12}$$

The giant's optimal decision rule in equation (11) reflects its directional leadership and advantage: its dominant market share (λ) and influence over typical investors ($\partial\mathbb{E}[\bar{a}_0^{\text{sq}}|s_1]/\partial a_1 = \eta_a^{\text{sq}}$) allow it to steer the market, placing less weights on the aggregate market ($\bar{A}^{\text{sq}}$).

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

$$a_1^{\text{sq}}(s_1) = \underbrace{\left\{\frac{(1-\omega)+\omega(1-\lambda)^2(1-\eta_a^{\text{sq}})\left(\psi^{\text{sq}}+\eta_s^{\text{sq}}\frac{s_1}{\mathbb{E}[f|s_1]}\right)}{(1-\omega)+\omega(1-\lambda)^2(1-\eta_a^{\text{sq}})^2}\right\}}_{=1 \quad \because\, \mathbb{E}[f|s_1]=\theta_1 s_1 \text{ and } \psi^{\text{sq}}+\eta_s^{\text{sq}}/\theta_1+\eta_a^{\text{sq}}=1}\mathbb{E}[f|s_1] = \phi^{\text{sq}}s_1, \tag{13}$$

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

3.3 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).

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

$$a_i^{\text{sm}} = (1-\omega)\mathbb{E}[f|s_i] + \omega\mathbb{E}[\bar{A}^{\text{sm}}(a_1^{\text{sm}}, \bar{a}_0^{\text{sm}})|s_i](1-\lambda_i). \tag{14}$$

Unlike in the sequential-move case in equation (5), where investors consider the investment giant's signal (s_1) and action (a_1), typical investors here rely only on their own private signal s_j. In addition, although the giant still benefits from its market dominance (represented by $1-\lambda$), it loses a first-move advantage, $\partial\mathbb{E}[\bar{a}_0^{\text{sm}}|s_1]/\partial a_1 = 0$, compared to the sequential case. Appendix A provides details on the case of simultaneous-move ($r_1 = \text{sm}$).

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

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

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

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

Investment Giant Similar to typical investors, the optimal strategy of the investment giant under the simultaneous-move case is determined only by its own signal: $a_1^{\mathrm{sm}}(s_1) = \phi^{\mathrm{sm}} s_1$ as in equation (A.4). Comparing this with equation (13), we also find the differences between the optimal strategies of the giant under simultaneous- and sequential-moves. The giant reacts less actively to its own signal under the sequential-move structure than under the simultaneous-move structure:

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

This inequality holds because ψ^{sm} is less than one.

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

4 The Role of the Investment Giant: Lead and Influence

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

4.1 Optimal Timing Structure of Actions

The Giant's Ex-Ante payoffs under the Sequential-Move Under the sequential-move, the investment giant's ex-ante payoff is:

$$\mathbb{E}[\pi_1^{\text{sq}}] \equiv -(1-\omega)\text{var}(a_1^{\text{sq}} - f) - \omega\text{var}(a_1^{\text{sq}} - \bar{A}^{\text{sq}}). \tag{15}$$

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

$$\text{var}(a_1^{\text{sq}} - f) = \sigma_f^2 \Upsilon(\phi^{\text{sq}}; \theta_1), \quad \text{where} \quad \Upsilon(x; z) \equiv \frac{x^2}{z} - 2x + 1. \tag{16}$$

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 giant's signal (θ_1). Importantly, this is because the giant's optimal action is identical to the solution of the signal-noise extraction problem, as shown in equation (13).

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

$$\text{var}(a_1^{\text{sq}} - \bar{A}^{\text{sq}}) = \sigma_f^2 (1-\lambda)^2 (\psi^{\text{sq}})^2 \Upsilon(\phi^{\text{sq}}; \theta_1). \tag{17}$$

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

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

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

$$\mathbb{E}[\pi_1^{\text{sm}}] \equiv -(1-\omega)\text{var}(a_1^{\text{sm}} - f) - \omega \text{var}(a_1^{\text{sm}} - \bar{A}^{\text{sm}}). \tag{18}$$

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

$$\text{var}(a_1^{\text{sm}} - f) = \sigma_f^2 \Upsilon(\phi^{\text{sm}}; \theta_1) > \text{var}(a_1^{\text{sq}} - f). \tag{19}$$

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

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

$$\text{var}(a_1^{\text{sm}} - \bar{A}^{\text{sm}}) = \sigma_f^2 (1-\lambda)^2 (\psi^{\text{sm}})^2 \Upsilon(\phi^{\text{sm}}/\psi^{\text{sm}}; \theta_1) > \text{var}(a_1^{\text{sq}} - \bar{A}^{\text{sq}}), \tag{20}$$

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

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

$$\mathbb{E}[\pi_1^*] \equiv \max\left\{\mathbb{E}[\pi_1^{\text{sq}}], \mathbb{E}[\pi_1^{\text{sm}}]\right\} = \mathbb{E}[\pi_1^{\text{sq}}], \tag{21}$$

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

4.2 Influences on Typical Investors and Market Movements

Typical Investor's Optimal Choices In equilibrium, the investment giant's signal s_1 not only determines its optimal action a_1^* in equation (13), but also influences the optimal decisions of typical investors both individually (a_j^*) and as a group ($\bar{a}_0^*$); each shown in equations (6) and (7), respectively. By substituting s_1 with a_1^* in these equations, we derive:

$$a_j^* = \psi^* s_j + (1-\psi^*)a_1^* = \psi^* f + (1-\psi^*)a_1^* + \psi^* \epsilon_j, \tag{22}$$

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

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

$$\bar{A}^* = (1-\lambda)\psi^* f + [1-(1-\lambda)\psi^*]a_1^*. \tag{23}$$

Hence, the influence of the giant's decision on the market aggregate increases with its market share (λ) and with typical investors' reliance on the giant's action ($1 - \psi^*$). This corresponds to the country-level regression specification in Section 7, showing the model prediction that the giant's action positively affects market aggregates. Therefore, these predictions from equations (22) and (23) guide our empirical investigation into how giants influence other investors' decisions and aggregate market dynamics.

The above two equations also reveal how strategic complementarity and the giant's market share shape typical investors' behavior. Specifically, as either the giant's market share (λ) or strategic complementarity (ω) increases, typical investors place less weight on their private signals ($\partial a_j^*/\partial s_j = \psi^*$) and rely more heavily on the giant's action ($\partial a_j^*/\partial a_1^* = 1 - \psi^*$) in equation (22):

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

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

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

where $\partial \bar{A}^*/\partial f$ and $\partial \bar{A}^*/\partial a_1^*$ denote the market reliance on the fundamentals and the giant's action, each derived from equation (23) as $(1 - \lambda)\psi^*$ and $1 - (1 - \lambda)\psi^*$, respectively.

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

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

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

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

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

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

$$\mathrm{var}(\bar{A}^* - f) = [1 - (1-\lambda)\psi^*]^2(1-\theta_1) \times \sigma_f^2, \tag{24}$$

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

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

Furthermore, the sequential move reduces the market-wide deviation through information provision, an effect that strengthens as the giant's signal becomes more precise:

$$\frac{\partial}{\partial \theta_1}\text{var}(\bar{A}^* - f) < 0.$$

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

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

Further details and discussions can be found in Appendix B.

5 Investment Giant's Contrarian Equity Flow

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

5.1 Measure for the Giant's Idiosyncratic Decisions

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

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

5.2 Benchmark Measure

As a proxy for the giant's idiosyncratic investment decisions (*contrarian investment*), we primarily use the difference between the average equity growth of giants ($\bar{g}_{c,t}^{\text{giant}}$) and that of typical investors ($\bar{g}_{c,t}^{\text{typical}}$).

$$\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}} = \frac{1}{N^{\mathcal{G}}} \sum_{i \in \mathcal{G}} \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}) - \frac{1}{N_t - N^{\mathcal{G}}} \sum_{i \notin \mathcal{G}} \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}), \tag{25}$$

where $N^{\mathcal{G}}$ and N_t denote the number of investment giants and the total number of investors, respectively. Here, 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 $t+h$:

$$\Delta^h \text{IHS}(\text{Equity}_{ic,t}) = \text{IHS}(\text{Equity}_{ic,t+h}) - \text{IHS}(\text{Equity}_{ic,t}). \tag{26}$$

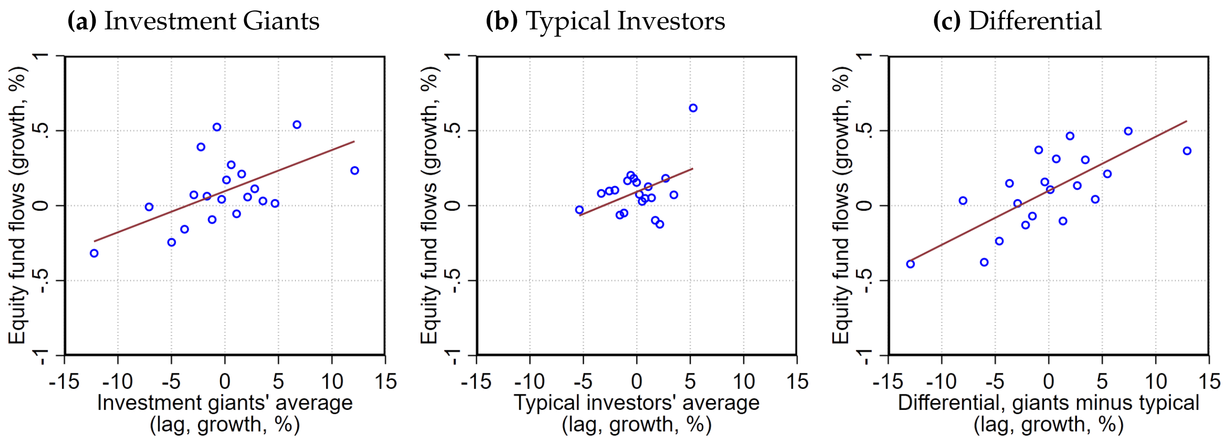

Figure 2: Equity Flows over the Lagged Giants' and Typical Investors' Average Equity Flows

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 panels, investors are divided into 20 bins on the x-axis based on their average one-month lagged valuation-adjusted equity investment growths as investment giants (top 10 largest investors; $\bar{\bar{g}}^{\text{giant}}_{c,t-1}$) and typical investors (non-giants; $\bar{\bar{g}}^{\text{typical}}_{c,t-1}$), respectively. The x-axis of last panel is the investment giants' equity flow differential, ($\bar{g}^{\text{giant}}_{c,t-1} - \bar{g}^{\text{typical}}_{c,t-1}$). The dots show the average valuation-adjusted equity investment growths of each group (ventile), and the lines present the fitted values.

Because there are instances where an institutional investor does not invest in equities in a particular market or country, both the logarithmic value of equity investment and its time differences are not available in such cases.

The investment giants' contrarian investment measures the extent to which their investment growth surpasses that of typical investors. A positive differential, $\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t} > 0$, indicates that giants increased their equity investments in country c more than typical investors. This suggests that giants are more aggressive or optimistic in their investment decisions compared to typical investors.

Figure 2 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. Global investor equity flows increase following a rise in giants' investments in the prior month (panel a), whereas no such pattern emerges for typical investors' flows (panel b). This pattern becomes even more pronounced (panel c) when examining the giant's contrarian flows (the differential between giants and typical investors). Global investors tend to increase their equity flows when giants' growth rates exceed those of typical investors. These observations suggest that giants' decisions may substantially influence other investors and shape aggregate trends in emerging equity markets.

5.3 Alternative Measures

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

$$\frac{1}{N^{\mathcal{G}}} \sum_{i \in \mathcal{G}} \Delta^1 \left(\frac{\text{Equity}_{ic,t-1}}{\text{Equity}_{c,t-1}} \right) \approx \bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{agg}} \tag{27}$$

where $\text{Equity}_{c,t-1} (\equiv \sum_i \text{Equity}_{ic,t-1})$ is the aggregate equity, and $\bar{g}_{c,t}^{\text{agg}} (\equiv \Delta^1 \ln \text{Equity}_{c,t-1})$ denotes the growth of aggregate equity between t and $t-1$ in country c. This measure approximates the giants' average investment growth relative to the aggregate market.

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

$$\sum_i \left(\frac{\text{Equity}_{ic,t-1}}{\sum_j \text{Equity}_{jc,t-1}} \right) \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}) - \frac{1}{N_t} \sum_i \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}). \tag{28}$$

The benchmark and alternative measures are positively correlated as shown in Appendix Figure A.2. The correlation coefficients between the benchmark measure and the two alternative measures are 36.9% (with the giants' changing market share) and 66.8% (with the differential between size-weighted and unweighted investment growth). Additionally, the correlation between the two alternative measures is 32.8%. Such strong correlations predict that the three measures capture similar dynamics of giants' idiosyncratic behavior, and all empirical results remain robust across the different measurements, reinforcing the consistency of our findings.

6 Equity Flow Dynamics with Investment Giants

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

6.1 Empirical Specification

Our regression analyses examine the predictability of investment giants' contrarian equity flow growth for subsequent equity flow growth of other investors and its time-varying nature. The main hypothesis, derived from our model predictions in Section 4, posits that individual fund flows in emerging markets are influenced by the giants' investments. To simplify our empirical framework, we assume that each investor perceives the overall stock market of an emerging economy as a representative asset and determines their investment considering the specific characteristics of the market. These characteristics systematically vary with the macroeconomic conditions in each country. Since investment giants are also affected by the conditions, we rely on their contrarian (idiosyncratic) investment decisions, as discussed in Section 5, to isolate their distinct influence.

Motivated by our theoretical model as in equation (22), we employ the investor-level demand model specified as a linear function of all covariates. The regression is estimated using panel local projection *à la* Jordà (2005) as follows.

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

for the time horizon considered $h = 1, 2, \cdots, 10$. The dependent variable is the valuation-adjusted cumulative equity growth between t and $t+h$ as follows. The (unadjusted) equity growth in equation (26) includes valuations resulting from equity returns and exchange rates. Hence, even when investors do not adjust their investments, high (low) equity returns and currency appreciation (depreciation) lead to an increase (decrease) in the investors' equity holdings. In this case, the equity growths overestimate (underestimate) investment allocation. To isolate the valuation effect, we compute the cumulative equity growth based on the adjusted equity growth accounting for market returns:

$$\tilde{\Delta}^h \mathrm{IHS}(\mathrm{Equity}_{ic,t}) = \mathrm{IHS}\left(\mathrm{Equity}_{ic,t+h} \times \frac{\mathrm{StockIndex}_{c,t}}{\mathrm{StockIndex}_{c,t+h}} \frac{\mathrm{FX}_{c,t+h}}{\mathrm{FX}_{c,t}}\right) - \mathrm{IHS}(\mathrm{Equity}_{ic,t}), \quad (30)$$

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

Most importantly, among the right-hand side variables, we include the investment giants' contrarian investment (i.e., average equity growth differential between equity investments made by the top 10 largest investors and other investors; $\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}$ in equation 25) as a main regressor. As discussed in Section 5, it is constructed to exclude the effects of fundamentals shared among investors. Thus, its coefficients β^h gauge the influence of giants' distinct portfolio decisions on the demand of individual investors for equity flows and their dynamics.

The regression further accounts for overall economic conditions by incorporating standard control variables. The vector $\mathbf{Pull}_{c,t}$ and $\mathbf{Push}_t$ include other control variables, encompassing both pull and push factors at time t along with their three lags.[6] By controlling for the factors associated with economic and financial conditions, the regression excludes the latent impacts from spurious comovements or similar reactions among investors induced by the fundamentals (Bikhchandani and Sharma 2001). It is empirically important to isolate such correlated behavior because it merely reflects an efficient asset reallocation driven by common factors. Pull factors capture domestic aspects, consisting of real interest rates, growth rates of industrial production, total reserves, exchange rates, and the stock market index for each emerging country c. Push factors encompass external or global conditions, including the corresponding US variables, such as US real interest rates and growth rates of the VIX, US industrial production and stock market index.[7]

There may be unobserved heterogeneity among investors and countries that is not

[6] 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, refer to Hannan (2017), Hannan and Cubeddu (2018), and Koepke (2019).

[7] Further details on data collection and variable construction are available in Appendix C.2. Appendix Table A.3 report summary statistics.

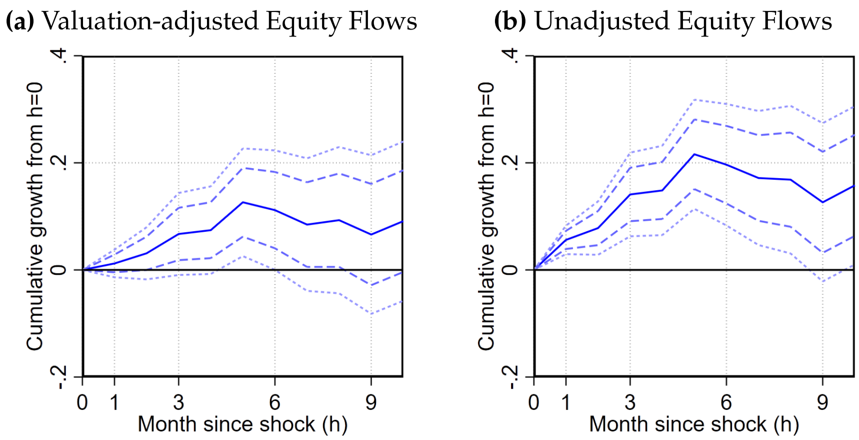

Figure 3: Investor-Level Responses to Investment Giants' Contrarian Equity Flows

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. In panel (a), individual investor's equity flows are adjusted using stock market index and exchange rate growths to remove valuation effects; panel (b) reports unadjusted flows. The responses to investment giants' flows relative to typical investors are the estimates of β^h in equation (29). 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, %).

captured by the pull and push factors. Thus, we incorporate various fixed effects to account for unobserved heterogeneity among investors and emerging markets. Investor-specific fixed effects (δ_i^h) and market country fixed effects (δ_c^h) capture time-invariant investor-specific characteristics and time-invariant market traits, respectively. Additionally, time (month) fixed effects (δ_m^h, 11 dummies) are included to handle seasonality.

6.2 Regression Results

Figure 3 provides the impulse responses (β^h) of valuation-adjusted (left chart) and unadjusted (right chart) equity flows to an increase in shocks to investment giants' contrarian investment. The impulse responses provide information on the predictability of average growth rate differentials between giants and typical investor flows for subsequent equity flows among other individual investors. The confidence intervals are drawn from the clustered standard errors at the investor-level.

Two noteworthy findings emerge from the results. First, institutional investors tend to follow the lead of investment giants, corroborating the model prediction. An increase in the giants' disproportionate equity investment compared to typical investors has a positive impact on the equity investment of individual institutional investors. The result suggests that contrarian investment made by giants leads the overall market participants, presumably providing positive signals to them. This observation is also consistent with the feature presented in Figure 2, which suggests that international investors place more weight on the leading movements of giants when determining global portfolio allocation.

Second, the valuation-adjusted equity flows exhibit larger and more persistent responses to the giants' contrarian investments than the non-valuation-adjusted flows. The contrarian flows have significant and positive effects on other investor's unadjusted flows, peaking around 0.2% at $h = 5$. After adjusting for valuation effects, the estimated impulse-response coefficients drop to about 2/3 of their unadjusted counterparts. The stronger responses of valuation-adjusted equity flows compared to non-adjusted flows implies that valuation effects work in a way to absorb the impacts of the giants' flow shock. In other words, stock returns may decrease and/or exchange rates may depreciate after the shock. This point will be further discussed in Section 7. This result implies the significant amounts of valuation channels. The contrarian flows are related to variables related to valuations in stock and currency markets. In Section 7, we will discuss this issue by investigating the giant's contrarian flow's relationship with stock price index and exchange rate.

Robustness Checks To ensure the robustness of our findings, we consider the alternative measures of investment giants' contrarian behavior, presented in Section 5, that help isolate their idiosyncratic influence from broader market movements. Specifically, we estimate the local projections of equation (29), replacing our main regressor with the two alternative measures: (*i*) the investment giants' share of equity flows into each market (country), defined in equation (27), and (*ii*) the differential between the size-weighted and unweighted averages of equity flows across all investors in equation (28).

Figure 4 presents the results. Panels (a) and (b) report investor-level equity flow responses to changes in the two measures, respectively. The results largely align with the baseline: in the post-crisis period, individual investors' equity flows respond positively to

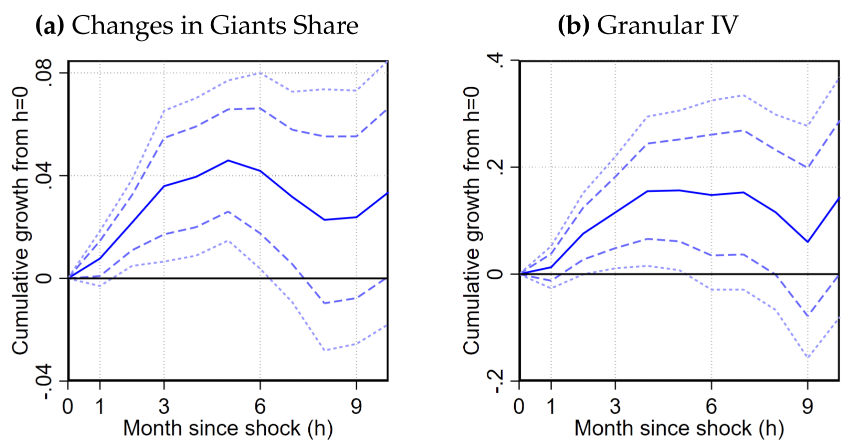

Figure 4: Investor-Level Response to Changes in Alternative Measures of Contrarian Investments

Notes: The figures depict the predictive capacity of alternative measures of contrarian investments made by the top 10 investment giants. In panel (a), the alternative measure is the change in the share of investments made by the top 10 investment giants, as defined in equation (27). In panel (b), the alternative measure (labeled '*Granular IV*') is the difference between size-weighted and unweighted averages of investors' flows, as defined in equation (28). The responses of valuation-adjusted equity flows to contrarian flows are the estimates of β^h in equation (29). 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, %).

giants' contrarian flow shocks. These patterns reinforce the robustness of our findings in Figure 3, underscoring the influence of giants on other investors and the predictive power of giants' contrarian investment decisions.

Further Robustness Checks In Appendix E, we summarize the results from a battery of robustness checks. The strong predictability of investment giants' flows for equity markets is highly robust to (*i*) restricting the sample to active flows, (*ii*) alternative fixed-effects structures, and (*iii*) alternative definitions of giants.

6.3 Falsification Tests

A primary concern regarding our identification strategy is whether the contrarian flows of investment giants truly represent idiosyncratic strategic shocks or, instead, reflect the giants' superior ability to forecast future macroeconomic fundamentals. If giants possess private information about forthcoming '*pull*' factors—such as anticipated shocks to industrial production or shifts in monetary policy—the subsequent market reactions could be attributed to fundamental news rather than strategic directional leadership. To address this, we conduct a series of falsification tests by estimating the response of future macroeconomic variables to our giant's contrarian flows. Specifically, we estimate country-level local projections where the dependent variables are future realizations of local real interest rates, industrial production growth, and foreign reserve growth.[8]

As illustrated in Figures A.3–A.6 of Appendix D, the granular shocks to giants' flows do not predict future changes in these fundamental macro variables across any of the considered horizons. The coefficients are statistically indistinguishable from zero, suggesting that our contrarian flow measure is not merely proxying for omitted pull factors. This lack of predictive power for fundamentals provides empirical support for the exclusion restriction underlying our approach. It reinforces our interpretation that the subsequent reactions observed in the market—including the persistent capital inflows and price appreciations analyzed in the current and following sections—are driven by strategic coordination and the leadership of giants rather than a mere anticipation of macro-level shifts.

7 Aggregate Dynamics and Implications

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

[8] The specification follows the country-level regressions detailed in Section 7.3, substituting financial market returns with macro fundamentals.

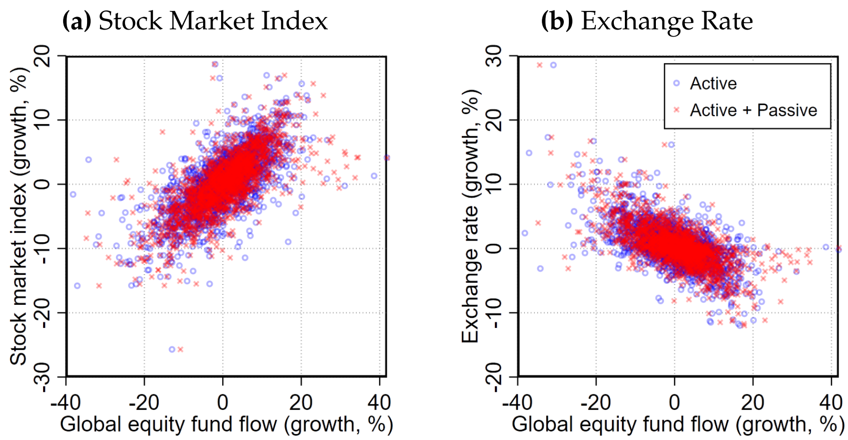

Figure 5: Global Equity Fund Flows, Stock Prices, and Exchange Rates in Emerging Economies

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 with active funds and all funds (active and passive), respectively.

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

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

Figure 5 indeed exhibits a strong correlation between global equity fund flows (aggregated EPFR), stock prices, and exchange rates (local currency per USD) across 20 emerging markets. Despite accounting for only 1–10% of market capitalization, EPFR fund flows exhibit strong co-movement with aggregate flows (Jotikasthira et al. 2012) and market returns (Rey et al. 2024). This suggests that even relatively small cross-border equity flows can exert outsized influence, and also raises an important empirical question: do investment giants, through their contrarian flows, systematically impact country-level equity flows and financial conditions in emerging markets?

Prior research has documented the link between capital flows and financial factors, both local and global, such as domestic stock indices, US equity market movements, and exchange rate fluctuations. Warther (1995) and Edelen (1999) highlight the contemporaneous impact of aggregate mutual fund flows on stock returns, while Coval and Stafford (2007) document the price pressures exerted by large-scale fund flows in the US equity market. Also, Lilley, Maggiori, Neiman and Schreger (2022) find that US purchases of foreign bonds have been a key driver of currency dynamics post-Global Financial Crisis. However, these relationships remain debatable (Wardlaw 2020; Gabaix and Maggiori 2015).

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

7.2 Investment Giants and Aggregate Equity Flows

We initiate aggregate-level examination by assessing the investment giants' role in the dynamics of aggregate equity flows. Given their limited market coverage, the predictive power of giants' contrarian flows within the investor-level EPFR universe does not necessarily imply their predictability for the entire equity flows (e.g., those in the Institute of International Finance (IIF) database). Hence, beyond testing the theoretical predictions, this exercise also addresses an important empirical question that remains open.

Regression Specification Mapping our theoretical model prediction in equation (23) to the data, we estimate country-month panel local projections for the aggregate flows as:

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

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

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

While the adjusted and non-adjusted aggregate equity flows are computed based on the EPFR data, the data for aggregate equity net flows are supplemented by the IIF database

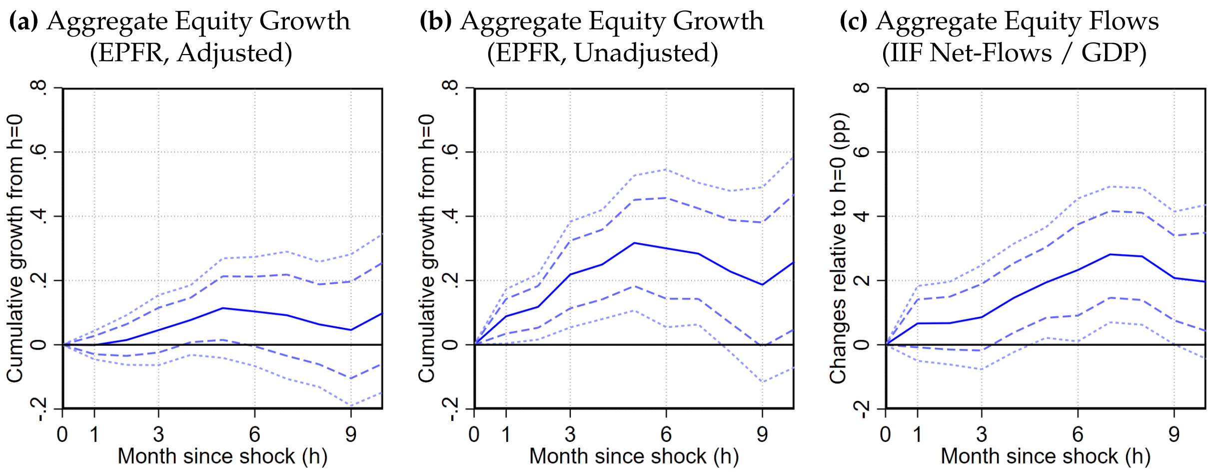

Figure 6: Aggregate Flow Responses to Giants' Contrarian Flows

Notes: The figures depict the predictive content of the differential between investment giants' (the top 10) and typical investors' average equity growth for valuation-adjusted and unadjusted EPFR aggregate equity growth, as well as IIF aggregate equity net-flows (% of GDP). The responses to investment giants' flows are the estimates of β^h in equation (31). 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 (%).

from the IMF. In addition, identically to our investor-level estimations, the cumulative growth of equity flows between time t and $t + h$ is winsorized, ranging from $-h\times$100% to $h\times$100%, to rule out extreme values. Similar to previous regressions, equation (31) includes standard control variables—push and pull factors and various fixed effects—that are defined comparably to those in equation (29).

Regression Results Figure 6 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 of equation (23). They also align with our earlier findings from investor-level regressions in Section 6.

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

Robustness Checks To ensure the robustness of these findings, we conduct additional analyses using alternative specifications similar to those in Section 6: (*i*) dataset with active flows, (*ii*) different fixed effects, (*iii*) different definitions of investment giants, and (*iv*) alternative main regressors (changes in giants' share and differential between size-weighted and unweighted average of equity flows). The results of aggregate-level regressions remain by and large robust across different data and specifications. We present the results for our robustness checks in Appendix F.1.

7.3 Investment Giants, Future Stock Returns and Exchange Rates

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

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

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

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

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

Other terms are defined identically to those in equation (31).

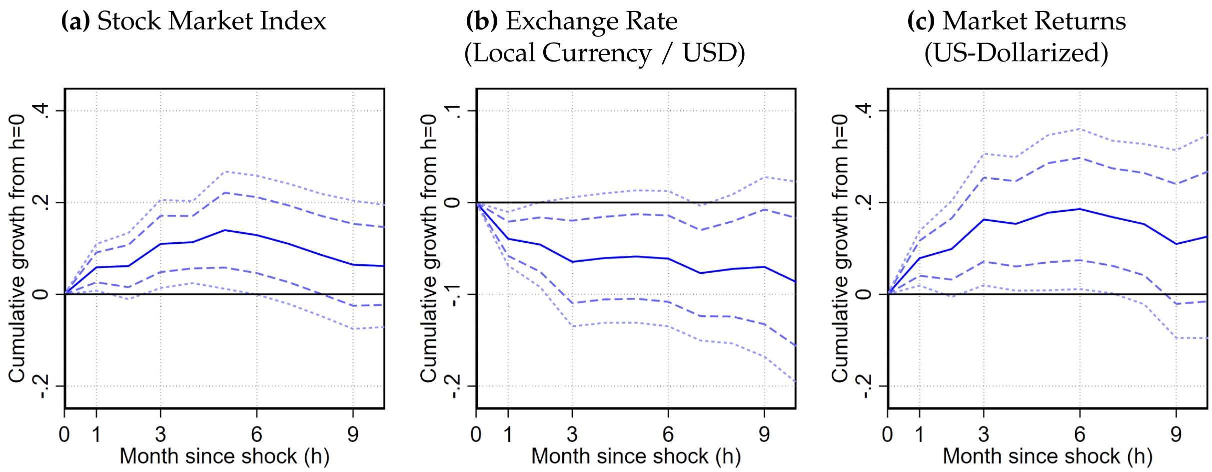

Figure 7: Stock and Currency Markets Responses to Giants' Contrarian Flows

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 index growth, exchange rate changes, and stock market returns (defined as stock price index growth net of exchange rate growth). The responses to investment giants' flows are the estimates of β^h in equation (31). 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 summarizes the results, corresponding to the three measures of market returns. In the first chart, the investment giant idiosyncratic flows have incremental effects on stock market indices in emerging markets. The response is the strongest around five months after the shock, rising by around 0.15%. This finding is consistent with the literature that documents a strong positive link between capital flows and stock valuations in international financial markets (Gourinchas and Rey 2014; Anaya, Hachula and Offermanns 2017; Bathia, Bouras, Demirer and Gupta 2020, and many others).

Moreover, foreign exchange rates appreciate by up to 0.09% in response to a 1% increase in giant flow shocks (second chart). A large body of literature has documented a similar positive relationship between (aggregate) capital flows and currency values in both advanced economies (Hau and Rey 2006) and emerging economies (Borio 2019). In conjunction with our previous finding—the positive predictability of investment giant flows on aggregate equity flows—the relationship between giant flows and exchange rates supports the earlier findings and further identifies giants as an important driving force.

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

While giants' flows have significant predictive power for financial prices (stock and FX) through strategic coordination, the falsification test results in Section 6.3 show that they do not predict subsequent fluctuations in real macroeconomic fundamentals. This suggests that the observed price appreciation reflects directional leadership and portfolio reallocation rather than anticipation of real shocks.

Policy Implications Our findings have significant policy implications, particularly for emerging markets. As the influence of global factors, often referred to as *the global financial cycle*, has substantially grown, small open economies—especially those that have experienced large credit inflows—face increasing challenges in shielding their financial markets from external shocks (*dilemma*, e.g., Rey 2015; Kalemli-Özcan 2019; Goldberg and Krogstrup 2023). In light of this, economies highly exposed to cross-border portfolio flows must refine their policy frameworks to better monitor capital flow shocks.

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

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

8 Conclusion

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

Despite its critical importance, however, our understanding of global portfolio allocations remains limited, with much of the focus centered on the aggregate-level interplay among the flows and macroeconomic factors. Studies at the fund or investor level, which explore the interactions among investors, their effects on aggregate flows, and the underlying mechanisms, are still scarce. This knowledge gap is particularly concerning in an environment where the composition of investors and investment strategies has become increasingly complex. A lack of granular insights not only constrains our understanding of capital flow dynamics but also limits policymakers' ability to respond proactively to shifts in global capital flows.

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

By shedding light on the investor-level determinants of portfolio flows, this study contributes to a more nuanced understanding of global capital markets. Our findings highlight the necessity of developing a new analytical framework that captures the strategic decision-making processes of global institutional investors. From a policy perspective, closely monitoring investment giants could provide valuable early warning signals for emerging market vulnerabilities. In a world where policy options are constrained by the global financial cycle (Rey 2015), such insights offer critical guidance for policymakers and market participants navigating the complexities of international capital flows. Moreover, by uncovering the micro-level determinants of fund flows, policymakers gain valuable insights for designing macro-prudential or foreign exchange-related policy frameworks aimed at ensuring financial stability, particularly in emerging market economies deeply integrated into the global financial market.

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

Investment Giant's Optimal Strategy The giant's first-order condition is:

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

Then, the optimal strategy can be reexpressed as:

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

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

B Typical Investor 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:

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

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

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

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

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

While the 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 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 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:

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

By committing to an early decision, the 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 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:

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

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

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

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

This reflects the giant's dual advantage. The giant shapes market direction through leadership, thereby enhancing coordination. Also, the giant leverages the public information, which it generates, to improve others' information, benefiting all 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 are 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.

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 in equation (1): $\text{Equity}_{ic,t} = \sum_{a \in \text{AssetClass}} \text{EquityShare}_{aic,t} \times \text{TotalNetAssets}_{ai,t}$. 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 classes 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$\times$0.101 + 2,085.92$\times$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 ($\mathrm{IHS}(x) = \ln[x + (x^2 + 1)^{0.5}]$) for the computation of the equity growths (flows) between t and $t + h$ as in equation (26), where the cumulative growth is winsorized at both ends by –$h\times$100% and $h\times$100% (i.e., 100% monthly growth rate), to prevent our regression results from being potentially influenced by a few extreme flows. This is similar to one that winsorizes the top and bottom 1% of observations in the case of $h = 1$. To exclude this valuation channel, we compute the cumulative equity growth based on the adjusted equity growth with market returns as in equation (30), which is also winsorized at both ends by $-h\times$100% and $h\times$100%. We checked the estimation results without winsorization, and found that the main results remain robust.

Appendix C.3 provides the summary statistics.

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. variables.

More specifically, we calculate the ex-post real interest rates by subtracting year-over-year CPI inflation from nominal interest rates. CPI data is sourced from the IMF's International Financial Statistics (IFS) dataset, with the exception of Taiwan, where CPI data is collected from Bloomberg. For nominal interest rates, we use treasury bill rates (or deposit rates) from the IFS dataset and supplement them with treasury bill yields from the Global Financial Database for some countries where the data is not available in the IFS dataset. More pointedly, we take nominal interest rates from three sources as follows.

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

- For Chile, Colombia, Czech Rep., Indonesia, Korea Rep., Malaysia, Peru, Philippines, Russia, and Turkey, we choose the deposit rates from the IFS dataset. This is because the IFS dataset lacks treasury bill rate data for these countries, but the deposit rates closely resemble treasury bill rates.

- For China, India, Poland, and Taiwan, we turn to the treasury bill yield from the Global Financial Database. This alternative source is selected because their appropriate proxies for nominal interest rates are absent in the IFS dataset.

In addition, we obtain non-seasonally adjusted industrial production indices from the World Bank's GEM (Global Economic Monitor) dataset. Total reserves excluding gold (in US dollars) are taken from the IFS dataset. Monthly exchange rates and stock market indices for each country are sourced from Bloomberg. The list of stock market indices that we employ is as follows:

- (US) Wilshire 5000, (Brazil) Bovespa, (Chile) S&P CLX IPSA, (China) Shanghai Composite, (Colombia) COLCAP, (Czech Rep.) PX, (Hungary) Budapest SE, (India) BSE

Sensex 30, (Indonesia) Jakarta Stock Exchange Composite Index, (Israel) TA 35, (Korea Rep.) KOSPI, (Malaysia) FTSE Malaysia KLCI, (Mexico) S&P/BMV IPC, (Peru) S&P Lima General, (Philippines) PSEI Composite, (Poland) WIG 20, (Russia) MOEX Russia, (South Africa) South Africa Top 40, (Taiwan) Taiwan Weighted, (Thailand) SET Index, and (Turkey) BIST 10.

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

The monthly (country) aggregate equity flow is extracted from the International Institute of Finance (IIF) dataset. To facilitate cross-country comparisons, we scale equity flows by nominal GDP. Nominal GDP is available quarterly and is transformed into monthly series using cubic spline interpolation.

Appendix C.3 provides the summary statistics for the macroeconomic variables.

C.3 Summary Statistics

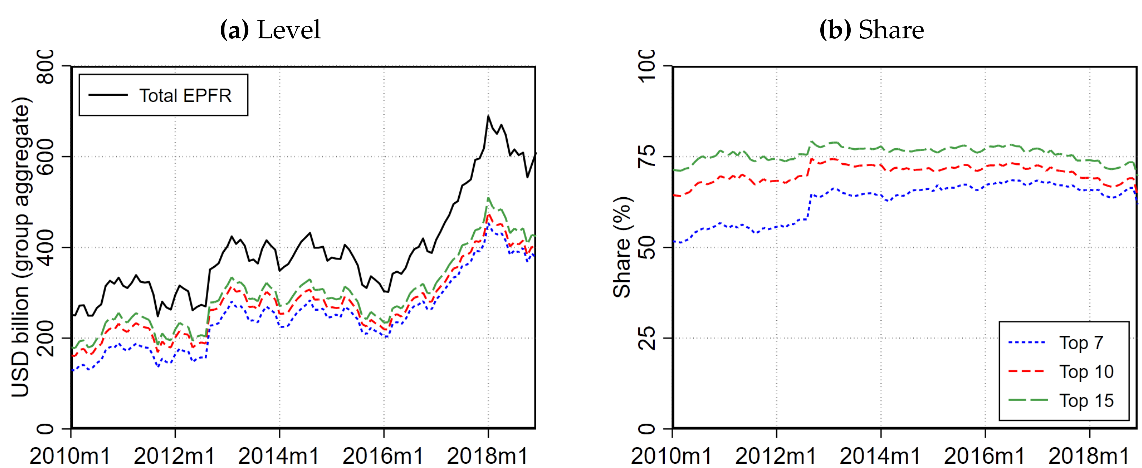

Figure A.1: Trends of EPFR Aggregate Equity Fund Flows

Notes: The left panel plots aggregate equity investments by institutional investor groups (all investors, top 7, 10 and top 15) in the 20 emerging equity markets. The right panel displays the shares of the top 7, 10, and 15 investors (blue, red, and green lines) in total global equity flows allocated to these markets.

Table A.1: Summary Statistics: Equity Flows

Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Panel A. Individual Investor Flows						
Equity flow (mil. US dollars)						
All investors	269,480	157.78	986.94	0.00	1.79	231.37
Nontop 10 largest investors	247,880	50.71	177.50	0.00	0.72	122.35
Top 10 largest investors	21,600	1,386.53	3,185.84	3.78	412.40	3297.73
Equity flow (monthly growth, %)						
All investors	261,780	0.09	19.48	–10.77	0.00	10.50
Nontop 10 largest investors	240,180	0.11	19.73	–10.43	0.00	10.26
Top 10 largest investors	21,600	–0.08	16.47	–13.01	0.00	12.07
Adjusted equity flow (monthly growth, %)						
All investors	261,780	0.09	18.89	–8.00	0.00	7.92
Nontop 10 largest investors	240,180	0.10	19.17	–7.81	0.00	7.78
Top 10 largest investors	21,600	–0.11	15.35	–9.27	0.00	8.88
Panel B. Average Flows						
Cross-sectional average of equity flow growth (monthly growth, %)						
Nontop 10 largest investors	2,160	0.08	4.39	–5.10	0.17	5.33
Top 10 largest investors	2,160	–0.08	7.82	–9.94	0.05	9.30
Cross-sectional average of adjusted equity flow growth (monthly growth, %)						
Nontop 10 largest investors	2,160	0.07	2.51	–2.95	0.09	3.12
Top 10 largest investors	2,160	–0.11	5.23	–5.82	–0.14	5.77

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

Table A.2: Summary Statistics: Equity Flows (Active Funds Only)

Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Panel A. Individual Investor Flows						
Equity investment (mil. US dollars)						
All investors	282,980	89.20	377.58	0.00	0.00	166.35
Nontop 10 largest investors	262,120	43.49	168.32	0.00	0.00	98.98
Top 10 largest investors	20,860	663.61	1105.38	0.00	203.21	1,868.69
Equity flow (monthly growth, %)						
All investors	273,840	–0.08	19.11	–9.93	0.00	9.34
Nontop 10 largest investors	253,000	–0.07	19.14	–9.42	0.00	8.91
Top 10 largest investors	20,840	–0.21	18.81	–13.68	0.00	12.48
Adjusted equity flow (monthly growth, %)						
All investors	273,840	–0.09	18.58	–7.43	0.00	6.89
Nontop 10 largest investors	253,000	–0.07	18.63	–7.07	0.00	6.56
Top 10 largest investors	20,840	–0.24	17.98	–10.27	0.00	9.43
Panel B. Average Flows						
Cross-sectional average of equity flow growth (monthly growth, %)						
Nontop 10 largest investors	2,160	–0.08	4.04	–4.93	0.08	4.65
Top 10 largest investors	2,160	–0.19	7.95	–10.35	0.26	9.39
Cross-sectional average of adjusted equity flow growth (monthly growth, %)						
Nontop 10 largest investors	2,160	–0.09	2.39	–2.90	–0.08	2.76
Top 10 largest investors	2,160	–0.23	6.03	–7.29	–0.10	6.77

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

Table A.3: Summary Statistics: Macroeconomic Variables

Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Panel A. Country-Month Level						
Real interest rate (per annum, %)	2,160	0.99	2.40	–1.38	0.75	3.61
Industrial production (monthly growth, %)	2,151	0.24	7.38	–8.25	0.41	9.11
Stock market index (monthly growth, %)	2,160	0.35	4.55	–5.26	0.56	5.86
Reserve excl. gold (USD, monthly growth, %)	2,160	0.36	2.32	–1.92	0.28	2.86
Exchange rate (monthly growth, %)	2,160	0.31	3.13	–3.00	0.04	3.91
IIF equity net-flows / GDP (ratio, %)	1,593	0.10	0.69	–0.51	0.06	0.78
EPFR aggregate (unadjusted) flows (monthly growth, %)	2,160	0.64	8.32	–9.54	1.06	10.14
EPFR aggregate (adjusted) flows (monthly growth, %)	2,160	0.60	4.80	–4.20	0.44	5.38
Panel B. Month Level						
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.

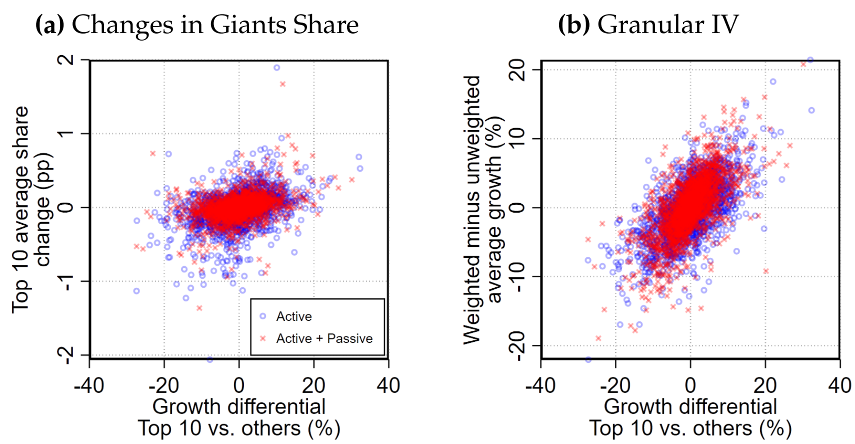

Figure A.2: Investment Giant's Contrarian Investment: Benchmark and Alternative Measures

Notes: The figures illustrate the relationship between the benchmark and alternative measures of investment giants' contrarian investment. In both panels, the x-axis represents our benchmark measure, defined in equation (25), which captures the differential between the average equity growth of investment giants and that of typical investors. The y-axis in the left and right panels corresponds to the alternative measures from equations (27) and (28), respectively: the giants' changing market share in each equity market and the differential between size-weighted and unweighted investment growth of all investors, referred to as granular instruments. The red crosses and blue circles are observations of all (active + passive) fund flows and active fund flows, respectively.

D Falsification Test Results

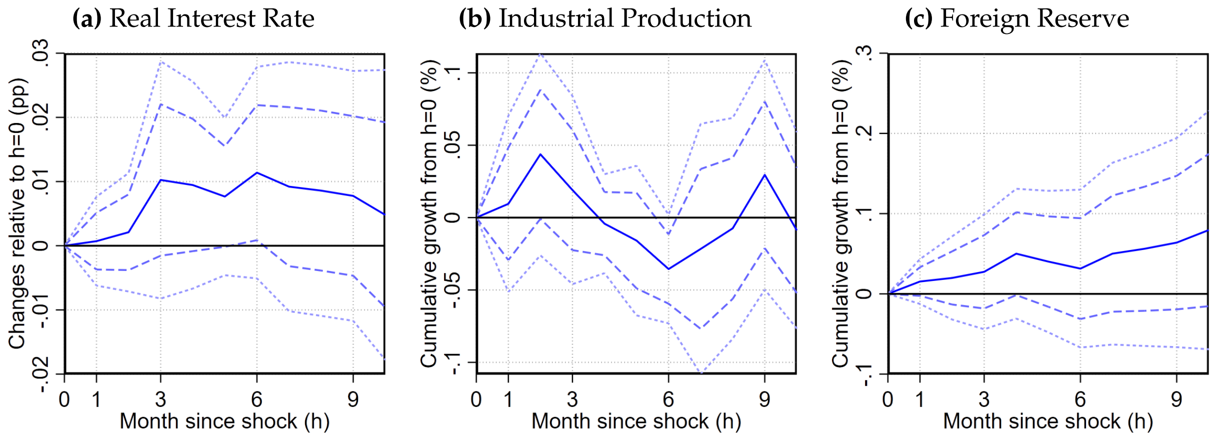

Figure A.3: Macro Fundamental Responses to Giants' Contrarian Flows

Notes: The figures depict the predictive content of the differential between investment giants' (the top 10) and typical investors' average equity growth for real interest rates, industrial production growth rates, and foreign reserve growth rates. The responses to investment giants' flows are the estimates of β^h in equation (31). The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

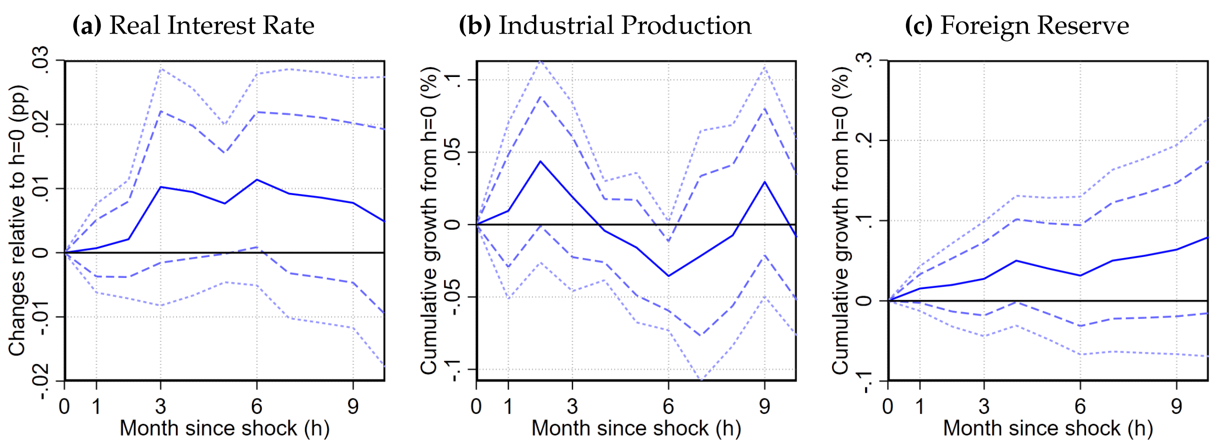

Figure A.4: Macro Fundamental Responses to Giants' Contrarian Flows: Alternative Specification

Notes: The figures depict the predictive content of the differential between investment giants' (the top 10) and typical investors' average equity growth for real interest rates, industrial production growth rates, and foreign reserve growth rates. The responses to investment giants' flows are the estimates of β^h in equation (A.10). The specification controls for country and time fixed effects, and contemporaneous growth of pull factors and their three lags. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

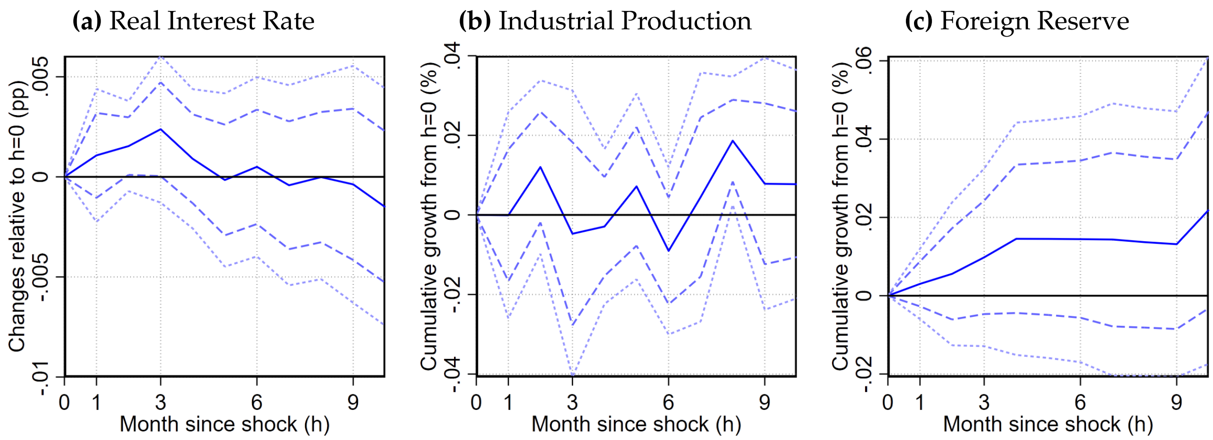

Figure A.5: Macro Fundamental Responses to Investment Giants Share

Notes: The figures depict the predictive content of the change in share of equity investments made by the top 10 investment giants (equation 27) for real interest rates, industrial production growth rates, and foreign reserve growth rates. The responses to investment giants' flows are the estimates of β^h in equation (31). The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

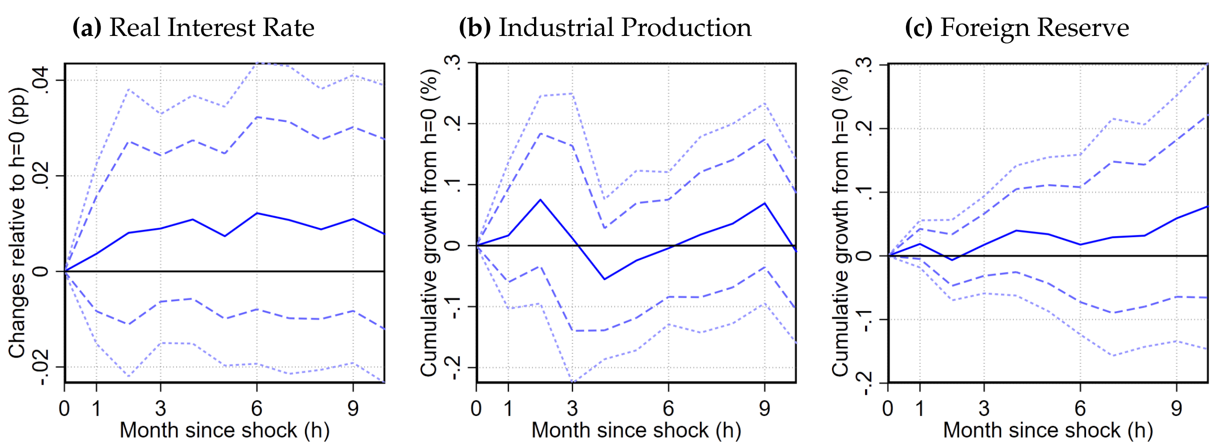

Figure A.6: Macro Fundamental Responses to Equity Flow Differential Between Size-Weighted and Unweighted Averages

The figures depict the predictive content of the difference between size-weighted and unweighted averages of investor flows (Granular IV, equation 28) for real interest rates, industrial production growth rates, and foreign reserve growth rates. The responses to investment giants' flows are the estimates of β^h in equation (31). 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 Robustness Checks of Investor-Level Analyses

Active fund flows We estimate investor's responses using a sample that includes active fund flows but excludes passive ones. Passive funds, also known as index or index-style funds, are investment vehicles that replicate a stock market index in their portfolio composition.[9] Thus, their performance tends to track that of the market index. Unlike passive funds, active funds select specific stocks for their own portfolios. Due to these different investment strategies, active and passive funds can display different dynamics. For example, active funds can exhibit lower responsiveness to aggregate factors, including pull and push factors, than passive funds (Chari et al. 2022; Chari 2023).[10]

To address this concern, we estimate regression equation (29) using active fund flows as both the dependent variable and the key flow measure used to construct contrarian investments. The estimation results with active funds data are broadly consistent with those from the full sample (active and passive funds). Specifically, as shown in Figure A.7, the impulse responses implied by equation (29) using active funds flows are broadly similar to those in Figure 3. Active-fund flows increase following positive shocks to investment giants' flows relative to typical investors, confirming strong predictability of giants' contrarian decisions for subsequent equity flows.

Taking the two alternative measures of investment giants' contrarian active equity flows, we further check robustness of our main results. Figure A.8 summarizes 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 (27) and (28), respectively. Consistent with the observations in Figures 3 and A.7, active equity flows exhibit the positive influence of investment giants on investors, in particular.

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

[10] 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.

Alternative fixed effects Regression equation (29) controls for time-varying push and pull factors by including U.S. (global) and destination-country variables, as well as firm and country fixed effects. Nevertheless, the baseline specification may not fully capture heterogeneity in investor-level dynamics, particularly unobserved time-varying shocks specific to individual investors.

To address this concern, we estimate an augmented specification of equation (29). Because the EPFR data do not provide detailed investor characteristics, we introduce investor–time fixed effects ($\delta^h_{i,t}$), yielding

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

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

We further consider a specification with more granular fixed effects. Instead of including investor and country fixed effects separately, we introduce investor–country fixed effects (δ^h_{ic}):

$$\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = \beta^h \left(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\right) + \mathbf{\Gamma}^h_{\text{pull}} \mathbf{Pull}_{c,t} + \mathbf{\Gamma}^h_{\text{push}} \mathbf{Push}_t + \delta^h_{ic} + \delta^h_m + \varepsilon^h_{ic,t}. \tag{A.9}$$

This specification controls for all time-invariant investor-specific heterogeneity within each destination country, thereby accounting for persistent bilateral investment patterns.

Figure A.9 presents the impulse responses implied by equations (A.8) and (A.9). In both cases, the estimated dynamics are qualitatively and quantitatively comparable to those obtained from the baseline specification. These results indicate that our findings are robust to rich controls for investor-level heterogeneity, whether time-varying or time-invariant.

Definition of investment giants A natural concern is whether our baseline results depend on the specific definition of investment giants. In the baseline specification, we define investment giants (large investors) as the top 10 investors ranked by their average equity investment in emerging markets. Although this threshold is motivated by the upper-tail concentration documented earlier, it remains inherently discretionary. To assess robustness, we consider two alternative classifications, redefining investment giants as either the top 15 (broader definition) or the top 7 (narrower definition) largest investors. Under each alternative threshold, we reconstruct the fund-level aggregates and re-estimate equation (29).

Figure A.10 reports the corresponding impulse response functions. Panels (a) and (b) display the responses of equity flows to shocks in the average growth differential between investment giants' and typical investors' flows, based on the top 15 and top 7 definitions, respectively. Under the narrower definition (top 7), the impulse responses closely resemble the baseline dynamics in both magnitude and persistence. By contrast, the broader definition (top 15) attenuates the initial responses and yields wider confidence intervals, consistent with the inclusion of relatively smaller investors that dilute the distinct behavior of the largest institutions. Overall, the qualitative pattern of strategic interaction remains intact across alternative thresholds, indicating that our main findings are not driven by a particular cutoff choice.

(a) Valuation-adjusted Equity Flows **(b)** Unadjusted Equity Flows

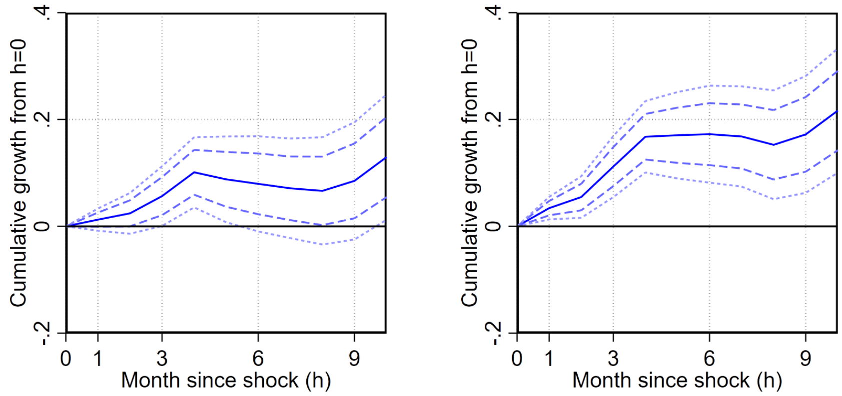

Figure A.7: Investor-Level Responses to Giants' Contrarian Flows: Active Fund Flows

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 growth rates. In panel (a), individual investor's active fund flows are are adjusted by stock market index and exchange rate growth to remove valuation effects; panel (b) reports unadjusted flows. The responses to active fund flows of investment giants relative to typical investors are the estimates of β^h in equation (29). 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, %).

(a) Changes in Giants Share **(b)** Granular IV

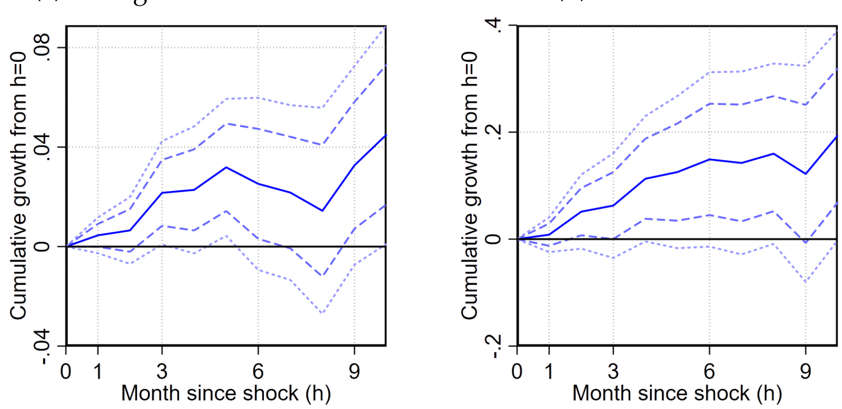

Figure A.8: Investor-Level Response to Changes in Alternative Measures of Contrarian Investments: Active Fund Flows

Notes: The figures depict the predictive capacity of alternative measures of contrarian investments made by the top 10 investment giants. In panel (a), the alternative measure is the change in the share of investments made by the top 10 investment giants, as defined in equation (27). In panel (b), the alternative measure (labeled "Granular IV") is the difference between size-weighted and unweighted averages of investors' active fund flows, as defined in equation (28). The responses of valuation-adjusted active fund flows to contrarian flows are the estimates of β^h in equation (29). 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) Investor-time fixed effects　　(b) Investor-country fixed effects

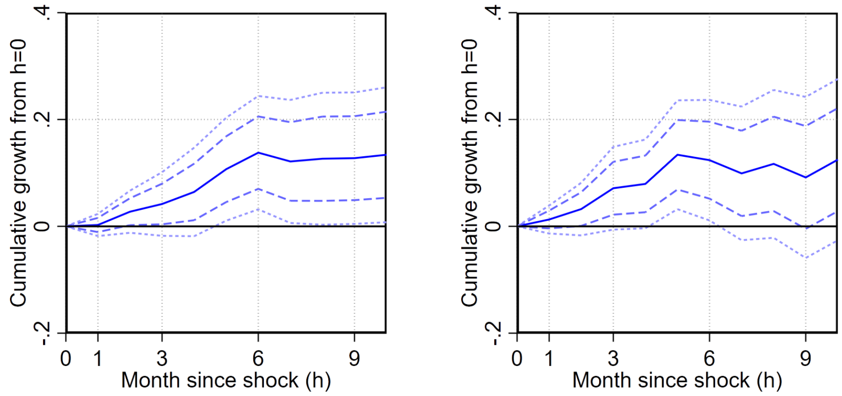

Figure A.9: Investor-Level Responses to Giants' Contrarian Flows: Alternative Specification

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 growth rates. In panels (a) and (b), the responses to investment giants' flows relative to typical investors are the estimates of β^h in equations (A.8) and (A.9), respectively. In both panels, the regression includes contemporaneous growth of pull factors and their three lags. In panel (a), we control for investor-time and country fixed effects. In panel (b), we control for investor-country fixed effects as well as contemporaneous growth of push factors. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

(a) Top 15 Largest Investors　　(b) Top 7 Largest Investors

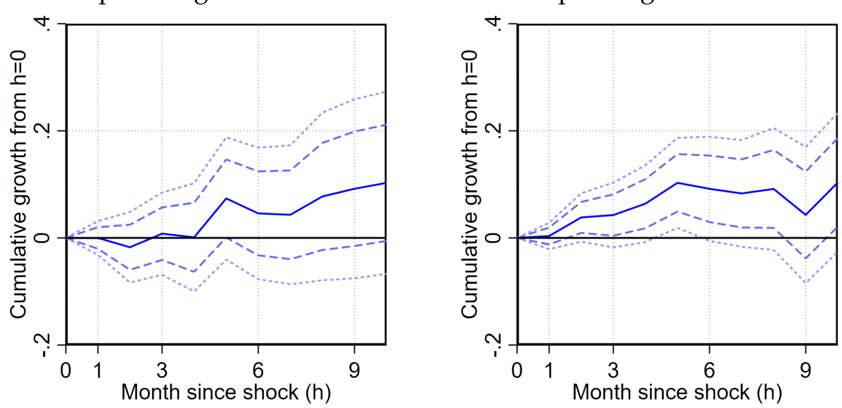

Figure A.10: Investor-Level Response to the Equity Flow Differential between Giants (Top 15 or 7 Largest Investors) and Typical Investors

Notes: The figures depict the predictive capacity of average equity flows from the differential between giants' (the top 15 and 7 in panels (a) and (b), 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). 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, %).

F Robustness Checks of Country-Level Analyses

F.1 Robustness: Impact of Giants on Aggregate Flows

The results of aggregate-level regressions remain broadly robust across alternative data sources and specifications, reaffirming the substantial information embedded in investment giants' decisions about aggregate equity-flow conditions in emerging markets. More specifically, we first compare our baseline results with those estimated using only active fund flows (Figure A.11). Similar to the baseline, aggregate equity flows computed using valuation-adjusted EPFR data exhibit relatively weak and sometimes insignificant responses (first chart), whereas those computed using unadjusted EPFR data (second chart) and IIF net flows (third chart) show significant and persistent increases.

Second, we estimate a regression that includes time fixed effects, given by:

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

where δ_t^h denotes the time fixed effect.[11] As summarized in Figure A.12, the responses of aggregate equity flows, based on the three measures, to the giants' contrarian investment are consistent with our baseline when the time fixed effect is explicitly accounted for.

Third, we test the sensitivity of the results to different definitions of investment giants. Figures A.13 and A.14 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 robustness using alternative main regressors—the investment giants' share and the differential between size-weighted and unweighted averages—as defined in equations (27) and (28), respectively. The impulse responses of aggregate flows to these shocks are also in line with the baseline results (Figures A.15 and A.16).

In short, our aggregate-level analyses consistently reveal a clear pattern: contrarian investments by investment giants precede movements in aggregate equity flows in emerging markets. This highlights the importance of monitoring the activities of investment giants

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

as an early-warning indicator of potential distress, such as sudden stops and surges in emerging equity markets.

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

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

In more details, the impulse responses of stock and currency markets to active fund flows are first reported in Figure A.17. Second, we estimate a regression similar to equation (A.10), which explicitly includes time fixed effects; the results are summarized in Figure A.18. Third, we consider alternative definitions of investment giant flows. Specifically, labeling the top 7 and top 15 largest investors in our EPFR dataset as investment giants, we assess whether our main findings remain consistent; the corresponding results are provided in Figures A.19 and A.20. Fourth, Figures A.21 and A.22 present the responses of stock returns and exchange rate changes to shocks in alternative measures of giants' contrarian flows: the investment giants' share and differential between size-weighted and unweighted averages, as defined in equations (27) and (28), respectively.

(a) Aggregate Equity Growth (EPFR, Adjusted) **(b)** Aggregate Equity Growth (EPFR, Unadjusted) **(c)** Aggregate Equity Flows (IIF Net-Flows / GDP)

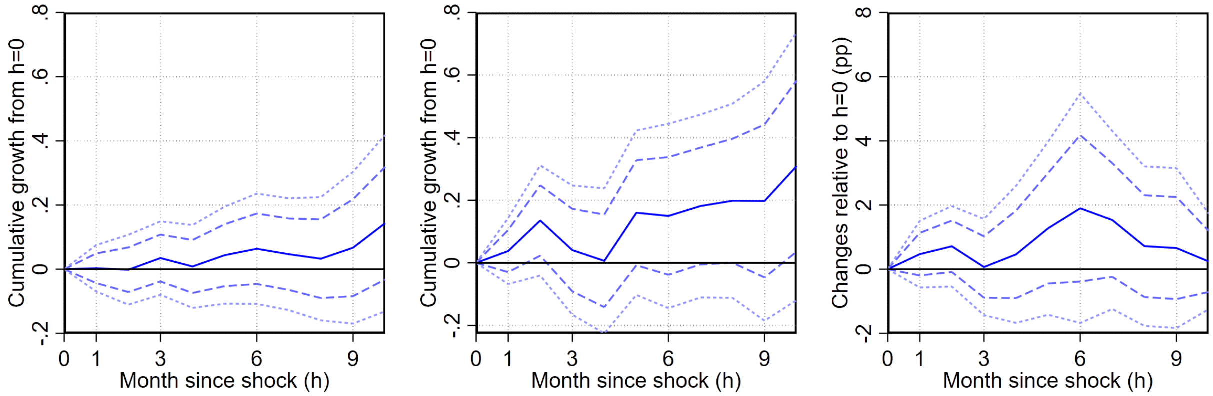

Figure A.11: Aggregate Flow Responses to Giants' Contrarian Flows: Active Fund Flows

Notes: The figures depict the predictive content of the differential between investment giants' (the top 10) and typical investors' average active fund's equity growth for the valuation-adjusted and non-adjusted EPFR aggregate active fund's equity growths and IIF aggregate equity net-flows (% of GDP). The responses to investment giants' flows are the estimates of β^h in equation (31). 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) Aggregate Equity Growth (EPFR, Adjusted) **(b)** Aggregate Equity Growth (EPFR, Unadjusted) **(c)** Aggregate Equity Flows (IIF Net-Flows / GDP)

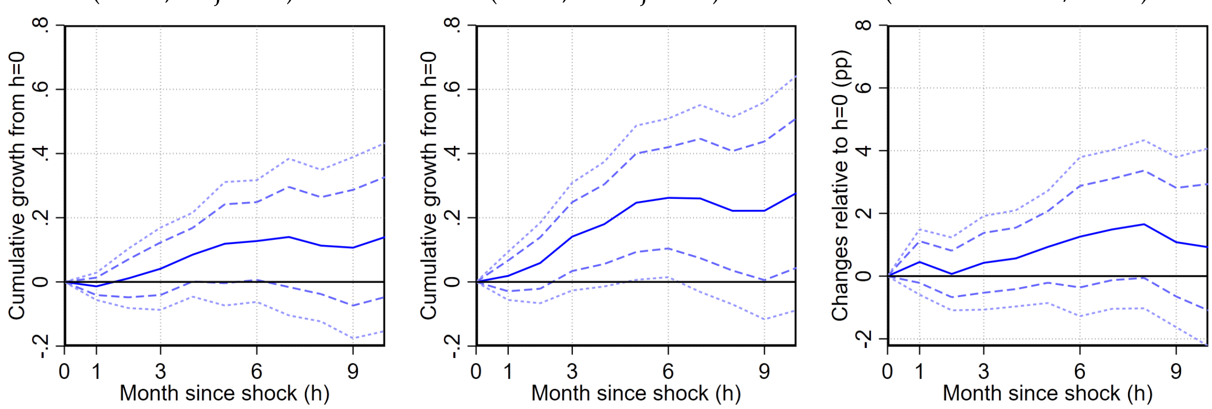

Figure A.12: Aggregate Flow Responses to Giants' Contrarian Flows: Alternative Specification

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

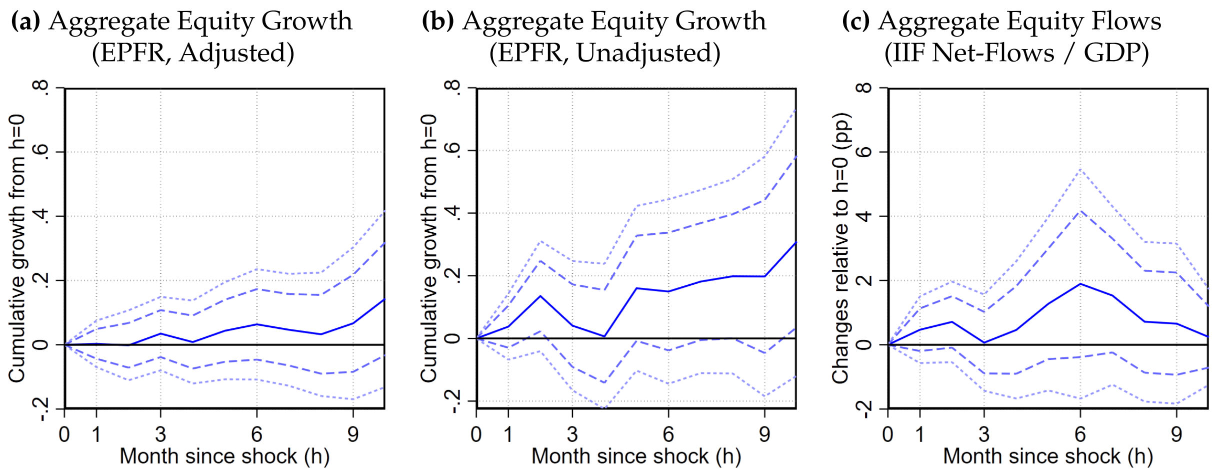

Figure A.13: Aggregate Flow Responses to Giants' (Top 15 Largest Investors) Contrarian Equity Flows

Notes: The figures depict the predictive content of the differential between investment giants' (the top 15) and typical investors' average equity growth for the valuation-adjusted and non-adjusted EPFR aggregate equity growths and IIF aggregate equity net-flows (% of GDP). The responses to investment giants' flows are the estimates of β^h in equation (31). The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

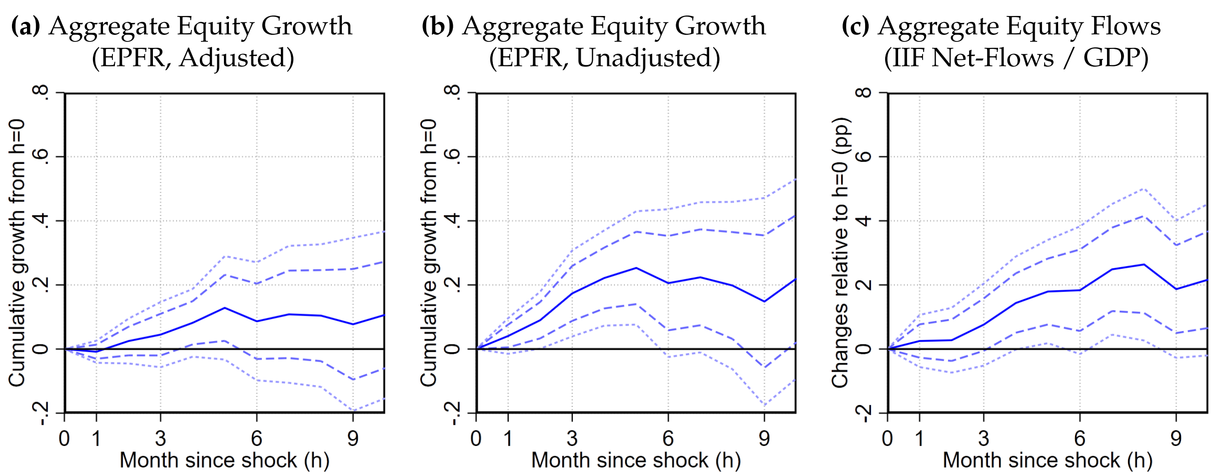

Figure A.14: Aggregate Flow Responses to Giants' (Top 7 Largest Investors) Contrarian Equity Flows

Notes: The figures depict the predictive content of the differential between investment giants' (the top 7) and typical investors' average equity growth for the valuation-adjusted and non-adjusted EPFR aggregate equity growths and IIF aggregate equity net-flows (% of GDP). The responses to investment giants' flows are the estimates of β^h in equation (31). 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) Aggregate Equity Growth (EPFR, Adjusted) | (b) Aggregate Equity Growth (EPFR, Unadjusted) | (c) Aggregate Equity Flows (IIF Net-Flows / GDP)

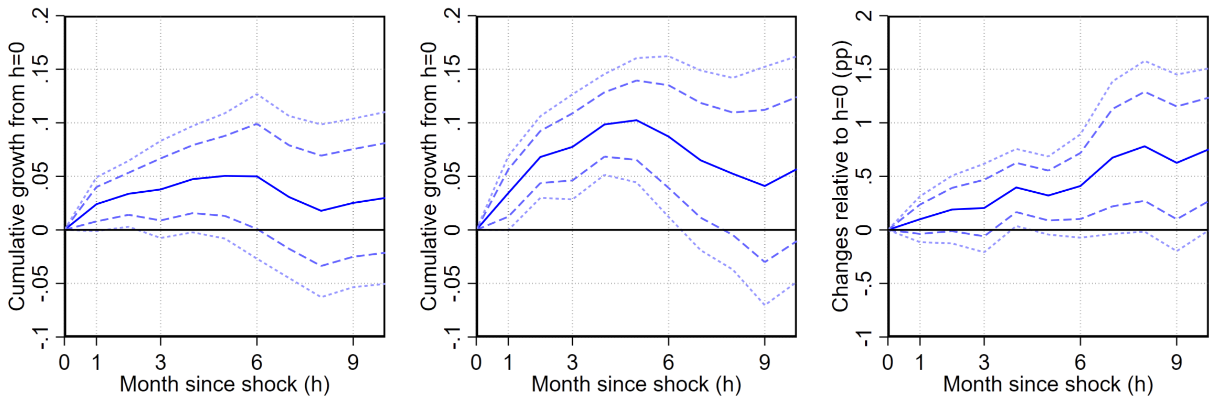

Figure A.15: Aggregate Flow Responses to Investment Giants Share

Notes: The figures depict the predictive content of the change in share of equity investments made by the top 10 investment giants (equation 27) for the valuation-adjusted and non-adjusted EPFR aggregate equity growths and IIF aggregate equity net-flows (% of GDP). The responses to investment giants' flows are the estimates of β^h in equation (31). 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) Aggregate Equity Growth (EPFR, Adjusted) | (b) Aggregate Equity Growth (EPFR, Unadjusted) | (c) Aggregate Equity Flows (IIF Net-Flows / GDP)

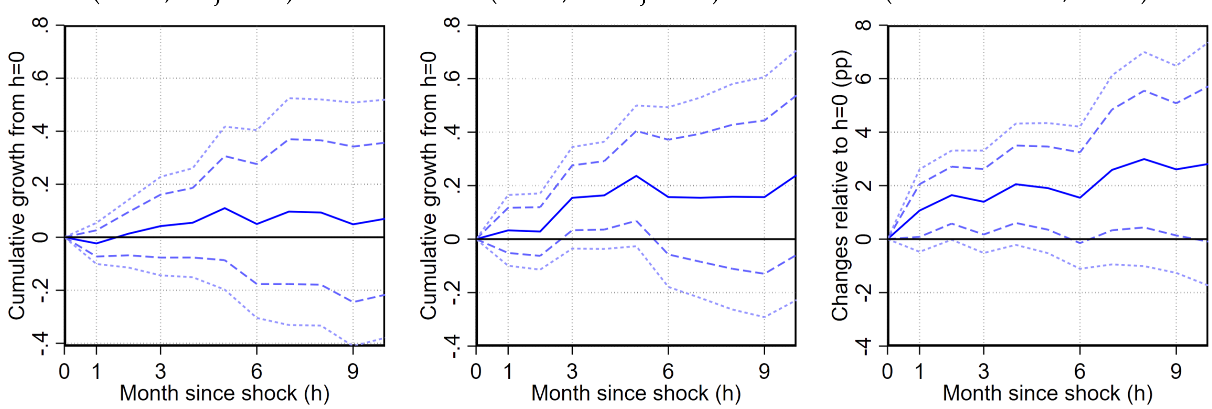

Figure A.16: Aggregate Flow Responses to Equity Flow Differential Between Size-Weighted and Unweighted Averages

Notes: The figures depict the predictive content of the difference between size-weighted and unweighted averages of investor flows (Granular IV, equation 28) for the valuation-adjusted and non-adjusted EPFR aggregate equity growths and IIF aggregate equity net-flows (% of GDP). The responses to investment giants' flows are the estimates of β^h in equation (31). The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

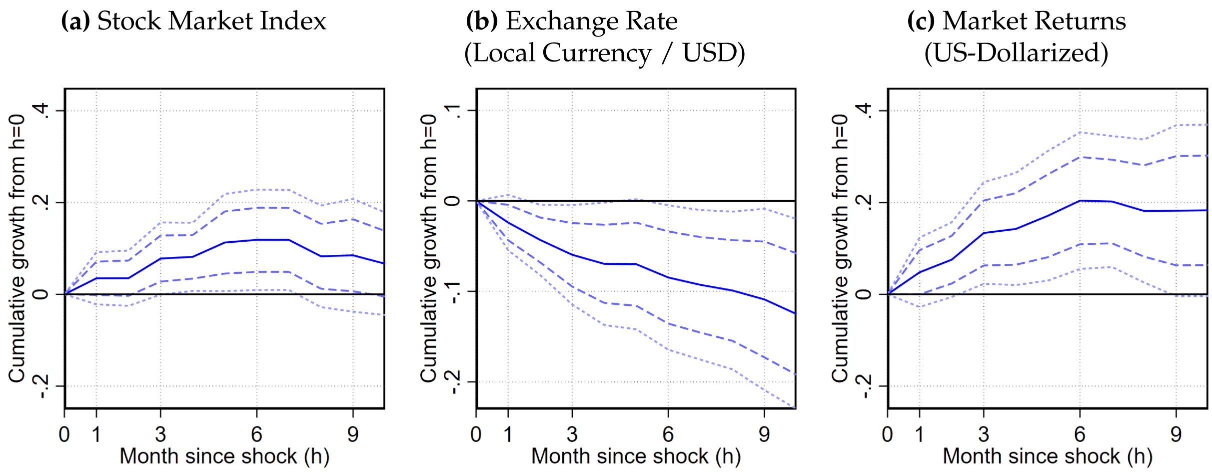

Figure A.17: Stock and Currency Markets Responses to Giants' Contrarian (Active Fund) Equity Flows.

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 index growths, exchange rate changes, and stock market returns (defined as stock price index growth net of exchange rate growth). The responses to investment giants' flows are the estimates of β^h in equation (31). The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

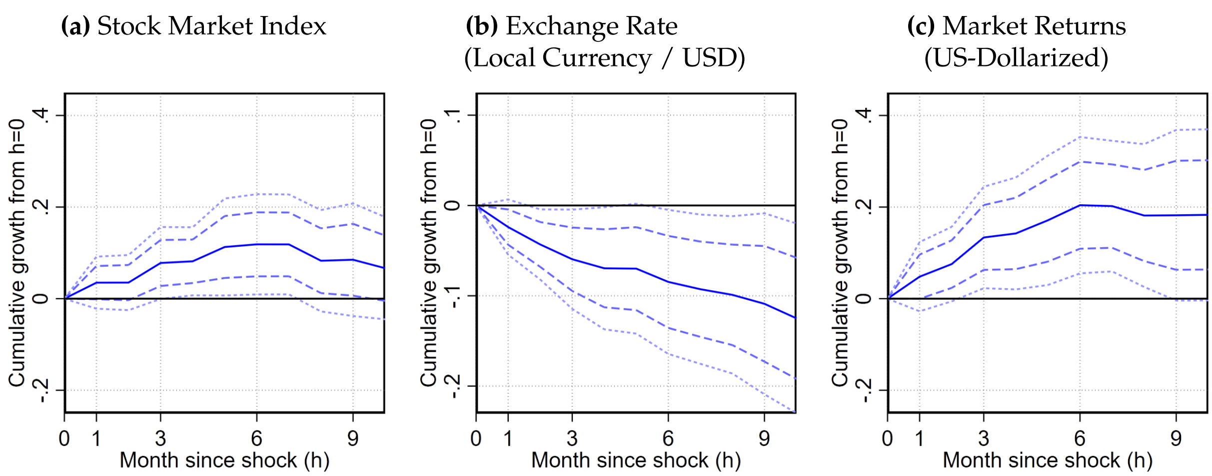

Figure A.18: Stock and Currency Markets Responses to Giants' Contrarian Flows: Alternative Specification

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 index growths, exchange rate changes, and stock market returns (defined as stock price index growth net of exchange rate growth). The responses to investment giants' flows are the estimates of β^h in equation (A.10). The specification controls for country and time fixed effects, and contemporaneous growth of pull factors and their three lags. The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

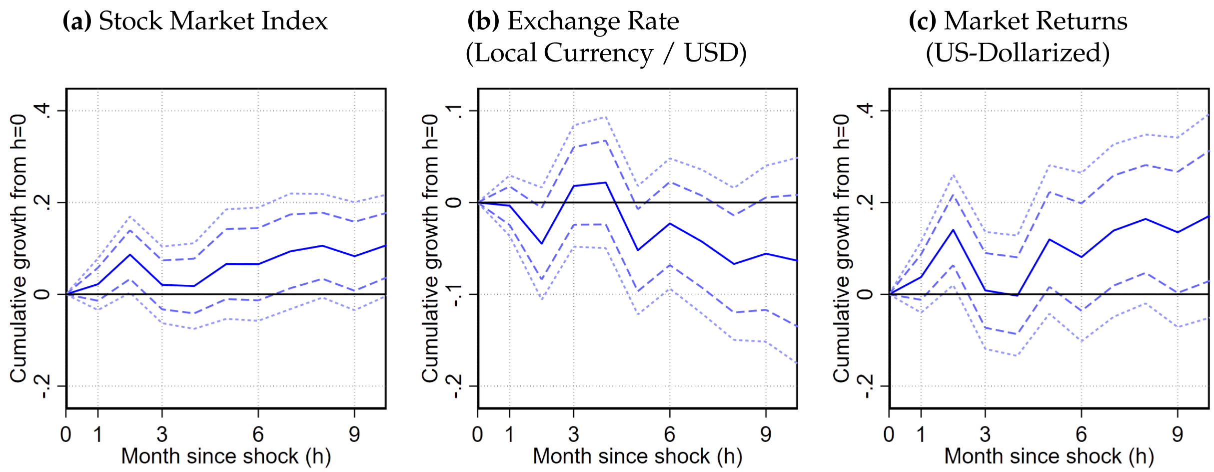

Figure A.19: Stock and Currency Markets Responses to Giants' (Top 15 Largest Investors) Contrarian Equity Flows

Notes: The figures depict the predictive content of the differential between investment giants' (the top 15) and typical investors' average equity growth for stock price index growths, exchange rate changes, and stock market returns (defined as stock price index growth net of exchange rate growth). The responses to investment giants' flows are the estimates of β^h in equation (31). The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

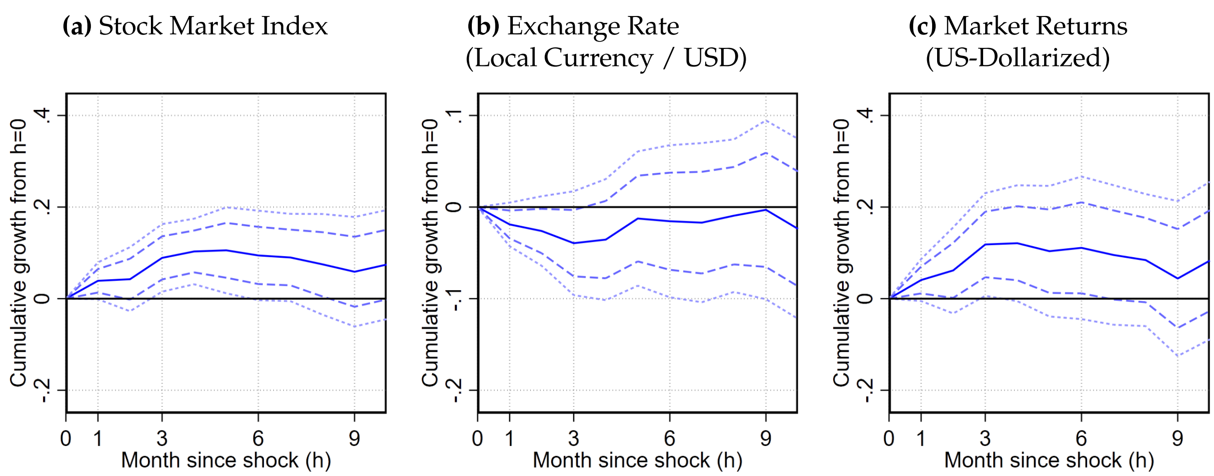

Figure A.20: Stock and Currency Markets Responses to Giants' (Top 7 Largest Investors) Contrarian Equity Flows

Notes: The figures depict the predictive content of the differential between investment giants' (the top 7) and typical investors' average equity growth for stock price index growths, exchange rate changes, and stock market returns (defined as stock price index growth net of exchange rate growth). The responses to investment giants' flows are the estimates of β^h in equation (31). The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

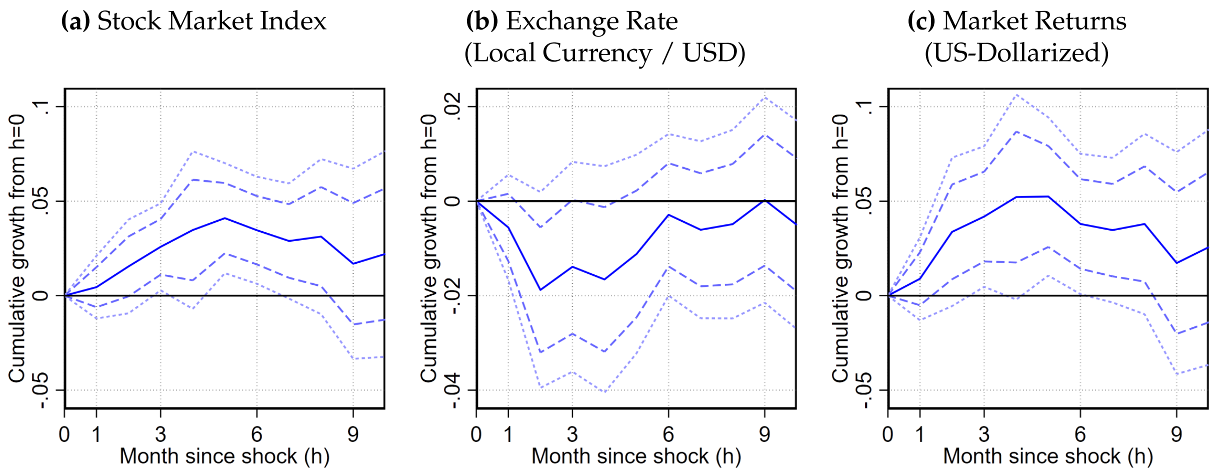

Figure A.21: Stock and Currency Markets Responses to Investment Giants Share

Notes: The figures depict the predictive content of the change in share of equity investments made by the top 10 investment giants (equation 27) for stock price index growths, exchange rate changes, and stock market returns (defined as stock price index growth net of exchange rate growth). The responses to investment giants' flows are the estimates of β^h in equation (31). The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

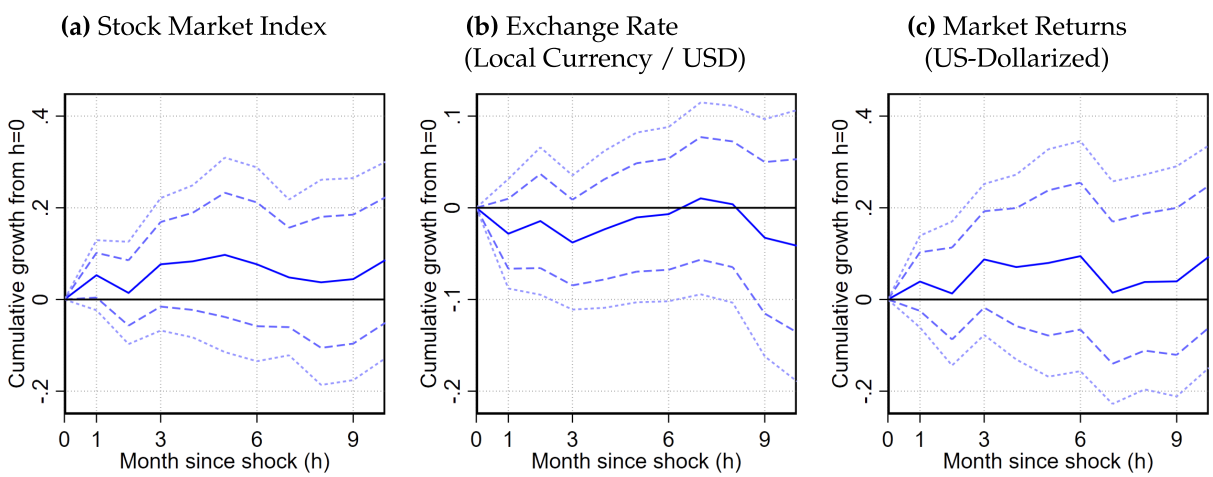

Figure A.22: Stock and Currency Markets Responses to Equity Flow Differential Between Size-Weighted and Unweighted Averages

The figures depict the predictive content of the difference between size-weighted and unweighted averages of investor flows (Granular IV, equation 28) for stock price index growths, exchange rate changes, and stock market returns (defined as stock price index growth net of exchange rate growth). The responses to investment giants' flows are the estimates of β^h in equation (31). 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 (growth, %).