Investment Giants in Emerging Markets

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Abstract

Cross-border equity allocations to emerging markets are highly concentrated among a small group of dominant institutional investors—textitinvestment giants. We show that giants' contrarian investment flows (excess growth relative to peer allocations) predict persistent increases in peer fund flows, aggregate capital inflows, stock returns, and currency values. To rationalize these patterns, we build a theoretical model of delegated asset management featuring private signal extraction and relative performance benchmark tracking. In equilibrium, the investment giant strictly prefers to move first rather than simultaneously because sequential leadership maximizes its ex-ante expected payoff by insulating itself from relative benchmark tracking risk. The giant's sequential decision-making amplifies its market influence through public information disclosure and strategic peer portfolio synchronization. Our findings reveal how investor concentration shapes strategic timing and the dynamics of global portfolio allocation.

JEL Classification: F32, G11, G15, G23.
Keywords: Emerging equity markets, Institutional investors, Global equity flows, Dominant players, Portfolio management, Fund-level data.

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1 Introduction

Global equity allocations to emerging markets are highly concentrated among a small group of dominant institutional investors, which we term "*investment giants*." In the EPFR (Emerging Portfolio Fund Research) database, for example, the ten largest global institutional investors account for more than half of total equity positions across 20 emerging markets. Such high concentration may give these mega-institutions outsized influence over cross-border capital flows and market dynamics, 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).

In this paper, we empirically and theoretically examine how investment giants influence emerging markets through their strategic interactions with peer investors. We show that their investment decisions affect financial markets far beyond their direct market share by actively shaping peer behavior, thereby predicting aggregate capital flows, stock returns, and exchange rate movements. To rationalize these observations, we build a theoretical model of delegated asset management, demonstrating how a dominant giant endogenously chooses to lead the market to insulate itself from benchmark tracking risk. Our findings highlight the macroeconomic value of monitoring investment giants, particularly when their portfolio choices diverge from broader market patterns.

Using EPFR fund-level data across 20 emerging markets, we first document portfolio allocation dynamics in emerging equity markets. To isolate the giants' unique influence from their shared dependence on common fundamentals, we focus on giants' *contrarian investment flows*, measured as the growth differential between their allocations and those of typical market participants (or market-wide averages). This measure filters out common macroeconomic shocks, isolating the giant institutions' distinct portfolio allocation choices.[1] From panel local projections across 20 emerging markets, we find that giants'

[1]We also consider two alternative measures of the giants' idiosyncratic investment decisions: (*i*) their share of equity flows into each market (country) and (*ii*) the difference between size-weighted and unweighted average equity flows across all investors, following Gabaix and Koijen (2024). We refer to the latter as a granular measure, but use it as a regressor rather than as an instrument in our context.

contrarian investment flows significantly predict subsequent equity flows by other individual investors. These findings demonstrate that the investment decisions of a small group of dominant investors can directly coordinate broader market behavior.

We next examine whether this predictive relationship extends to country-level outcomes. Although EPFR funds represent only 1–10% of market capitalization in emerging markets (Jotikasthira, Lundblad and Ramadorai 2012), our country-level analysis shows that aggregate EPFR flows respond significantly and positively to giants' contrarian investment flows. This result is robust to using broader aggregate net-flow data from the Institute of International Finance (IIF). Beyond aggregate capital flows, giants' contrarian investment flows also predict higher stock market returns and currency appreciation. Taken together, these empirical findings reveal that the investment decisions of a small group of dominant global investors contain systematic information about both future international capital allocation and broader financial market conditions in emerging economies.

To understand the underlying mechanisms driving these empirical regularities, we develop a theoretical model of delegated asset management featuring a market-dominant institutional giant, private signal extraction, and relative performance benchmark tracking. In our framework, the timing structure of market actions is endogenously determined: prior to signal realization, the investment giant strictly commits to a sequential leadership regime over simultaneous play because moving first maximizes its ex-ante expected payoff. By taking the lead, the giant anchors aggregate market expectations toward its private fundamental signal, neutralizing relative benchmark tracking risk and enabling unshaded fundamental trading. Followers' allocations are coordinated through two complementary micro-channels: a *public information channel*, wherein typical investors filter fundamental information from the giant's observed position via joint Bayesian updating, and a *directional leadership channel*, wherein peer tracking penalties induce strategic portfolio synchronization behind the giant's revealed allocation.

Our model's equilibrium expressions map directly into our empirical specifications, providing microfoundations for why the giant's contrarian rebalancing dynamically predicts peer fund-level allocations and aggregate country-level capital flows across multi-period

horizons. The primary theoretical contribution of our paper is to demonstrate that investor concentration endogenously shapes strategic timing and the dynamics of global portfolio allocation. In an asset management industry increasingly dominated by mega-institutional asset managers, regulatory frameworks cannot evaluate capital flows purely as aggregate, homogeneous responses to global macroeconomic shocks. Rather, our framework highlights that market concentration alters information transmission, strategic action timing, and cross-border flow synchronization. For macroprudential regulators and central banks in emerging markets, monitoring the portfolio choices of investment giants provides critical early-warning indicators for capital flow volatility, guiding targeted macroprudential measures and foreign exchange interventions within modern Integrated Policy Frameworks (Basu, Boz, Gopinath, Roch and Unsal, 2025).

Overall, our findings show that investment giants exert an outsized influence on emerging equity markets: their behavior provides valuable information for predicting broader market movements, consistent with the growing importance of large financial institutions in global capital allocation (Rey, Planat, Stavrakeva and Tang, 2024). Monitoring their portfolio movements therefore helps market participants and policymakers anticipate shifts in foreign portfolio flows and identify emerging market vulnerabilities.

Our paper complements the literature on *granular* macroeconomics and the *inelastic markets hypothesis* (Gabaix, 2011; Gabaix and Koijen, 2024). This literature emphasizes how concentrated ownership and inelastic demand amplify the price impact of large investors' trades. We augment this mechanical demand channel by introducing a strategic mechanism through which large investors actively influence peer decisions. By embedding a delegated asset management framework with relative performance tracking into a granular market setting, we provide a theoretical explanation for why typical investors wait and respond to the actions of dominant institutions. The giant's move serves not only as a substantial portfolio shock but also as an informative public signal that shapes peer beliefs and allocations. This mechanism highlights how concentration, information revelation, and strategic timing jointly generate predictability in investor flows and market outcomes.

We further contribute to the literature on informational cascades, herding, and strate-

gic interactions in financial markets. Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992) develop sequential decision-making models in which agents imitate predecessors' actions, while Avery and Zemsky (1998) incorporate market price mechanisms. We complement this literature by examining how market-dominant institutional investors influence peer choices in international equity markets. Rather than focusing solely on passive imitation, our framework emphasizes how the giant's position actively conveys private information and strategically coordinates aggregate market allocations.

Finally, our paper contributes to the literature on international capital flows by studying the investment decisions of individual funds and their implications for aggregate emerging-market outcomes. While foundational work focuses on macro-level "push" factors such as global risk sentiment and U.S. monetary policy (e.g., Calvo, Leiderman and Reinhart, 1993, 1996; Fernandez-Arias, 1996; Taylor and Sarno, 1997; Forbes and Warnock, 2012), subsequent research highlights global financial cycles and institutional portfolio allocations (e.g., Jotikasthira et al., 2012; Raddatz and Schmukler, 2012; Rey, 2015; Kalemli-Özcan, 2019; Goldberg and Krogstrup, 2023; Rey et al., 2024). Building on these insights, we use granular fund-level data to demonstrate how the portfolio rebalancing of a small group of dominant global investors predicts peer fund allocations, aggregate capital inflows, stock returns, and exchange rate dynamics across emerging markets.

The remainder of the paper is organized as follows. Section 2 describes the data and introduces our measure of giants' contrarian flows. Section 3 presents the investor-level empirical analysis, while Section 4 extends the analysis to country-level market outcomes. Section 5 develops the theoretical model, and Section 6 analyzes its theoretical properties. Section 7 concludes.

2 Investment Giants and Equity Flows

We begin by constructing a dataset that measures global investor behavior at a granular level, allowing us to study equity flows systematically. We then document stylized facts about equity flows in emerging markets, highlighting the role of investment giants. To

examine how these giants interact with other investors and shape aggregate market dynamics, we introduce the concept of *giants' contrarian investment flows*, defined as the idiosyncratic deviation of giants' investments from those of other investors or the market. This measure helps identify the influence of giants by mitigating empirical challenges arising from investors' shared dependence on fundamentals.

2.1 Investment Giants in Emerging Equity Markets

Mutual Funds Data We compile data on global mutual funds' equity flows to 20 emerging markets from the Emerging Portfolio Fund Research (EPFR) database.[2] This database offers relatively high-frequency (monthly) information on portfolio investment at the individual investor level, noting that it exclusively encompasses institutional investors.[3] 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 investor i's equity investment in country c at time (month) t, as:

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

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. Appendix A.1 provides further details on data collection and variable construction. Appendix Tables A.1–A.3 report summary statistics.

[2]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.

[3]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.

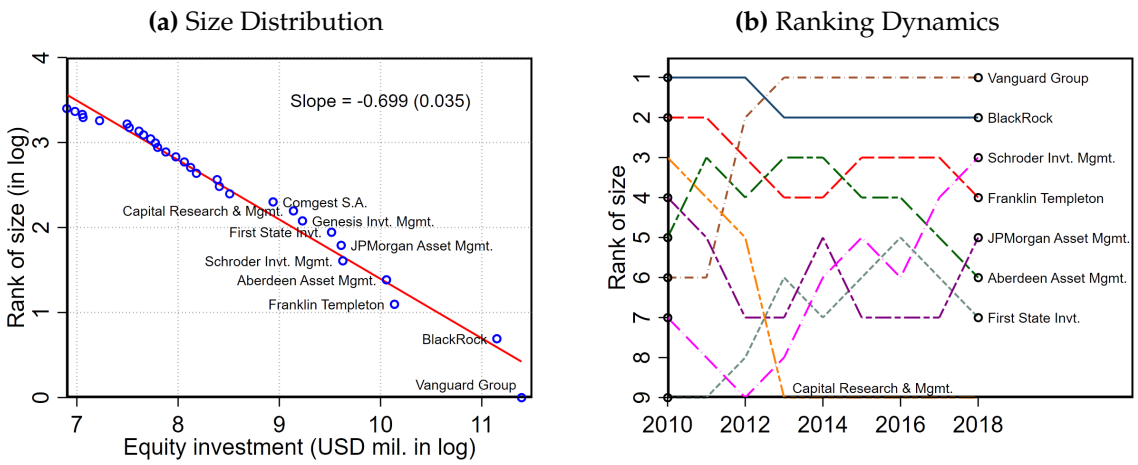


Figure 1: Global Investor Size Distribution and Ranking Dynamics

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 are 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.[4] 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.

2.2 Investment Giant's Contrarian Equity Flow

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

[4]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.

confounding effects of shared fundamentals.

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

$$\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}} \equiv \frac{1}{N^{\mathcal{G}}} \sum_{i \in \mathcal{G}} \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}) - \frac{1}{N_t - N^{\mathcal{G}}} \sum_{i \notin \mathcal{G}} \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}), \quad (2)$$

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 $t + h$:

$$\Delta^h \text{IHS}(\text{Equity}_{ic,t}) \equiv \text{IHS}(\text{Equity}_{ic,t+h}) - \text{IHS}(\text{Equity}_{ic,t}). \quad (3)$$

Because there are instances where an institutional investor does not invest in equities in a particular market or country, neither the logarithmic value of equity investment nor its time differences is 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, $\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}} > 0$, indicates that giants increased their equity investments in country c more than typical investors. This suggests that giants are more aggressive or optimistic in their investment decisions compared to typical investors.

Figure 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

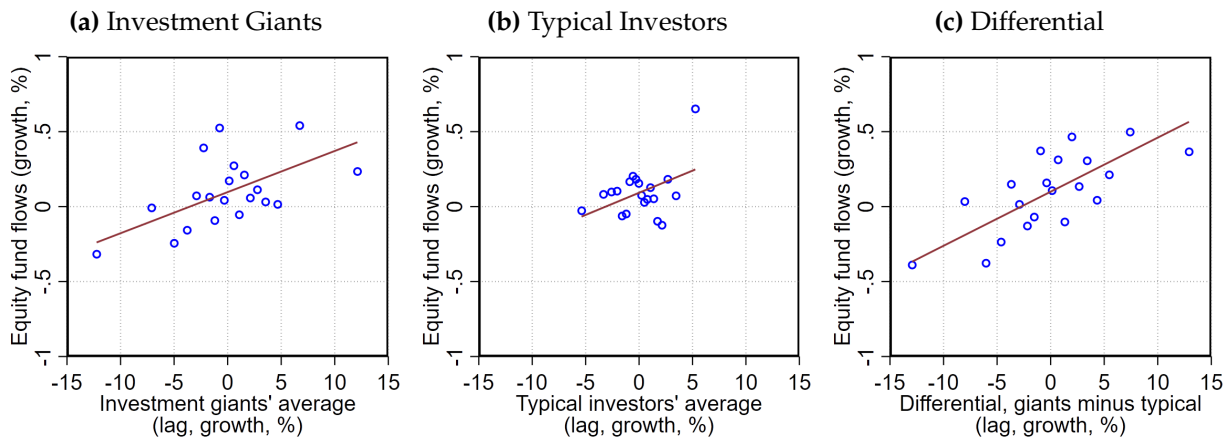


Figure 2: Equity Flows over the Lagged Giants' and Typical Investors' Average Equity Flows

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; $\bar{\tilde{g}}^{\text{giant}}_{c,t-1}$) and typical investors (non-giants; $\bar{\tilde{g}}^{\text{typical}}_{c,t-1}$), 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.

influence other investors and shape aggregate trends in emerging equity markets.

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

$$\frac{1}{N^{\mathcal{G}}} \sum_{i \in \mathcal{G}} \Delta^1 \left(\frac{\text{Equity}_{ic,t-1}}{\text{Equity}_{c,t-1}} \right) \approx \bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{agg}}_{c,t} \tag{4}$$

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

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

unweighted investment growth of all investors:

$$\sum_i \left(\frac{\text{Equity}_{ic,t-1}}{\sum_j \text{Equity}_{jc,t-1}} \right) \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}) - \frac{1}{N_t} \sum_i \Delta^1 \text{IHS}(\text{Equity}_{ic,t-1}). \tag{5}$$

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 suggest 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.

3 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.

3.1 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 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 2.2, to isolate their distinct influence.

More specifically, 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.

$$\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = \beta^h \left(\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}\right) + \mathbf{\Gamma}^h_{\text{pull}} \mathbf{Pull}_{c,t} + \mathbf{\Gamma}^h_{\text{push}} \mathbf{Push}_t + \delta_i^h + \delta_c^h + \delta_m^h + \varepsilon_{ic,t}^h, \tag{6}$$

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

$$\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = \text{IHS}\left(\text{Equity}_{ic,t+h} \times \frac{\text{StockIndex}_{c,t}}{\text{StockIndex}_{c,t+h}} \frac{\text{FX}_{c,t+h}}{\text{FX}_{c,t}}\right) - \text{IHS}(\text{Equity}_{ic,t}), \tag{7}$$

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 2) as a main regressor. As discussed in Section 2.2, 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 vectors $\mathbf{Pull}_{c,t}$ and $\mathbf{Push}_t$ include other control variables,

encompassing both pull and push factors at time t along with their three lags.[5] By controlling for the factors associated with economic and financial conditions, the regression excludes the latent impacts from spurious comovements or similar reactions among investors induced by the fundamentals (Bikhchandani and Sharma 2001). It is empirically important to isolate such correlated behavior because it merely reflects an efficient asset reallocation driven by common factors. Pull factors capture domestic aspects, consisting of real interest rates, growth rates of industrial production, total reserves, exchange rates, and the stock market index for each emerging country c. Push factors encompass external or global conditions, including the corresponding US variables, such as US real interest rates and growth rates of the VIX, US industrial production and stock market index.

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

3.2 Regression Results

Figure 3 provides the impulse responses (β^h) of valuation-adjusted (panel a) and unadjusted (panel b) equity flows to an increase in shocks to investment giants' contrarian flows. 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 systematically follow the lead of investment giants, corroborating the model prediction in Section 5. An increase in the giants' disproportionate equity investment compared to

[5]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).

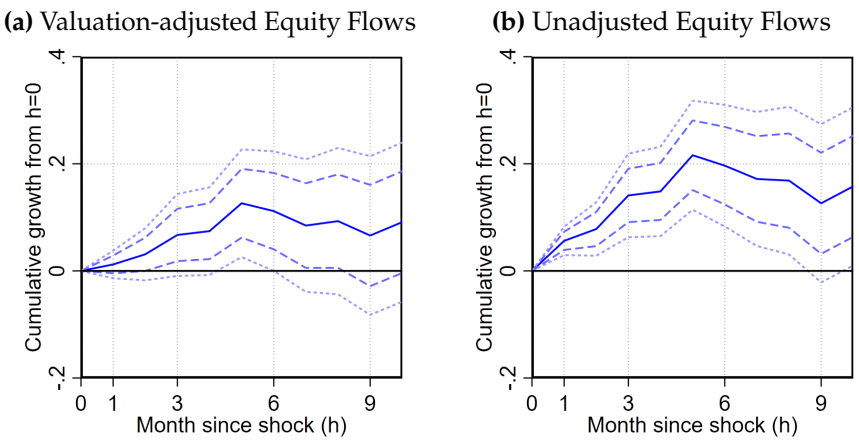


Figure 3: Investor-Level Responses to Investment Giants' Contrarian Equity Flows

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 (6). The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are 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, %).

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, comparing the two panels highlights the presence of both active portfolio reallocation and positive valuation effects. In panel b, the giants' contrarian flows have significant and positive effects on other investors' unadjusted flows, peaking around 0.2% at $h = 5$. After adjusting for valuation effects (panel a), the estimated impulse-response coefficients drop to about 2/3 of their unadjusted counterparts. The less 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. This result implies that the giants' contrarian inflows are accompanied by positive valuation gains—namely,

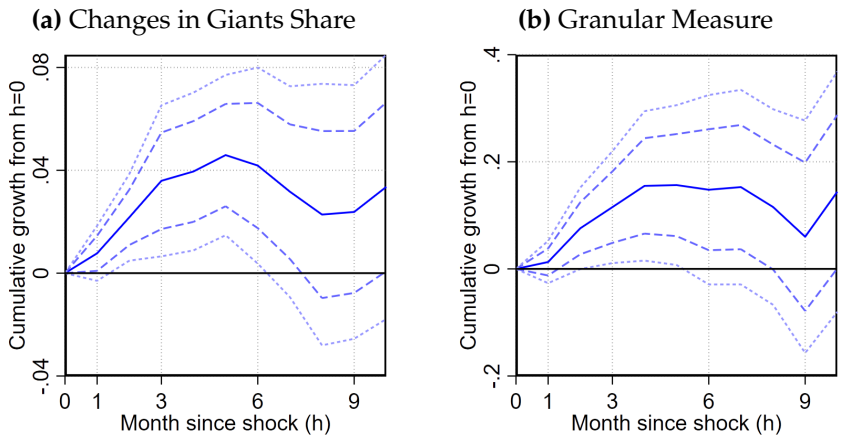


Figure 4: Investor-Level Response to Changes in Alternative Measures of Contrarian Investments

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 (4). In panel (b), the alternative measure (labeled '*Granular Measure*') is the difference between size-weighted and unweighted averages of investors' flows, as defined in equation (5). The responses of valuation-adjusted equity flows to contrarian flows are the estimates of β^h in equation (6). The specification controls for investor and country fixed effects, and contemporaneous growth of pull and push factors, and their three lags. Also, the regression includes monthly fixed effects (11 dummies) to remove seasonality. The 90% and 99% confidence intervals (long- and short-dashed lines) are 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, %).

rising local stock prices and/or local currency appreciation—which further amplify the dollar-denominated value of investors' holdings. In Section 4, 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 2.2, that help isolate their idiosyncratic influence from broader market movements. Specifically, we estimate the local projections of equation (6), replacing our main regressor with the two alternative measures: (*i*) the investment giants' share of equity flows into each market (country), defined in equation (4), and (*ii*) the differential between the size-weighted and unweighted averages of equity flows across all investors in equation (5). In Figure 4, Panels (a) and (b) report the estimated equity flow responses to changes in the two measures, respectively. The results largely align with the baseline findings in Figure 3, supporting

the influence of giants on other investors and the predictive power of giants' contrarian investment decisions.

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

3.3 Falsification Tests

A potential concern with 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 coordination.

To rule out this alternative explanation, 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 in which the dependent variables are future realizations of local real interest rates, industrial production growth, and foreign reserve growth.[6]

As illustrated in Figures A.3–A.6 of Appendix B, the granular shocks to giants' flows do not significantly predict future changes in these fundamental macro variables across any of the considered horizons, with the estimated coefficients statistically indistinguishable from zero. These results suggest that our contrarian flow measure does not merely proxy for predicted changes in omitted pull factors. This lack of predictive power for fundamentals provides strong empirical support for the exclusion restriction underlying our approach.

[6]The specification follows the country-level regressions detailed in Section 4.3, substituting financial market returns with macro fundamentals.

It reinforces our interpretation that the subsequent reactions observed in the market—including the persistent capital inflows and price appreciations analyzed in this and following sections—are driven by the giants' strategic coordination of market beliefs rather than a mere anticipation of macro-level shifts. That is, the giants' contrarian flows lead persistent follower flows and asset price adjustments through strategic interaction.

4 Aggregate Dynamics and Implications

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.

To address this issue, we investigate the unique influence and predictive power of these giants on aggregate capital flows, stock returns, and exchange rates in emerging markets.

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

While prior studies on cross-border capital flows emphasize aggregate flows and their market-wide consequences, particularly in emerging economies (e.g., Hau and Rey 2006; Gyntelberg, Loretan and Subhanij 2018; Goldberg and Krogstrup 2023), the role of individual global investors remains relatively underexplored. Specifically, less attention has been given to how large institutional players drive these financial and foreign exchange dynamics.

Investors' decisions at a more granular level may account for stock prices and exchange rates remarkably well in emerging markets. Figure 5 exhibits a strong correlation between global equity fund flows (aggregated EPFR), stock prices, and exchange rates (local

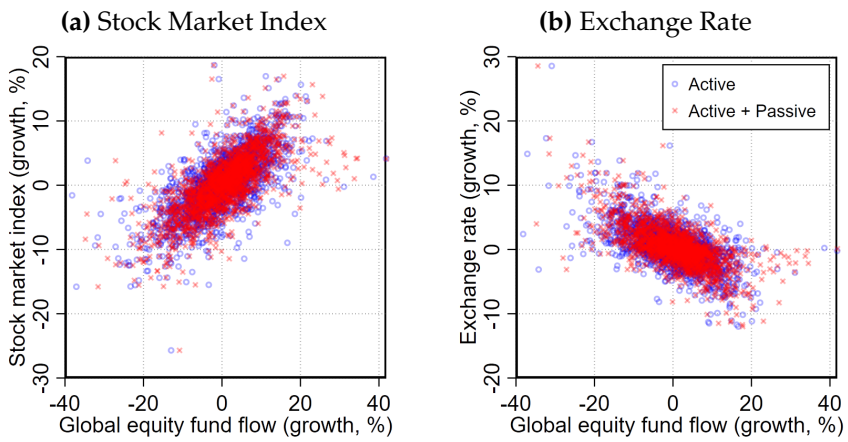


Figure 5: Global Equity Fund Flows, Stock Prices, and Exchange Rates in Emerging Economies

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.

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.

This striking co-movement between micro-level fund flows and aggregate market variables further 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.

4.2 Investment Giants and Aggregate Equity Flows

We initiate aggregate-level examination by assessing the 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 IIF database). Hence, this exercise addresses an important empirical question that remains open.

Regression Specification We estimate country-month panel local projections as:

$$Y_{c,t}^{h} = \beta^{h}\left(\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}\right) + \mathbf{\Gamma}_{\text{pull}}^{h}\mathbf{Pull}_{c,t} + \mathbf{\Gamma}_{\text{push}}^{h}\mathbf{Push}_{t} + \delta_{c}^{h} + \delta_{m}^{h} + \varepsilon_{c,t}^{h}, \tag{8}$$

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

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

While the adjusted and non-adjusted aggregate equity flows are computed based on the EPFR data, the data for aggregate equity net flows are supplemented by the IIF database from the IMF. In addition, identically to our investor-level estimations, the cumulative growth of equity flows between time t and $t+h$ is winsorized, ranging from $-h\times100\%$ to $h\times100\%$, to rule out extreme values. Similar to previous regressions, equation (8) includes standard control variables—push and pull factors and various fixed effects—that are defined comparably to those in equation (6).

Regression Results Figure 6 presents the impulse responses of the three measures of aggregate equity flows ($Y_{c,t}^{h}$) to shocks in the differential between investment giant and typical investor flows, respectively. Overall, the results from the country-level data are consistent with our earlier findings from investor-level regressions in Section 3.

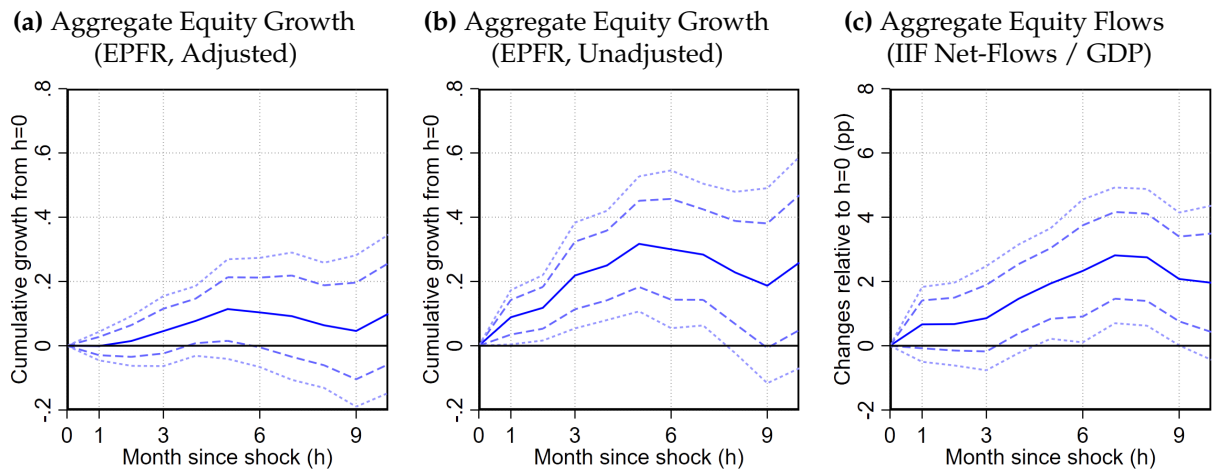


Figure 6: Aggregate Flow Responses to Giants' Contrarian Flows

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 (8). 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 (%).

Both the valuation-adjusted (panel a) and non-adjusted average equity flow growths (panel b) react positively to changes in the giants' contrarian flows, although the former exhibits relatively short-lived and weaker responses.[7] Similarly, aggregate net flows (IIF) relative to GDP increase persistently after the shock (panel c). 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 3: (*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

[7] As discussed in Section 3, this slightly tempered response after valuation adjustments is a consequence of controlling for stock returns and currency appreciation (Section 4.3), which are themselves positively driven by the giants' inflows.

size-weighted and unweighted average of equity flows). The results of aggregate-level regressions remain by and large robust across different data and specifications. We present the results for our robustness checks in Appendix D.1.

4.3 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:

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

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

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

Other terms are defined identically to those in equation (8).

Regression Results Figure 7 summarizes the results, corresponding to the three measures of market returns. In panel a, 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).

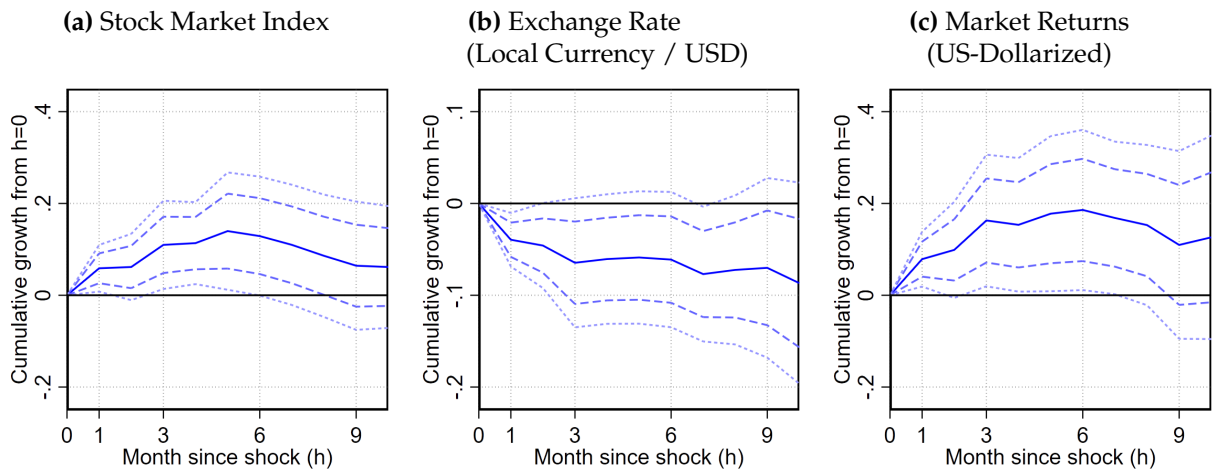


Figure 7: Stock and Currency Markets Responses to Giants' Contrarian Flows

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 (8). 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 (%).

Moreover, foreign exchange rates appreciate by up to 0.09% in response to a 1% increase in giant flow shocks (panel b). 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 3.3 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 D.2 presents the results for our robustness checks.

5 A Model of Delegated Asset Management

To rationalize the empirical patterns documented in the previous sections, specifically the significant predictive power of investment giants' portfolio choices for peer allocations and aggregate market dynamics, we construct a theoretical model of delegated asset

management. The framework incorporates three key features: a market-dominant investor with non-negligible mass, strategic peer interactions driven by benchmark tracking-error penalties, and sequential decision-making.

5.1 Model Environment

We consider a single risky asset paying an excess return $r_x \sim \mathcal{N}(0, \sigma_x^2)$. Without loss of generality, we normalize the mean return to zero for expositional simplicity. Prior to forming their portfolios, institutional fund managers receive private information regarding the fundamental return r_x.

Investors and Market Structure There is a continuum of institutional investors indexed by $i \in [0, 1]$, each holding a market share λ_i. The market consists of two types of participants: a single market-dominant investor (*investment giant*, $i = 1$) holding a substantial market share $\lambda_1 \equiv \lambda \in (0, 1)$, and a continuum of atomic "typical investors" ($j \in [0, 1)$) who are ex-ante identical, each holding an infinitesimal market weight ($\lambda_j \approx 0$). Typical investors collectively account for the remaining market share of $1 - \lambda$. By the law of large numbers, individual noise across typical investors washes out in aggregate allocations, whereas the giant's portfolio choice directly shifts aggregate market exposure.

Payoffs and Institutional Incentives The payoff of investor i combines absolute portfolio returns with absolute holding risk and a relative tracking-error disutility measured against the aggregate market benchmark:

$$\pi_i = r_x a_i - \frac{\gamma_{\text{abs}}}{2}\sigma_x^2 a_i^2 - \frac{\gamma_{\text{rel}}}{2}\sigma_x^2 (a_i - \bar{A})^2, \tag{10}$$

where a_i denotes investor i's allocation to the risky asset, and $\bar{A} \equiv \int_0^1 \lambda_i a_i \, di = \lambda a_1 + (1 - \lambda)\bar{a}_0$ is the value-weighted aggregate market allocation (with $\bar{a}_0 \equiv \int_0^1 a_j \, dj$ denoting the average position of typical investors), which serves as the endogenous market benchmark.

The structural parameters in equation (10) reflect standard institutional incentives:

1. **Absolute Revenue Stream ($r_x a_i$):** Captures management fee revenues that scale directly with total asset returns and portfolio size (AUM).

2. **Absolute Holding Risk ($\frac{1}{2}\gamma_{\text{abs}}\sigma_x^2 a_i^2$):** Represents fundamental portfolio return variance $\text{Var}(r_x a_i) = \sigma_x^2 a_i^2$ and balance-sheet capacity constraints, scaled by absolute risk aversion $\gamma_{\text{abs}} > 0$.

3. **Tracking-Error Penalty ($\frac{1}{2}\gamma_{\text{rel}}\sigma_x^2(a_i - \bar{A})^2$):** Reflects client benchmark evaluations, mandate constraints, and career concerns that penalize relative return variance $\text{Var}(r_x a_i - r_x \bar{A}) = \sigma_x^2(a_i - \bar{A})^2$, scaled by relative tracking disutility $\gamma_{\text{rel}} > 0$.[8]

To cleanly separate unconstrained fundamental demand from peer benchmark interactions, we define the strategic coordination weight ω and fundamental unconstrained demand f as:

$$\omega \equiv \frac{\gamma_{\text{rel}}}{\gamma_{\text{abs}} + \gamma_{\text{rel}}} \in (0,1) \qquad \text{and} \qquad f \equiv \frac{r_x}{\gamma_{\text{abs}}\sigma_x^2} \sim \mathcal{N}\left(0, \sigma_f^2\right), \quad \text{where } \sigma_f^2 \equiv \frac{1}{\gamma_{\text{abs}}^2\sigma_x^2}. \tag{11}$$

Information and Beliefs Managers do not directly observe the fundamental demand f. Instead, prior to forming their portfolios, each investor $i \in [0,1]$ receives a noisy private signal s_i regarding f:

$$s_i = f + \epsilon_i, \quad \text{where} \quad \epsilon_i \sim \mathcal{N}(0, \sigma_{\epsilon,i}^2). \tag{12}$$

The idiosyncratic noise terms ϵ_i are independent across investors ($\epsilon_i \perp \epsilon_k$ for all $i \neq k$) and independent of f. By the law of large numbers, individual signal errors among typical investors cancel out in the aggregate, so that the average signal across typical investors reveals the true fundamental: $\bar{s}_0 \equiv \int_0^1 s_j \, dj = f$.

Signal precisions are uniform across typical investors ($\sigma_{\epsilon,j}^{-2} = \tau_0$ for all $j \in [0,1)$), but may differ for the investment giant ($\sigma_{\epsilon,1}^{-2} = \tau_1$). Letting $\tau_f \equiv \sigma_f^{-2}$ denote the prior

[8] Tracking-error penalty term can be linked to an alternative mechanism 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, for example, in Pástor and Stambaugh (2012), the payoff can be represented as $[r - \omega(a_i/\bar{A})]a_i$ with the marginal effect given by $-2\omega(a_i - \bar{A})$.

fundamental precision, standard Gaussian updating implies that conditional expectations of f given individual and joint signal realizations are linear:

$$\mathbb{E}[f|s_1] = \theta_1 s_1, \qquad \mathbb{E}[f|s_j] = \theta_0 s_j, \qquad \text{and} \qquad \mathbb{E}[f|s_j, s_1] = \gamma_0 s_j + \gamma_1 s_1, \tag{13}$$

where the Bayesian updating weights are defined as:

$$\theta_0 \equiv \frac{\tau_0}{\tau_f + \tau_0}, \qquad \theta_1 \equiv \frac{\tau_1}{\tau_f + \tau_1}, \qquad \gamma_0 \equiv \frac{\tau_0}{\tau_f + \tau_0 + \tau_1}, \qquad \text{and} \qquad \gamma_1 \equiv \frac{\tau_1}{\tau_f + \tau_0 + \tau_1}. \tag{14}$$

Timing of Actions Before receiving private signals, the investment giant endogenously chooses its preferred timing regime $r_1 \in \{\text{sm}, \text{sq}\}$:

- **Simultaneous Regime ($r_1 = $ sm):** The giant and typical investors choose their allocations simultaneously without observing peer actions.
- **Sequential Regime ($r_1 = $ sq):** The giant moves first. After observing the giant's position a_1, typical investors subsequently form their allocations.

Under the simultaneous regime ($r_1 = \text{sm}$), all investors $i \in [0, 1]$ choose a_i to maximize their conditional expected payoff $\mathbb{E}[\pi_i|s_i]$ based solely on their private signal s_i. Under the sequential regime ($r_1 = \text{sq}$), typical investors $j \in [0, 1)$ condition on both their private signal s_j and the giant's public position a_1, choosing a_j to maximize $\mathbb{E}[\pi_j|s_j, a_1]$.[9] Anticipating typical investors' best-response schedule $a_j^{\text{sq}}(s_j, a_1)$, the giant acts as a Stackelberg leader, choosing a_1 to maximize $\mathbb{E}[\pi_1|s_1]$.

Prior to signal realization, the giant endogenously commits to the sequential regime whenever its ex-ante expected payoff satisfies $\mathbb{E}[\pi_1^{\text{sq}}] \geq \mathbb{E}[\pi_1^{\text{sm}}]$. In the following subsections, we first derive investors' equilibrium strategies under each timing structure, and then the next section will characterize the giant's endogenous choice of market timing.

[9] Because the giant's equilibrium strategy $a_1^{\text{sq}}(s_1)$ is strictly monotonic and fully invertible in its private signal, observing a_1 is informationally equivalent to directly observing s_1.

5.2 Sequential Regime: The Investment Giant Moves First

We solve for the Subgame Perfect Bayesian Equilibrium (SPBE) under sequential play ($r_1 = \text{sq}$) via backward induction. First, we characterize typical investors' optimal portfolio response after observing the giant's public position. Second, we solve the giant's first-stage optimization problem, internalizing how its leadership steers peer allocations and shapes aggregate benchmark tracking.

Typical Investor Decision In the second stage, each typical investor $j \in [0, 1)$ observes their private signal s_j and the giant's publicly observed allocation a_1. In equilibrium, the giant's strategy is strictly monotonic in its private signal s_1. Consequently, observing a_1 is informationally equivalent to observing s_1, allowing typical investors to condition their expectations on the information set $\{s_j, s_1, a_1\}$.

Maximizing conditional expected payoff $\mathbb{E}[\pi_j|s_j, s_1, a_1]$, typical investor j's first-order condition yields the following.[10]

$$a_j^{\text{sq}} = (1-\omega)\mathbb{E}[f|s_j, s_1] + \omega\mathbb{E}[\bar{A}^{\text{sq}}|s_j, s_1, a_1], \tag{15}$$

where $\mathbb{E}[\bar{A}^{\text{sq}}|s_j, s_1, a_1] \equiv \lambda a_1 + (1-\lambda)\mathbb{E}[\bar{a}_0^{\text{sq}}|s_j, s_1, a_1]$ represents the expectation of aggregate market exposure. We conjecture that typical investor j's equilibrium allocation is linear in its private signal s_j, the giant's signal s_1, and the giant's action a_1:

$$a_j^{\text{sq}}(s_j, s_1, a_1) = \psi^{\text{sq}} s_j + \eta_s^{\text{sq}} s_1 + \eta_a^{\text{sq}} a_1. \tag{16}$$

By the law of large numbers, integrating over $j \in [0, 1)$ yields the average allocation of typical investors:

$$\bar{a}_0^{\text{sq}}(f, s_1, a_1) \equiv \int_0^1 a_j^{\text{sq}}\, dj = \psi^{\text{sq}} f + \eta_s^{\text{sq}} s_1 + \eta_a^{\text{sq}} a_1. \tag{17}$$

[10] Relatedly, Bao, Hommes and Makarewicz (2017) establish a similar result, showing that return-forecasting problems can be formally mapped into linear quantity-choice problems in asset-pricing models with standard market-clearing mechanisms (e.g., Beja and Goldman 1980).

Substituting typical investors' belief regarding average peer investment, $\mathbb{E}[\bar{a}_0^{\text{sq}}|s_j, s_1, a_1] = \psi^{\text{sq}}\mathbb{E}[f|s_j, s_1] + \eta_s^{\text{sq}} s_1 + \eta_a^{\text{sq}} a_1$, into the first-order condition (15) and matching coefficients yields:

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

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

$$\eta_a^{\text{sq}} = \frac{\omega\lambda}{1-\omega(1-\lambda)} = 1 - \psi^{\text{sq}} - \frac{\eta_s^{\text{sq}}}{\theta_1}. \tag{20}$$

To build intuition, consider two key limiting cases:

- **No Strategic Interactions ($\omega \to 0$):** As relative tracking-error penalties vanish, typical investors engage in pure signal extraction:

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

  Here, the giant's position a_1 carries no direct strategic coordination value, and peer allocations respond solely to fundamental information content (γ_0, γ_1).

- **Infinitesimal Giant Mass ($\lambda \to 0$):** When the giant's market share vanishes, its direct position impact disappears ($\lim_{\lambda\to 0}\eta_a^{\text{sq}} = 0$), and the giant functions purely as an unweighted public signal provider.

Investment Giant Decision In the first stage, the giant acts as a Stackelberg leader, choosing a_1 to maximize its expected payoff $\mathbb{E}[\pi_1|s_1]$. Internalizing typical investors' aggregate reaction function of equation (17), the giant recognizes that its position a_1 shifts aggregate benchmark exposure $\bar{A}$. Its first-order condition yields:

$$a_1^{\text{sq}} = (1-\omega)\mathbb{E}[f|s_1] + \omega\mathbb{E}[\bar{A}^{\text{sq}}|s_1]\underbrace{(1-\lambda)}_{\substack{\text{mkt share}\\ \text{weight}}}\underbrace{\left\{1 - \frac{\partial\mathbb{E}[\bar{a}_0^{\text{sq}}|s_1]}{\partial a_1}\right\}}_{\substack{\text{first-mover strategic}\\ \text{leverage}}}, \tag{21}$$

where $\mathbb{E}[\bar{A}^{\text{sq}}|s_1] = \lambda a_1 + (1-\lambda)\mathbb{E}[\bar{a}_0^{\text{sq}}|s_1]$ is the giant's expected market benchmark, and average peer demand simplifies to $\mathbb{E}[\bar{a}_0^{\text{sq}}|s_1] = (1-\eta_a^{\text{sq}})\mathbb{E}[f|s_1] + \eta_a^{\text{sq}} a_1$.

Substituting peer responses into equation (21) and solving for the giant's equilibrium position loading yields:

$$a_1^{\text{sq}}(s_1) = \phi^{\text{sq}} s_1 = \theta_1 s_1 = \mathbb{E}[f|s_1], \tag{22}$$

where the policy loading ϕ^{sq} satisfies:

$$\phi^{\text{sq}} = \left\{ \frac{(1-\omega) + \omega(1-\lambda)^2(1-\eta_a^{\text{sq}})(\psi^{\text{sq}} + \eta_s^{\text{sq}}/\theta_1)}{(1-\omega) + \omega(1-\lambda)^2(1-\eta_a^{\text{sq}})^2} \right\} \theta_1 = \theta_1,$$

because of the structural coefficient identity $\psi^{\text{sq}} + \eta_s^{\text{sq}}/\theta_1 + \eta_a^{\text{sq}} = 1$.

The giant's optimal response highlights a key feature of sequential play: the investment giant completely neutralizes relative benchmark tracking risk. By taking the lead, the giant anchors the market benchmark $\bar{A}$ to its private signal s_1 via peer strategic imitation ($\eta_a^{\text{sq}} > 0$). Consequently, the tracking penalty term $(a_1 - \bar{A})$ is minimized, allowing the giant to trade purely on its fundamental signal extraction loading ($a_1^{\text{sq}}(s_1) = \mathbb{E}[f|s_1]$) as if relative performance constraints were non-existent.

5.3 Comparison Between Sequential and Simultaneous Regimes

To illuminate the strategic role of market leadership, we compare the equilibrium portfolio choices under sequential and simultaneous play ($r_1 = \text{sq}$ and $r_1 = \text{sm}$).

Simultaneous-Move Regime In the simultaneous regime ($r_1 = \text{sm}$), each investor $i \in [0,1]$ independently chooses allocation a_i without observing peer decisions. The first-order condition for investor i is:

$$a_i^{\text{sm}} = (1-\omega)\mathbb{E}[f|s_i] + \omega(1-\lambda_i)\mathbb{E}[\bar{A}^{\text{sm}}|s_i]. \tag{23}$$

Comparing equation (23) with the sequential first-order condition in equation (15) highlights two defining features of simultaneous play. First, typical investors rely exclusively

on their private signal s_j, as the giant's position a_1 is unobservable at the time of portfolio construction. Second, while the giant internalizes its market share $\lambda_1 = \lambda$, it forfeits first-mover leverage: its action can no longer influence peer expectations ($\partial \mathbb{E}[\bar{a}_0^{\text{sm}}|s_1]/\partial a_1 = 0$). As shown in Appendix E, linear equilibrium strategies take the form $a_j^{\text{sm}}(s_j) = \psi^{\text{sm}} s_j$ for typical investors and $a_1^{\text{sm}}(s_1) = \phi^{\text{sm}} s_1$ for the giant.

Typical Investor Behavior (ψ^{sm} vs. ψ^{sq}) Compared to the simultaneous-move benchmark, the optimal strategy of typical investors under sequential play differs in two key respects: a strictly weaker response to private signals and a direct dependence on the giant's observed position.

Typical investors respond strictly less aggressively to their private signals under sequential play than under simultaneous play:

$$\psi^{\text{sq}} = \left[\frac{1-\omega}{1-\omega(1-\lambda)\gamma_0}\right]\gamma_0 < \psi^{\text{sm}} = \left[\frac{1-\omega+\omega\lambda\phi^{\text{sm}}}{1-\omega(1-\lambda)\theta_0}\right]\theta_0. \tag{24}$$

This inequality ($\psi^{\text{sq}} < \psi^{\text{sm}}$) follows from $\theta_0 - \gamma_0$, ω, λ, $\phi^{\text{sm}} > 0$ and reflects the combination of an informational effect and a strategic effect.

First, consider the *informational effect*, which operates even in the absence of benchmark-tracking incentives ($\omega = 0$). In simultaneous play, typical investors rely solely on their private signal s_j to forecast the fundamental f, assigning it a Bayesian updating weight of $\theta_0 \equiv \frac{\tau_0}{\tau_f+\tau_0}$. Under sequential play, however, observing $a_1 = \theta_1 s_1$ provides an additional independent signal of the fundamental (s_1). Through joint Bayesian updating, this public information dilutes reliance on private signal noise s_j, reducing its weight to $\gamma_0 \equiv \frac{\tau_0}{\tau_f+\tau_0+\tau_1} < \theta_0$.

Second, when relative performance incentives are present ($\omega > 0$), a *strategic decoupling* mechanism emerges. In simultaneous play, because the giant's position a_1 is unobserved, a typical investor's private signal s_j serves a dual role: forecasting the fundamental ($\mathbb{E}[f|s_j] = \theta_0 s_j$) and forecasting the giant's unobserved position ($\mathbb{E}[a_1|s_j] = \phi^{\text{sm}}\theta_0 s_j$). In sequential play, observing a_1 decouples these two roles. Because the giant's position directly shifts aggregate market exposure $\bar{A} = \lambda a_1 + (1-\lambda)\bar{a}_0$, typical investors react to

a_1 directly via the loading coefficient $\eta_a^{\text{sq}} > 0$. This direct reaction absorbs the benchmark-tracking motive, relieving the private signal s_j from carrying the burden of forecasting peer allocations and further dampening its policy loading ($\psi^{\text{sq}} < \psi^{\text{sm}}$). The giant's position acts as a public strategic anchor, causing follower investors to shift weight away from private information in order to coordinate directly with a_1.

Investment Giant Behavior (ϕ^{sm} vs. ϕ^{sq}) In the sequential regime, the giant acts as a Stackelberg leader and sets $\phi^{\text{sq}} = \theta_1$, anchoring its allocation strictly to its pure Bayesian fundamental estimate $\mathbb{E}[f|s_1] = \theta_1 s_1$. By contrast, under simultaneous play, the giant forfeits directional leadership and is forced to strategically shade its fundamental reaction to mitigate relative tracking-error risk:

$$\phi^{\text{sq}} = \theta_1 > \phi^{\text{sm}} = \left[\frac{1 - \omega + \omega(1-\lambda)^2\psi^{\text{sm}}}{(1-\omega) + \omega(1-\lambda)^2}\right]\theta_1, \tag{25}$$

which holds strictly because $\psi^{\text{sm}} < 1$.

Equation (25) establishes that the giant responds strictly more aggressively to its private signal under sequential play than under simultaneous play ($\phi^{\text{sq}} > \phi^{\text{sm}}$). In simultaneous play, the giant cannot influence or observe typical investors' concurrent choices. Fearing that peer investors will react conservatively to fundamental news ($\psi^{\text{sm}} < 1$), the giant anticipates an aggregate market exposure $\bar{A}$ that under-adjusts relative to the fundamental. To minimize relative tracking penalty $\frac{1}{2}\gamma_{\text{rel}}\sigma_x^2(a_1 - \bar{A})^2$, the giant is forced to shade down its signal loading below its fundamental extraction weight ($\phi^{\text{sm}} < \theta_1$).

Under sequential play, this strategic shading friction disappears entirely. By moving first, the giant transparently commits to its unshaded fundamental loading $\phi^{\text{sq}} = \theta_1$. It does so knowing that peer followers will herd behind its observed position ($\eta_a^{\text{sq}} > 0$), effectively pulling aggregate market exposure $\bar{A}$ toward a_1 and insulating the giant from benchmark tracking penalties.

6 Investment Giant: Leadership and Market Influence

Having established the equilibrium strategy loadings under both sequential and simultaneous play, we now analyze the giant's endogenous choice of market timing and its broader consequences for peer allocations and aggregate price formation. This section connects our theoretical framework directly to the empirical lead-lag patterns documented earlier.

6.1 Optimal Timing Structure of Action

Rather than being fixed exogenously, the timing structure of market actions is chosen endogenously by the investment giant before observing private signals. The giant selects sequential leadership ($r_1 = \text{sq}$) over simultaneous play ($r_1 = \text{sm}$) whenever its ex-ante expected payoff advantage is non-negative: $\mathbb{E}[\pi_1^{\text{sq}}] - \mathbb{E}[\pi_1^{\text{sm}}] \geq 0$.

Rather than being fixed exogenously, the investment giant endogenously chooses whether to commit to sequential leadership ($r_1 = \text{sq}$) or play simultaneously ($r_1 = \text{sm}$) before observing private signals. The giant thus selects the sequential regime whenever its ex-ante expected payoff advantage is non-negative: $[\pi_1^{\text{sq}}] - \mathbb{E}[\pi_1^{\text{sm}}] \geq 0$.

The Giant's Ex-Ante Payoffs Using the normalized payoff structure, the giant's ex-ante expected payoff under regime $r \in \{\text{sq}, \text{sm}\}$ satisfies:

$$\mathbb{E}[\pi_1^r] = -\frac{1}{2}(1-\omega)\left[\text{Var}(a_1^r - f) - \sigma_f^2\right] - \frac{1}{2}\omega\,\text{Var}(a_1^r - \bar{A}^r), \tag{26}$$

which decomposes the giant's expected payoff into two distinct economic components:

1. **Fundamental Forecasting Risk (**$\text{Var}(a_1^r - f)$**):** The variance of allocation errors relative to unconstrained fundamental demand f.

2. **Benchmark Tracking Risk (**$\text{Var}(a_1^r - \bar{A}^r)$**):** The relative performance disutility arising from deviations between the giant's portfolio and aggregate market exposure $\bar{A}^r$.

The Giant's Optimal Choice: Sequential Leadership To establish the giant's optimal timing decision rigorously, we substitute the equilibrium policy loadings into ex-ante expected payoffs. After algebraic simplification, the giant's ex-ante payoffs under each regime can be expressed in closed form as:

$$\mathbb{E}[\pi_1^{\text{sq}}] = -\frac{1}{2}(1-\omega)\sigma_f^2\Upsilon(\phi^{\text{sq}};\theta_1) - \frac{1}{2}\omega(1-\lambda)^2(\psi^{\text{sq}})^2\sigma_f^2\Upsilon(\phi^{\text{sq}};\theta_1) + \frac{1}{2}(1-\omega)\sigma_f^2, \tag{27}$$

$$\mathbb{E}[\pi_1^{\text{sm}}] = -\frac{1}{2}(1-\omega)\sigma_f^2\Upsilon(\phi^{\text{sm}};\theta_1) - \frac{1}{2}\omega(1-\lambda)^2(\psi^{\text{sm}})^2\sigma_f^2\Upsilon\left(\frac{\phi^{\text{sm}}}{\psi^{\text{sm}}};\theta_1\right) + \frac{1}{2}(1-\omega)\sigma_f^2, \tag{28}$$

where the auxiliary function $\Upsilon(x;\theta_1)$ measures normalized forecast error variance $\text{Var}(xs_1 - f)/\sigma_f^2$:

$$\Upsilon(x;\theta_1) \equiv \frac{x^2}{\theta_1} - 2x + 1 \geq \Upsilon(\theta_1;\theta_1) = 1 - \theta_1. \tag{29}$$

The quadratic function $\Upsilon(x;\theta_1)$ is strictly convex in x, decreasing for $x \in (0,\theta_1)$, and attains its unique global minimum value of $1-\theta_1$ at $x = \theta_1$.

In the modified ex-ante payoff equations (27) and (28), the first term captures Fundamental Forecasting Risk ($\text{Var}(a_1^r - f)$), which is governed by how far the giant's action loading deviates from its pure Bayesian expectation $\mathbb{E}[f \mid s_1] = \theta_1 s_1$. The second term captures Benchmark Tracking Risk ($\text{Var}(a_1^r - \bar{A}^r)$), where the scale factor $(1-\lambda)^2$ reflects the giant's market-share advantage in insulating itself against peer deviations.

Equations (27) and (28) reveal the fundamental strategic advantage of sequential leadership:

- **Sequential Play ($r_1 = $ sq):** The giant faces no trade-off between fundamental signal extraction and benchmark risk management. By taking the lead, the giant anchors aggregate market allocations to its private signal ($\eta_a^{\text{sq}} > 0$). Setting $\phi^{\text{sq}} = \theta_1$ simultaneously minimizes both fundamental error variance and benchmark tracking error, since $\Upsilon(\phi^{\text{sq}};\theta_1) = \Upsilon(\theta_1;\theta_1) = 1-\theta_1$.

- **Simultaneous Play ($r_1 = $ sm):** The giant faces a severe strategic conflict. Optimal fundamental signal extraction requires setting $\phi = \theta_1$, but minimizing peer tracking disutility relative to typical investors (who trade at weight ψ^{sm}) requires setting ϕ

closer to ψ^{sm}. Consequently, the equilibrium loading under simultaneous play is distorted downward ($\phi^{\text{sm}} < \theta_1$), causing both error factors to strictly exceed their theoretical minimum: $\Upsilon(\phi^{\text{sm}}; \theta_1) > 1 - \theta_1$ and $\Upsilon(\phi^{\text{sm}}/\psi^{\text{sm}}; \theta_1) > 1 - \theta_1$.

Because sequential leadership resolves this strategic conflict and eliminates policy shading distortions, $\mathbb{E}[\pi_1^{\text{sq}}] > \mathbb{E}[\pi_1^{\text{sm}}]$ holds strictly for all $\omega \in (0, 1)$ and $\lambda \in (0, 1)$.[11] The investment giant strictly prefers sequential play over simultaneous play to exploit these dual strategic advantages.

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

$$\mathbb{E}[\pi_1^*] \equiv \max\left\{\mathbb{E}[\pi_1^{\text{sq}}], \mathbb{E}[\pi_1^{\text{sm}}]\right\} = \mathbb{E}[\pi_1^{\text{sq}}], \tag{30}$$

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

In sum, the investment giant's ex-ante expected payoff is globally maximized under sequential market leadership:

$$\mathbb{E}[\pi_1^*] \equiv \max\left\{\mathbb{E}[\pi_1^{\text{sq}}], \mathbb{E}[\pi_1^{\text{sm}}]\right\} = \mathbb{E}[\pi_1^{\text{sq}}], \tag{31}$$

where asterisks (*) denote the subgame perfect equilibrium outcomes: $r_1^* = \text{sq}$, $a_1^* = a_1^{\text{sq}}$, and $a_j^* = a_j^{\text{sq}}$, associated with the equilibrium policy loadings $\{\phi^*, \psi^*, \eta_s^*, \eta_a^*\} = \{\phi^{\text{sq}}, \psi^{\text{sq}}, \eta_s^{\text{sq}}, \eta_a^{\text{sq}}\}$.

This sequential equilibrium—wherein the market-dominant giant moves first and typical investors follow—aligns with strategic market leadership models (e.g., Corsetti et al., 2004). Central to this equilibrium is the public visibility of the giant's portfolio choice. Peer investors observe the giant's position, extracting the underlying fundamental information conveyed by its allocation (*public information channel*). This signal disclosure reduces informational uncertainty for typical investors, enabling them to condition portfolio decisions on both private news and the giant's revealed action. Concurrently, our model

[11] This result follows directly from the fact that $\Upsilon(\theta_1; \theta_1)$ is the unique global minimum of $\Upsilon(x; \theta_1)$ together with the policy loading ordering $\phi^{\text{sq}} = \theta_1 > \phi^{\text{sm}}$ and $\psi^{\text{sm}} > \psi^{\text{sq}}$ established in Section 5.3.

highlights the giant's first-mover advantage: by acting first, the giant steers the market benchmark in a favorable direction, aligning aggregate exposure with fundamental value while insulating itself from benchmark tracking disutility (*directional leadership channel*). Consequently, the giant possesses a strict incentive to take the lead. The next subsection examines the joint impact of these two channels on typical investors and aggregate market dynamics.

6.2 Influences on Typical Investors and Market Movements

Having established that the investment giant endogenously chooses sequential leadership ($r_1^* = \text{sq}$), we now analyze how the giant's portfolio decision a_1^* shapes typical investors' individual choices (a_j^*) and aggregate market exposure ($\bar{A}^*$). In doing so, we directly link our theoretical equilibrium expressions to our micro- and macro-level empirical regression results.

Micro-Level Allocation: Typical Investor Behavior In equilibrium, the investment giant's private signal s_1 determines its optimal position $a_1^* = \theta_1 s_1$ (equation (22)). Substituting $s_1 = a_1^*/\theta_1$ into typical investors' optimal reaction function (equation (16)) yields typical investor j's equilibrium allocation rule:

$$a_j^* = \psi^* s_j + (1-\psi^*)a_1^* = \psi^* f + (1-\psi^*)a_1^* + \psi^* \epsilon_j, \tag{32}$$

where $\psi^* \equiv \psi^{\text{sq}} \in (0,1)$.

This equation demonstrates that a typical investor's optimal allocation is a convex combination of their own private signal s_j and the giant's observed position a_1^*. This theoretical result maps directly into our fund-level empirical specification of regression equation (6) where the empirical local projection slope coefficient β^h captures the structural weighting parameter $(1-\psi^*) > 0$. Thus, our model provides a microfounded explanation for the statistically significant, positive peer-following response ($\beta^h > 0$) documented in our investor-level estimations.

Macro-Level Market Exposure: Aggregate Benchmark Dynamics Aggregating individual allocations across all market participants yields the value-weighted aggregate market allocation $\bar{A}^* = \lambda a_1^* + (1-\lambda)\bar{a}_0^*$. Substituting average typical demand $\bar{a}_0^* = \psi^* f + (1-\psi^*)a_1^*$ into $\bar{A}^*$ gives:

$$\bar{A}^* = (1-\lambda)\psi^* f + [1-(1-\lambda)\psi^*]\, a_1^*, \tag{33}$$

which establishes that aggregate market exposure is a convex combination of fundamental demand f and the giant's allocation a_1^*, with weight loadings $(1-\lambda)\psi^*$ and $1-(1-\lambda)\psi^*$, respectively.

This structural result maps directly into our macro/country-level empirical local projection specification of regression equation (8) where the aggregate local projection coefficient β^h corresponds to $1-(1-\lambda)\psi^* > 0$. The theoretical model confirms that the giant's portfolio rebalancing directly shifts aggregate capital flows and market positions, explaining the strong positive predictive power ($\beta^h > 0$) observed in our country-level regressions across horizons h.

Economic Channels and Impulse Response Dynamics Equations (32) and (33) delineate the two complementary micro-mechanisms governing these empirical local projection dynamics:

1. **Public Information Channel:** Because the giant moves first, its public allocation a_1^* acts as a informative benchmark signal. Peer investors update their conditional expectations ($\mathbb{E}[f \mid s_j, a_1^*]$), using the giant's action to reduce fundamental uncertainty and guide their own allocations.

2. **Directional Leadership Channel:** Through its non-negligible market mass λ and relative benchmark evaluation constraints (ω), the giant shifts aggregate exposure $\bar{A}^*$ toward its position. Peer investors face relative tracking disutilities if they diverge from a_1^*, inducing strategic peer synchronization behind the giant's allocation.

Together, these dual channels explain why an initial portfolio shift by the investment giant

generates persistent, positive dynamic responses in peer funds' portfolios and country-level capital flows over time horizon h.

Policy Implications and Theoretical Contribution Beyond providing microfoundations for our empirical findings, our theoretical model yields important policy implications for modern institutional financial markets dominated by mega-asset managers. In an asset management industry increasingly concentrated among a small set of market-dominant institutions, regulatory emphasis often focuses purely on direct size risk. However, our framework reveals that market concentration also alters market equilibrium dynamics by endogenously shaping strategic action timing and information transmission. Because large market share ($\lambda > 0$) enables investment giants to resolve relative benchmark tracking risk via sequential market leadership, mega-institutions naturally emerge as structural market leaders whose portfolio decisions coordinate broader institutional flows. For macroprudential regulators and central banks, this highlights that systemic liquidity shocks and cross-border capital flow synchronization are driven not only by exogenous fundamental news, but by the strategic leadership and disclosure of key market giants. The primary theoretical contribution of our model is to show how investor concentration shapes strategic timing and the dynamics of global portfolio allocation, offering a unified framework linking market structure, asymmetric timing incentives, and aggregate capital movements.

7 Conclusion

The global financial landscape has undergone a structural transformation over recent decades, driven by a growing shift from bank-intermediated credit to market-based cross-border capital flows. In emerging market economies, these portfolio flows play a pivotal role in shaping local asset prices, exchange rates, and financial stability. However, despite the systemic importance of these capital movements, existing literature has predominantly focused on aggregate macro-level drivers, treating international portfolio flows as homogeneous responses to global shocks or monetary policy cycles. This top-down perspective

leaves critical micro-foundational questions unanswered: How do large institutional asset managers interact strategically, how do their portfolio allocations aggregate to drive market-wide capital flows, and what are the underlying mechanisms governing these dynamics?

This paper fills this gap by providing a unified empirical and theoretical framework to analyze the strategic role of market-dominant institutional investors (*investment giants*) in shaping global portfolio allocations and asset market dynamics. Empirically, we isolate the idiosyncratic decisions of investment giants from common macroeconomic fundamentals by constructing a fund-level measure of *contrarian investment*. Our local projection estimations demonstrate that contrarian rebalancing by a small group of investment giants consistently predicts both peer fund-level allocations and aggregate emerging market country-level equity flows across multi-period horizons h. Furthermore, these giant contrarian flows exert strong predictive power over future stock returns and currency movements. Crucially, these systemic effects manifest even though sample holdings represent a modest fraction (1–10%) of total emerging market capitalization, indicating the disproportionate influence of giant institutions.

To rationalize these empirical patterns, we develop a theoretical model of delegated asset management featuring a market-dominant institutional giant, private signal extraction, and relative performance benchmark tracking. The model establishes that the timing structure of market actions is endogenously determined: prior to signal realization, the giant strictly commits to sequential leadership over simultaneous play to maximize its ex-ante expected payoff. By taking the lead, the giant anchors aggregate market expectations toward its private fundamental signal, neutralizing relative tracking-error risk and enabling unshaded fundamental trading. Followers' portfolio responses are driven by two complementary micro-mechanisms: a *public information channel*, wherein peer investors extract fundamental information from the giant's disclosed position via joint Bayesian updating, and a *directional leadership channel*, wherein peer tracking penalties induce strategic portfolio synchronization behind the giant's allocation. Together, these dual channels provide clear microfoundations for the dynamic, persistent capital flow responses documented in our empirical specifications.

Our theoretical and empirical findings deliver important implications for macroprudential regulation and international finance. From a theoretical perspective, the key contribution of this paper is to demonstrate that investor concentration shapes strategic timing and the dynamics of global portfolio allocation. In an asset management industry increasingly dominated by mega-institutional asset managers, regulatory focus must extend beyond traditional balance-sheet size metrics to consider how market concentration alters strategic action timing, peer synchronization, and price discovery. From a policy perspective, monitoring the portfolio rebalancing of investment giants provides central banks and regulatory authorities in EMEs with valuable early-warning indicators of impending capital flow surges or reversals. In a global economy where monetary autonomy is constrained by the global financial cycle (Rey, 2015), these granular institutional insights can inform targeted macroprudential and foreign exchange intervention toolkits, such as Integrated Policy Frameworks (Basu et al., 2025), to mitigate systemic vulnerabilities and preserve financial stability.

References

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

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

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

Bao, Te, Cars Hommes, and Tomasz Makarewicz, "Bubble formation and (in)efficient markets in learning-to-forecast and optimise experiments," *The Economic Journal*, 10 2017, *127* (605), F581–F609.

Basu, Suman S., Emine Boz, Gita Gopinath, Francisco Roch, and D. Filiz Unsal, "Integrated Monetary and Financial Policies for Small Open Economies," *Econometrica*, 2025, *93* (6), 2201–2234.

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

Beja, Avraham and M. Barry Goldman, "On the dynamic behavior of prices in disequilibrium," *The Journal of Finance*, 1980, *35* (2), 235–248.

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

Berk, Jonathan B. and Richard C. Green, "Mutual Fund Flows and Performance in Rational Markets," *Journal of Political Economy*, 2004, *112* (6), 1269–1295.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Gabaix, Xavier, "The granular origins of aggregate fluctuations," *Econometrica*, 2011, *79* (3), 733–772.

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

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

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

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

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

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

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

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

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

Kalemli-Özcan, Sebnem, "U.S. monetary policy and international risk spillovers," Working Paper 26297, National Bureau of Economic Research September 2019.

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

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

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

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

Pástor, Luboš and Robert F. Stambaugh, "On the Size of the Active Management Industry," *Journal of Political Economy*, 2012, *120* (4), 740–781.

Perold, Andre F. and Robert S. Salomon Jr., "The Right Amount of Assets Under Management," *Financial Analysts Journal*, 1991, *47* (3), 31–39.

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

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

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

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

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

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

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

A Data Appendix

A.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 (8,825.83×0.101 + 2,085.92×0.168). The same procedure is applied consistently across all funds and host countries.

There are instances where an investor does not invest in equities in a particular market or country. Thus, we employ the inverse hyperbolic sine (IHS) transformation ($\text{IHS}(x) = \ln[x + (x^2 + 1)^{0.5}]$) for the computation of the equity growths (flows) between t and $t + h$ as in equation (3), where the cumulative growth is winsorized at both ends by –h×100% and h×100% (i.e., 100% monthly growth rate), to prevent our regression results from being potentially influenced by a few extreme flows. This is similar to one that winsorizes the top and bottom 1% of observations in the case of $h = 1$. To exclude this valuation channel, we compute the cumulative equity growth based on the adjusted equity growth with market returns as in equation (7), which is also winsorized at both ends by $-h$×100% and h×100%. We checked the estimation results without winsorization, and found that the main results remain robust.

Appendix A.3 provides the summary statistics.

A.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 A.3 provides the summary statistics for the macroeconomic variables.

A.3 Summary Statistics

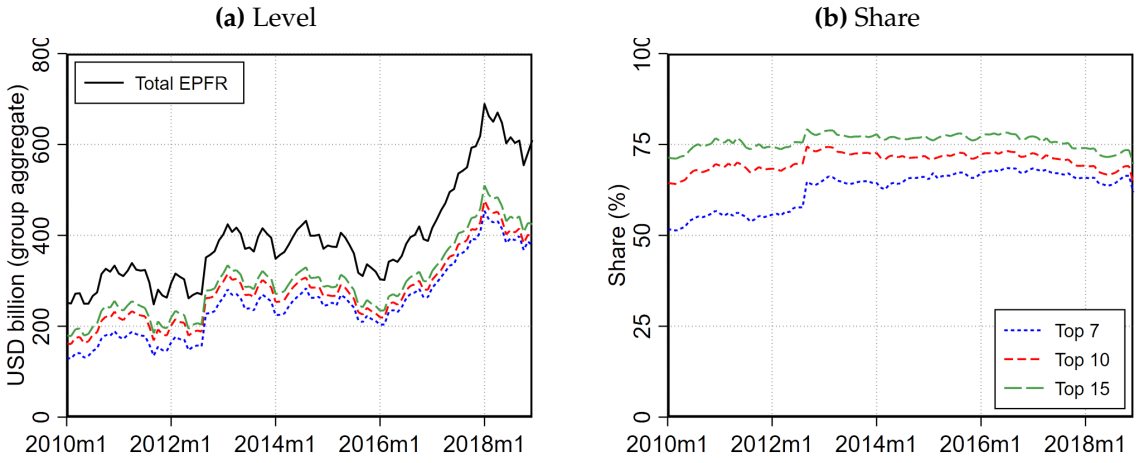


Figure A.1: Trends of EPFR Aggregate Equity Fund Flows

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.

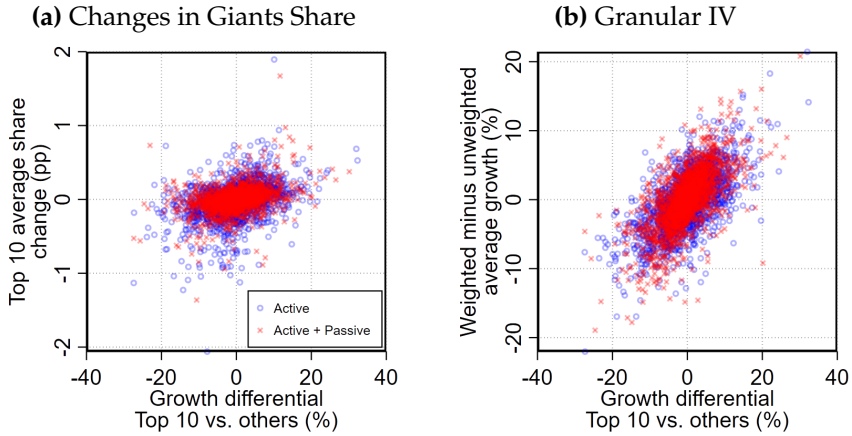


Figure A.2: Investment Giant's Contrarian Investment: Benchmark and Alternative Measures

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 (2), 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 (4) and (5), 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.

B Falsification Test Results

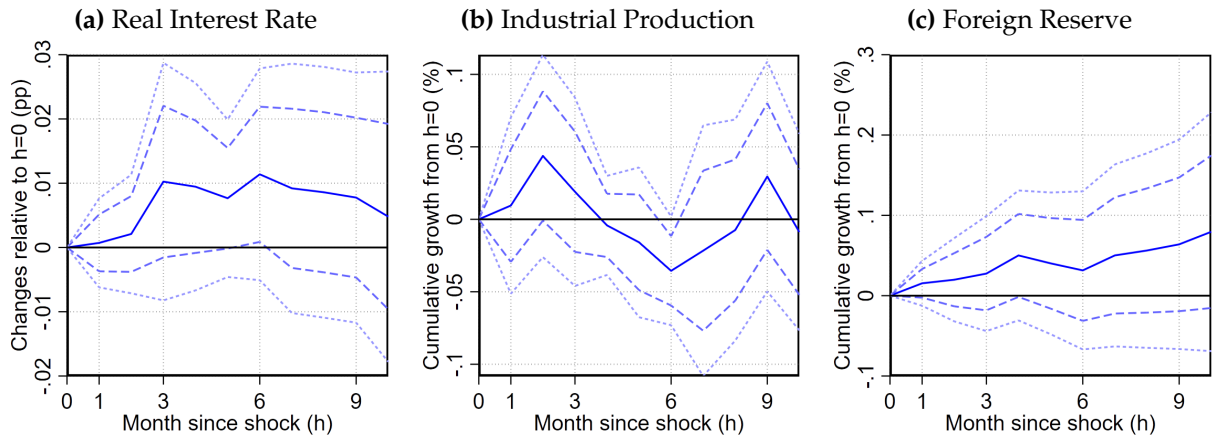


Figure A.3: Macro Fundamental Responses to Giants' Contrarian Flows

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 (8). 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 (%).

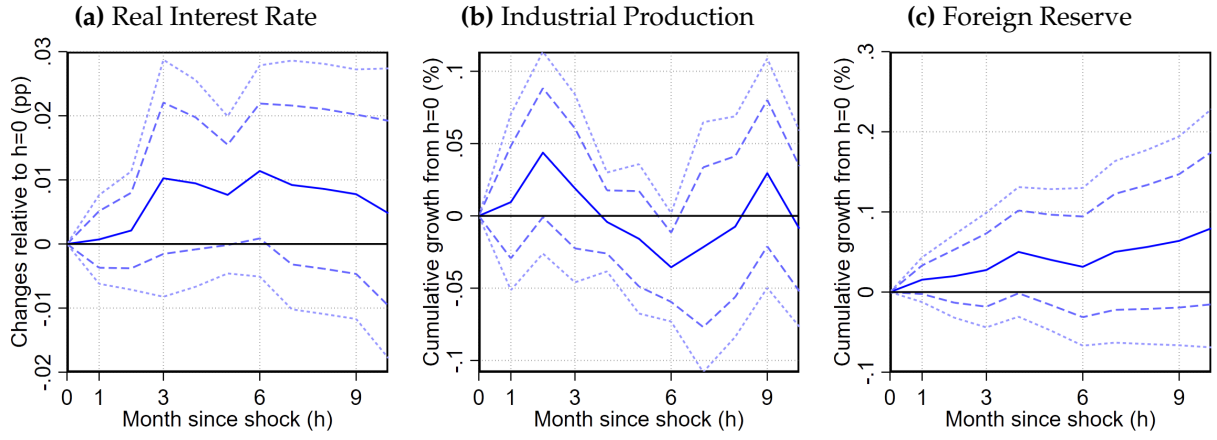


Figure A.4: Macro Fundamental Responses to Giants' Contrarian Flows: Alternative Specification

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.3). 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 (%).

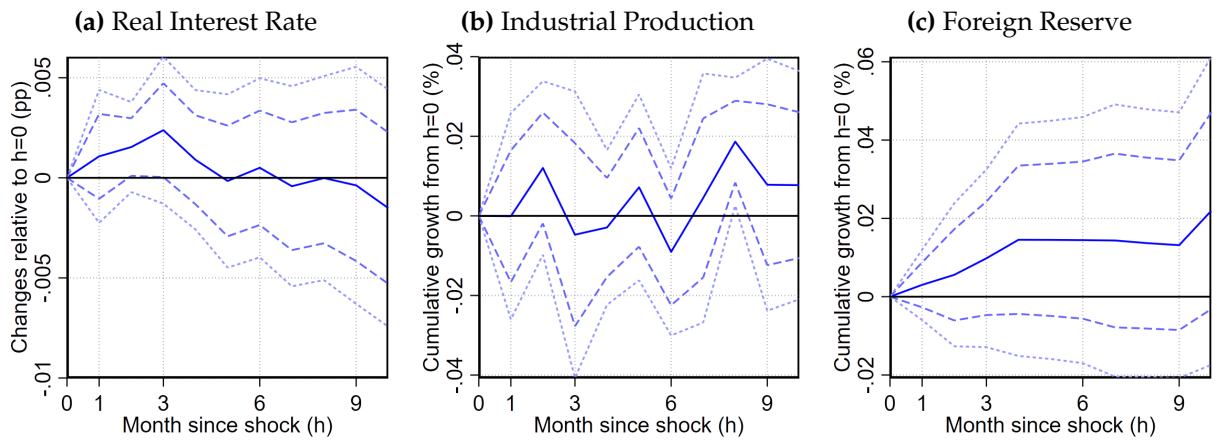


Figure A.5: Macro Fundamental Responses to Investment Giants Share

Notes: The figures depict the predictive content of the change in share of equity investments made by the top 10 investment giants (equation 4) 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 (8). 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 (%).

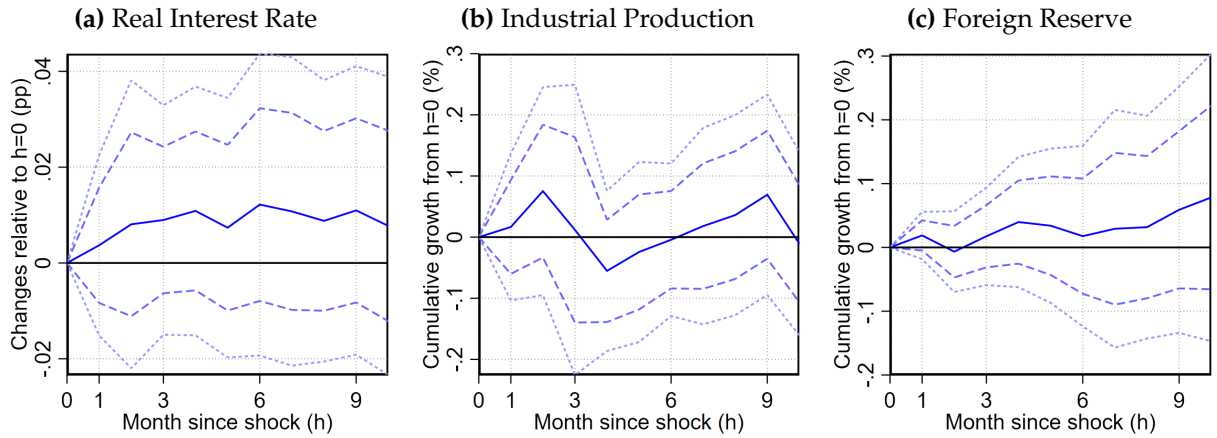


Figure A.6: Macro Fundamental Responses to Equity Flow Differential Between Size-Weighted and Unweighted Averages

The figures depict the predictive content of the difference between size-weighted and unweighted averages of investor flows (Granular IV, equation 5) 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 (8). 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 (%).

C 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.[12] 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).[13]

To address this concern, we estimate regression equation (6) 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 (6) 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 (4) and (5), 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.

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

[13] 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 (6) 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 (6). Because the EPFR data do not provide detailed investor characteristics, we introduce investor–time fixed effects ($\delta^h_{i,t}$), yielding

$$\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = \beta^h \left(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\right) + \mathbf{\Gamma}^h_{\text{pull}} \mathbf{Pull}_{c,t} + \delta^h_{i,t} + \delta^h_c + \varepsilon^h_{ic,t}, \tag{A.1}$$

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}):

$$\tilde{\Delta}^h \text{IHS}(\text{Equity}_{ic,t}) = \beta^h \left(\bar{g}^{\text{giant}}_{c,t} - \bar{g}^{\text{typical}}_{c,t}\right) + \mathbf{\Gamma}^h_{\text{pull}} \mathbf{Pull}_{c,t} + \mathbf{\Gamma}^h_{\text{push}} \mathbf{Push}_t + \delta^h_{ic} + \delta^h_m + \varepsilon^h_{ic,t}. \tag{A.2}$$

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.1) and (A.2). 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 (6).

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.

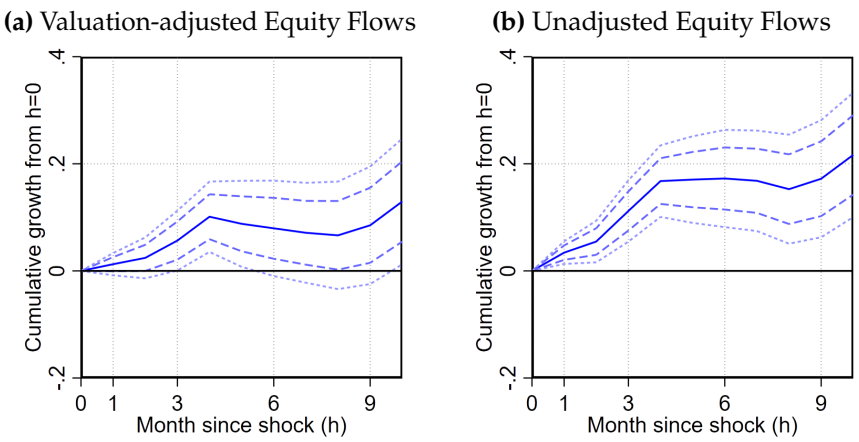


Figure A.7: Investor-Level Responses to Giants' Contrarian Flows: Active Fund Flows

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 (6). The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. In each regression, singleton observations are dropped. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

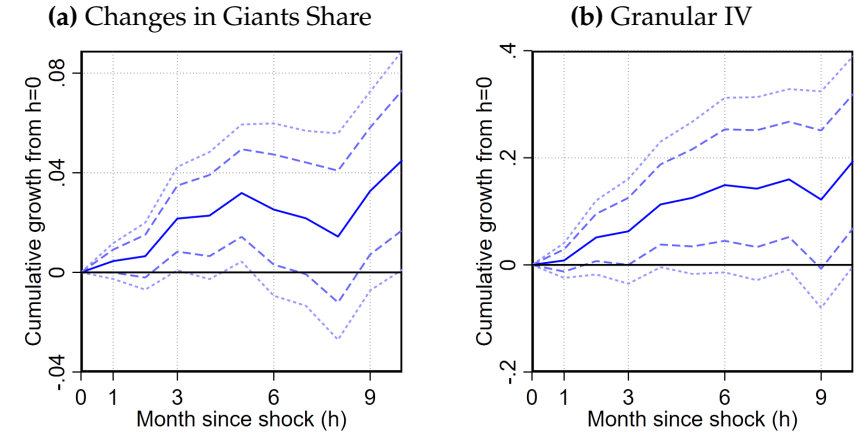


Figure A.8: Investor-Level Response to Changes in Alternative Measures of Contrarian Investments: Active Fund Flows

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 (4). 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 (5). The responses of valuation-adjusted active fund flows to contrarian flows are the estimates of β^h in equation (6). The 90% and 99% confidence intervals (long- and short-dashed lines) are computed based on standard errors corrected for arbitrary correlation within investors. The x-axis is months after the shock, and the y-axis is cumulative changes (growth, %).

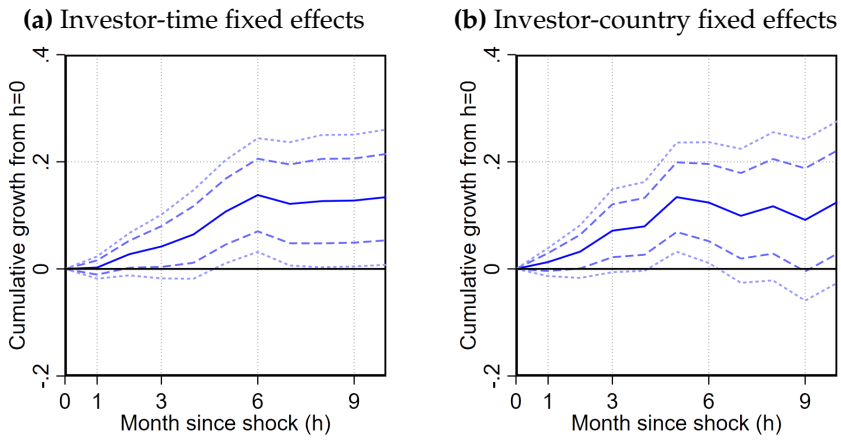


Figure A.9: Investor-Level Responses to Giants' Contrarian Flows: Alternative Specification

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.1) and (A.2), 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, %).

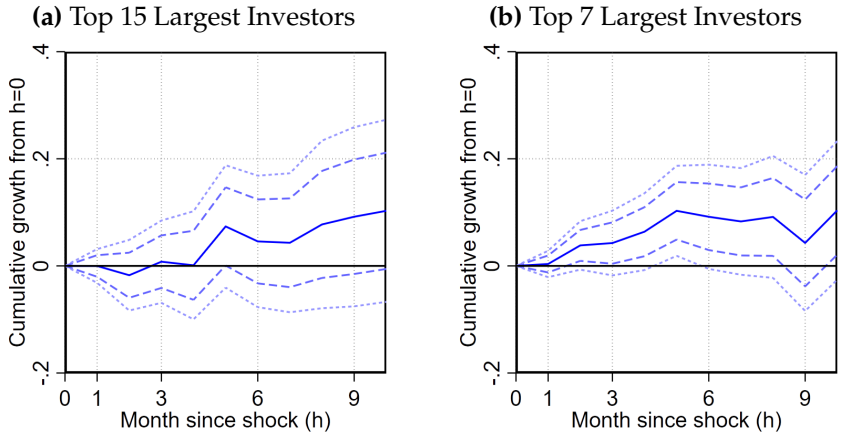


Figure A.10: Investor-Level Response to the Equity Flow Differential between Giants (Top 15 or 7 Largest Investors) and Typical Investors

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 (6). 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, %).

D Robustness Checks of Country-Level Analyses

D.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:

$$Y_{c,t}^{h} = \beta^{h}\left(\bar{g}_{c,t}^{\text{giant}} - \bar{g}_{c,t}^{\text{typical}}\right) + \mathbf{\Gamma}_{\text{pull}}^{h}\mathbf{Pull}_{c,t} + \delta_{c}^{h} + \delta_{t}^{h} + \varepsilon_{c,t}^{h}, \tag{A.3}$$

where δ_t^h denotes the time fixed effect.[14] 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 (4) and (5), 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

[14] Note that, similar to equation (A.1), 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.

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

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

In more details, the impulse responses of stock and currency markets to active fund flows are first reported in Figure A.17. Second, we estimate a regression similar to equation (A.3), 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 (4) and (5), respectively.

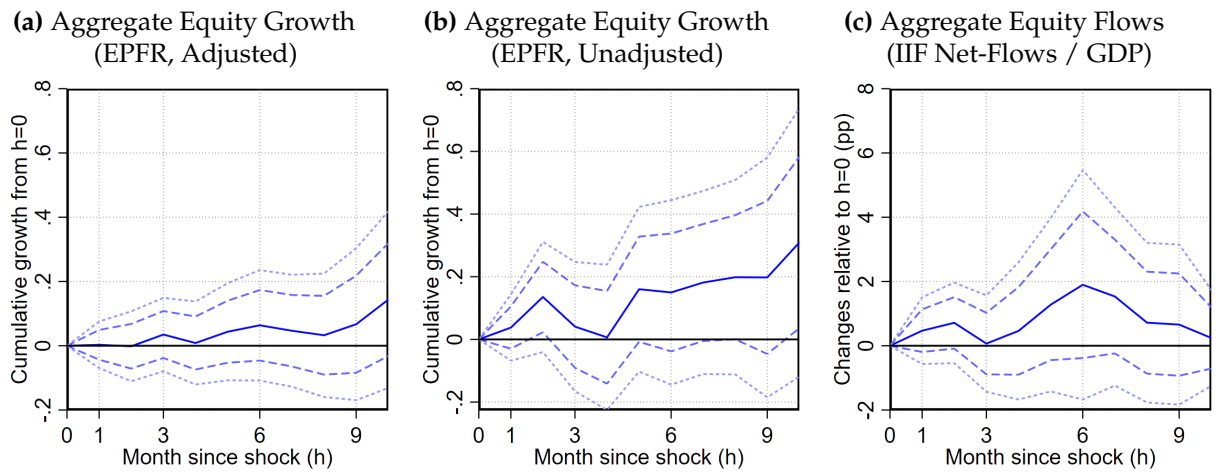


Figure A.11: Aggregate Flow Responses to Giants' Contrarian Flows: Active Fund Flows

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 (8). The 90% and 99% confidence intervals (long- and short-dashed lines) are based on standard errors corrected for arbitrary correlation within countries. The x-axis is time in months, and the y-axis is cumulative changes (%).

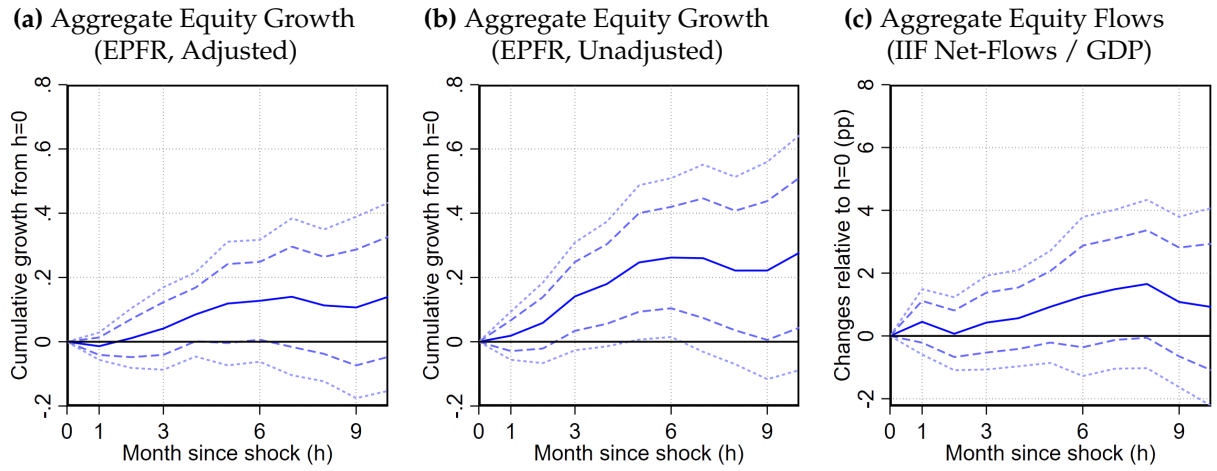


Figure A.12: Aggregate Flow Responses to Giants' Contrarian Flows: Alternative Specification

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.3). 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 (%).

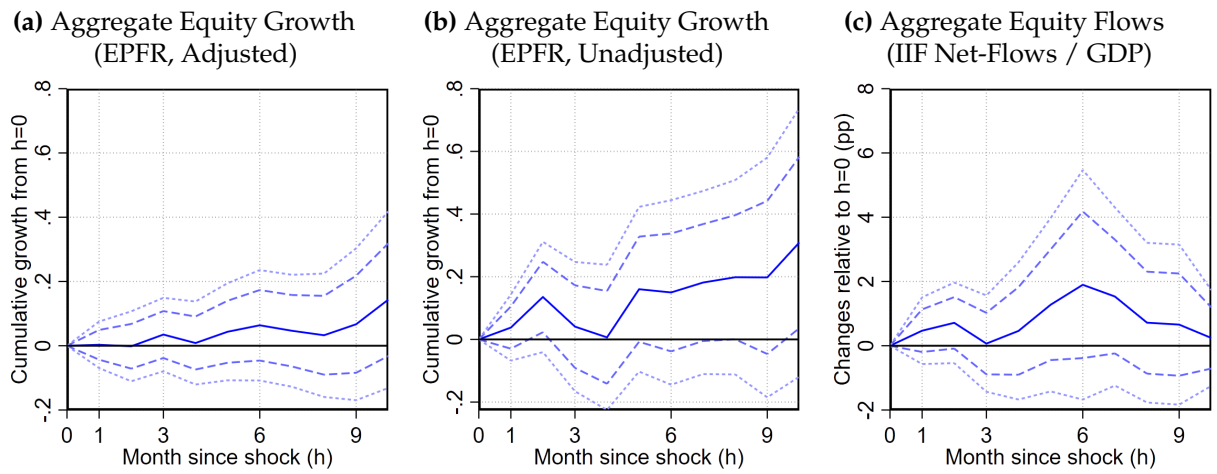


Figure A.13: Aggregate Flow Responses to Giants' (Top 15 Largest Investors) Contrarian Equity Flows

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 (8). 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 (%).

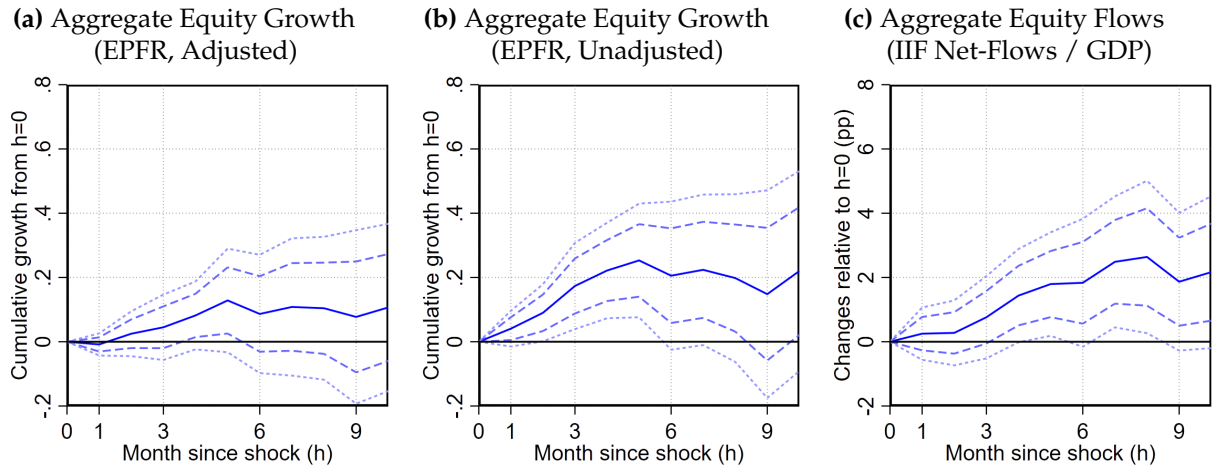


Figure A.14: Aggregate Flow Responses to Giants' (Top 7 Largest Investors) Contrarian Equity Flows

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 (8). 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 (%).

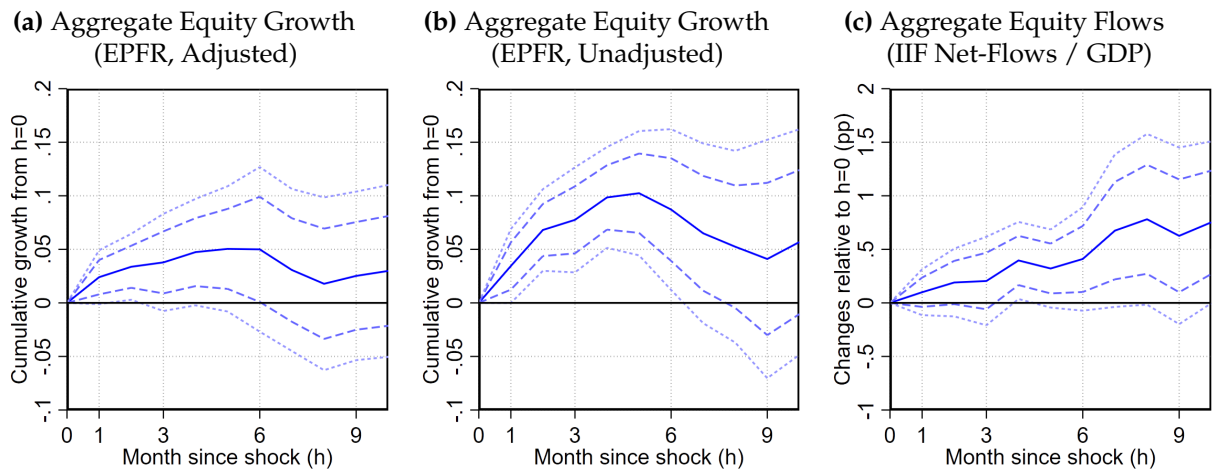


Figure A.15: Aggregate Flow Responses to Investment Giants Share

Notes: The figures depict the predictive content of the change in share of equity investments made by the top 10 investment giants (equation 4) 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 (8). 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 (%).

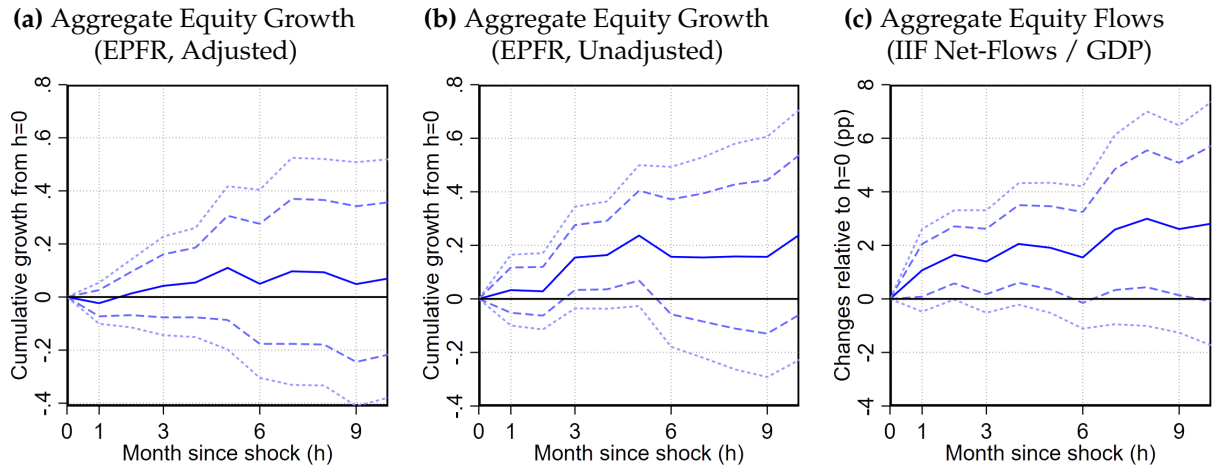


Figure A.16: Aggregate Flow Responses to Equity Flow Differential Between Size-Weighted and Unweighted Averages

Notes: The figures depict the predictive content of the difference between size-weighted and unweighted averages of investor flows (Granular IV, equation 5) 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 (8). 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 (%).

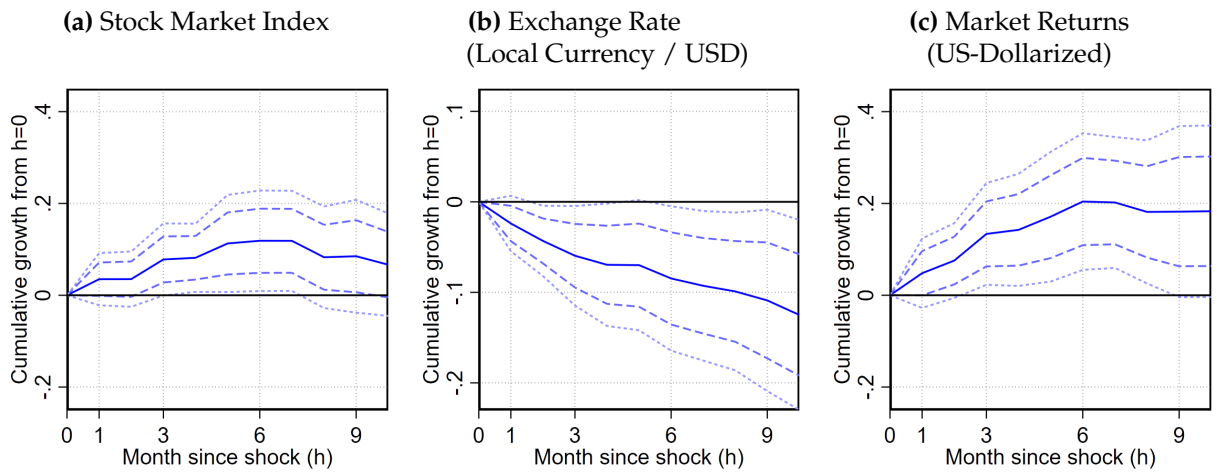


Figure A.17: Stock and Currency Markets Responses to Giants' Contrarian (Active Fund) Equity Flows.

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 (8). 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 (%).

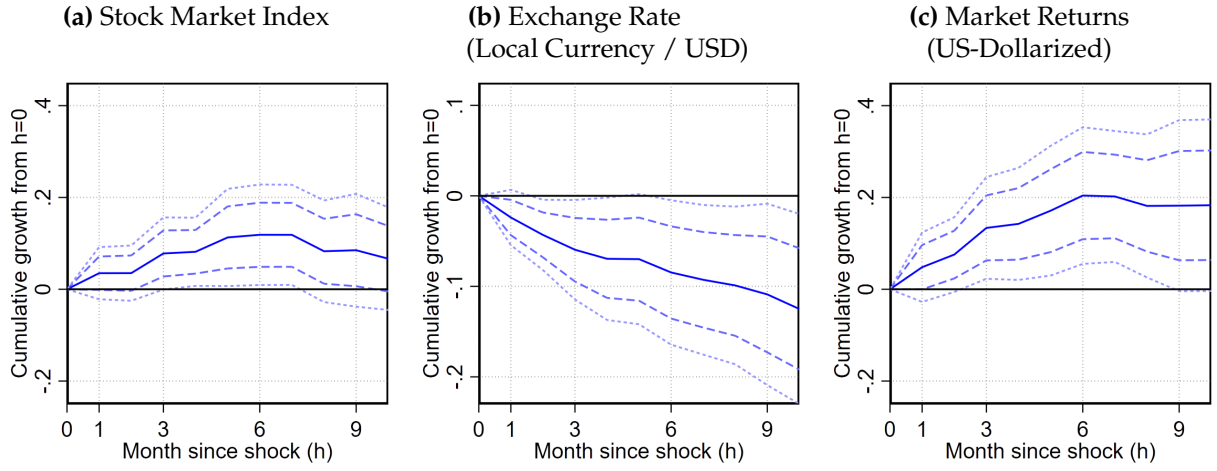


Figure A.18: Stock and Currency Markets Responses to Giants' Contrarian Flows: Alternative Specification

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.3). 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 (%).

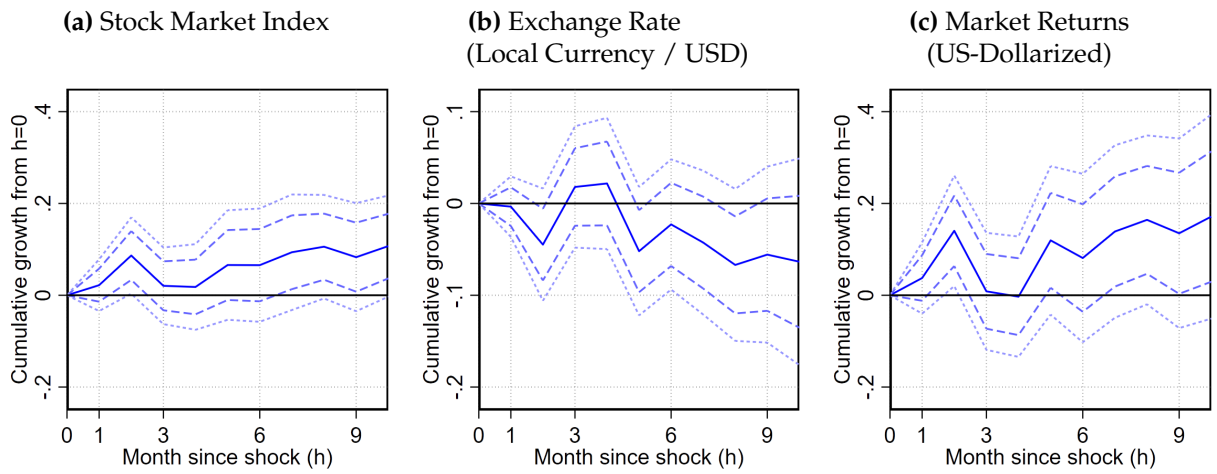


Figure A.19: Stock and Currency Markets Responses to Giants' (Top 15 Largest Investors) Contrarian Equity Flows

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 (8). 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 (%).

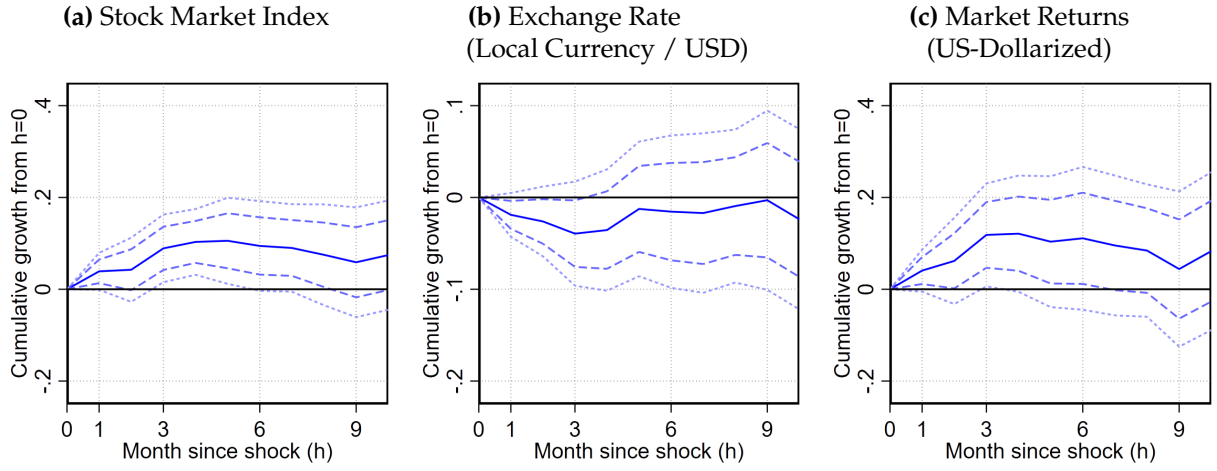


Figure A.20: Stock and Currency Markets Responses to Giants' (Top 7 Largest Investors) Contrarian Equity Flows

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 (8). 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 (%).

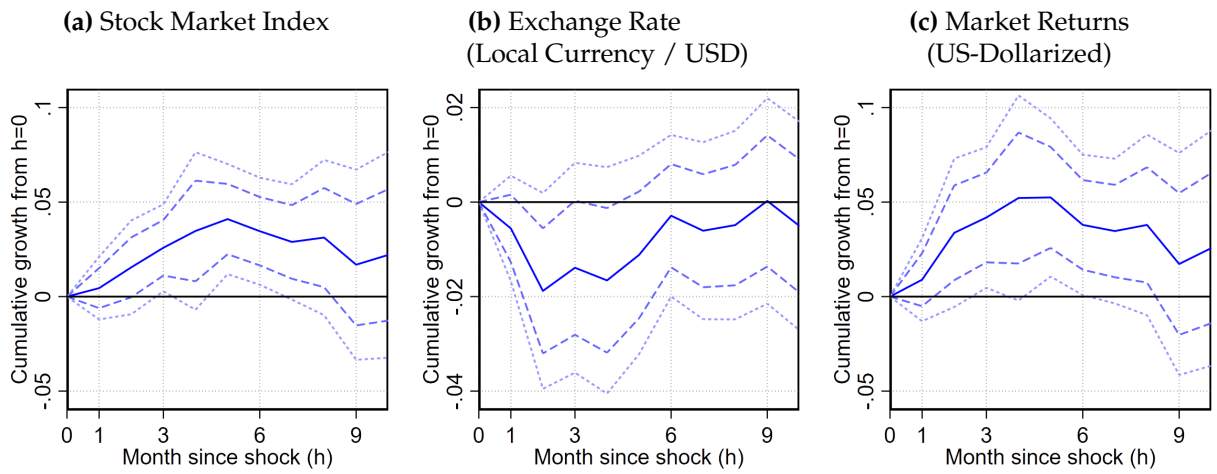


Figure A.21: Stock and Currency Markets Responses to Investment Giants Share

Notes: The figures depict the predictive content of the change in share of equity investments made by the top 10 investment giants (equation 4) 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 (8). 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 (%).

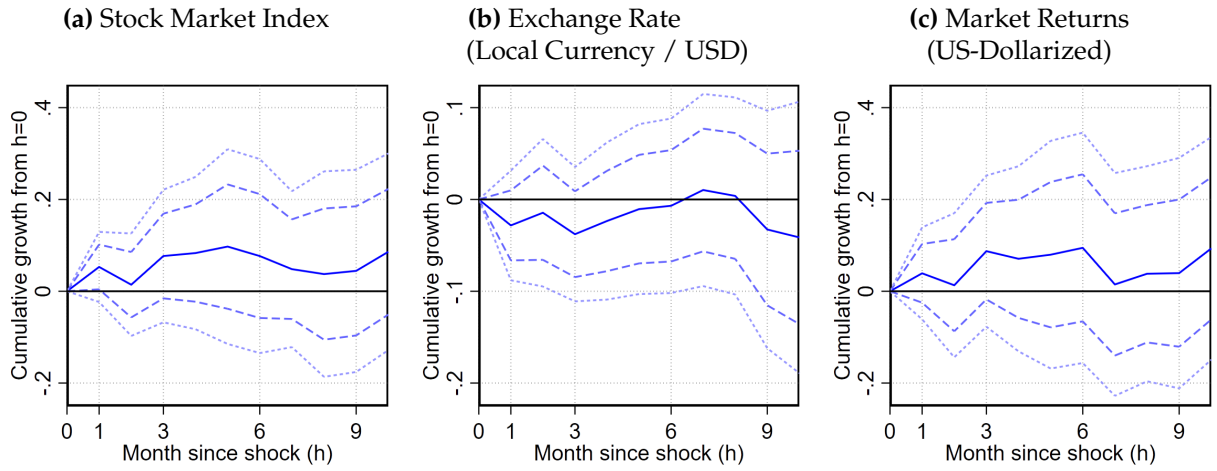


Figure A.22: Stock and Currency Markets Responses to Equity Flow Differential Between Size-Weighted and Unweighted Averages

The figures depict the predictive content of the difference between size-weighted and unweighted averages of investor flows (Granular IV, equation 5) 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 (8). 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, %).

E Simultaneous Regime: Simultaneous Play

In the simultaneous regime ($r_1 = \text{sm}$), all investors $i \in [0, 1]$—the investment giant ($i = 1$) and typical investors ($j \in [0, 1)$)—independently choose their asset allocations a_i at the same time to maximize conditional expected payoffs $\mathbb{E}[\pi_i|s_i]$, relying solely on their private signals.

Typical Investor's Optimal Strategy The first-order condition for typical investor $j \in [0, 1)$ yields:

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

where $\mathbb{E}[\bar{A}^{\text{sm}}|s_j] \equiv \lambda\mathbb{E}[a_1^{\text{sm}}|s_j] + (1-\lambda)\mathbb{E}[\bar{a}_0^{\text{sm}}|s_j]$ is the expected market allocation.

We conjecture linear equilibrium strategy rules for typical investors, $a_j^{\text{sm}}(s_j) = \psi^{\text{sm}} s_j$, and for the giant investor, $a_1^{\text{sm}}(s_1) = \phi^{\text{sm}} s_1$. Evaluating conditional expectations using $\mathbb{E}[f|s_j] = \theta_0 s_j$, $\mathbb{E}[a_1^{\text{sm}}|s_j] = \phi^{\text{sm}}\theta_0 s_j$, and $\mathbb{E}[\bar{a}_0^{\text{sm}}|s_j] = \psi^{\text{sm}}\theta_0 s_j$, typical investor j's optimal strategy reduces to:

$$a_j^{\text{sm}}(s_j) = \psi^{\text{sm}} s_j, \qquad \text{where} \qquad \psi^{\text{sm}} \equiv \left[\frac{(1-\omega) + \omega\lambda\phi^{\text{sm}}}{1 - \omega(1-\lambda)\theta_0}\right]\theta_0. \tag{A.5}$$

Equation (A.5) demonstrates that a typical investor's sensitivity to their own private signal (ψ^{sm}) increases with the giant's signal responsiveness (ϕ^{sm}). Because typical investors face tracking-error penalties relative to aggregate market exposure $\bar{A}$, they place higher weight on their own signal when anticipating that the giant will trade aggressively on its private information. This strategic feedback channel is strengthened when the giant holds a larger market share (λ) or when benchmark-tracking concerns (ω) intensify.

Investment Giant's Optimal Strategy The giant investor internalizes its non-negligible market mass λ on aggregate exposure $\bar{A} = \lambda a_1 + (1-\lambda)\bar{a}_0$. Differentiating its expected payoff with respect to a_1 yields the first-order condition:

$$a_1^{\text{sm}}(s_1) = \frac{(1-\omega)\mathbb{E}[f|s_1] + \omega(1-\lambda)\mathbb{E}[\bar{a}_0^{\text{sm}}|s_1]}{1 - \omega + \omega(1-\lambda)^2}. \tag{A.6}$$

Substituting $\mathbb{E}[f|s_1] = \theta_1 s_1$ and $\mathbb{E}[\bar{a}_0^{\text{sm}}|s_1] = \psi^{\text{sm}}\theta_1 s_1$ into equation (A.6) yields the giant's equilibrium action rule:

$$a_1^{\text{sm}}(s_1) = \phi^{\text{sm}} s_1, \qquad \text{where} \qquad \phi^{\text{sm}} \equiv \left[\frac{(1-\omega) + \omega(1-\lambda)^2\psi^{\text{sm}}}{(1-\omega) + \omega(1-\lambda)^2}\right]\theta_1, \tag{A.7}$$

with ψ^{sm} given by equation (A.5).

Explicit Solutions Solving the linear system of equations (A.5) and (A.7) yields the unique equilibrium loading coefficients $(\psi^{\text{sm}}, \phi^{\text{sm}})$ under simultaneous play:

$$\psi^{\text{sm}} = \frac{\theta_0(1-\omega)\left[1 - \omega(1-\lambda) + \omega\lambda\theta_1(1-\lambda)\right]}{\left[1 - \omega(1-\lambda)\theta_0\right]\left[1 - \omega + \omega(1-\lambda)^2\right] - \omega^2\lambda(1-\lambda)^2\theta_0\theta_1}, \tag{A.8}$$

$$\phi^{\text{sm}} = \frac{\theta_1(1-\omega)\left[1 - \omega(1-\lambda)\theta_0 + \omega(1-\lambda)^2\theta_0\right]}{\left[1 - \omega(1-\lambda)\theta_0\right]\left[1 - \omega + \omega(1-\lambda)^2\right] - \omega^2\lambda(1-\lambda)^2\theta_0\theta_1}. \tag{A.9}$$

Comparing ϕ^{sm} in equation (A.7) to $\phi^{\text{sq}} = \theta_1$ under sequential play reveals the core friction of simultaneous play: when the giant cannot move first, it cannot steer peer benchmark allocations. Consequently, $\phi^{\text{sm}} < \theta_1$, meaning the giant is forced to shade its fundamental trading intensity downward due to unhedged tracking-error risk.