Granular International Portfolios*

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Abstract

Granular international portfolios generate substantial expectation-driven capital-flow spillovers. A delegated-portfolio model with sticky fund weights predicts that negative expectations about countries that account for large fund shares mechanically reduce capital flows to other countries held in the same funds – a co-ownership spillover that operates alongside the standard excess-return and hedging channels. We identify each channel's structural elasticity using a unique dataset that matches the GDP growth forecasts of global financial institutions to the assets under management and cross-country allocations of their equity mutual funds. Because the estimated elasticities imply a high degree of portfolio stickiness, and because country weights in global portfolios are highly granular, expectation shocks to large economies generate substantial spillovers to countries that share fund ownership: co-ownership spillovers account for 57% of expectation-driven capital-flow reallocation. Small advanced and emerging economies are the primary recipients; the G7 and BRICS are the main sources, producing a Large-to-Small rather than North-to-South transmission.

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1 Introduction

Why do asset prices and business cycles comove across countries? Existing explanations emphasize correlated fundamentals, global financial cycles, and real and financial contagion.[1] A large literature highlights financial contagion driven by funding shocks to global banks, which typically transmit disturbances from advanced economies–home to most of these banks–to emerging markets. Yet the role of expectations in shaping international financial spillovers remains poorly understood, in part because direct evidence on how expectations affect cross-country portfolio allocation is scarce.

This paper shows that granular and sticky international portfolios generate substantial expectation-driven spillovers. To fix ideas, consider a mutual fund whose portfolio is concentrated in two countries, A and B. When investors become pessimistic about country A's growth, they reduce their holdings of the fund. If the fund adjusted its portfolio weights, it would insulate country B by raising its weight; in practice, country weights within funds adjust slowly. The withdrawal therefore translates mechanically into reduced capital flows to country B, even though expectations about B itself are unchanged. We call this channel "co-ownership spillovers." Because country weights in global mutual fund portfolios are highly concentrated—the ten largest countries account for 65% of fund holdings—expectation shocks to a small number of large economies generate substantial capital-flow reallocations across the broader cross-section of countries that share fund ownership with them.[2]

To formalize this mechanism and trace its aggregate implications, we develop a delegated-portfolio model with sticky fund weights. The model decomposes expectation-driven capital flows into three channels operating side by side: an *excess-return* channel through which country-specific expectations shift within-fund weights; a *co-ownership* channel through which fund-level expectations spill over mechanically across the fund's holdings when portfolios are sticky;[3] and a *hedging* adjustment driven by the covariance of country returns with the fund portfolio. The relative strength of these channels depends on three structural elasticities, which we identify in the data and feed back into the model to quantify each channel.

Whether such spillovers generate meaningful international contagion depends on the structure of expectations. Suppose that expectations are driven by global shocks and by country-specific shocks. If the country-specific shocks averaged out across countries, the spillovers would be driven only by global shocks that are relevant for all countries. However, the concentration of fund portfolios in a small number of large economies prevents this:

[1]See Forbes and Rigobon (2001), Karolyi (2003), Forbes (2012), and Rigobón (2019) for surveys.
[2]Mutual funds manage a large and growing share of global capital flows; see Schmidt and Yesin (2022).
[3]We borrow the term "co-ownership spillovers" from Jotikasthira et al. (2012).

shocks specific to these large countries do not average out and propagate to the rest of the cross-section through co-ownership. The "granularity" of fund shares is thus key (Gabaix, 2011).

To take the model to the data, we construct a unique dataset that matches the in-house country-level GDP growth forecasts produced by global financial institutions—typically large banks and asset managers—to the cross-country allocations of the equity mutual funds they manage. Throughout the paper, we refer to these financial institutions as "investors": the in-house forecast is our empirical proxy for the information that shapes both the end-client's allocation across funds and the fund manager's allocation across countries within the fund.[4] Mapping the model elasticities to a regression specification, we document a sharp asymmetry: inflows into a fund respond strongly to the fund's in-house portfolio-weighted growth expectation, whereas within-fund country weights respond only weakly to country-level expectations. This is the empirical reflection of the portfolio stickiness that drives co-ownership spillovers.

Plugging our elasticity estimates back into the three-channel decomposition, co-ownership spillovers account for 57% of the variance of expectation-driven capital-flow reallocation, with 42% accounted for by the country-specific excess return channel, and less than 1% by the hedging channel. Because co-ownership spillovers are unrelated to recipient countries' fundamentals, they constitute a distinct source of cross-border capital misallocation, operating alongside the funding-shock channels traditionally emphasized in the contagion literature.

Small advanced and emerging economies are the primary recipients of these spillovers, while large advanced and emerging economies–such as the G7 and BRICS–are the main contributors. Unlike traditional funding contagion, this channel does not imply a systematic North-South transmission, but rather a Large-to-Small-country one. As a result, some large emerging economies, such as China and Brazil, contribute strongly to spillovers while being relatively insulated themselves. These findings suggest that policymakers in small economies should pay attention not only to large shocks on global financial centers but also on large countries with overlapping investor bases.

Methodologically, our approach combines two complementary identification strategies. To address the missing-variable bias arising from incomplete observation of country-level expectations within fund portfolios, we construct a granular residual (Gabaix and Koijen, 2021, 2024) that aggregates the country-specific component of investor expectations using lagged portfolio weights; this construction is equivalent to a shift-share design à la Borusyak et al. (2022), with portfolio weights playing the role of shares and country-specific expectation de-

[4] We develop this institutional setting in Section 3.1 and verify the assumption with an IV strategy that uses publicly available IMF forecasts in Section 3.2.

viations playing the role of shifts.[5] To address measurement error in subjective forecasts and potential reverse causality from capital flows to growth expectations, we further instrument the investor's expectation with the contemporaneous IMF growth forecast, which is publicly available and is not directly affected by fund portfolios.

We contribute to several strands of literature. First, we contribute to the literature on granularity in financial markets. Existing work emphasizes that aggregate and cross-country fluctuations may arise from idiosyncratic shocks to large actors—such as firms or sectors—when size distributions are fat-tailed.[6] In financial markets, related mechanisms operate through shocks to large banks, mutual funds, or other institutional investors.[7] In contrast, granularity in our setting arises from the distribution of country weights within portfolios, not from investor size. A small number of countries account for a disproportionate share of global equity fund holdings, so expectation shocks to these countries propagate internationally even when investors themselves are small and diversified. A complementary line of recent work identifies granular forces in firm-level sentiment that aggregate to drive macroeconomic fluctuations (Jamilov et al., 2026); our mechanism is structurally distinct, operating through the granularity of country weights in portfolios rather than through the granularity of firms.

Second, we contribute to the literature on international shock transmission through mutual funds. Existing work shows that shocks to the investor base generate comovement across emerging markets and affect asset prices.[8] Methodologically, the closest antecedent is Camanho et al. (2022), who apply a granular instrumental-variable strategy to fund-level portfolio flows in order to identify the effect of mutual-fund rebalancing on exchange rates. We differ from theirs in both the identifying variation—we exploit direct survey expectations rather than flow shocks driven by benchmark deviations and FX hedging—and in the target of inference: rather than estimating a price effect, we identify the structural elasticities of capital flows to expectations and feed them back into the model to quantify the co-ownership channel. Relative to Jotikasthira et al. (2012), who infer co-ownership spillovers indirectly through calibrated reactions to flow shocks, we identify them directly from investor-level expectations.

Third, we contribute to the literature on portfolio adjustment frictions. Our model

[5] See Gabaix and Koijen (2024) for a survey of papers using GIVs.

[6] See Gabaix (2011); Acemoglu et al. (2012); di Giovanni et al. (2014); Carvalho and Grassi (2019); Herskovic et al. (2020); Gaubert and Itskhoki (2021).

[7] See Ben-David et al. (2016); Amiti and Weinstein (2018); Galaasen et al. (2020); Camanho et al. (2022); Gabaix and Koijen (2021); Aldasoro et al. (2023); Bippus et al. (2023); Eugster et al. (2025).

[8] See Broner et al. (2006); Gelos (2011); Raddatz and Schmukler (2012); Puy (2016). Coval and Stafford (2007) document this in U.S. domestic equity markets, and Jotikasthira et al. (2012) extend the finding to global funds, showing significant effects on prices, country betas, and return comovement.

delivers a simple mapping between portfolio stickiness and the relative elasticity of capital flows to country- versus fund-level expectations: $p = \beta/(\beta+\eta)$. Using our estimates, we infer a portfolio updating frequency of roughly 8 months for the average fund and 6 months for active funds—faster than the delayed-adjustment estimates of Bacchetta and van Wincoop (2017), consistent with the idea that direct survey expectations identify a larger underlying elasticity than expectations imputed from past returns or portfolio persistence.[9]

Fourth, we contribute to the growing literature linking survey-based expectations to investment behavior.[10] Closest to us, Dahlquist and Ibert (2021) show that asset managers tilt portfolios toward assets about which they are more optimistic. Our contribution is to estimate how investors' beliefs shape the *cross-country* allocation of equity, and to document a sharp asymmetry between the elasticity of fund flows and that of within-fund country reallocation–an asymmetry that, combined with the granularity of country shares, drives the co-ownership channel.[11]

Section 2 develops a delegated portfolio-choice model and characterizes co-ownership spillovers. Section 3 describes the data, maps the model to the data, and identifies the key elasticities. Section 4 quantifies the contribution of co-ownership spillovers.

2 Model

This section develops a two-period delegated-portfolio model that serves three purposes in the analysis that follows. First, it makes precise what we mean by *co-ownership spillovers*: capital flows to country k driven not by expectations about country k itself, but by expectations about other countries held in the same funds. Second, it identifies the conditions under which these spillovers aggregate into meaningful capital-flow volatility, tying their relevance to two distinct sources of granularity — the granularity of country shares within portfolios, and the granularity of investors. Third, it pins down the parameters that the next section identifies in the data.

The building blocks are standard: mean–variance preferences and a Calvo-style portfolio adjustment friction (Bacchetta et al., 2022).[12] The new element is their combination in a

[9] Bohn and Tesar (1996) and Froot et al. (2001) find that international portfolio flows are highly persistent and strongly related to lagged returns; more recently, Bacchetta et al. (2020) test a delayed-adjustment model using mutual fund data.

[10] See Vissing-Jorgensen (2003); Glaser and Weber (2005); Kézdi and Willis (2011); Weber et al. (2012); Piazzesi and Schneider (2009); Malmendier and Nagel (2015); Dahlquist and Ibert (2021); Agarwal et al. (2022); Giglio et al. (2021); Ma et al. (2022).

[11] The cross-country allocation of sovereign bond holdings and bank credit supply have been investigated respectively by De Marco et al. (2021) and Li and Ongena (2025).

[12] Bacchetta et al. (2022) use explicit adjustment costs and show that the modeling of the portfolio friction does not affect the main implications. We assume that investors and fund managers share the same

delegated setting. End-investors choose how much to allocate across funds; fund managers choose how to allocate fund assets across countries. When country weights are sticky, an investor's optimal fund-allocation response to a country-specific shock no longer reallocates capital towards that one country — it mechanically channels capital into every other country the fund happens to hold. Whether this generates extra volatility in aggregate capital flows then depends on the granularity of country shares: if a small number of countries hold disproportionate weight in global portfolios, idiosyncratic expectation shocks to *those* countries do not wash out across funds and contribute to aggregate capital-flow volatility.

The section proceeds as follows. Section 2.1 lays out agents, returns, and the friction. Section 2.2 derives optimal portfolios. Section 2.3 decomposes country-level capital flows into an excess-return channel, a co-ownership spillover, and hedging terms. Section 2.4 aggregates these flows, shows that the friction affects only portfolio reallocation, not portfolio growth, and pinpoints the key parameters to estimate.

2.1 Setup

Agents. There are M *investors* indexed by $i = 1, \ldots, M$, where "investor" refers throughout to the entity whose fund-allocation decisions are informed by financial institution i's expectations — in our empirical setting, primarily the institution's own portfolio managers and its wealth-management clients.[13] Each investor i is associated with $\mathcal{J}(i)$ *equity mutual funds* indexed by $j = 1, \ldots, \mathcal{J}(i)$. There are K countries in which the funds can invest, indexed by $k = 1, \ldots, K$, and fund (i, j) invests in a subset $\mathcal{S}(i, j)$ of $\mathcal{K}(i, j)$ countries.

Timing and friction. In the first period, after receiving new information, investors allocate wealth between a safe asset and the funds, and funds allocate received assets across countries. The portfolio friction is at the fund level: a fund updates its country weights only with probability $p \leq 1$, and otherwise keeps them at predetermined values. In the second period, country returns realize and investors consume terminal wealth. Investors and funds share the same information and maximize the same mean–variance objective; the only friction relative to the frictionless benchmark is the fund-level updating probability.

Returns and information. An equity share held in country $k = 1, \ldots, K$ is traded at a normalized price of one in the first period and pays a stochastic return R_k in the second

information and the same objective, ruling out agency frictions: the spillover mechanism we identify arises purely from sticky country weights.

[13] We discuss the institutional setting in detail in Section 3.1.

period. Stacking returns into the vector $R = (R_1, \ldots, R_K)'$, we assume $R \sim \mathcal{N}(\bar{R}, \Sigma)$, with unconditional mean $\bar{R}$ and variance-covariance Σ.

Investor i and the funds it is associated with share the same information about R. Within the first period we distinguish beginning-of-period information $\bar{\mathcal{I}}^i$ from end-of-period information $\mathcal{I}^i$, with corresponding operators $\bar{E}^i(\cdot)$ and $E^i(\cdot)$, variances $\bar{V}(\cdot)$ and $V(\cdot)$, and shorthand $\bar{V}^R = \bar{V}(R)$ and $V^R = V(R)$. Throughout, we assume learning between the two stages is gradual:

Assumption 2.1 $\bar{V}^R - V^R \ll V^R$.

This assumption ensures that the change in the conditional variances between the two stages of the first period is small, which keeps the default portfolio weights tractable.

2.2 Optimal portfolios

The investor's problem. Investor i enters the first period with wealth Ω^i, allocates a share $a^{i,j}$ to each fund j, and the residual $1 - \sum_j a^{i,j}$ to a safe asset paying r. The decision is taken after observing $\mathcal{I}^i$ but *before* fund j's realized country allocation is known. Second-period terminal wealth is $\left[\mathcal{R}_p^i \left(\sum_j a^{i,j}\right) + r\left(1 - \sum_j a^{i,j}\right)\right]\Omega^i$, where $\mathcal{R}_p^i$ is the return on the investor's portfolio of funds:

$$\mathcal{R}_p^i = \sum_{j=1}^{\mathcal{J}(i)} \frac{a^{i,j}}{\sum_{j'} a^{i,j'}} R_p^{i,j}, \tag{1}$$

with $R_p^{i,j}$ the period-2 return of fund j (defined below). The investor chooses $a^i = (a^{i,1}, \ldots, a^{i,\mathcal{J}(i)})'$ to maximize a standard mean–variance objective with risk aversion γ, conditional on $\mathcal{I}^i$. The first-order conditions yield:

Lemma 2.1 *Total equity investments must satisfy*

$$\sum_{j=1}^{\mathcal{J}(i)} a^{i,j} = \frac{E^i(\mathcal{R}_p^i) - r}{\gamma V^i} \tag{2}$$

with $V^i = V(\mathcal{R}_p^i)$, and the optimal allocation to equity funds j $a^{i,j}$ must satisfy, for all $j = 1, .., \mathcal{J}(i)$,

$$a^{i,j} = \frac{E^i(R_p^{i,j}) - r}{\gamma V^{i,j}} - Cov_{i,j}\left(\sum_{j=1}^{\mathcal{J}(i)} a^{i,j}\right) \tag{3}$$

where $V^{i,j} = Cov(R_p^{i,j}, R_p^{i,j} - \mathcal{R}_p^{i,j-})$ *and* $Cov_{i,j} = Cov(R_p^{i,j}, \mathcal{R}_p^{i,j-})/V^{i,j}$ *are constant terms, and* $\mathcal{R}_p^{i,j-} = \sum_{j',j'\neq j} a^{i,j'} R_p^{i,j'} / \left(\sum_{j'=1,j'\neq j}^{\mathcal{J}(i)} a^{i,j'}\right)$ *is the return of the full portfolio of funds when excluding fund* j*.*

Proof. See proof in Appendix A.1. ■

Equation (3) is the standard mean–variance allocation rule applied at the fund-allocation level: the investor loads on funds with high expected excess return, scaled by risk tolerance and variance, with a hedging adjustment for the covariance between fund j and the rest of the investor's portfolio (Markowitz, 1952; Lintner, 1965). Equation (2) pins down total equity demand from the same mean–variance logic applied to the aggregate portfolio.

The fund's problem. The country allocation of fund (i, j) determines its portfolio return

$$R_p^{i,j} = \sum_{k\in\mathcal{S}(i,j)} w_k^{i,j} R_k = w^{i,j\prime} R, \tag{4}$$

where $w_k^{i,j}$ is the share of fund j invested in country k, with $w_k^{i,j} = 0$ for $k \notin \mathcal{S}(i, j)$. The portfolio friction operates at this stage. At the beginning of the period, fund weights are fixed at predetermined values $\bar{w}_k^{i,j}$ conditional on $\bar{\mathcal{I}}^i$. At the end of the period, once a^i has been chosen, fund j reoptimizes its weights with probability p and otherwise keeps them at $\bar{w}_k^{i,j}$. When reoptimizing, the fund maximizes the same mean–variance objective as the investor subject to $\sum_{k\in\mathcal{S}(i,j)} w_k^{i,j} = 1$, taking the distribution of country returns as given. The resulting allocation $w^{i,j*}$ is characterized by:

Lemma 2.2 *The optimal allocation* $w^{i,j*}$ *is such that* $a_k^{i,j*} = w_k^{i,j*} a^{i,j}$*, the total investment share of investor* i *that is channeled to country* k *through fund* j*, satisfies, for all* $k \in \mathcal{S}(i, j)$

$$a_k^{i,j*} = \frac{E^i(R_k) - r}{\gamma V_k^{i,j}} - Cov_k^{i,j} \left(\sum_{j=1}^{\mathcal{J}(i)} a^{i,j}\right) - \Delta Cov_k^{i,j} a^{i,j} \tag{5}$$

where $V_k^{i,j} = Cov(R_k, R_k - R_{p,k-}^{i,j})$, $Cov_k^{i,j} = Cov(R_k, \mathcal{R}_p^{i,j-})/V_k^{i,j}$ *and* $\Delta Cov_k^{i,j} = \left(Cov(R_k, R_{p,k-}^{i,j}) - Cov(R_k, \mathcal{R}_p^{i,j-})\right)/V_k^{i,j}$ *are constant terms, and* $R_{p,k-}^{i,j} = \sum_{k',k'\neq k} w_k^{i,j} R_{k'}/(1-w_k^{i,j})$ *is the return of the fund portfolio that when excluding country* k*.*

Proof. See proof in Appendix A.2. ■

The first two terms of (5) parallel (3): the fund loads on country k in proportion to its expected excess return scaled by risk tolerance and variance, with a hedging adjustment for the covariance between k and the rest of the investor's portfolio. The third term is the new piece introduced by the delegated structure. It is proportional to $a^{i,j}$ and loads on $-\Delta Cov_k^{i,j}$, which can be read as the fixed share of investor i's allocation to fund j that is routed to country k to hedge exposure to fund j itself. As $a^{i,j}$ rises, the investor's exposure to the fund rises, while the exposure to the rest of her portfolio falls; the fund therefore allocates less to k when k is a poor hedge for the fund and more when k is a poor hedge for the investor's wider portfolio.

2.3 A three-channel decomposition of country flows

Conditional on the investor's end-of-period information $\mathcal{I}^i$ but *before* learning whether the fund will reoptimize, the expected share of investor i's wealth channeled to country k through fund j is the probability-weighted mixture of the updated and default allocations:

$$a_k^{i,j} = p\, a_k^{i,j*} + (1-p)\, \bar{w}_k^{i,j}\, a^{i,j}, \tag{6}$$

where $a_k^{i,j*}$ is given by (5), $a^{i,j}$ follows Equation (3), and $\bar{w}_k^{i,j}$ is set at the beginning of the period conditional on the beginning-of-period information $\bar{\mathcal{I}}^i$. Substituting both expressions, and taking into account the fund's optimal setting of the default portfolio shares yields a representation in which country-level flows respond to expectation surprises ("news") at three nested levels — country, fund, and the investor's overall portfolio:

Proposition 2.1 *Let $E^i(r_k) = E^i(R_k) - \bar{E}^i(R_k)$, $E^i(r_p^{i,j}) = E^i(R_p^{i,j}) - \bar{E}^i(R_p^{i,j})$, and $E^i(\mathfrak{r}_p^i) = E^i(\mathcal{R}_p^i) - \bar{E}^i(\mathcal{R}_p^i)$ denote the period-2 "news" about expected country, fund, and investor-portfolio returns. Under Assumption 2.1,*

$$\begin{aligned} a_k^{i,j} = \;& \underbrace{p\,\frac{E^i(r_k)}{\gamma V_k^{i,j}}}_{\text{Excess return}} + \underbrace{(1-p)\,\frac{\bar{a}_k^{i,j}}{\bar{E}^i(a^{i,j})}\,\frac{E^i(r_p^{i,j})}{\gamma V^{i,j}}}_{\text{Co-ownership spillover}} \\ & \underbrace{-\Delta Cov_k^{i,j}\,\frac{E^i(r_p^{i,j})}{\gamma V^{i,j}} - \widetilde{Cov}_k^{i,j}\,\frac{E^i(\mathfrak{r}_p^i)}{\gamma V^i} - (1-p)\left(\frac{\bar{a}_k^{i,j}}{\bar{E}^i(a^{i,j})} Cov^{i,j} - Cov_k^{i,j}\right)\frac{E^i(\mathfrak{r}_p^i)}{\gamma V^i}}_{\text{Hedging (fund-level and investor-level)}} \\ & + \bar{E}(a_k^{i,j}), \end{aligned} \tag{7}$$

where $\widetilde{Cov}_k^{i,j}$, $\bar{a}_k^{i,j}$, $\bar{E}(a_k^{i,j})$, and $\bar{E}^i(a^{i,j})$ are constants defined in Appendix A.3.

Proof. See Appendix A.3. ■

Proposition 2.1 groups the response of country flows into three channels. The *excess-return* channel (first term) is the standard mean–variance response: a positive surprise in country k's own expected return raises the allocation to k. However, the friction attenuates this elasticity: the channeling of more capital flows to country k can happen only if the fund reallocates its portfolio shares towards country k, which is less likely when $p < 1$. In the frictionless limit $p = 1$, this term reduces to the textbook mean–variance prediction.

The *co-ownership spillover* (second term) is the channel introduced by the delegated structure combined with sticky weights, and is the new mechanism of the paper. It loads on *fund-level* news $E^i(r_p^{i,j})$, which can be driven by expectations about any country in fund j's portfolio, not just k. To see why, suppose news raises the expected return on some other country $k' \neq k$ inside fund j. The investor responds by increasing her allocation $a^{i,j}$ to the fund (Equation 3). In the frictionless benchmark, the fund manager would immediately rebalance towards k' alone, leaving k untouched. With sticky weights, the fund instead splits the inflow across all its countries in proportion to its predetermined weights $\bar{w}_k^{i,j}$, mechanically channeling capital to k. The intensity of the spillover is governed by the share $\bar{a}_k^{i,j}/\bar{E}^i(a^{i,j})$, which is roughly the ex-ante fraction of fund j's flows going to k. The spillover vanishes in the frictionless limit $p = 1$.

The remaining *hedging* terms collect mean–variance hedging adjustments, operating both at the fund and at the investor level. They reflect how country k co-varies with the rest of fund j's portfolio and with the rest of the investor's portfolio. They are not the focus of the mechanism, but matter quantitatively for the identification of p below. However, it is important to note at this stage that the fund-wide hedging term, which loads on the news on fund j's return $E^i(r_p^{i,j})$, is independent of the portfolio friction p. Indeed, the hedging of fund flows arise automatically from the optimal fixed part of the portfolio share, which does not depend on new information.[14]

Equation (7) can be re-expressed compactly in terms of three elasticities, one per expectation surprise:

Corollary 2.1 *Equation* (7) *can be rewritten as*

$$\frac{a_k^{i,j} - \bar{E}^i(a_k^{i,j})}{\bar{E}^i(a_k^{i,j})} = \beta_k^{i,j}\, E^i(r_k) + \delta_k^{i,j}\, E^i(r_p^{i,j}) + \theta_k^{i,j}\, E^i(\mathfrak{r}_p^i), \tag{8}$$

where $\beta_k^{i,j}$, $\delta_k^{i,j}$, *and* $\theta_k^{i,j}$ *are the elasticities of capital flows to country-, fund-, and investor-*

[14]Here, Assumption 2.1 ensures that the "fixed" part of the portfolio shares, which depends on the ratio of the conditional covariance to the variance, is invariant whether the fund updates its shares or not and that the default shares are not significantly affected by any precautionary behavior. The investor-level hedging term, that loads on the news on the investor's overall portfolio return $E^i(\mathfrak{r}_p^i)$, depends on p in general, but becomes independent from p under the symmetry assumption we use for aggregation (Section 2.4).

level expectation surprises. The fund-level elasticity admits the further decomposition

$$\delta_k^{i,j} = \eta_k^{i,j} - \phi_k^{i,j} \Delta Cov_k^{i,j}, \tag{9}$$

where $\eta_k^{i,j} \propto 1 - p$ *is the co-ownership elasticity and* $\phi_k^{i,j} \Delta Cov_k^{i,j}$ *is the fund-level hedging adjustment. Explicit expressions for* $\beta_k^{i,j}$*,* $\eta_k^{i,j}$*,* $\phi_k^{i,j}$*, and* $\theta_k^{i,j}$ *are given in Appendix A.3.*

The two equations (8) and (9) are the structural representation that the empirical section will map to regressions. The country-level elasticity β comes from country-allocation regressions, the fund-level elasticity $\delta = \eta - \phi \Delta Cov$ comes from fund-flow regressions, and the ratio $\beta/\eta = p/(1-p)$ identifies the friction parameter, as we show next.

2.4 Aggregation and the role of the friction

We now aggregate the investor-fund flow surprises of Corollary 2.1 to the country level, and characterize how the portfolio friction shapes the aggregate response of capital flows to expectations.

From investor-fund flows to country flows. Total capital flows to country k are $A_k = \sum_{i=1}^{M} \sum_{j=1}^{\mathcal{J}(i)} A_k^{i,j}$, where $A_k^{i,j} = a_k^{i,j} \Omega^i$. We focus on $a_k = A_k/\Omega$, the share of global wealth $\Omega = \sum_{i=1}^{M} \Omega^i$ flowing to country k:

$$a_k = \sum_{i=1}^{M} \sum_{j=1}^{\mathcal{J}(i)} \frac{\Omega^i}{\Omega} a_k^{i,j}. \tag{10}$$

Scaling by the ex-ante share, the surprise in country-k flows is a weighted average of investor-fund surprises:

$$\frac{a_k - \bar{E}(a_k)}{\bar{E}(a_k)} = \sum_{i=1}^{M} \sigma_k^i \sum_{j=1}^{\mathcal{J}(i)} \sigma_k^{i,j} \frac{a_k^{i,j} - \bar{E}^i(a_k^{i,j})}{\bar{E}^i(a_k^{i,j})}, \tag{11}$$

where $\sigma_k^{i,j} = \bar{E}^i(A_k^{i,j})/\bar{E}^i(A_k^i)$ is fund j's ex-ante share in investor i's flows to k, and $\sigma_k^i = \bar{E}^i(A_k^i)/\bar{E}^i(A_k)$ is investor i's ex-ante share in aggregate flows to k. The investor-fund surprises, which are described in Corollary 2.1, receive more weight when the fund's average contribution to country k is larger.

Structure of expectations. The aggregate consequences of co-ownership spillovers depend on whether country-specific and fund-specific expectation shocks line up. We therefore impose a simple structure on expectations:

Assumption 2.2 (Structure of expectations) *We assume that expectations $E^i(r_k)$ are equal to the sum of a global component W^i and an idiosyncratic country-specific one l^i_k:*

$$E^i(r_k) = W^i + l^i_k \tag{12}$$

with $E(l^i_k) = 0$, $Cov(l^i_k, W^i) = 0$ and $Cov(l^i_k, l^i_{k'}) = 0$ for all i and and $k \neq k'$.

Under Assumption 2.2, the common component W^i can be recovered as the simple cross-country average of investor i's expectations, and the local components l^i_k as the country-specific residual. Substituting into the fund- and investor-portfolio return expectations gives a decomposition of fund and investor return news into a granular term and a global term:

$$E^i(r^{i,j}_p) = \Gamma^{i,j} + W^i, \qquad \Gamma^{i,j} \simeq \sum_{k \in \mathcal{S}(i,j)} w^{i,j}_k l^i_k = w^{i,j\prime} l^i, \tag{13}$$

$$E^i(\mathfrak{r}^i_p) = \Gamma^i + W^i, \qquad \Gamma^i \simeq \sum_{k=1}^{K} w^i_k l^i_k = w^{i\prime} l^i, \tag{14}$$

where $l^i = (l^i_1, \ldots, l^i_K)'$ stacks the local components and $w^i_k = \sum_j a^{i,j}_k / \sum_j \sum_k a^{i,j}_k$ is country k's share at the investor level. The granular components $\Gamma^{i,j}$ and Γ^i are weighted averages of the investor-specific country shocks l^i_k, with weights given respectively by fund-level and investor-level country shares. They will be key elements in the aggregation of capital flows and will play a key role for the co-ownership spillovers.

In order to aggregate capital flows, we define the aggregated version of the coefficients:

Definition 2.1 (Aggregate coefficients) *For $x \in \{\beta, \delta, \eta, \phi\Delta Cov, \theta\}$, define $x^i_k = \sum_{j=1}^{\mathcal{J}(i)} \sigma^{i,j}_k x^{i,j}_k$, $x_k = \sum_{i=1}^{M} \sigma^i_k x^i_k$ and $x = \sum_{k=1}^{K} \sigma_k x_k$, with $\sigma_k = \bar{E}^i(a_k)/\bar{E}^i(a)$ the ex-ante share of country k in the total equity investments.*

The aggregation result also relies on two technical assumptions — an orthogonality condition (Assumption A.1) that lets us aggregate the elasticity coefficients, and a symmetry condition (Assumption A.2) that lets us treat them as homogeneous across countries within a fund. Both are stated and discussed in Appendix A.4.

Combining the investor-fund flow surprises in Corollary 2.1, the aggregation formula (11), and the structure of expectations, we obtain the central aggregate result:

Proposition 2.2 *Under Assumptions 2.2, A.1, and A.2 (see Appendix A.4 for the latter two), with $\Theta = \beta + \delta + \theta$ and $\sigma^i = \bar{E}^i(A^i)/\bar{E}^i(A)$ the ex-ante share of investor i in total* *equity, country-k flow surprises decompose as:*

$$\frac{a_k - \bar{E}(a_k)}{\bar{E}(a_k)} = \underbrace{\beta\left(\sum_{i=1}^{M} \sigma_k^i (l_k^i - \Gamma^i)\right) + \delta\left(\sum_{i=1}^{M} \sigma_k^i \sum_{j=1}^{\mathcal{J}(i)} \sigma_k^{i,j} (\Gamma^{i,j} - \Gamma^i)\right)}_{\tilde{\Delta} a_k}$$
$$+ \underbrace{\Theta\left(\sum_{i=1}^{M} \sigma^i (W^i + \Gamma^i)\right)}_{\Delta a} \tag{15}$$

where $\beta \propto p$ *and* $\delta = \eta - (\psi \Delta Cov)$ *with* $\eta \propto 1 - p$.

Proof. See proof in Appendix A.4. ■

Proposition 2.2 decomposes country-k flow surprises into a *portfolio reallocation* component $\tilde{\Delta} a_k$ and a *portfolio growth* component Δa:

$$\frac{a_k - \bar{E}(a_k)}{\bar{E}(a_k)} = \underbrace{\frac{a_k - \bar{E}(a_k)}{\bar{E}(a_k)} - \frac{a - \bar{E}(a)}{\bar{E}(a)}}_{\tilde{\Delta} a_k} + \underbrace{\frac{a - \bar{E}(a)}{\bar{E}(a)}}_{\Delta a}, \tag{16}$$

where $a = A/\Omega$ and $A = \sum_{k=1}^{K} A_k$ is total equity. Portfolio reallocation $\tilde{\Delta} a_k$ captures changes in country k's share of equity flows –capital moving between countries. Portfolio growth Δa captures changes in total equity flows –capital moving into or out of equity overall. The proposition separates how each responds to expectations. Portfolio growth Δa is driven only by the investor-wide common components $W^i + \Gamma^i$, which raise the demand for equity across all countries and funds uniformly. Portfolio reallocation $\tilde{\Delta} a_k$ has two sources: $l_k^i - \Gamma^i$, the country-specific excess-return expectation relative to the rest of investor i's portfolio (with elasticity β), and $\Gamma^{i,j} - \Gamma^i$, the fund-specific excess-return expectation relative to the rest of investor i's portfolio (with elasticity δ). The first is the textbook excess-return motive; the second includes the textbook hedging motive and the co-ownership spillover.

Whether the friction matters for these objects is not obvious a priori. Reallocation depends on β and δ, both functions of p; growth depends on the aggregate $\Theta = \beta + \delta + \theta$, which mixes all three elasticities. The next corollary settles the comparative statics:

Corollary 2.2 *We assume that Assumptions A.1 and A.2 are satisfied. In that case,*

(i) β *is decreasing in* $1 - p$,

(ii) δ *is increasing in* $1 - p$ *and is positive for a large* $1 - p$,

(iii) Θ *is independent of* p,

(iv) $\beta/\eta = p/(1-p)$.

Proof. See proof in Appendix A.5. ■

The corollary provides four insights. First, the country-expectation elasticity β is dampened by the friction: when the funds' country allocation is sticky, capital flows respond less to country-k-specific news than they would in the frictionless benchmark (point (i)). Second, the friction inflates the response to the granular component. Because $\eta \propto 1-p$, as portfolios become stickier the co-ownership spillover grows; if $1-p$ is large enough that η dominates the hedging adjustment $\phi \Delta Cov$, then δ turns positive and the granular term generates extra capital-flow volatility (point (ii). Third, the friction does not affect the response to common components: Θ is the same as in the frictionless world (point (iii). Together, these three results imply that the friction reshapes the cross-country *portfolio reallocation* of capital but leaves the aggregate *portfolio growth* of equity unchanged.

In the remainder of the paper, we thus focus on portfolio reallocation $\tilde{\Delta} a_k$, which can be decomposed into three terms:

$$\tilde{\Delta} a_k = \underbrace{\beta\, \tilde{l}_k}_{\text{excess return}} + \underbrace{\eta\, \Gamma_k}_{\text{co-ownership spillover}} - \underbrace{\phi \Delta Cov\, \Gamma_k}_{\text{hedging}}, \tag{17}$$

where $\tilde{l}_k$ is a country-specific excess-return aggregator and Γ_k is a granular aggregator:

$$\tilde{l}_k = \sum_{i=1}^{M} \sigma_k^i \, (l_k^i - \Gamma^i), \tag{18}$$

$$\Gamma_k = \sum_{i=1}^{M} \sigma_k^i \sum_{j=1}^{\mathcal{J}(i)} \sigma_k^{i,j} \, (\Gamma^{i,j} - \Gamma^i). \tag{19}$$

We used the expression of $\tilde{\Delta} a_k$ in Proposition 2.2 and substituted $\delta = \eta - \phi \Delta Cov$ (Corollary 2.1). The friction increases the contribution of the granular term Γ_k to portfolio reallocation through $\eta \propto 1-p$, while it dampens the contribution of the country-specific excess-return through $\beta \propto 1-p$. β and η are thus key objects of interest that we will seek to identify.

Finally, as point (iv) of the corollary states, the ratio $\beta/\eta = p/(1-p)$ provides a model-based mapping from the data to the friction parameter p. If the elasticities β and η can be identified empirically, then their ratio pins down the implied portfolio updating frequency. The next section turns to the identification and estimation of these parameters.

3 Data and Empirical Analysis

This section identifies the structural elasticities derived in the model: β (the excess-return channel), η (the co-ownership spillover), and ϕ (the hedging adjustment). Together with the structural relation $\beta/\eta = p/(1-p)$ from Corollary 2.2, these estimates also pin down the portfolio-updating friction p. The next section then plugs these elasticities back into the model to quantify the contribution of each channel to the variance of expectation-driven capital-flow reallocation.

After describing the matched panel of investor expectations and mutual-fund allocations and the institutional setting that links the two, we map Corollary 2.1 into a regression specification that identifies β, η, and ϕ. Identification confronts two challenges. First, investor-specific expectations are observed only for a subset of the countries in each fund's portfolio; we handle this missing-variable problem with a granular-instrumental-variable strategy in the spirit of Gabaix and Koijen (2024). Second, measurement error in forecasts and reverse causality from capital flows to growth expectations are addressed by instrumenting with publicly available IMF forecasts.

3.1 Data and institutional setting

Our dataset combines economic expectations data from Consensus Economics with investor and mutual fund data from Emerging Portfolio Fund Research (EPFR).

Institutional setting. The financial institutions we study are typically global financial groups – global banks and asset managers – that conduct two activities relevant for our analysis. The first is in-house macroeconomic research: a forecasting department produces country-level forecasts of GDP growth and other indicators, which the institution reports to Consensus Economics. The second is asset management: through one or several mutual funds, the institution allocates capital across countries on behalf of end-investors who hold shares in those funds.

Throughout the paper, we refer to the financial institution as the "investor," to its in-house forecast as the "investor's expectation," and to the mutual funds managed by the financial institution as the "investor's funds". This terminology reflects the modeling assumption that the institution's in-house forecasts – propagated through internal communications, sales material, and investment committees – are the relevant information that shapes the allocation decisions made for and by its mutual-fund clients. Mapping this assumption to the data requires that the in-house forecast is a reasonable proxy for the information used by the decision-makers, namely, the end-investor allocating capital to the fund and by the fund manager allocating capital across countries within the fund. We relax this assumption in Section 3.2.

By using in-house forecasts, we are relying on expectations that are a better reflection of the decision-makers' subjective expectations, instead of the objective expectations based on econometric regressions used in the capital-flow literature to estimate investment elasticities so far. While this tradition assumes rational expectations, our approach allows for deviations from it, which is consistent with a now-substantial body of evidence rejects rational expectations in macroeconomic forecasting (Bordalo et al., 2020; Adam et al., 2025). Our matched data on the financial institutions' *own* GDP growth forecasts let us sidestep this issue.

Expectation dataset: Consensus Economics Data. We use forecast data from Consensus Economics, a survey firm that collects monthly projections from professional forecasters. Each month, respondents provide their current-year and next-year forecasts for key macroeconomic indicators for a range of countries. The dataset spans the period 1989–2023. Our primary variable of interest is the forecasted real GDP growth for 51 advanced and emerging economies. Consensus Economics reports the institutional affiliation of each forecaster, which we extract, clean, and match to the corresponding financial institutions reporting information in the EPFR mutual fund data. Throughout, we use investor i's month-t next-year GDP growth forecast for country k, denoted $E_t^i g_{k,t}^{\text{next year}}$, as the empirical proxy for the return news $E_t^i(r_{k,t+1})$ defined in Section 2.

Investor and mutual fund dataset: EPFR Data. EPFR provides monthly fund-level country allocations, cash shares, assets under management, weekly fund flows, and valuation changes. These data are widely used to study international equity and bond investments and capture between 5 and 20% of market capitalization for most countries; existing work shows they closely match CRSP and balance-of-payments data in terms of equity flows and returns.[15]

The EPFR data identify the financial institution managing each fund. We match these institutions to those reported by Consensus Economics using token-based fuzzy matching complemented by manual verification using additional sources on corporate relationships. Using this procedure, we match country allocations, flows, and forecasts for 52 countries and 64 investors. One limitation of the matched data is that we observe in-house expectations for only an average of 17% of countries into which our mutual funds invest (24% when

[15]See Jotikasthira et al. (2012); Miao and Pant (2012); Schmidt and Yesin (2022).

weighted by portfolio shares). We address this issue through the granular-instrumental-variable strategy described in Section 3.2.

Our matched set of investors and mutual funds is a representative subset of the EPFR universe.[16] Over our sample from January 2000 to December 2023, there are 3,428 mutual funds reporting their monthly allocations in the EPFR data, with the median fund managing 258 million USD in assets. Of these funds, 1,096 funds are matched to Consensus Economics data, with the median fund managing 272 million USD in assets; their assets and allocations closely resemble those of the full EPFR sample.[17]

To clean our data, we adopt the following steps. In our regressions, we keep countries that have forecast information and an allocation of at least 0.5% in the fund, resulting in a sample with 168,000 observations, 827 funds, 50 investors, and 46 countries. We also impose restrictions on the computation of fund-level expectations. We restrict the sample to countries with forecasts in at least 90% of periods to limit entry and exits, and to funds investing in at least 5 such countries and with forecast coverage exceeding 20% of portfolio weight. Regressions involving fund-level expectations thus exploit a smaller number of observations (38'000), funds (213), and investors (13).[18] The results that follow are not sensitive to our specific cleaning methodology, as our robustness analysis will show.

3.2 Identification of β, η, and ϕ

We now add time subscripts to the model and map the structural equations to empirically testable regressions, at the country-allocation level and at the fund level. We assume that the elasticities $\beta_k^{i,j}$, $\delta_k^{i,j}$, $\eta_k^{i,j}$, $\phi_k^{i,j}$, and $\theta_k^{i,j}$ defined in Corollary 2.1 are homogeneous across countries, investors, and funds, and we therefore drop the (i, j, k) indices. This homogeneity is the empirical counterpart of the symmetry condition (Assumption A.2) used in the aggregation result of Proposition 2.2. The identification strategy follows directly from Corollary 2.1.

Excess-return channel Equation (8) delivers a natural mapping to the data. Noting that $\frac{a_{k,t}^{i,j} - \bar{E}^i(a_{k,t}^{i,j})}{\bar{E}^i(a_{k,t}^{i,j})} \simeq \log(a_{k,t}^{i,j}) - \log(\bar{E}^i(a_{k,t}^{i,j}))$, and that $A_{k,t}^{i,j} = a_{k,t}^{i,j}\Omega_t^i$ Equation (8) can be rewritten as the following fund–country regression:

$$\log\left(A_{k,t}^{i,j}\right) = \beta\, E_t^i g_{k,t}^{\text{next year}} + \lambda_{k,t} + \lambda_t^{i,j} + \lambda_k^{i,j} + \epsilon_{k,t}^{i,j}, \tag{20}$$

[16]A fund is classified as passive if its country allocation tracks a buy-and-hold benchmark.

[17]These results are available upon request.

[18]The use of subjective expectations, which are not available for all fund-country pairs, thus limit our coverage of fund-level variables. However, when using the IMF forecasts as an instrument, we will be able to expand coverage.

where $A^{i,j}_{k,t}$ is fund j's total allocation to country k at month t and $E^i_t g^{\text{next year}}_{k,t}$ is used as a proxy for $E^i_t(R_{k,t+1})$.

The share of investor assets allocated to fund j is $a^{i,j}_t = A^{i,j}_t/\Omega^i_t$. Because we include fund-time fixed effects $\lambda^{i,j}_t$, the specification is equivalent to one with $\ln(a^{i,j}_t)$ as the dependent variable, with Ω^i_t absorbed in the fund-time fixed effects. The fund-time fixed effects then absorb the investor- and fund-level expectation surprises $\delta E^i_t(r^{i,j}_{p,t+1}) + \theta E^i_t(\mathfrak{r}^i_{p,t+1})$ from Corollary 2.1. Fund-time fixed effects also capture other unobserved developments at the investor level – including funding shocks identified in the literature and alternative investment opportunities – that could be correlated with expectations. Country-investor-fund fixed effects $\lambda^{i,j}_k$ absorb the time-invariant terms $-\beta \bar{E}^i(R_{k,t+1}) + \log(\bar{E}^i(a^{i,j}_{k,t}))$, capturing time-invariant fund preferences across countries. This specification provides an estimate for β, the elasticity to the country-level expectation. This elasticity reflects the reallocation between countries by fund managers.

Country-time fixed effects $\lambda_{k,t}$ play a crucial identification role. First, they account for changes in allocations mechanically driven by country asset prices. Second, they account for country growth and monetary policy that simultaneously drive the country's supply of capital and expectations, and for reverse causality from aggregate capital flows to growth expectations. Third, they also capture potential general-equilibrium effects that could bias the estimated elasticity downward. For instance, if all investors become optimistic about a country, capital flows into the country are mitigated by the equilibrium increase in the equity price. These global surges in optimism are absorbed by $\lambda_{k,t}$, so that the coefficient β identifies the impact of a change in expectations that is specific to investor i, and can be interpreted as a partial-equilibrium elasticity.

Results are reported in Table 1, Column (1), the response of mutual funds to investor forecasts is significant but relatively small: when an investor anticipates a 1 percentage point rise in a country's growth forecast, investment in that country increases by about 2.2% in all the funds managed by that investor, so a country with an initial 10% share will benefit from a 0.22 percentage point increase. This provides an estimate of β of 0.022 In Table D.1 in the Appendix, we provide the results for passive and active funds. Passive funds show no active reallocation, while active funds react to country expectations with a slightly higher elasticity of $\beta = 0.028$ (Columns (1) and (2)).

Co-ownership and hedging channels We next focus on the elasticity to fund-level expectations, which captures the co-ownership and hedging channels jointly. Equation (8)

VARIABLES	(1) log($A^{i,j}_{k,t}$)	(2) log($A^{i,j}_{k,t}$)	(3) log($A^{i,j}_{k,t}$)	(4) log($A^{i,j}_{k,t}$)	(5) log($A^{i,j}_{k,t}$) IV (boot SE)	(6) log($A^{i,j}_{k,t}$) IV (boot SE)
$E^i_t(g^{\text{next year}}_k)$	0.022***				0.051***	
	(0.007)				(0.012)	
$E^i_t(g^{j,\text{next year}}_p)$		0.186**				
		(0.074)				
$\Gamma^{i,j}_t$			0.277**	0.290**		0.343***
			(0.121)	(0.138)		(0.079)
$\Delta Cov^{i,j}_t \times \Gamma^{i,j}_t$				-0.173**		-0.176**
				(0.073)		(0.077)
$\Delta \log(Q^{i,j}_t)$		-0.011***	-0.011***	-0.011***		-0.010***
		(0.003)	(0.003)	(0.003)		(0.001)
$\Delta \log(Q^{i,j}_{t-1})$		-0.007**	-0.008***	-0.008**		-0.007***
		(0.003)	(0.003)	(0.003)		(0.001)
$\Delta \log(Q_{k,t})$					0.584***	
					(0.021)	
$\Delta \log(Q_{k,t-1})$					0.559***	
					(0.020)	
Observations	150,039	35,287	35,287	30,928	486,892	94,410
R-squared	0.974	0.927	0.926	0.926	0.943	0.904
Country-fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-time FE	Yes	No	No	No	No	No
Fund-time FE	Yes	No	No	No	Yes	No
Manager-country-time FE	No	Yes	Yes	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1: Fund-Country Allocations and Investor Expectations

Notes: Standard errors in parentheses. Columns (1)–(5) are OLS with analytic standard errors clustered at the manager–country level. Columns (6)–(7) report two-step IV estimates that use generated regressors from first-stage projections; their standard errors are computed via a pairs cluster bootstrap with 200 replications and clusters at the manager–country level, which propagates the first-stage estimation uncertainty into the reported standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

can be rewritten as:

$$\ln\left(A_{k,t}^{i,j}\right) = \eta\, E_t^i g_{p,t}^{j,\text{next year}} - \phi\, \Delta Cov_k^{i,j}\, E_t^i g_{p,t}^{j,\text{next year}} + \lambda_k^j + \lambda_{k,t}^i + \epsilon_t^{i,j}, \tag{21}$$

where the portfolio expectation $E_t^i g_{p,t}^{j,\text{next year}}$ proxies for fund-level return news $E_t^i(r_{p,t+1}^{i,j})$. The specification separately identifies the two elasticities: η as the coefficient on the linear term and $-\phi$ as the coefficient on its interaction with $\Delta Cov_k^{i,j}$. Cross-fund variation in $\Delta Cov_k^{i,j}$ thus disentangles co-ownership from hedging, and the combined elasticity $\delta = \eta - \phi\Delta Cov$ can be read off as the coefficient on the linear term in a specification that omits the interaction. Appendix B.1 details the construction of $\Delta Cov_k^{i,j}$, and Appendix B.2 reports its summary statistics.

The fixed effects absorb a rich set of confounders. Country-investor-time fixed effects $\lambda_{k,t}^i$ absorb the country- and investor-level surprises $\beta E_t^i(r_{k,t+1}) + \theta E_t^i(\mathfrak{r}_{p,t+1}^i)$ from Corollary 2.1, variations in the investor's total wealth $\log(\Omega_t^i)$, investor-specific outside investment opportunities and funding shocks, and the country-specific developments that were previously captured by $\lambda_{k,t}$. Country-investor-fund fixed effects $\lambda_k^{i,j}$ absorb the time-invariant terms $-\delta \bar{E}^i(R_{p,t+1}^{i,j}) + \log(\bar{E}^i(a_{k,t}^{i,j}))$.

We construct the portfolio expectation as a weighted average of country-level forecasts using the previous period's portfolio weights:

$$E_t^i g_{p,t}^{j,\text{next year}} = \sum_{k \in \mathcal{S}(i,j)} w_{k,t-1}^{i,j}\, E_t^i g_{k,t}^{\text{next year}}, \tag{22}$$

where $\mathcal{S}(i,j)$ is the set of countries in which fund j invests *and for which we observe investor i's expectations*, so the weights $w_{k,t-1}^{i,j}$ do not necessarily sum to one. We return to this missing-expectation issue below.

A potential concern is that the documented fund-level elasticity could reflect the well-known *flow-performance* relationship in mutual funds: high past returns mechanically generate inflows (Chevalier and Ellison, 1997; Sirri and Tufano, 1998), and managers whose in-house forecasts have been more optimistic are typically those whose funds have recently performed well, so the apparent expectation–flow link could be spurious. To address this concern, we add to Equation (21) a measure of the fund's portfolio return $\Delta\log(Q_t^j)$, derived from the underlying asset prices in the portfolio, together with its lag.[19] The estimated expectation elasticity reported below is therefore identified holding contemporaneous and recent past fund performance fixed.

[19]The results do not change if we construct $\Delta\log(Q_t^j)$ based on country-level MSCI indices, or if we include additional lags to capture the slower retail-investor response documented in the flow-performance literature.

Column (2) of Table 1 reports the results for Equation (21), without the interaction term. In that case, the estimated impact of the fund portfolio corresponds to the δ elasticity, that combines the co-ownership and hedging channels. The investor's portfolio expectations are positively associated with the flows allocated to country k in the portfolio: an increase in the expected portfolio GDP growth by one percentage point is associated with an increase in investor allocations to the fund by about 19 percent.

Missing-expectation issue and granular instrument The coverage-weighted proxy in Equation (22) sums only over countries with observed forecasts, $\mathcal{S}(i,j)$. The true fund-level expectation also loads on the unobserved set $\tilde{\mathcal{S}}(i,j)$, generating a missing-variable bias that is not fully absorbed by the fixed effects.[20]

To address this, we exploit the structure of expectations from Assumption 2.2, $E_t^i g_{k,t}^{\text{next year}} \simeq W_t^i + l_{k,t}^i$, and adopt a granular-instrumental-variable strategy à la Gabaix and Koijen (2024). The simple cross-country average over the observed set, $\frac{1}{K(i,j)} \sum_{k \in \mathcal{S}(i,j)} E_t^i g_{k,t}^{\text{next year}} \simeq W_t^i$, estimates the investor-common component, and the empirical counterpart of the granular term $\Gamma^{i,j}$ in Equation (13) is

$$\Gamma_t^{i,j} = \sum_{k \in \mathcal{S}(i,j)} w_{k,t-1}^{i,j} \left[E_t^i g_{k,t}^{\text{next year}} - \frac{1}{K(i,j)} \sum_{k \in \mathcal{S}(i,j)} E_t^i g_{k,t}^{\text{next year}} \right] \simeq \sum_{k \in \mathcal{S}(i,j)} w_{k,t-1}^{i,j} \, l_{k,t}^i, \qquad (23)$$

where $K(i,j)$ is the number of countries in $\mathcal{S}(i,j)$. Since $Cov(l_{k,t}^i, W_t^i) = 0$ and $Cov(l_{k,t}^i, l_{k',t}^i) = 0$ for $k \neq k'$ by Assumption 2.2, $\Gamma_t^{i,j}$ is orthogonal to expectations on the missing countries in $\tilde{\mathcal{S}}(i,j)$, and the missing-variable bias is corrected.

This construction is equivalent to a shift-share design (Borusyak et al., 2022): the lagged portfolio weights $w_{k,t-1}^{i,j}$ play the role of shares and the country-level forecast deviations $l_{k,t}^i$ that of shifts. The identifying assumption is the standard one – that the shifts $l_{k,t}^i$ are quasi-random conditional on the shares.

Column (3) reports the regression in which the granular residual $\Gamma_t^{i,j}$ replaces $E_t^i g_{p,t}^{j,\text{next year}}$. The coefficient is positive and significant at 0.28. Column (4) adds the interaction term, which now helps us disentangle the co-ownership channel from the hedging channel. The interaction term is significantly negative at -0.17, consistent with the model and implying $\phi = 0.17$. Hedging at play: investors do consider the covariance of returns and the potential for risk-sharing (when ΔCov is negative), as well as arbitrage opportunities (when ΔCov

[20] The fixed effects $\lambda_{k,t}^i$ would suffice if the bias were proportional to a uniform investor-time common component W_t^i. But the loading on W_t^i in our proxy is $\sum_{k \in \mathcal{S}(i,j)} w_{k,t-1}^{i,j}$, which varies across funds with the portfolio coverage and is therefore outside the span of $\lambda_{k,t}^i$. The granular construction below replaces the regressor with a term that is mean-zero by construction across the observed set, closing this channel.

is positive), when reacting to their expectations. The coefficient of the linear term is 0.24, implying $\eta = 0.29$, not very different from the estimated δ. This is consistent with values of $\Delta Cov_k^{i,j}$ that is symmetrically distributed across positive and negative values, with a low average of 0.05 (see Appendix B.2).

IV estimations We have so far made the assumption that our Consensus Economics data, which collects the forecasts produced by the financial institutions' forecasting departments, are a good representation of the decision-makers' (the end-investors' and the fund managers') information. We have also made the assumption that the fund portfolios' exposure to different countries does not influence the forecasts produced by the forecasting teams. If these assumptions are violated, then we are facing, respectively, a measurement error and a reverse causality issue.

We address these two issues by using the contemporaneous IMF growth forecasts as an instrumental variable. As the IMF forecasts are publicly available, they represent a public signal that would equally affect the decision-maker and the forecaster, thus overcoming the measurement error issue.[21] They are also not directly affected by the funds' exposure to different countries, thus overcoming the reverse causality issue. Note also that while the subjective expectation is missing for many countries in the fund's portfolios, an IMF forecast is in general available. Using the IMF forecasts, we can thus compute a fund-level expectation with a broader coverage than with the subjective Consensus Economics expectations. We thus perform the first stage on the reduced sample of funds with subjective expectations, and the second stage on an extended sample with IMF expectations and a more comprehensive fund-wide expectation coverage.

The results are shown in Columns (5) and (6) of Table 1. Column (5) estimates the β elasticity, where $E_t^i(g_{k,t}^{\text{next year}})$ is instrumented with $E_t^{IMF}(g_{k,t}^{\text{next year}})$. Note that, because $E_t^{IMF} g_{k,t}^{j,\text{next year}}$ is country- and time-specific, but not investor specific, we cannot use country-time fixed effects. We thus control for valuation effects by adding the change in the country log equity prices $\Delta \log(Q_{k,t})$ and its first lag, using the MSCI equity price index. This has a significant impact on the estimated elasticity, as it increases to $\beta = 0.051$. Similarly, as Table D.1 in the Appendix shows, passive funds are still inelastic, while active funds have a higher elasticity $\beta = 0.067$.

Column (6) estimates η, where $E_t^i(g_{p,t}^{j,\text{next year}})$ is instrumented with $E_t^{IMF}(g_{p,t}^{j,\text{next year}})$, with $E_t^{IMF}(g_{p,t}^{j,\text{next year}})$ computed on the same universe as $E_t^i g_{p,t}^{j,\text{next year}}$ in the first stage, but on the whole available universe in the second stage (reported). η increases slightly to 0.34. This suggests that the in-house growth forecasts are a good measure of the end-investor

[21] See Appendix C.2 for a detailed formalization of the measurement error issue.

information, but are more weakly correlated with the fund manager's information. The fact that the η elasticity does not change much when extending the scope of the fund's expectation measure suggests that the granular residual handles the missing expectation issue already quite well. The fact that the results extend to a sample that is three times as large also show that our results are robust.

Implied portfolio-updating frequency The estimates of β and η provide a direct estimate of the portfolio friction. By point (iv) of Corollary 2.2, the portfolio adjustment probability satisfies $p = \beta/(\beta + \eta)$. Our OLS estimates imply $p = 0.022/(0.022 + 0.29) \simeq 0.07$, corresponding to portfolio updating every 14 months for the average fund; for active funds, $p \simeq 0.10$, or once every 10 months. Our IV estimates imply $p = 0.051/(0.051 + 0.34) \simeq 0.13$, corresponding to portfolio updating every 8 months for the average fund; for active funds, $p \simeq 0.17$, or once every 6 months.

These values are lower than the estimates of Bacchetta and van Wincoop (2017). One potential explanation is that our use of subjective expectations that are more relevant to the decision-makers helps us estimate a larger elasticity.

Taken together, the estimates validate the model's mechanism: flows into funds respond strongly to investors' fund-level expectations, while cross-country allocations within funds respond only weakly to country-specific expectations. The fund-level elasticity is dominated by the co-ownership spillover η rather than by the hedging adjustment $\phi\Delta Cov$, which is small because ΔCov averages near zero. With (β, η, ϕ) now identified, the remaining quantitative question is how much of expectation-driven capital-flow reallocation is accounted for by each of the three channels in Equation (17). The next section answers this, taking the IV point estimates as the baseline calibration.

3.3 Robustness

We perform several robustness checks. We consider alternative assumptions about the expectation formation of forecasters and decision-makers, the role of individual investors, and alternative data cuts.

Alternative assumptions about expectation formation So far, we have assumed that the forecaster and the decision-maker (the end-investor or fund manager) process information in the same way. They may not. The decision-maker may, for instance, perceive her private information as more precise than the forecaster does – whether or not this belief is objectively correct – and therefore place less weight on the public IMF signal and more weight on her own private signal (as documented by, e.g., Broer and Kohlhas, 2024; Adam et al., 2025). She may be discounting the forecaster expectation against other sources of information. Alternatively, the forecaster may face career-related strategic concerns that the decision-maker does not share (e.g., Ottaviani and Sørensen, 2006; Gemmi and Valchev, 2025). These specifications generate asymmetries in the way the IMF forecast ends up influencing the forecaster and decision-maker. Under either source of asymmetry, the IMF-forecast IV is biased.

We show in Appendix C.3 that, in all three cases cases, the structural elasticity is bracketed by a complementary pair of estimators: (i) the IMF-forecast IV that additionally controls for realized (vintage) GDP growth, and (ii) the vintage-growth IV that additionally controls for the IMF forecast. The intuition is that each first stage identifies the *forecaster*'s weight on a single signal: the public signal (in the controlled IMF-IV case) and the private signal (in the controlled vintage-IV case). The second-stage estimate is then biased by the weight put by the *decision-maker* on that signal relative to the forecaster. For instance, if the decision-maker believes her private information is more precise than the forecaster's – perhaps because she has access to her institution's proprietary research or to deeper country expertise – she places a lower weight on the IMF forecast and a higher weight on her own private signal, as compared to the forecaster. The controlled IMF-IV estimate then *understates* the elasticity, and the controlled vintage-IV estimate *overstates* it. The bounds reverse when the decision-maker instead believes her private information is less precise. The same approach applies to nested information sets and heterogeneous strategic motives in the use of public and private information because they generate the same kind of asymmetric weighting.

Figure E.1 in the Appendix reports the bounds for β and η. The two estimates are not statistically distinguishable from each other and their confidence intervals contain our baseline IMF-IV estimate from Table 1, suggesting that the asymmetry between the forecaster and the decision-maker is empirically small. However, even though we cannot distinguish it statistically from the lower bound, we can use the estimated upper bound for β, 0.075, together with the estimated lower bound for η, 0.36, to obtain an upper bound for p of 0.17, which remains close to our baseline of $p = 0.13$. We will use these values in one of our quantitative robustness exercises.

The influence of individual investors Second, we consider the potential influence of individual investors in our results. Indeed, our panel is imbalanced, with some individual investors accounting for a disproportionate share of observations. We produce results by removing one investor at a time, focusing on the 10 investors with the highest observation share, to determine whether our results are driven by one single investor. Figure E.2 in the Appendix provides the results. We can see that the leave-one-out results are stable and broadly in the line with the full-sample results.[22]

Alternative data cuts Finally, we consider alternative data cuts. In our baseline, we focus on fund-country pairs with average fund allocations above 0.5%. We now consider also the case with no filtering on the allocations, with allocations above 1% and above 3%. In the baseline, we also compute fund-level expectations and their granular residuals for funds for which the expectation data covers at least 20% of the portfolio, and funds with at least 6 countries. We consider now also the case with at least 10 countries, and with at least 10%, 30% or 50% coverage. The results are shown in Figure E.3 in the Appendix. The results are similar across the specifications.

4 Quantifying Co-ownership Spillovers

We focus on the contribution of co-ownership spillovers to portfolio reallocation rather than aggregate portfolio growth because Corollary 2.2 implies that portfolio growth is unaffected by the portfolio-updating friction, while reallocation is shaped by it. In this quantitative exercise, we are not restricted by the availability of subjective expectations and are able to exploit *all* the fund-level information available in EPFR.

Plugging our IV estimates of (β, η, ϕ) into the three-channel decomposition of expectation-driven capital-flow reallocation in Equation (17), we find that co-ownership spillovers account for 70% of the cross-country variance of reallocation, the excess-return channel for 29%, and the hedging channel for less than 1%. Adjusting conservatively for the share of the granular term that mechanically reflects own-country expectations brings the co-ownership contribution to 57% and raises the excess-return contribution to 43%. Either way, co-ownership spillovers explain a substantial fraction of expectation-driven reallocation.

We then dissect the anatomy of these spillovers. We show that what drives them is the *global structure* of portfolios – the cross-country dispersion in average portfolio weights – not the heterogeneity of individual investors. Quantitatively, *country* granularity dominates *investor* granularity by about two orders of magnitude. This implies that our results generalize outside our EPFR dataset as long as the portfolio structure in this dataset is representative.

[22] One exception is the OLS estimate of the β elasticity obtained without the largest investor, which is non-significant and –marginally– significantly different from the baseline. However, the IV estimate is in line with the baseline. It is likely that the forecasts of this particular investor differ more significantly from the fund managers', generating a more severe measurement error.

4.1 Decomposing capital flow reallocation

The three-channel decomposition of reallocation introduced in Equation (17) applies period by period, with $\tilde{l}_{k,t}$ and $\Gamma_{k,t}$ defined as the time-t analogs of (18)–(19), constructed from contemporaneous weights $\sigma^i_{k,t}$, $\sigma^{i,j}_{k,t}$ and time-t expectation residuals $l^i_{k,t}$, Γ^i_t, $\Gamma^{i,j}_t$. Our purpose is to evaluate the contribution of each of the three terms in (17) to the variance of capital-flow reallocation. We parametrize β, η, ϕ, and ΔCov using our estimates from Section 3, and compute $\Gamma_{k,t}$ and $\tilde{l}_{k,t}$ from fund allocations and investor GDP growth expectations.

Measurement and calibration $\tilde{l}_{k,t}$ captures investors' *excess* optimism about country k relative to their overall portfolios, aggregated using investors' shares in flows to k $\sigma^i_{k,t}$. $\Gamma_{k,t}$ captures investors' *excess* optimism about funds investing in k relative to their overall portfolios, aggregated using fund- and investor-level flow shares $\sigma^i_{k,t}$ and $\sigma^{i,j}_{k,t}$.

We construct the expectation components as

$$l^i_{k,t} = E^i_t g^{\text{next year}}_{k,t} - \frac{1}{K}\sum_{k=1}^{K} E^i_t g^{\text{next year}}_{k,t},$$

$$\Gamma^i_t = \sum_{k=1}^{K} w^i_{k,t}\left(E^i_t g^{\text{next year}}_{k,t} - \frac{1}{K}\sum_{k=1}^{K} E^i_t g^{\text{next year}}_{k,t}\right),$$

$$\Gamma^{i,j}_t = \sum_{k\in\mathcal{S}(i,j)} w^{i,j}_{k,t}\left(E^i_t g^{\text{next year}}_{k,t} - \frac{1}{\mathcal{K}(i,j)}\sum_{k\in\mathcal{S}(i,j)} E^i_t g^{\text{next year}}_{k,t}\right),$$

Because expectations are missing for many investor–country pairs, we expand coverage by imputing missing expectations using an estimated expectation process; the expanded panel contains 468 investors, 2,282 funds, and 2,660,000 monthly observations (Appendix B.3).[23]

We estimate the flow-share weights as $\sigma^i_{k,t} = A^i_{k,t}/A_{k,t}$ and $\sigma^{i,j}_{k,t} = A^{i,j}_{k,t}/A^i_{k,t}$, then compute $\tilde{l}_{k,t}$ and $\Gamma_{k,t}$ from (18) and (19) using contemporaneous weights $\sigma^i_{k,t}$, $\sigma^{i,j}_{k,t}$ and $w^{i,j}_{k,t}$ (results are similar with lagged or average weights).

We set $\beta = 0.051$, $\eta = 0.34$, and $\phi = 0.17$, reflecting our IV point estimates from Section 3. We set $\Delta Cov = 0.07$, the average of $\Delta Cov^{i,j}_k$ across all fund-country pairs (see Table B.2 in Appendix B.2).

[23] Because there are some countries in which investor i invests and for which we do not have expectations (real or imputed), we use the formulas $\Gamma^{i,j}_t = \sum_{k\in\kappa(i,j)} w^{i,j}_{k,t}\left[E^i_t g^{\text{next year}}_{k,t} - \sum_{k\in\kappa(i,j)} E^i_t g^{\text{next year}}_{k,t}/\kappa^{i,j}\right]$, and $\Gamma^i_t = \sum^K_{k\in\kappa(i)} w^i_{k,t}\left[E^i_t g^{\text{next year}}_{k,t} - \sum^K_{k\in\kappa(i)} E^i_t g^{\text{next year}}_{k,t}/\kappa^i\right]$, where κ^i and $\kappa^{i,j}$ are the set of countries for which we observe investor i's expectations or impute expectations at the fund and investor level. This amounts to setting the expectations of these countries to zero, so the estimated co-ownership spillovers will be under-estimated. In this sense, we provide a conservative estimate of the variance of $\Gamma_{k,t}$.

Expectations			
Variance	$V\left(\tilde{l}_{k,t}\right)$	$V\left(\Gamma_{k,t}\right)$	
Value	.91	.10	
	[.19,1.79]	[.02,.19]	
Implied capital flows			
Coefficients	β	η	$-\phi\Delta Cov$
	.051	.34	-.01
Variance	$V\left(\beta\tilde{l}_{k,t}\right)$	$V\left(\eta\Gamma_{k,t}\right)$	$V\left(-\phi\Delta Cov_{k,t}\right)$
Value	.0025	.0066	.0000
	[.0005,.0053]	[.0011,.0120]	[.0000,.0000]
Contribution	29%	70%	.1%
	[11%,61%]	[39%,89%]	[.1%,.1%]
Variance	$V\left(\beta\tilde{l}_{k,t}+\eta\Gamma_{k,k,t}\right)$	$V\left(\eta\Gamma_{k,t}-\eta\Gamma_{k,k,t}\right)$	$V\left(-\phi\Delta Cov_{k,t}\right)$
Value	.0043	.0059	.0000
	[.0008,.0103]	[.0009,.0110]	[.0000,.0000]
Contribution	43%	57%	.1%
	[15%,79%]	[21%,85%]	[.1%,.1%]

Table 2: Variance decomposition of expectation-driven capital flow reallocation

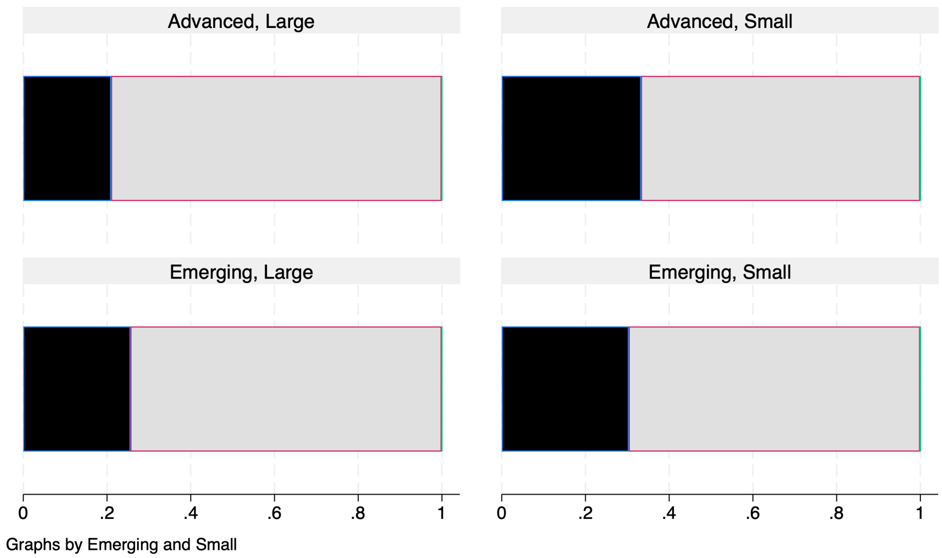
Note: We report the average variances of expectations and implied capital flow reallocation across countries, as well as the 10^{th} and 90^{th} percentile (in brackets). The contributions are the ratio of the variance to the total variance of expectation-driven flow reallocation.

Contributions Table 2 reports the variance of expectations and the contribution of each of the three channels in (17) – excess returns $\beta\tilde{l}_{k,t}$, co-ownership spillovers $\eta\Gamma_{k,t}$, and hedging $-\phi\Delta Cov\,\Gamma_{k,t}$ – to the variance of expectation-driven capital flow reallocation $\tilde{\Delta}a_{k,t}$, with cross-country averages and $[p_{10},p_{90}]$ ranges in brackets. First, consider the variance of expectations (upper part of Table 2). The variance of the idiosyncratic, country-specific expectations, $\tilde{l}_{k,t}$ (0.91), is 9 times higher on average than the variance of the granular term $\Gamma_{k,t}$ (0.10). Despite this, the co-ownership term contributes more than twice as much to the variance of reallocation as the excess-return term: co-ownership spillovers explain on average 70% of the variance, while the excess return term explains 29% (lower part of the Table). The hedging component is negligible at less than 1%. This is because β is much lower than η.

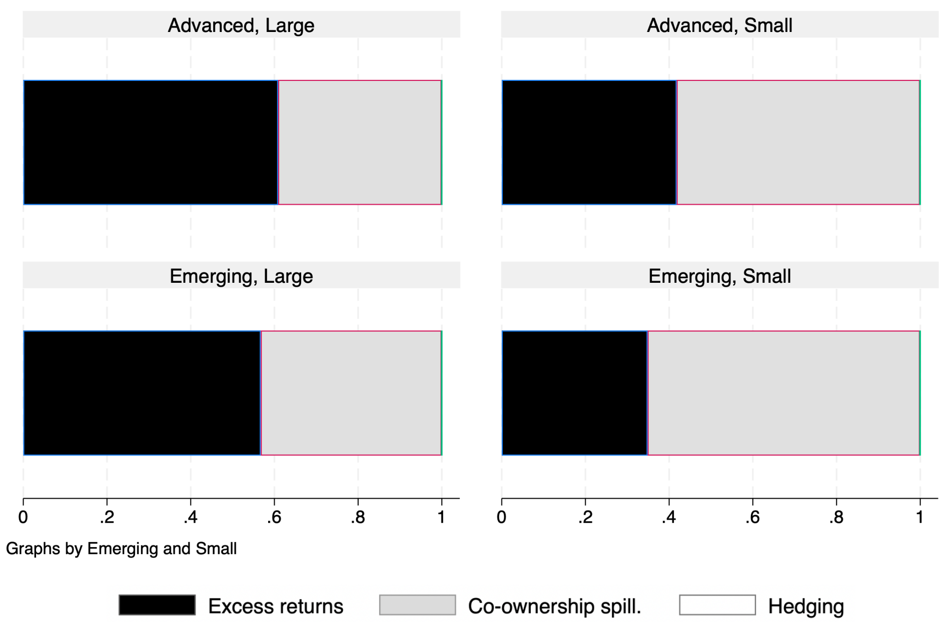
Figure 1 splits countries by development status (Advanced/Emerging) and portfolio size (Large/Small). A "Large" country has an average share in portfolios in the top quartile (i.e., higher than 3.5%). The Large countries include the United States, the United Kingdom, Japan, Germany, France, Switzerland, the Russian Federation, South Korea, China, India,

Figure 1: Variance decomposition of expectation-driven capital flows

a) Implied capital flows



b) Implied capital flows (adjusted)



Note: Panel a) represents the contribution of the variance of $\beta\tilde{l}_{k,t}$, $\eta\Gamma_{k,t}$ and $-\phi\Delta Cov_{k,t}$ to the variance of implied capital flow reallocation. Panel b) represents the contribution of the variance of $\beta\tilde{l}_{k,t} + \eta\Gamma_{k,k,t}$, $\eta\Gamma_{k,t} - \eta\Gamma_{k,k,t}$ and $-\phi\Delta Cov_{k,t}$ to the variance of implied capital flow reallocation.

Mexico, and Brazil. The excess-return contribution is slightly higher for small economies (about 32%) than for large economies (about 23%).

The granular aggregator $\Gamma_{k,t}$ for country k also loads on investors' expectations about k itself, because k appears in the very portfolios over which the aggregator is computed. For a large country, this own-country loading is mechanically non-trivial – investors' expectations about, say, the US enter $\Gamma_{\text{US},t}$ through every fund that holds the US – and part of what we labelled a "co-ownership spillover" is really the country's own excess return acting through the granular term. To be conservative about how much of the reallocation we attribute to spillovers, we therefore isolate the own-country piece

$$\Gamma_{k,k,t} = \sum_{i=1}^{M} \sigma^i_{k,t} w^i_{k,t} (l^i_{k,t} - \Gamma^i_t) \tag{24}$$

and reclassify $\eta\,\Gamma_{k,k,t}$ as part of the excess-return channel rather than the spillover channel. This yields a diminished co-ownership term $\eta(\Gamma_{k,t} - \Gamma_{k,k,t})$ and an augmented excess-return term $\beta\tilde{l}_{k,t} + \eta\Gamma_{k,k,t}$. Under this adjustment, the average co-ownership contribution falls from 70% to 57% and the excess-return contribution rises from 29% to 43%, with the change concentrated where the own-country loading bites: in Panel b) of Figure 1, the co-ownership share among Large economies drops from 76% to 41%, while for Small countries it edges down only from 68% to 62%.

4.2 Dissecting co-ownership spillovers

The role of co-ownership linkages Using the definition of $\Gamma^{i,j}_t$ and Γ^i_t, we can notice that $\Gamma^{i,j}_t - \Gamma^i_t$ is a weighted average of the country-specific expectations:

$$\Gamma^{i,j}_t - \Gamma^i_t = \sum_{k=1}^{K} \Delta w^{i,j}_{k,t} l^i_{k,t}$$

where the weight $\Delta w^{i,j}_{k,t} = w^{i,j}_{k,t} - w^i_{k,t}$ is a relative allocation. It is the difference between the country portfolio share in the fund and in the full investor portfolio. What makes this term relevant is the extent to which the fund portfolios are concentrated relative to the investor's portfolio.

The granular component that is relevant for country k, $\Gamma_{k,t}$ can then itself be written as a weighted average of all the country-specific expectations:

$$\Gamma_{k,t} = \sum_{k'=1}^{K} \sum_{i=1}^{M} \sigma_{k'}^{i} \Delta w_{k,k',t}^{i} l_{k',t}^{i} \tag{25}$$

where the country-specific expectations, $l_{k',t}^{i}$, are weighted by the share of investor i in the total flows to k $\sigma_{k,t}^{i}$ and by $\Delta w_{k,k',t}^{i}$, with

$$\Delta w_{k,k',t}^{i} = \left(\sum_{j=1}^{J(i)} \sigma_{k,t}^{i,j} \Delta w_{k',t}^{i,j} \right) \tag{26}$$

$\Delta w_{k,k',t}^{i}$ measures the *co-ownership linkages* between country k and country k' at the investor level. It is a weighted average of country k''s relative allocations across investor i's funds, where the weights are represented by the importance of a given fund in the total flows of investor i to country k. It thus reflects the exposure of country k to country k': investor i's expectations about country k' will matter to country k if the funds managed by i that invest in country k also invest a large share in country k'.

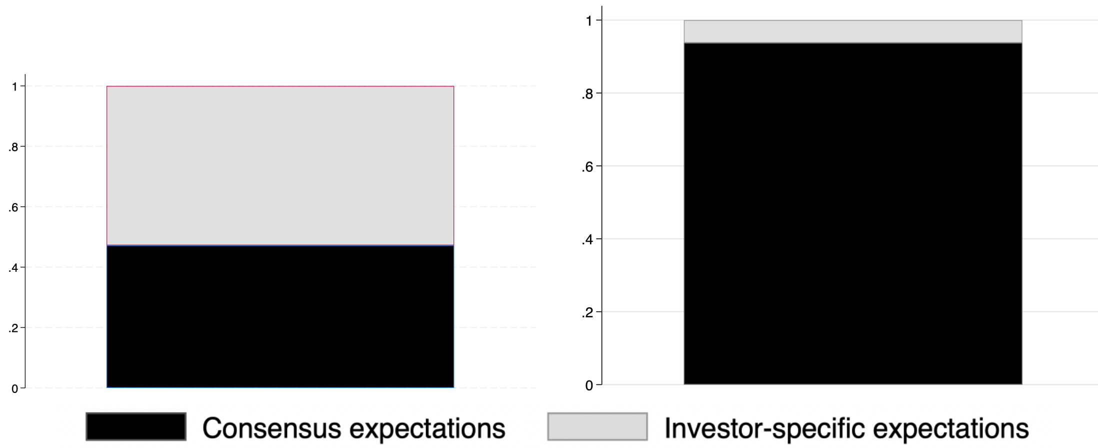
Country granularity versus investor granularity Equation (25) provides a definition of the granular term as an average of *investor-specific* expectations $l_{k',t}^{i}$ weighted by co-ownership linkages at the *investor* level. Here, we provide a further decomposition showing the distinct role of the global architecture of portfolios as opposed to the role of specific investors.

To do so, notice that the idiosyncratic expectations $l_{k,t}^{i}$ are both country-specific and investor-specific. We therefore decompose them into the average country-specific component of expectations across investors for country k, $l_{k,t} = (\sum_{i=1}^{M} l_{k,t}^{i})/M$ and their investor-specific component $l_{k,t}^{i} - l_{k,t}$. We can then decompose the granular term into a term that is driven by "country granularity", and two terms that are driven by "investor granularity":

$$\Gamma_{k,t} = \underbrace{\sum_{k'=1}^{K} \Delta w_{k,k',t} l_{k',t}}_{\Gamma_{k,t}^{country}} + \underbrace{\sum_{k'=1}^{K} \sum_{i=1}^{M} \sigma_{k,t}^{i} \left(\Delta w_{k,k',t}^{i} - \Delta w_{k,k',t} \right) (l_{k',t}^{i} - l_{k',t}) + \sum_{k'=1}^{K} \Delta w_{k,k',t} \sum_{i=1}^{M} \left(\sigma_{k,t}^{i} - \frac{1}{M} \right) (l_{k',t}^{i} - l_{k',t})}_{\Gamma_{k,t}^{investor}} \tag{27}$$

Figure 2: Variance decomposition of expectations and co-ownership spillovers

a) Expectations b) Co-ownership spillovers



Note: The figure represents the relative contributions of consensus expectations $l_{k,t}$ and investor-specific expectations $l^i_{k,t} - l_{k,t}$, to expectations $l^i_{k,t}$ themselves (Panel a)), and to co-ownership spillovers $\Gamma_{k,t}$ (Panel b)). In Panel a), the contribution of consensus expectations $l_{k,t}$ to expectations $l^i_{k,t}$ is measured as $V(l_{k,t})/V(l^i_{k,t})$, and the contribution of investor-specific expectations $l^i_{k,t} - l_{k,t}$ to expectations $l^i_{k,t}$ is measured as $V(l^i_{k,t} - l_{k,t})/V(l^i_{k,t})$. In Panel b), the contribution of consensus expectations to co-ownership spillovers $\Gamma_{k,t}$ is measured as $V(\Gamma^{country}_{k,t})/V(\Gamma^i_{k,t})$, and the contribution of investor-specific expectations to co-ownership spillovers $\Gamma_{k,t}$ is measured as $V(\Gamma^{investor}_{k,t})/V(\Gamma^i_{k,t})$.

where $\Delta w_{k,k',t}$ is an average of the co-ownership linkages between country k and country k' across all investors, weighted by the importance of a given investor in the total flows to country k:

$$\Delta w_{k,k',t} = \left(\sum_{i=1}^{M} \sigma^i_{k,t} \Delta w^i_{k,k',t} \right) \tag{28}$$

The first term in Equation (27) shows that "consensus expectations" $l_{k,t}$ will matter if average co-ownership spillovers are granular. We refer to this term as the "country granular component" because its importance is driven by the granularity of countries in global portfolio shares. Investor-specific expectations $l^i_{k,t} - l_{k,t}$ will matter when the linkages are heterogeneous at the investor level (first term), and when the investor's contribution to country k capital flows is granular (second term). The second and third terms thus constitute the "investor granular component".

Figure 2 shows the relative contributions of consensus expectations and investor-specific expectations, to expectations $l^i_{k,t}$ themselves (Panel a)), and to co-ownership spillovers $\Gamma_{k,t}$ (Panel b)). The variance of $l^i_{k,t}$ is due for almost equal shares to the consensus and investor-specific components. However, consensus expectations contribute to more than 95% to the variance of $\Gamma_{k,t}$. This is due to the granularity of the associated weights, which can be measured by their standard deviation (Gabaix, 2011; di Giovanni et al., 2014). The weights of the consensus expectations, the average co-ownership linkages $\Delta w_{k,k',t}$, have a much higher standard deviation (by a factor of 2 orders of magnitude) than the weights of the investor-specific expectations ($\sigma^i_{k,t}(\Delta w^i_{k,k',t} - \Delta w_{k,k',t})$ and $\Delta w_{k,k',t}(\sigma^i_{k,t} - 1/M)$), which explains the disproportionate contribution of consensus expectations (see Figure E.4 in the Appendix).

Implications for external validity and data sparsity. This implies that co-ownership spillovers boil down, quantitatively, to the contribution of country granularity, and that only the global architecture of portfolios matter:

$$\Gamma_{k,t} \simeq \underbrace{\sum_{k'=1}^{K} \Delta w_{k,k',t} l_{k',t}}_{\Gamma^{country}_{k,t}} \tag{29}$$

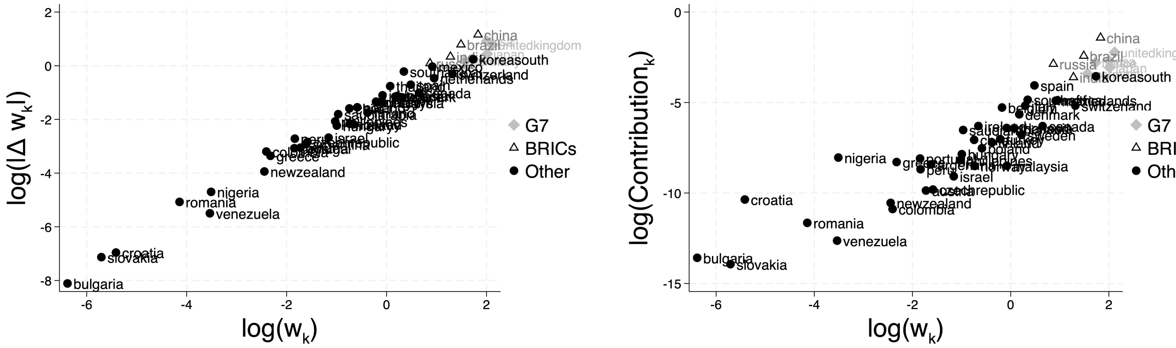
This is reassuring for the external validity of our exercise: the aggregate co-ownership spillover is governed almost entirely by (i) consensus country shocks $l_{k'}$ and (ii) average co-ownership linkages $\Delta w_{k,k'}$. The contribution of investor-level heterogeneity in expectations and in portfolios is negligible. Quantifying the aggregate effect therefore does not require a full account of the universe of investors. It only requires that the observed portfolios deliver a representative estimate of $\Delta w_{k,k'}$ and that we observe consensus forecasts.

Contributors Noting that the variance of country k co-ownership spillovers can be written as $\eta^2 V(\Gamma_k)$, and that $V(\Gamma_k) = \sum_{l=1}^{K} (\Delta w_{k,l})^2 V(l_l)$, we compute a measure of the contribution of country k' to country k co-ownership spillovers as follows:

$$Contribution_{k,k'} = \frac{(\Delta w_{k,k'})^2 V(l_{k'})}{\sum_{l=1}^{K} (\Delta w_{k,l})^2 V(l_l)} \tag{30}$$

We find that the large contributors are mostly countries with large allocations in portfolios. Figure E.5 in the appendix shows the average contribution of country k' across our sample, computed as $Contribution_{k'} = \sum_{k=1}^{K} \sigma_k Contribution_{k,k'}$. Among emerging economies, those are the BRICs (Brazil, Russian Federation, India, China), but also South Africa, South Korea and Mexico. Among advanced economies, those are the main G7 countries: UK, the US, France, Japan and Germany. Next, we explore the role of country size in portfolios. Figure E.6 in the appendix shows that the variation in the contribution is driven mostly by

Figure 3: Role of country average allocation



Note: The left panel represents the scatter plot of the average allocations $w_k = \sum_{i=1}^{M} \sigma_k^i w_k^i$ against the log of the average absolute value of co-ownership linkages $|\Delta w_k| = \sum_{k'=1}^{K} \sigma_{k'} |\Delta w_{k',k}|$. The right panel represents the scatter plot of the average allocations $w_k = \sum_{i=1}^{M} \sigma_k^i w_k^i$ against the log of average contributions $Contribution_k = \sum_{k'=1}^{K} \sigma_{k'} Contribution_{k',k}$.

the average absolute weights $|\Delta w_{k,k'}|$, not by the idiosyncratic volatility $V(l_{k'})$. The country volatility is not per se a systematic source of contribution. For instance, Nigeria, Argentina, Greece and Venezuela have volatile expectations but do not contribute meaningfully to co-ownership spillovers. These average absolute weights $|\Delta w_{k,k'}|$ are highly correlated with the average shares in portfolios $w_{k'}$, resulting in a high correlation between the average portfolio shares and the contributions, as shown in Figure 3. Large countries are more likely to have disproportionate shares in individual portfolios, which is at the source of their large contribution.

Taking stock. The variance decomposition delivers three takeaways. First, co-ownership spillovers account for 57–70% of expectation-driven capital-flow reallocation, depending on whether the large-country own-expectation component of $\Gamma_{k,t}$ is treated as spillover or as excess return. Second, what drives these spillovers is the cross-country dispersion of global portfolio weights, not the heterogeneity of individual investors. This is also what makes our identification robust to the partial coverage of EPFR fund allocation data: the aggregate quantification rides on consensus forecasts and on the average portfolio architecture, both of which we observe well. Third, the active contributors are the countries with the largest portfolio shares – the BRICs, the G7 – so that news about a few large economies propagates, through the architecture of global portfolios, to the cross-section of countries that share fund ownership with them. This is the granular footprint that the introduction described: the international transmission of expectation shocks runs through portfolios as much as through fundamentals.

5 Conclusion

This paper has identified and quantified a channel of international financial contagion that operates through the granularity of country weights in delegated mutual fund portfolios. Linking the in-house GDP growth forecasts produced by global financial institutions to the assets under management and cross-country allocations of their equity mutual funds, we document a sharp asymmetry between the strong elasticity of fund flows and the weak elasticity of within-fund country weights – a reflection of portfolio stickiness. A delegated-portfolio model with sticky fund weights formalizes this asymmetry and decomposes expectation-driven capital flows into three channels: an excess-return channel, a hedging adjustment, and a *co-ownership spillover* that operates through the fund-level expectation. Plugging our estimates back into the model, co-ownership spillovers account for 57% of the variance of expectation-driven capital-flow reallocation, with the country-specific excess-return channel accounting for 42% and the hedging adjustment for less than 1%.

These findings carry several implications. First, because co-ownership spillovers are unrelated to recipient countries' fundamentals, they constitute a distinct source of cross-border capital misallocation that operates alongside the funding-shock channels traditionally emphasized in the contagion literature. Second, the spatial pattern of transmission is Large-to-Small rather than North-to-South: the G7 and BRICS are the primary sources of spillovers, while small advanced and emerging economies are the primary recipients; some large emerging economies – notably China and Brazil – contribute strongly to spillovers abroad while remaining relatively insulated themselves. Third, the quantitative result rests on the granularity of country weights, not on the granularity of investor wealth, so external validity requires only that the observed portfolios are representative of the global portfolio architecture. Policy-makers in small economies should therefore monitor not only the financial centers from which most capital originates, but also the large countries with which they share fund ownership.

This paper abstracts from several important dimensions of investor behavior and capital flows, which we leave for future work. In particular, one might consider how our spillovers compare in contribution to overall capital volatility to the more usual suspects, such as funding shocks, which are central to the literature on capital flow contagion, and what is the global origin-destination structure of co-ownership linkages.

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A Proofs

A.1 The investor's optimal asset allocation

We proceed to solving the investors' program and derive Equations (2) and (3).

Maximizing (**??**) with respect to $a^{i,j}$, subject to (1), yields the following first-order condition:

$$\begin{aligned} E^i(R_p^{i,j}) - r &= \gamma \sum_{j'=1}^{\mathcal{J}(i)} a^{i,j'} Cov(R_p^{i,j}, R_p^{i,j'}) \\ &= \gamma \left(a^{i,j} V(R_p^{i,j}) + \left(\sum_{j'=1}^{\mathcal{J}(i)} a^{i,j'} - a^{i,j} \right) \sum_{j'=1, j'\neq j}^{\mathcal{J}(i)} \frac{a^{i,j'}}{\sum_{j'=1,j'\neq j}^{\mathcal{J}(i)} a^{i,j'}} Cov(R_p^{i,j}, R_p^{i,j'}) \right) \\ &= \gamma \left(a^{i,j} V(R_p^{i,j}) + \left(\sum_{j'=1}^{\mathcal{J}(i)} a^{i,j'} - a^{i,j} \right) Cov \left(R_p^{i,j}, \underbrace{\sum_{j'=1,j'\neq j}^{\mathcal{J}(i)} \frac{a^{i,j'}}{\sum_{j'=1,j'\neq j}^{\mathcal{J}(i)} a^{i,j'}} R_p^{i,j'}}_{\mathcal{R}_p^{i,j-}} \right) \right) \end{aligned} \tag{31}$$

This yields Equation (3).

Equation (2) is obtained either by taking the sum of the above first-order condition across funds, weighted by $a^{i,j}/\sum_{j=1}^{\mathcal{J}(i)} a^{i,j}$, or by taking the derivative of (**??**) with respect to $\sum_{j=1}^{\mathcal{J}(i)} a^{i,j}$.

A.2 The fund's optimal asset allocation

We proceed to solving the fund's program and derive Equations (5).

Maximizing (**??**) with respect to $w_k^{i,j}$, subject to (1) and (4), yields the following first-order condition for any $(k, K) \in \mathcal{S}(i,j)^2$ pair of countries in the fund's portfolio:

$$\begin{aligned} \big(E^i(R_k) - E^i(R_K)\big) &= \gamma \sum_{j=j'}^{\mathcal{J}(i)} a^{i,j'} \left(\sum_{k'\in\mathcal{S}(i,j)} w_{k'}^{i,j'} Cov(R_k, R_k') - \sum_{k'\in\mathcal{S}(i,j)} w_{k'}^{i,j'} Cov(R_K, R_k') \right) \\ &= \gamma \sum_{j=j'}^{\mathcal{J}(i)} a^{i,j'} \left(\sum_{k'\in\mathcal{S}(i,j)} w_{k'}^{i,j'} Cov(R_k, R_k') - \sum_{k'\in\mathcal{S}(i,j)} w_{k'}^{i,j'} Cov(R_K, R_k') \right) \end{aligned}$$

Noting that this is true for all $K \in \mathcal{S}(i,j)$, this can be written in vector form as follows:

$$Id(i,j) \left[E^i(R_k) - E^i(R) \right] = \gamma Id(i,j)(V_k^R - V^R) W^i a^i \tag{32}$$

where $W^i = (w^{i,1}, .., w^{i,j}, .., w^{i,\mathcal{J}(i)}$ is a $K \times \mathcal{J}(i)$ matrix of portfolio weights, $Id(i,j)$ is a $K \times K$ diagonal matrix, where the k^{th} element of the diagonal is equal to one if $k \in \mathcal{S}(i,j)$, and zero otherwise. For $k' \notin \mathcal{S}(i,j)$, $w_{k'}^{i,j} = 0$. Therefore, $w^{i,j'} Id(i,j) = w^{i,j'}$.

Left-multiplying by $w^{i,j'}$, we obtain

$$E^i(R_k) - E^i(R_p^{i,j}) = \gamma w^{i,j'} (V_k^R - V^R) W^i a^i \tag{33}$$

Note that (31) can also be written in a vector form:

$$E^i(R_p^{i,j}) - r = \gamma w^{i,j'} V^R W^i a^i$$

Substituting into (33), we obtain

$$\begin{aligned}
E^i(R_k) - r &= \gamma w^{i,j'} V_k^R W^i a^i \\
&= \gamma \sum_{j'=1}^{\mathcal{J}(i)} a^{i,j'} \sum_{k' \in \mathcal{S}(i,j')} w_{k'}^{i,j'} Cov(R_k, R_{k'}) \\
&= \gamma \left(a^{i,j} \sum_{k' \in \mathcal{S}(i,j)} w_{k'}^{i,j} Cov(R_k, R_{k'}) + \left(\sum_{j'=1}^{\mathcal{J}(i)} a^{i,j'} - a^{i,j} \right) \underbrace{\sum_{j'=1, j' \neq j}^{\mathcal{J}(i)} \frac{a^{i,j'}}{\sum_{j'=1, j' \neq j}^{\mathcal{J}(i)} a^{i,j'}} \underbrace{\sum_{k' \in \mathcal{S}(i,j')} w_{k'}^{i,j'} Cov(R_k, R_{k'})}_{Cov(R_k, R_p^{i,j'})}}_{Cov(R_k, \mathcal{R}_p^{i,j-})} \right) \\
&= \gamma \left(a^{i,j} \left(w_k^{i,j} V(R_k) + (1 - w_k^{i,j}) \underbrace{\sum_{k' \in \mathcal{S}(i,j), k' \neq k} \frac{w_{k'}^{i,j}}{1 - w_k^{i,j}} Cov(R_k, R_{k'})}_{Cov(R_k, R_{p,k-}^{i,j})} \right) + \left(\sum_{j'=1}^{\mathcal{J}(i)} a^{i,j'} - a^{i,j} \right) Cov(R_k, \mathcal{R}_p^{i,j-}) \right)
\end{aligned}$$

This yields Equation (5).

A.3 Proof of Proposition 2.1

We follow similar steps as in A.2 to derive the default shares $\bar{w}_k^{i,j}$, taking into account the fact that the fund investments $a^{i,j}$ are not known:

$$\bar{w}^{i,j} = \frac{\bar{E}^i(R_k) - r}{\gamma \bar{V}_k^{i,j} \bar{E}^i(a^{i,j})} - \overline{Cov}_k^{i,j} \frac{\left(\sum_{j=1}^{\mathcal{J}(i)} \bar{E}^i(a^{i,j}) \right)}{\bar{E}^i(a^{i,j})} - \overline{\Delta Cov}_k^{i,j}$$

with $\bar{V}_k^{i,j} = \overline{Cov}(R_k, R_k - R_{p,k-}^{i,j})$, $\overline{Cov}_k^{i,j} = \overline{Cov}(R_k, \mathcal{R}_p^{i,j-})/\bar{V}_k^{i,j}$ and $\overline{\Delta Cov}_k^{i,j} = \left(\overline{Cov}(R_k, R_{p,k-}^{i,j}) - \overline{Cov}(R_k, \mathcal{R}_p^{i,j-})\right)/\bar{V}_k^{i,j}$. $\bar{V}(.)$ and $\overline{Cov}(.)$ are the variance and covariance conditional on the beginning-of-period information $\bar{\mathcal{I}}^i$. Under Assumption 2.1, these terms can be replaced by their end-of-period counterparts:

$$\bar{w}^{i,j} = \frac{\bar{E}^i(R_k) - r}{\gamma V_k^{i,j} \bar{E}^i(a^{i,j})} - Cov_k^{i,j} \frac{\left(\sum_{j=1}^{\mathcal{J}(i)} \bar{E}^i(a^{i,j})\right)}{\bar{E}^i(a^{i,j})} - \Delta Cov_k^{i,j} \tag{34}$$

Using the definition of $a_k^{i,j}$, (6), the optimal updated and ex ante allocations, (5), and Equation (34), we obtain:

$$\begin{aligned}
a_k^{i,j} =& p \left(\frac{E^i(R_k) - r}{\gamma V_k^{i,j}} - Cov_k^{i,j} \left(\sum_{j=1}^{\mathcal{J}(i)} a^{i,j} \right) - \Delta Cov_k^{i,j} a^{i,j} \right) \\
&+ (1-p) \left(\frac{\bar{E}^i(R_k) - r}{\gamma V_k^{i,j} \bar{E}^i(a^{i,j})} - Cov_k^{i,j} \frac{\left(\sum_{j=1}^{\mathcal{J}(i)} \bar{E}^i(a^{i,j})\right)}{\bar{E}^i(a^{i,j})} - \Delta Cov_k^{i,j} \right) a^{i,j} \\
=& p \left(\frac{E^i(R_k) - r}{\gamma V_k^{i,j}} - Cov_k^{i,j} \left(\sum_{j=1}^{\mathcal{J}(i)} a^{i,j} \right) \right) \\
&+ (1-p) \left(\frac{\bar{E}^i(R_k) - r}{\gamma V_k^{i,j} \bar{E}^i(a^{i,j})} - Cov_k^{i,j} \frac{\left(\sum_{j=1}^{\mathcal{J}(i)} \bar{E}^i(a^{i,j})\right)}{\bar{E}^i(a^{i,j})} \right) a^{i,j} - \Delta Cov_k^{i,j} a^{i,j}
\end{aligned} \tag{35}$$

We take the beginning-of-period expectation, and subtract it:

$$\begin{aligned}
a_k^{i,j} - \bar{E}^i(a_k^{i,j}) =& p \left(\frac{E^i(r_k)}{\gamma V_k^{i,j}} - Cov_k^{i,j} \left(\sum_{j=1}^{\mathcal{J}(i)} a^{i,j} - \sum_{j=1}^{\mathcal{J}(i)} E^i(a^{i,j}) \right) \right) \\
&+ (1-p) \left(\frac{\bar{E}^i(R_k) - r}{\gamma V_k^{i,j} \bar{E}^i(a^{i,j})} - Cov_k^{i,j} \frac{\left(\sum_{j=1}^{\mathcal{J}(i)} \bar{E}^i(a^{i,j})\right)}{\bar{E}^i(a^{i,j})} \right) \left(a^{i,j} - \bar{E}^i(a^{i,j})\right) \\
&- \Delta Cov_k^{i,j} \left(a^{i,j} - \bar{E}^i(a^{i,j})\right)
\end{aligned}$$

Using (2) and (3), we obtain:

$$
\begin{aligned}
a_k^{i,j} - \bar{E}^i(a_k^{i,j}) =& p\left(\frac{E^i(r_k)}{\gamma V_k^{i,j}} - Cov_k^{i,j}\frac{E^i(\mathfrak{r}_p^i)}{\gamma V^i}\right) \\
&+ (1-p)\left(\frac{\bar{E}^i(R_k)-r}{\gamma V_k^{i,j}\bar{E}^i(a^{i,j})} - Cov_k^{i,j}\frac{\left(\sum_{j=1}^{\mathcal{J}(i)}\bar{E}^i(a^{i,j})\right)}{\bar{E}^i(a^{i,j})}\right)\left(\frac{E^i(r_p^{i,j})}{\gamma V^{i,j}} - Cov^{i,j}\frac{E^i(\mathfrak{r}_p^i)}{\gamma V^i}\right) \\
&- \Delta Cov_k^{i,j}\left(\frac{E^i(r_p^{i,j})}{\gamma V^{i,j}} - Cov^{i,j}\frac{E^i(\mathfrak{r}_p^i)}{\gamma V^i}\right) \\
=& p\frac{E^i(r_k)}{\gamma V_k^{i,j}} + (1-p)\frac{\bar{a}_k^{i,j}}{\bar{E}^i(a^{i,j})}\frac{E^i(r_p^{i,j})}{\gamma V^{i,j}} - \Delta Cov_k^{i,j}\frac{E^i(r_p^{i,j})}{\gamma V^{i,j}} \\
&- \left(Cov_k^{i,j} - \Delta Cov_k^{i,j}Cov^{i,j}\right)\frac{E^i(\mathfrak{r}_p^i)}{\gamma V^i} - (1-p)\left(\frac{\bar{a}_k^{i,j}}{\bar{E}^i(a^{i,j})}Cov^{i,j} - Cov_k^{i,j}\right)\frac{E^i(\mathfrak{r}_p^i)}{\gamma V^i}
\end{aligned}
$$

with $\bar{a}_k^{i,j} = (\bar{E}^i(R_k) - r)/\gamma V_k^{i,j} - Cov_k^{i,j}\left(\sum_{j=1}^{\mathcal{J}(i)}\bar{E}^i(a^{i,j})\right)$.

Finally, the beginning-of-period expectation of $a_k^{i,j}$ obtained from (35) is $\bar{E}^i(a_k^{i,j}) = (\bar{E}^i(R_k) - r)/\gamma V_k^{i,j} - Cov_k^{i,j}\left(\sum_{j=1}^{\mathcal{J}(i)}\bar{E}^i(a^{i,j})\right) - \Delta Cov_k^{i,j}\bar{E}^i(a^{i,j})$. Then we take the beginning-of-period expectations of $a^{i,j}$ and $\sum_{j=1}^{\mathcal{J}(i)} a^{i,j}$ by using (3) and (2) and obtain $\bar{E}^i(a^{i,j}) = (\bar{E}^i(R_p^{i,j}) - r)/\gamma V^{i,j} - Cov^{i,j}\left(\sum_{j=1}^{\mathcal{J}(i)}\bar{E}^i(a^{i,j})\right)$ and $\sum_{j=1}^{\mathcal{J}(i)}\bar{E}^i(a^{i,j}) = (\bar{E}^i(\mathcal{R}_p^i) - r)/\gamma V^i$. This yields Proposition 2.1.

A.4 Proof of Proposition 2.2

The proof relies on two technical assumptions, which we state here.

Assumption A.1 (Orthogonality) *For all $i = 1,..,M$ and for all $k = 1,..,K$, $\sum_{j=1}^{\mathcal{J}(i)}\sigma_k^{i,j}(\theta_k^{i,j} - \theta_k^i)\Gamma^{i,j}$, $\sum_{i=1}^{M}\sigma_k^i(\beta_k^i - \beta_k)l_k^i$, $\sum_{i=1}^{M}\sigma_k^i(\delta_k^i - \delta_k)\left(\sum_{j=1}^{\mathcal{J}(i)}\sigma_k^{i,j}\Gamma^{i,j}\right)$, $\sum_{i=1}^{M}\sigma_k^i(\theta_k^i - \theta_k)\Gamma^i$, $\sum_{i=1}^{M}\sigma_k^i(\beta_k^i + \delta_k^i + \theta_k^i - \beta_k - \delta_k - \theta_k)W^i$, $\sum_{k=1}^{K}\sigma_k(\beta_k - \beta)l_k$ and $\sum_{k=1}^{K}\sigma_k(\delta_k - \delta)\Gamma_k$ are small relative to $\sum_{k\in\mathcal{S}(i,j)} w_k^{i,j} l_k^i$.*

Assumption A.2 (Symmetry) *For all $i = 1,..,M$, $j = 1,..,\mathcal{J}(i)$ and $(k,k') \in \mathcal{S}(i,j)^2$, $k \neq k$:*

(a) $\bar{E}^i(R_k) \simeq \bar{E}^i(R_{k'})$;

(b) $Cov(R_k, \mathcal{R}_p^{i,j-}) \simeq Cov(R_{k'}, \mathcal{R}_p^{i,j-})$ and $Cov(R_k, R_{p,k-}^{i,j}) \simeq Cov(R_{k'}, R_{p,k'-}^{i,j})$;

(c) $\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\left(\frac{\bar{E}^i(A_k^{i,j})}{\bar{E}^i(A_k)} - \frac{\bar{E}^i(A^{i,j})}{\bar{E}^i(A)}\right)x^{i,j} \simeq 0$, where $x^{i,j} = \sum_{k\in\mathcal{S}(i,j)} w_k^{i,j} x_k^{i,j}$ for all $x_k^{i,j} \in \{\beta_k^{i,j}, \eta_k^{i,j}, (\phi\Delta Cov)_k^{i,j}, \delta_k^{i,j}, \theta_k^{i,j}\}$.

Assumption A.1 ensures that the granular residual remains relevant while allowing useful approximations during aggregation: the elasticity coefficients are required to be orthogonal to portfolio shares and expectations. Assumption A.2 ensures that the elasticity coefficients can be treated as homogeneous across countries: two countries in a given fund must have (a) sufficiently similar ex-ante return expectations and (b) sufficiently similar hedging properties, and (c) fund-level elasticities must be unrelated to a fund's contribution to total country flows.

We first prove the following lemma:

Lemma A.1 (Aggregation) *We assume that Assumptions 2.2 and A.1 are satisfied. In that case, Equation* (11) *can be written as:*

$$\frac{a_k - \bar{E}(a_k)}{\bar{E}(a_k)} = \underbrace{\beta_k \left(\sum_{i=1}^{M} \sigma_k^i (l_k^i - \Gamma^i) \right) + \delta_k \left(\sum_{i=1}^{M} \sigma_k^i \sum_{j=1}^{\mathcal{J}(i)} \sigma_k^{i,j} (\Gamma^{i,j} - \Gamma^i) \right) + (\Theta_k - \Theta) \left(\sum_{i=1}^{M} \sigma^i (W^i + \Gamma^i) \right)}_{\tilde{\Delta} a_k}$$
$$+ \underbrace{\Theta \left(\sum_{i=1}^{M} \sigma^i (W^i + \Gamma^i) \right)}_{\Delta a} \tag{36}$$

where $\Theta_k = \beta_k + \delta_k + \theta_k$ is the sum of the country-, fund- and investor-level elasticities, $\sigma^i = \bar{E}^i(a^i)\Omega^i / \bar{E}^i(a)\Omega = \bar{E}^i(A^i)/\bar{E}^i(A)$ is the ex-ante share of investor i in total equity investments.

Proof. Using Assumption 2.2, the surprise capital flows (8) admit the following decomposition:

$$\frac{a_k^{i,j} - \bar{E}^i(a_k^{i,j})}{\bar{E}^i(a_k^{i,j})} = \beta_k^{i,j} l_k^i + \delta_k^{i,j} \Gamma^{i,j} + \theta_k^{i,j} \Gamma^i + \Theta_k^{i,j} W^i$$

with $\Theta_k^{i,j} = \beta_k^{i,j} + \delta_k^{i,j} + \theta_k^{i,j}$.

We replace in Equation (11):

$$\begin{aligned} \frac{a_k - \bar{E}(a_k)}{\bar{E}(a_k)} &= \sum_{i=1}^{M} \sigma_k^i \sum_{j=1}^{\mathcal{J}(i)} \sigma_k^{i,j} \left(\beta_k^{i,j} l_k^i + \delta_k^{i,j} \Gamma^{i,j} + \theta_k^{i,j} \Gamma^i + \Theta_k^{i,j} W^i \right) \\ &= \sum_{i=1}^{M} \sigma_k^i \beta_k^i l_k^i + \sum_{i=1}^{M} \sigma_k^i \sum_{j=1}^{\mathcal{J}(i)} \sigma_k^{i,j} \delta_k^{i,j} \Gamma^{i,j} + \sum_{i=1}^{M} \sigma_k^i \theta_k^i \Gamma^i + \sum_{i=1}^{M} \sigma_k^i \Theta_k^i W^i \end{aligned}$$

Note that

$$\sum_{j=1}^{\mathcal{J}(i)} \sigma_k^{i,j} \delta_k^{i,j} \Gamma^{i,j} = \delta_k^i \sum_{j=1}^{\mathcal{J}(i)} \sigma_k^{i,j} \Gamma^{i,j} + \underbrace{\sum_{j=1}^{\mathcal{J}(i)} \sigma_k^{i,j} (\delta_k^{i,j} - \delta_k^i) \Gamma^{i,j}}_{\simeq 0}$$

where we used Assumption A.1. Therefore:

$$\frac{a_k - \bar{E}(a_k)}{\bar{E}(a_k)} \simeq \sum_{i=1}^{M} \sigma_k^i \beta_k^i l_k^i + \sum_{i=1}^{M} \sigma_k^i \delta_k^i \left(\sum_{j=1}^{\mathcal{J}(i)} \sigma_k^{i,j} \Gamma^{i,j} \right) + \sum_{i=1}^{M} \sigma_k^i \theta_k^i \Gamma^i + \sum_{i=1}^{M} \sigma_k^i \Theta_k^i W^i$$

Take the first term:

$$\sum_{i=1}^{M} \sigma_k^i \beta_k^i l_k^i = \beta_k \sum_{i=1}^{M} \sigma_k^i l_k^i + \underbrace{\sum_{i=1}^{M} \sigma_k^i (\beta_k^i - \beta_k) l_k^i}_{\simeq 0}$$

where we used Assumption A.1 again. We apply similar steps to the other terms, and we obtain, using Assumption A.1:

$$\frac{a_k - \bar{E}(a_k)}{\bar{E}(a_k)} \simeq \beta_k \left(\sum_{i=1}^{M} \sigma_k^i l_k^i \right) + \delta_k \left(\sum_{i=1}^{M} \sigma_k^i \sum_{j=1}^{\mathcal{J}(i)} \sigma_k^{i,j} \Gamma^{i,j} \right) + \theta_k \left(\sum_{i=1}^{M} \sigma_k^i \Gamma^i \right) + \Theta_k \left(\sum_{i=1}^{M} \sigma_k^i W^i \right) \tag{37}$$

We aggregate the country flows using Equation (37):

$$\begin{aligned}
&\frac{a - \bar{E}(a)}{\bar{E}(a)} \\
&\simeq \sum_{k=1}^{K} \sigma_k \left(\beta_k \left(\sum_{i=1}^{M} \sigma_k^i l_k^i \right) + \delta_k \left(\sum_{i=1}^{M} \sigma_k^i \sum_{j=1}^{\mathcal{J}(i)} \sigma_k^{i,j} \Gamma^{i,j} \right) + \theta_k \left(\sum_{i=1}^{M} \sigma_k^i \Gamma^i \right) + \Theta_k \left(\sum_{i=1}^{M} \sigma_k^i W^i \right) \right) \\
&\simeq \sum_{k=1}^{K} \sigma_k \beta_k \left(\sum_{i=1}^{M} \sigma_k^i l_k^i \right) + \sum_{k=1}^{K} \sigma_k \delta_k \left(\sum_{i=1}^{M} \sigma_k^i \sum_{j=1}^{\mathcal{J}(i)} \sigma_k^{i,j} \Gamma^{i,j} \right) + \sum_{k=1}^{K} \sigma_k \theta_k \left(\sum_{i=1}^{M} \sigma_k^i \Gamma^i \right) + \sum_{k=1}^{K} \sigma_k \theta_k \Theta_k \left(\sum_{i=1}^{M} \sigma_k^i W^i \right)
\end{aligned}$$

Take the first term:

$$\begin{aligned}\sum_{k=1}^{K}\sigma_k\beta_k\left(\sum_{i=1}^{M}\sigma_k^i l_k^i\right) &= \beta\sum_{k=1}^{K}\sigma_k\left(\sum_{i=1}^{M}\sigma_k^i l_k^i\right)+\sum_{k=1}^{K}\sigma_k(\beta_k-\beta)\left(\sum_{i=1}^{M}\sigma_k^i l_k^i\right)\\ &= \beta\sum_{i=1}^{M}\sum_{k=1}^{K}\sigma_k\sigma_k^i l_k^i+\underbrace{\sum_{k=1}^{K}\sigma_k(\beta_k-\beta)l_k}_{\simeq 0}\\ &\simeq \beta\sum_{i=1}^{M}\sigma^i\sum_{k=1}^{K}w_k^i l_k^i=\beta\sum_{i=1}^{M}\sigma^i\Gamma^i\end{aligned}$$

Take the second term:

$$\begin{aligned}\sum_{k=1}^{K}\sigma_k\delta_k\left(\sum_{i=1}^{M}\sigma_k^i\sum_{j=1}^{\mathcal{J}(i)}\sigma_k^{i,j}\Gamma^{i,j}\right) &= \delta\sum_{k=1}^{K}\sigma_k\left(\sum_{i=1}^{M}\sigma_k^i\sum_{j=1}^{\mathcal{J}(i)}\sigma_k^{i,j}\Gamma^{i,j}\right)+\sum_{k=1}^{K}\sigma_k(\delta_k-\delta)\left(\sum_{i=1}^{M}\sigma_k^i\sum_{j=1}^{\mathcal{J}(i)}\sigma_k^{i,j}\Gamma^{i,j}\right)\\ &= \delta\sum_{k=1}^{K}\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\sigma_k\sigma_k^i\sigma_k^{i,j}\Gamma^{i,j}+\underbrace{\sum_{k=1}^{K}\sigma_k(\delta_k-\delta)\Gamma_k}_{\simeq 0}\\ &\simeq \delta\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\sigma^i\sigma^{i,j}\Gamma^{i,j}\underbrace{\sum_{k\in\mathcal{S}(i,j)}w_k^{i,j}}_{=1}\\ &\simeq \delta\sum_{i=1}^{M}\sigma^i\sum_{j=1}^{\mathcal{J}(i)}\sigma^{i,j}\sum_{k\in\mathcal{S}(i,j)}w_k^{i,j}l_k^i\\ &\simeq \delta\sum_{i=1}^{M}\sigma^i\sum_{j=1}^{\mathcal{J}(i)}\sum_{k\in\mathcal{S}(i,j)}\sigma^{i,j}w_k^{i,j}l_k^i\\ &\simeq \delta\sum_{i=1}^{M}\sigma^i\sum_{k=1}^{K}l_k^i\sum_{j=1}^{\mathcal{J}(i)}\sigma^{i,j}w_k^{i,j}\\ &\simeq \delta\sum_{i=1}^{M}\sigma^i\sum_{k=1}^{K}w_k^i l_k^i\\ &\simeq \delta\sum_{i=1}^{M}\sigma^i\Gamma^i\end{aligned}$$

Take the third term:

$$\sum_{k=1}^{K} \sigma_k \theta_k \left(\sum_{i=1}^{M} \sigma_k^i \Gamma^i \right) = \theta \sum_{k=1}^{K} \sigma_k \left(\sum_{i=1}^{M} \sigma_k^i \Gamma^i \right) + \sum_{k=1}^{K} \sigma_k (\theta_k - \theta) \left(\sum_{i=1}^{M} \sigma_k^i \Gamma^i \right)$$
$$= \theta \sum_{k=1}^{K} \sum_{i=1}^{M} \sigma_k \sigma_k^i \Gamma^i + \underbrace{\sum_{k=1}^{K} \sigma_k (\theta_k - \theta) \Gamma_k}_{\simeq 0}$$
$$\simeq \theta \sum_{i=1}^{M} \Gamma^i \sum_{k=1}^{K} \sigma_k \sigma_k^i$$
$$\simeq \theta \sum_{i=1}^{M} \sigma^i \Gamma^i$$

We follow similar steps for the fourth term and find

$$\sum_{k=1}^{K} \sigma_k \Theta_k \left(\sum_{i=1}^{M} \sigma_k^i W^i \right) \simeq \Theta \sum_{i=1}^{M} \sigma^i W^i$$

Noting that $\Theta = \beta + \delta + \theta$, aggregate capital flows can be written as

$$\frac{a - \bar{E}(a)}{\bar{E}(a)} \simeq \Theta \sum_{i=1}^{M} \sigma^i (W^i + \Gamma^i) \tag{38}$$

Combining (37) and (38) yields the decomposition (36).

■

We now prove the following lemma:

Lemma A.2 (Elasticity homogeneity) *Under Assumption A.2,* $\beta_k \simeq \beta$, $\eta_k \simeq \eta$, $(\phi \Delta Cov)_k \simeq (\phi \Delta Cov)$, $\delta_k \simeq \delta$ *and* $\Theta_k \simeq \Theta$. *Additionally,* $\beta \propto p$ *and* $\delta = \eta - (\phi \Delta Cov)$ *with* $\eta \propto 1 - p$.

Proof. Consider Assumption A.2. Denote

$$\Delta^i \simeq \bar{E}^i(R_k) \simeq \bar{E}^i(R_p^{i,j}) \simeq \bar{E}^i(\mathcal{R}_p^i)$$

$$\rho^{i,j} \simeq Cov(R_k, \mathcal{R}_p^{i,j-}) \simeq Cov(R_p^{i,j}, \mathcal{R}_p^{i,j-})$$

Then, notice that

$$V_k^{i,j} \bar{a}_k^{i,j} \simeq V^{i,j} \bar{E}^i(a^{i,j}) \simeq \frac{\Delta^i}{\gamma} \left(1 - \frac{\rho^{i,j}}{V^i} \right) \tag{39}$$

Similarly,

$$V_k^{i,j} Cov_k^{i,j} \simeq V^{i,j} Cov^{i,j} \simeq \rho^{i,j} \tag{40}$$

Note that Assumption A.2 implies $V_k^{i,j}\Delta Cov_k^{i,j} = V_{k'}^{i,j}\Delta Cov_{k'}^{i,j}$ for all $k' \neq k$. Let's denote

$$V_k^{i,j}\Delta Cov_k^{i,j} = \Delta\rho^{i,j} \tag{41}$$

Now, we can rewrite the coefficients as follows, using Corollary 2.1:

$$\begin{aligned}
\beta_k^{i,j} =& \frac{p}{\gamma V_k^{i,j}\bar{E}^i(a_k^{i,j})} \simeq \frac{p}{\Delta^i\left(1-\frac{\rho^{i,j}}{V^i}\right) - \Delta\rho^{i,j}\bar{E}^i(a^{i,j})} = \beta^{i,j} \\
\eta_k^{i,j} =& (1-p)\frac{\bar{a}_k^{i,j}}{\gamma V^{i,j}\bar{E}^i(a^{i,j})\bar{E}^i(a_k^{i,j})} = (1-p)\frac{V_k^{i,j}\bar{a}_k^{i,j}}{\gamma V^{i,j}\bar{E}^i(a^{i,j})V_k^{i,j}\bar{E}^i(a_k^{i,j})} \\
\simeq& \frac{1-p}{\gamma V_k^{i,j}\bar{E}^i(a_k^{i,j})} \simeq \frac{1-p}{\Delta^i\left(1-\frac{\rho^{i,j}}{V^i}\right) - \Delta\rho^{i,j}\bar{E}^i(a^{i,j})} = \eta^{i,j} \\
\phi_k^{i,j}\Delta Cov_k^{i,j} =& \frac{\Delta Cov_k^{i,j}}{\gamma V^{i,j}\bar{E}^i(a_k^{i,j})} = \frac{V_k^{i,j}\Delta Cov_k^{i,j}}{\gamma V^{i,j}V_k^{i,j}\bar{E}^i(a_k^{i,j})} = \frac{\Delta\rho^{i,j}}{V^{i,j}\left(\Delta^i\left(1-\frac{\rho^{i,j}}{V^i}\right) - \Delta\rho^{i,j}\bar{E}^i(a^{i,j})\right)} \\
=& (\phi\Delta Cov)^{i,j} \\
\delta_k^{i,j} =& \eta_k^{i,j} - \phi_k^{i,j}\Delta Cov_k^{i,j} \simeq \eta^{i,j} - (\phi\Delta Cov)^{i,j} = \delta^{i,j} \\
\theta_k^{i,j} =& -\frac{\widetilde{Cov}_k^{i,j}}{\gamma V^i\bar{E}^i(a_k^{i,j})} - (1-p)\frac{Cov^{i,j}\bar{a}_k^{i,j}/\bar{E}^i(a^{i,j}) - Cov_k^{i,j}}{\gamma V^i\bar{E}^i(a_k^{i,j})} \simeq -\frac{\widetilde{Cov}_k^{i,j}}{\gamma V^i\bar{E}^i(a_k^{i,j})} \\
\simeq& -\frac{Cov_k^{i,j} - Cov^{i,j}\Delta Cov_k^{i,j}}{\gamma V^i\bar{E}^i(a_k^{i,j})} \simeq -\frac{V_k^{i,j}Cov_k^{i,j} - Cov^{i,j}V_k^{i,j}\Delta Cov_k^{i,j}}{\gamma V^i V_k^{i,j}\bar{E}^i(a_k^{i,j})} \\
\simeq& -\frac{\rho^{i,j} - Cov^{i,j}\Delta\rho^{i,j}}{V^i\left(\Delta^i\left(1-\frac{\rho^{i,j}}{V^i}\right) - \Delta\rho^{i,j}\bar{E}^i(a^{i,j})\right)} = \theta^{i,j}
\end{aligned} \tag{42}$$

which also implies that $\Theta_k^{i,j} = \beta_k^{i,j} + \delta_k^{i,j} + \theta_k^{i,j} \simeq \beta^{i,j} + \delta^{i,j} + \theta^{i,j} \simeq \Theta^{i,j}$. Within a fund, all the coefficients are homogeneous across countries.

We now aggregate the country-specific coefficients across funds. For country $k = 1, .., K$, and for $x = \{\beta, \delta, \eta, \phi\Delta Cov, \Theta\}$, we have

$$x_k = \sum_{i=1}^{M}\sigma_k^i\sum_{j=1}^{\mathcal{J}(i)}\sigma_k^{i,j}x_k^{i,j} \simeq \sum_{i=1}^{M}\sigma_k^i\sum_{j=1}^{\mathcal{J}(i)}\sigma_k^{i,j}x^{i,j} \simeq x + \sum_{i=1}^{M}\sigma_k^i\sum_{j=1}^{\mathcal{J}(i)}\sigma_k^{i,j}(x^{i,j} - x)$$

where

$$x = \sum_{k=1}^{K}\sigma_k x_k$$

Consider the second term:

$$\begin{aligned}
\sum_{i=1}^{M}\sigma_k^i\sum_{j=1}^{\mathcal{J}(i)}\sigma_k^{i,j}(x^{i,j}-x) &= \sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\sigma_k^i\sigma_k^{i,j}x^{i,j} - \sum_{k'=1}^{K}\sigma_{k'}\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\sigma_{k'}^i\sigma_{k'}^{i,j}x^{i,j} \\
&= \sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\underbrace{\sigma_k^i\sigma_k^{i,j}}_{\frac{\bar{E}^i(a_k^{i,j})\Omega^i}{\bar{E}^i(a_k)\Omega}}x^{i,j} - \sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}x^{i,j}\underbrace{\sum_{k'=1}^{K}\underbrace{\sigma_{k'}\sigma_{k'}^i\sigma_{k'}^{i,j}}_{\frac{\bar{E}^i(a_k^{i,j})\Omega^i}{\bar{E}^i(a)\Omega}}}_{\frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega}} \\
&= \sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\left(\frac{\bar{E}^i(a_k^{i,j})\Omega^i}{\bar{E}^i(a_k)\Omega} - \frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega}\right)x^{i,j} \\
&= \sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\left(\frac{\bar{E}^i(A_k^{i,j})}{\bar{E}^i(A_k)} - \frac{\bar{E}^i(A^{i,j})}{\bar{E}^i(A)}\right)x^{i,j} \\
&\simeq 0
\end{aligned}$$

where we used Assumption A.2. Therefore, $x_k \simeq x$, for $x = \{\beta, \delta, \eta, \phi\Delta Cov, \Theta\}$. This proves coefficient homogeneity.

Now, note that, for $x = \{\beta, \delta, \eta, \phi\Delta Cov, \Theta\}$:

$$\begin{aligned}
x &= \sum_{k=1}^{K}\sigma_k x_k = \sum_{k=1}^{K}\sigma_k\sum_{i=1}^{M}\sigma_k^i\sum_{j=1}^{\mathcal{J}(i)}\sigma_k^{i,j}x^{i,j} = \sum_{k=1}^{K}\sigma_k\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\frac{\bar{E}^i(a_k^{i,j})\Omega^i}{\bar{E}^i(a_k)\Omega}x^{i,j} \\
&= \sum_{k=1}^{K}\sigma_k\left(\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega}x^{i,j} + \underbrace{\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\left(\frac{\bar{E}^i(a_k^{i,j})\Omega^i}{\bar{E}^i(a_k)\Omega} - \frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega}\right)x^{i,j}}_{\simeq 0}\right) \\
&= \sum_{k=1}^{K}\sigma_k\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega}x^{i,j} = \underbrace{\left(\sum_{k=1}^{K}\sigma_k\right)}_{=1}\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega}x^{i,j} = \sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)}\frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega}x^{i,j}
\end{aligned} \tag{43}$$

Using the expression for $\beta^{i,j}$ and $\eta^{i,j}$ in (42), we obtain:

$$\beta = \sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)} \frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega} \frac{p}{\Delta^i\left(1-\frac{\rho^{i,j}}{V^i}\right) - \Delta\rho^{i,j}\bar{E}^i(a^{i,j})}$$
$$= p\left(\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)} \frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega} \frac{1}{\Delta^i\left(1-\frac{\rho^{i,j}}{V^i}\right) - \Delta\rho^{i,j}\bar{E}^i(a^{i,j})}\right) \propto p \tag{44}$$

$$\eta = \sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)} \frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega} \frac{1-p}{\Delta^i\left(1-\frac{\rho^{i,j}}{V^i}\right) - \Delta\rho^{i,j}\bar{E}^i(a^{i,j})}$$
$$= (1-p)\left(\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)} \frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega} \frac{1}{\Delta^i\left(1-\frac{\rho^{i,j}}{V^i}\right) - \Delta\rho^{i,j}\bar{E}^i(a^{i,j})}\right) \propto 1-p \tag{45}$$

Moreover, since $\delta_k^{i,j} = \eta_k^{i,j} - \phi_k^{i,j}\Delta Cov_k^{i,j} = \eta_k^{i,j} - (\phi\Delta Cov_k)^{i,j}$, then $\delta = \eta - (\phi\Delta Cov)$.

■

Combining Lemma A.1 and A.2, we obtain decomposition (15) of Proposition 2.2.

A.5 Proof of Corollary 2.2

Point (i) derive directly from proposition 2.2, which states that $\beta \propto p$ and $\delta = \eta + (\phi\Delta Cov)$ with $\eta \propto 1-p$.

Point (ii) can be derived as follows. Note that $\Theta = \beta + \delta + \theta = \beta + \eta + (\phi\Delta Cov) + \theta$. Consider $\beta+\eta$, $(\phi\Delta Cov)$ and θ separately. First, using (44) and (45), we obtain:

$$\beta + \eta = \underbrace{(p + 1 - p)}_{=1} \underbrace{\left(\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)} \frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega} \frac{1}{\Delta^i\left(1-\frac{\rho^{i,j}}{V^i}\right) - \Delta\rho^{i,j}\bar{E}^i(a^{i,j})}\right)}_{\text{Independent from } p}$$

Second, using expression (43) with $x = \{\phi\Delta Cov, \theta\}$, along with the expressions for $(\phi\Delta Cov)^{i,j}$ and $\theta^{i,j}$ in (42)), we obtain:

$$(\phi\Delta Cov) = \underbrace{\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)} \frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega} \frac{\Delta\rho^{i,j}}{V^{i,j}\left(\Delta^i\left(1-\frac{\rho^{i,j}}{V^i}\right) - \Delta\rho^{i,j}\bar{E}^i(a^{i,j})\right)}}_{\text{Independent from } p}$$

$$\theta = \underbrace{\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)} \frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega} - \frac{\rho^{i,j} - Cov^{i,j}\Delta\rho^{i,j}}{V^i\left(\Delta^i\left(1-\frac{\rho^{i,j}}{V^i}\right) - \Delta\rho^{i,j}\bar{E}^i(a^{i,j})\right)}}_{\text{Independent from } p}$$

Therefore, Θ is independent from p.

To show point (iii), we take the ratio of β to η using (44) and (45):

$$\frac{\beta}{\eta} = \frac{p}{1-p}\underbrace{\frac{\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)} \frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega}\frac{1}{\Delta^i\left(1-\frac{\rho^{i,j}}{V^i}\right)-\Delta\rho^{i,j}\bar{E}^i(a^{i,j})}}{\sum_{i=1}^{M}\sum_{j=1}^{\mathcal{J}(i)} \frac{\bar{E}^i(a^{i,j})\Omega^i}{\bar{E}^i(a)\Omega}\frac{1}{\Delta^i\left(1-\frac{\rho^{i,j}}{V^i}\right)-\Delta\rho^{i,j}\bar{E}^i(a^{i,j})}}}_{=1}$$

B Data Appendix

B.1 Estimation of $\Delta Cov_k^{i,j}$

According to Lemma 2.2, $\Delta Cov_k^{i,j}$ is the difference between the scaled covariance of the country return k with the fund-level return excluding country k $Cov(R_k, R_{p,k^-}^{i,j})/V_k^{i,j}$ and the scaled covariance of the country return k with the investor-level return excluding fund j and $Cov(R_k, \mathcal{R}_{p,j^-}^{i,j})/V_k^{i,j}$, where $V_k^{i,j} = Cov(R_k, R_k - R_{p,k-}^{i,j})$. We proxy for these scaled covariances by using the country equity MSCI return data.

Define the aggregate fund-level return, the aggregate fund-level return excluding country k and the aggregate investor-level return excluding fund j respectively as follows:

$$\begin{aligned} R_{p,k-,t}^{i,j} &= \sum_{l\neq k, l\in\mathcal{S}(i,j)} \frac{w_{l,t}^{i,j}}{\sum_{l\neq k, l\in\mathcal{S}(i,j)} w_{l,t}^{i,j}} R_{l,t}, \\ R_{p,t}^{i,j} &= \sum_{l\in\mathcal{S}(i,j)} \frac{w_{l,t}^{i,j}}{\sum_{l\in\mathcal{S}(i,j)} w_{l,t}^{i,j}} R_{l,t}, \\ \mathcal{R}_{p,j-,t}^{i} &= \sum_{l\neq j, l=1}^{J(i)} \frac{A_t^{i,l}}{\sum_{l\neq j, l\in J(i)} A_t^{i,l}} R_{p,t}^{i,j}, \end{aligned} \tag{46}$$

where $w_{l,t}^{i,j}$ is mutual fund j's allocation to country l, $A_t^{i,l}$ is fund l total assets under management and $R_{l,t}$ is country l's equity MSCI return in month t. We then compute the covariances by country and fund pair, and compute $\Delta Cov_k^{i,j}$ as the differential

$$\Delta Cov_k^{i,j} = \frac{Cov(R_k, R_{p,k-}^{i,j})}{Cov(R_k, R_k - R_{p,k-}^{i,j})} - \frac{Cov(R_k, \mathcal{R}_{p,j-}^{i,j})}{Cov(R_k, R_k - R_{p,k-}^{i,j})}$$

B.2 Summary Statistics for $\Delta Cov^{i,j}$

Table B.1: Summary Statistics for $\Delta Cov_k^{i,j}$

Variable	Mean	Median	S.D.	p25	p75
$\Delta Cov^{i,j}$	.05	-.008	.51	-.13	.14

B.3 Imputation of Expectations

We assume that expectations are the sum of a year-specific term and a month-specific term that are independent from each other:

$$E_t^i(g_k^{\text{next year}}) = E_{year}^i(g_k^{\text{next year}}) + u_{year,month,k}^i \tag{47}$$

where $t = 12 \times year + month$. We make the identifying assumption that $E(u_{year,month,k}^i) = 0$, so that $E_{year}^i(g_k^{\text{next year}})$ can be estimated as $E_{year}^i(g_k^{\text{next year}}) = \frac{1}{12}\sum_{month=1}^{12} E_{year\times 12+month}^i(g_k^{\text{next year}})$, and $u_{year,month,k}^i = E_t^i(g_k^{\text{next year}}) - \frac{1}{12}\sum_{month=1}^{12} E_{year\times 12+month}^i(g_k^{\text{next year}})$.

The year-specific component $E_{year}^i(g_k^{j,\text{next year}})$ has three independent components: a country-time component, a country-investor component, and a year-country-investor-specific residual:

$$E_{year}^i(g_k^{\text{next year}}) = X_{k,year} + \zeta_k^i + v_{k,year}^i \tag{48}$$

Here as well, we make identifying assumption that $E(v_{k,year}^i) = 0$. We allow $v_{k,year}^i$ to be autocorrelated:

$$v_{k,year}^i = \rho^v v_{k,year-1}^i + \tilde{v}_{k,year}^i \tag{49}$$

with $v_{k,year}^i \sim N(0, \sigma_k^v)$. The autocorrelation parameter ρ^v is common across countries, but the variance of the innovation σ_k^v is country-specific.

We estimate Equation (48) using a fixed-effect regression. $X_{k,year}$ and ζ_k^i are estimated as the country-time and country-investor fixed effects. $v_{k,year}^i$ is estimated as the residual of the regression. We then fit the autoregressive process (49) on that residual to estimate ρ^v. The country-specific standard deviation σ_k^v is estimated as the standard deviation of the residuals of the autoregressive equation.

The month-specific component $u_{year,month,k}^i$ has two independent components: a country-time component and a residual specific to the investor:

$$u^i_{year,month,k} = Y_{year,month,k} + e^i_{year,month,k} \tag{50}$$

where we assume that both components are zero in expectations: $E(Y_{year,month,k}) = 0$ and $E(e^i_{year,month,k}) = 0$. We allow $e^i_{year,month,k}$ to be autocorrelated:

$$e^i_{year,month,k} = \rho^e e^i_{year,month-1,k} + \tilde{e}^i_{year,month,k} \tag{51}$$

with $e^i_{year,month,k} \sim N(0, \sigma^e_k)$. The autocorrelation parameter ρ^e is common across countries, but the variance of the innovation σ^e_k is country-specific.

We estimate Equation (50) using a fixed-effect regression. $Y_{k,year,month}$ are estimated as the country-time fixed effects. $e^i_{k,year,month}$ is estimated as the residual of the regression. We then fit the autoregressive process (51) on that residual to estimate ρ^e. The country-specific standard deviation σ^e_k is estimated as the standard deviation of the residuals of the autoregressive equation.

These estimations are performed on the subset of investors and countries for which we have expectation data. We then impute expectations for all the investors in our dataset as follows:

$$\widehat{E}^i_t(g^{\text{next year}}_k) = \widehat{X}_{k,year} + \widehat{v}^i_{k,year} + \widehat{Y}_{year,month,k} + \widehat{e}^i_{year,month,k} \tag{52}$$

where $\widehat{X}_{k,year}$ and $\widehat{Y}_{year,month,k}$ are the estimated fixed effects and $\widehat{v}^i_{k,year}$ and $\widehat{e}^i_{year,month,k}$ are either the residuals of Equations (48) and (50), if investor i has expectation data for country k, or they are simulated using the data-generating processes (49) and (51), using our estimates of ρ^v, ρ^e, σ^v_k and σ^e_k.

C IV Appendix

This appendix formalizes the argument behind our use of the IMF growth forecast as an instrumental variable for the in-house Consensus forecast. We work in a stylized environment in which the forecaster who produces the in-house forecast and the decision-maker (the fund manager or the end-investor) form their forecasts as linear functions of a common public signal — the IMF forecast — and of distinct private signals. We do *not* impose Bayesian rationality on either agent, and we allow the noise of the two private signals to have different variances. We show that, as long as the two agents weight signals in the same way, the OLS estimator that uses the in-house forecast as a proxy for the decision-maker's forecast is attenuated by a measurement-error bias, while the IV estimator that uses the IMF forecast as an instrument recovers the structural elasticity β exactly. When the two agents weight signals differently, the IV is biased, but a complementary pair of estimators that augment the instruments with controls — the IMF-forecast IV controlling for vintage growth, and the vintage-growth IV controlling for the IMF forecast — biases β in opposite directions and brackets β under standard behavioral models of expectation formation.

C.1 Setup

Let g denote the next-year GDP growth of a given country at a given date; throughout this appendix we suppress the country and time indices. The prior on g is $g \sim \mathcal{N}(0, \sigma_g^2)$, where the zero mean is without loss of generality (any nonzero mean is absorbed by the fixed effects in the empirical specification). Three pieces of information about g are available: a public signal embodied by the IMF forecast,

$$s^P = g + u^P, \qquad u^P \sim \mathcal{N}(0, \sigma_P^2),$$

a private signal of the forecaster $s^F = g + u^F$, with $u^F \sim \mathcal{N}(0, \sigma_F^2)$, and a private signal of the decision-maker $s^D = g + u^D$, with $u^D \sim \mathcal{N}(0, \sigma_D^2)$. The shocks g, u^P, u^F and u^D are mutually independent.[24] Rather than imposing Bayes' rule, we allow each agent to combine the signals into a forecast in an arbitrary linear way:

$$E^F[g] = a_P^F\, s^P + a^F\, s^F, \tag{53}$$

$$E^D[g] = a_P^D\, s^P + a^D\, s^D, \tag{54}$$

where any nonzero intercepts are absorbed by the fixed effects in the empirical specification. The structural equation that the empirical model maps to is

$$y = \beta\, E^D[g] + \varepsilon, \tag{55}$$

where y is the (log) allocation and ε collects all the determinants of the allocation that are orthogonal to expectations and absorbed by the fixed effects of Equation (20). As a baseline, we assume that the forecaster and the decision-maker weigh signals in the same way:

$$(a_P^F, a^F) = (a_P^D, a^D) \equiv (a_P, a). \tag{56}$$

[24] We treat the IMF forecast as the only public signal. The argument extends to the case in which s^P is itself a function of the IMF forecast and other public signals.

We relax this assumption in Section C.3.

C.2 Measurement-error bias and the IMF instrument

Under the symmetry restriction (56), the wedge between the in-house forecast and the decision-maker's forecast is

$$\xi \equiv E^F[g] - E^D[g] = a\,(u^F - u^D),$$

with mean zero and variance $\text{Var}(\xi) = a^2(\sigma_F^2 + \sigma_D^2)$. The wedge is correlated with the true regressor, $\text{Cov}(E^D[g], \xi) = -a^2\sigma_D^2$. The measurement error is non-classical, in the sense that ξ is not orthogonal to $E^D[g]$, but it is orthogonal to the public signal,

$$\text{Cov}(s^P, \xi) = 0, \tag{57}$$

because u^P is independent of (u^F, u^D). The two forecasts have the following unconditional variances

$$V_F \equiv \text{Var}(E^F[g]) = C + a^2\sigma_F^2, \qquad V_D \equiv \text{Var}(E^D[g]) = C + a^2\sigma_D^2, \tag{58}$$

where the common term depends on the variance of the public signal and of the fundamental:

$$C \equiv \text{Cov}(E^F[g], E^D[g]) = a_P^2(\sigma_g^2 + \sigma_P^2) + 2a_P a\,\sigma_g^2 + a^2\sigma_g^2.$$

OLS bias. Replacing $E^D[g]$ with the observable in-house forecast $E^F[g]$ in (55), the OLS estimator converges to

$$\text{plim}\,\hat{\beta}_{OLS} = \beta\,\frac{\text{Cov}(E^F[g], E^D[g])}{\text{Var}(E^F[g])} = \beta\,\frac{C}{C + a^2\sigma_F^2} = \beta\left(1 - \frac{a^2\sigma_F^2}{V_F}\right) < \beta. \tag{59}$$

OLS attenuates the structural elasticity. The size of the attenuation is governed by the share of the variance of the in-house forecast that is driven by the forecaster's private signal: when σ_F^2 is large relative to the rest of the variation in $E^F[g]$, the in-house forecast is a noisy proxy for the decision-maker's forecast and OLS is severely attenuated.

IV with the IMF forecast. The public signal s^P is relevant for the in-house forecast,

$$\text{Cov}(s^P, E^F[g]) = a_P(\sigma_g^2 + \sigma_P^2) + a\,\sigma_g^2 > 0, \tag{60}$$

and satisfies the exclusion restriction $\text{Cov}(s^P, \xi) = 0$ by (57) and $\text{Cov}(s^P, \varepsilon) = 0$ by assumption. The IV estimator then converges to

$$\text{plim}\,\hat{\beta}_{IV} = \frac{\text{Cov}(s^P, y)}{\text{Cov}(s^P, E^F[g])} = \beta\,\frac{\text{Cov}(s^P, E^D[g])}{\text{Cov}(s^P, E^F[g])} = \beta, \tag{61}$$

where the last equality uses $\text{Cov}(s^P, E^F[g]) = \text{Cov}(s^P, E^D[g]) = a_P(\sigma_g^2 + \sigma_P^2) + a\,\sigma_g^2$. The key step is that these two covariances depend only on the weights (a_P, a) and the public-signal precision σ_P^2 — they do not depend on σ_F^2 or σ_D^2. Asymmetry in the precision of the two private signals therefore does not contaminate the IV: the public signal s^P traces out variation in $E^F[g]$ that is identical to the variation it would induce in $E^D[g]$, and the IV recovers β exactly.

C.3 Asymmetric weights and bounds analysis

The symmetry of the weights in (56) is the key identifying assumption. If $(a_P^F, a^F) \neq (a_P^D, a^D)$, the IMF-forecast IV is no longer consistent and converges to

$$\text{plim}\,\hat{\beta}_{IV}^{\text{IMF}} = \beta\,\frac{a_P^D(\sigma_g^2 + \sigma_P^2) + a^D\sigma_g^2}{a_P^F(\sigma_g^2 + \sigma_P^2) + a^F\sigma_g^2} = \beta\,\frac{a_P^D\,r + a^D}{a_P^F\,r + a^F}, \tag{62}$$

where $r \equiv (\sigma_g^2 + \sigma_P^2)/\sigma_g^2 > 1$ is the ratio of the variance of the public signal to the variance of the fundamental. To bound the structural elasticity β, we consider two additional estimators that augment the instrument with a control variable: (i) the IMF-forecast IV with realized growth g added as a control, denoted $\hat{\beta}_{IV}^{\text{IMF}|g}$; and (ii) the vintage-growth IV with the IMF forecast s^P added as a control, denoted $\hat{\beta}_{IV}^{g|\text{IMF}}$. Under the general specification (53)–(54), these estimators converge to

$$\text{plim}\,\hat{\beta}_{IV}^{\text{IMF}|g} = \beta\,\frac{a_P^D}{a_P^F}, \tag{63}$$

$$\text{plim}\,\hat{\beta}_{IV}^{g|\text{IMF}} = \beta\,\frac{a^D}{a^F}. \tag{64}$$

The two controlled estimators isolate the two "primitive" loading ratios. The IMF-forecast IV with vintage-growth control uses, by Frisch–Waugh, the residual instrument $\tilde{s}^P = s^P - g = u^P$, the pure IMF noise. Because u^P is uncorrelated with g, s^F and s^D, only the public-signal loadings (a_P^F, a_P^D) enter the bias formula. Symmetrically, the vintage-growth IV with IMF-control uses the residual instrument $\tilde{g} = g - \lambda s^P$, with $\lambda = \sigma_g^2/(\sigma_g^2 + \sigma_P^2)$, which orthogonalizes the fundamental against the public-signal variation; only the private-signal loadings (a^F, a^D)

enter the bias formula.[25] We now show that under three natural specifications of expectation formation: heterogeneous subjective (or objective) signal precisions, and heterogeneous strategic concerns, the two controlled estimators bracket the structural elasticity β.

Heterogeneous subjective precisions Assume that each agent forms their forecast as a Bayesian posterior mean given a set of *subjective* precisions for the prior, the public signal, and their own private signal: $a^i_P = \tilde{\tau}_P/T^i$ and $a^i = \tilde{\tau}^i/T^i$ with $T^i \equiv \tilde{\tau}_g + \tilde{\tau}_P + \tilde{\tau}^i$, for $i \in \{F, D\}$. The subjective precisions $\tilde{\tau}_g$, $\tilde{\tau}_P$ and $\tilde{\tau}^i$ need not equal their objective counterparts, so the weights are not necessarily rational. This formulation relates to the behavioral-finance literature on overconfidence in own private information (e.g., Daniel et al., 1998) and to the macroeconomic-expectations literature documenting heterogeneous over- and under-reactions in survey forecasts (e.g., Bordalo et al., 2020; Broer and Kohlhas, 2024; Adam et al., 2025). We assume that the two agents share the same subjective prior and public-signal precisions, and that the only source of asymmetry between them is their subjective perception of the precision of their own private signal: $\tilde{\tau}_F \neq \tilde{\tau}_D$. Suppose the decision-maker perceives their private signal as more precise than the forecaster does, $\tilde{\tau}_D > \tilde{\tau}_F$. Direct computation gives

$$\frac{a^D_P}{a^F_P} = \frac{T^F}{T^D} < 1 \qquad \text{and} \qquad \frac{a^D}{a^F} = \frac{\tilde{\tau}_D}{\tilde{\tau}_F} \cdot \frac{T^F}{T^D} > 1. \tag{65}$$

The IMF-forecast IV with vintage-growth control therefore biases β *downward*, and the vintage-growth IV with IMF-control biases β *upward*. The two estimators bracket the structural elasticity:

$$\operatorname{plim} \hat{\beta}^{\text{IMF}|g}_{IV} \leq \beta \leq \operatorname{plim} \hat{\beta}^{g|\text{IMF}}_{IV}. \tag{66}$$

The bounds coincide with β when the symmetry restriction (56) holds. Symmetrically, when $\tilde{\tau}_F > \tilde{\tau}_D$ (the forecaster has the more aggressive private-signal perception), the inequalities in (66) reverse, and the two estimators bracket β from the opposite direction.

Heterogeneous strategic concerns A second potential source of asymmetric weights arises when the forecaster faces career or reputational incentives that the decision-maker does not share. Forecasting teams are routinely evaluated against the cross-section of professional forecasters, so deviating too far from the public benchmark is professionally costly; the decision-maker, by contrast, is evaluated on portfolio performance and has no analogous

[25] Both controls require the exogeneity restrictions $\text{Cov}(g, \varepsilon) = 0$ and $\text{Cov}(s^P, \varepsilon) = 0$, which are the same restrictions that support the use of g and s^P as instruments. The IMF-forecast IV without control, (62), lies between these two pure ratios by the mediant inequality: it interpolates between a^D_P/a^F_P and a^D/a^F as a function of r.

incentive to anchor on the IMF forecast. Following the strategic-forecasting literature (e.g., Ottaviani and Sørensen, 2006), we capture this asymmetry by letting the forecaster shift their forecast partially toward the public signal,

$$E^F[g] = (1-\mu)\, E^*[g \mid s^P, s^F] + \mu\, s^P, \qquad \mu \in [0,1), \tag{67}$$

where $E^*[g \mid s^P, s^F] \equiv w_P\, s^P + w\, s^F$ is the rational Bayesian forecast and μ parameterizes the strategic anchoring intensity. The decision-maker remains free of strategic distortion, $E^D[g] = w_P s^P + w s^D$. The implied weights are

$$a_P^F = w_P + \mu(1-w_P), \quad a^F = (1-\mu)\, w, \quad a_P^D = w_P, \quad a^D = w, \tag{68}$$

so strategic anchoring raises the forecaster's loading on the public signal and lowers their loading on the private signal: $a_P^F > a_P^D$ and $a^F < a^D$. Direct computation gives

$$\frac{a_P^D}{a_P^F} = \frac{w_P}{w_P + \mu(1-w_P)} < 1 \qquad \text{and} \qquad \frac{a^D}{a^F} = \frac{1}{1-\mu} > 1, \tag{69}$$

so the same bracketing result obtains as in the heterogeneous-precision case:

$$\text{plim}\, \hat{\beta}_{IV}^{\text{IMF}|g} \le \beta \le \text{plim}\, \hat{\beta}_{IV}^{g|\text{IMF}}. \tag{70}$$

Under both behavioral models, the IMF-forecast IV with vintage-growth control and the vintage-growth IV with IMF-control bound the structural elasticity β from below and above. Symmetrically, when the decision-maker strategically aligns on public information, while the forecaster does not, the inequalities in (70) reverse, and the two estimators bracket β from the opposite direction. The results carry through in the more general case where strategic motives are present for both, but with different strength.[26]

Nested information A third case of interest is when the decision-maker does not form her expectation from scratch but observes the in-house forecast $E^F[g]$ and combines it with her own private signal s^D. We discipline her weights through subjective Bayesian updating with precisions *shared* with the forecaster: both agents perceive the prior with precision $\tilde{\tau}_g$, the public signal with precision $\tilde{\tau}_P$, the forecaster's private signal with precision $\tilde{\tau}_F$, and the

[26] Gemmi and Valchev (2025) argue that professional forecasters in fact *diversify* from consensus (over-weighting their private signal and underweighting the public signal) the opposite direction from (67). This corresponds to $E^F[g] = (1-\nu)\, E^*[g \mid s^P, s^F] + \nu\, s^F$ with $\nu \in [0,1)$, which delivers $a_P^F = (1-\nu) w_P < a_P^D$ and $a^F = w + \nu(1-w) > a^D$; under this alternative the inequalities in (70) reverse, with the vintage-growth IV with IMF-control becoming the lower bound and the IMF-forecast IV with vintage-growth control becoming the upper bound, but the bracketing of β continues to hold.

decision-maker's own private signal with precision $\tilde{\tau}_D$. The forecaster's weights are then as in the heterogeneous-precision paragraph,

$$a_P^F = \frac{\tilde{\tau}_P}{T^F}, \qquad a^F = \frac{\tilde{\tau}_F}{T^F}, \qquad T^F \equiv \tilde{\tau}_g + \tilde{\tau}_P + \tilde{\tau}_F,$$

and the decision-maker, knowing that $E^F[g]$ summarizes (s^P, s^F) through this rule, performs a Bayesian update of g on (s^P, s^F, s^D) — equivalently, on (E^F, s^D). The resulting forecast is

$$E^D[g] = \alpha\, E^F[g] + \gamma\, s^D, \qquad \alpha = \frac{T^F}{T^D}, \quad \gamma = \frac{\tilde{\tau}_D}{T^D}, \quad T^D \equiv T^F + \tilde{\tau}_D, \tag{71}$$

with $\alpha+\gamma \leq 1$. Because $E^F[g]$ already incorporates the shared prior and the public signal, the decision-maker does not double-count them, and the weights α and γ are pinned down by the same primitive precisions that govern a^F. Substituting (53), the decision-maker's expectation loads on three signals — the public signal, the forecaster's private signal s^F (through E^F), and her own private signal s^D — with weights $\tilde{\tau}_P/T^D$, $\tilde{\tau}_F/T^D$ and $\tilde{\tau}_D/T^D$ respectively, which is precisely the Bayesian posterior on the full information set. Substituting into (63) and (64) yields

$$\operatorname{plim} \hat{\beta}_{IV}^{\mathrm{IMF}|g} = \beta\, \alpha = \beta\, \frac{T^F}{T^D}, \tag{72}$$

$$\operatorname{plim} \hat{\beta}_{IV}^{g|\mathrm{IMF}} = \beta \left(\alpha + \frac{\gamma}{a^F} \right) = \beta\, \frac{T^F}{T^D} \cdot \frac{\tilde{\tau}_F + \tilde{\tau}_D}{\tilde{\tau}_F}. \tag{73}$$

The IMF-instrument estimator understates β because $T^F/T^D \leq 1$, and the vintage-instrument estimator overstates β because $(T^F/T^D)(\tilde{\tau}_F + \tilde{\tau}_D)/\tilde{\tau}_F \geq 1$ — the latter follows directly from $T^F(\tilde{\tau}_F + \tilde{\tau}_D) - T^D\tilde{\tau}_F = (\tilde{\tau}_g + \tilde{\tau}_P)\tilde{\tau}_D \geq 0$. The bracket

$$\operatorname{plim} \hat{\beta}_{IV}^{\mathrm{IMF}|g} \leq \beta \leq \operatorname{plim} \hat{\beta}_{IV}^{g|\mathrm{IMF}} \tag{74}$$

therefore holds in the nested information case.

VARIABLES	(1) $\log(A^{i,j}_{k,t})$ Passive	(2) $\log(A^{i,j}_{k,t})$ Active	(3) $\log(A^{i,j}_{k,t})$ Passive IV (boot SE)	(4) $\log(A^{i,j}_{k,t})$ Active IV (boot SE)
$E^i_t(g^{\text{next year}}_k)$	0.013	0.028***	-0.017	0.067***
	(0.013)	(0.009)	(0.011)	(0.014)
$\Delta \log(Q_{k,t})$			0.451***	0.615***
			(0.033)	(0.025)
$\Delta \log(Q_{k,t-1})$			0.429***	0.590***
			(0.032)	(0.025)
Observations	36,483	112,507	115,489	371,403
R-squared	0.991	0.968	0.979	0.926
Country-fund FE	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	No	No
Fund-time FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

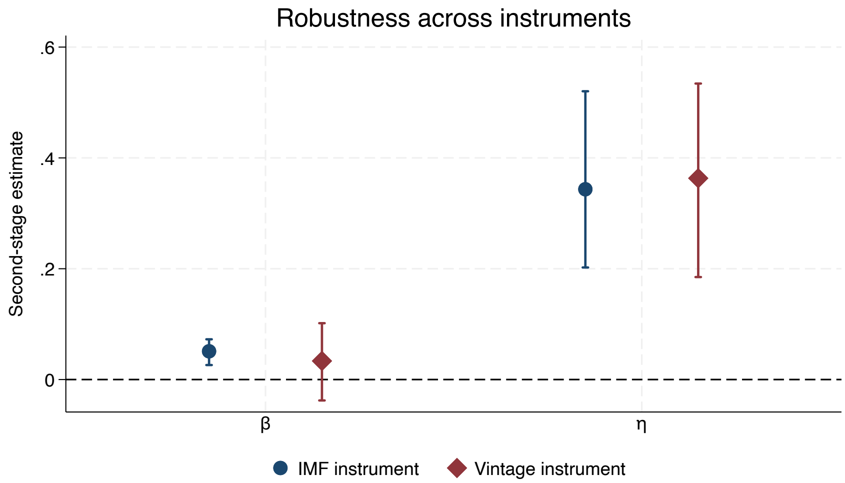
Table D.1: Fund-Country Allocations and Investor Expectations – Passive and Active Funds

Notes: Standard errors in parentheses. Columns (1)–(2) are OLS with analytic standard errors clustered at the manager–country level. Columns (3)–(4) report two-step IV estimates that use generated regressors from first-stage projections; their standard errors are computed via a pairs cluster bootstrap with 200 replications and clusters at the manager–country level, which propagates the first-stage estimation uncertainty into the reported standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D Additional Tables

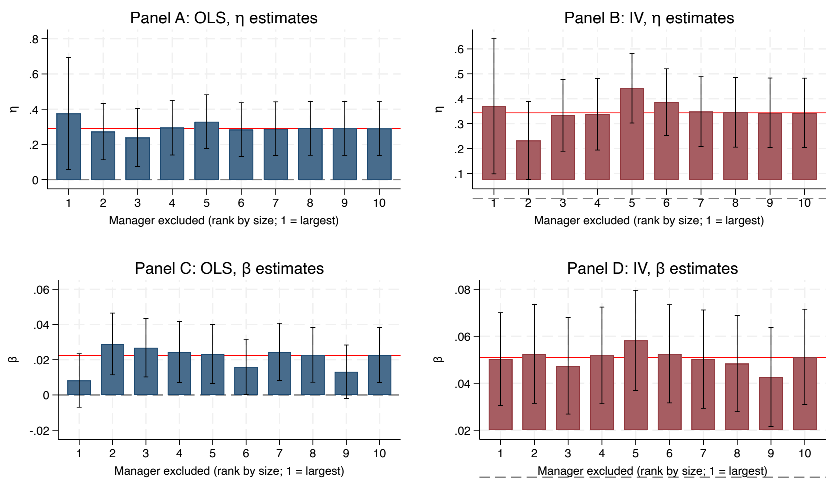
E Additional Figures

Figure E.1: Robustness – IMF forecasts vs vintage growth instruments



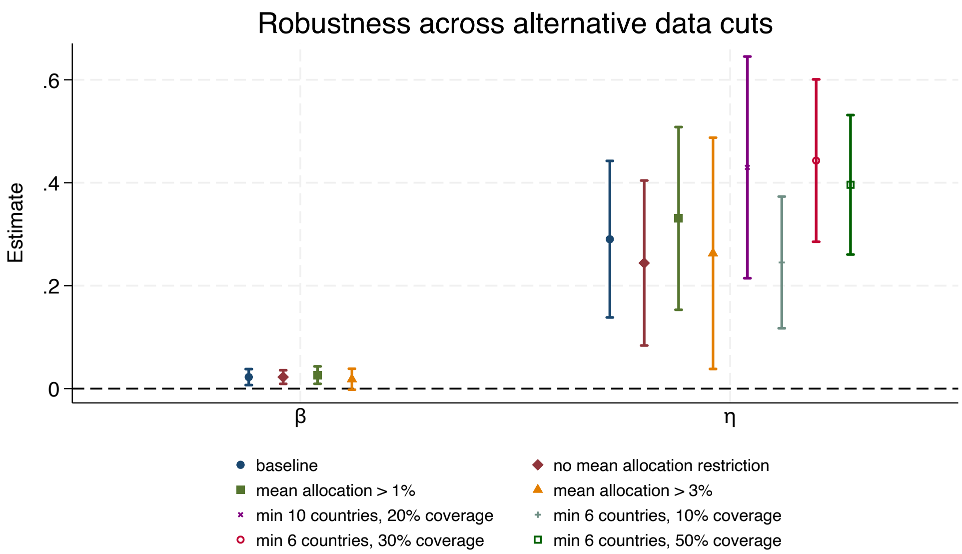
Note: The figure reports IV estimates of β and η coefficient under two complementary specifications: the IMF-forecast IV controlling for realized (vintage) GDP growth, and the vintage-growth IV controlling for the IMF forecast. Markers are point estimates and whiskers are 95% confidence intervals based on bootstrapped standard errors clustered on investor and country.
under two complementary specifications: the IMF-forecast IV controlling for realized (vintage) GDP growth, and the vintage-growth IV controlling for the IMF forecast

Figure E.2: Robustness – Leave-one-out estimates



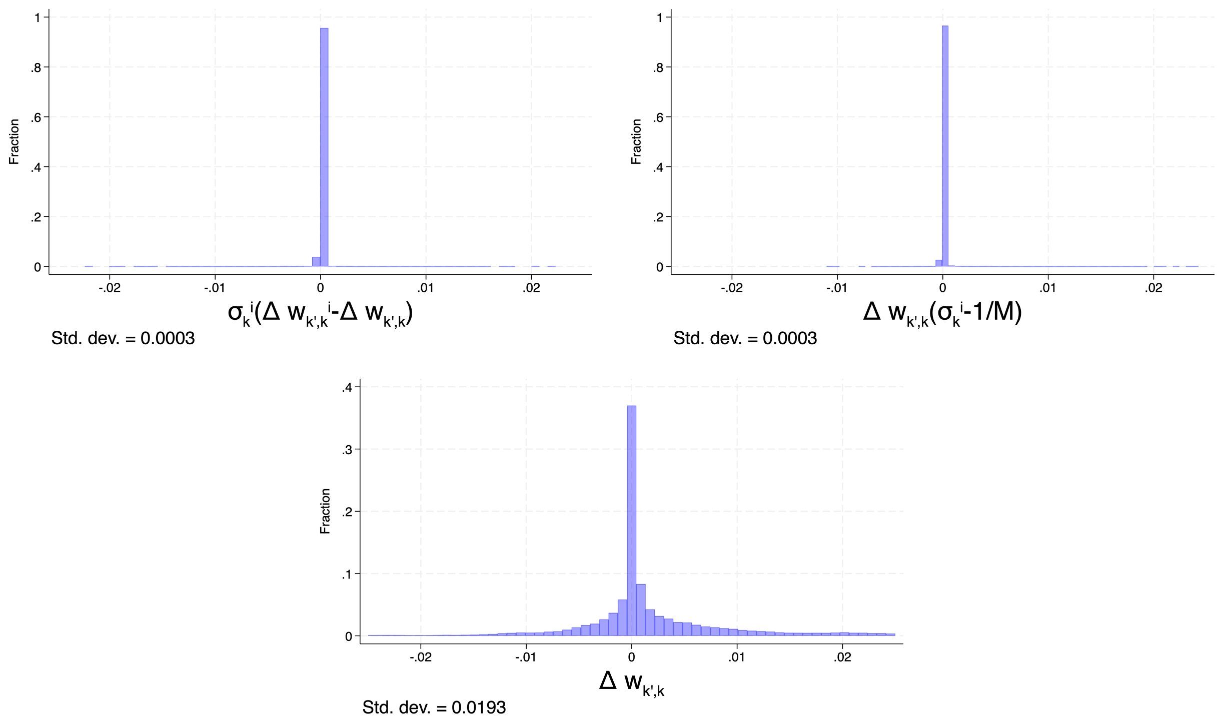
Note: The figure reports leave-one-out estimates of β and η obtained by re-estimating the OLS and IV specifications after dropping, one at a time, each of the ten managers with the largest number of observations in the baseline sample. Bars are point estimates and whiskers are 95% confidence intervals based on standard errors clustered on investor and country. Managers are ranked by their number of observations in the baseline sample, with rank 1 the largest. The horizontal dashed line in each panel marks the full-sample baseline estimate. Fixed-effect structure, instruments, and clustering follow the corresponding baseline specification.

Figure E.3: Robustness – Alternative data cuts



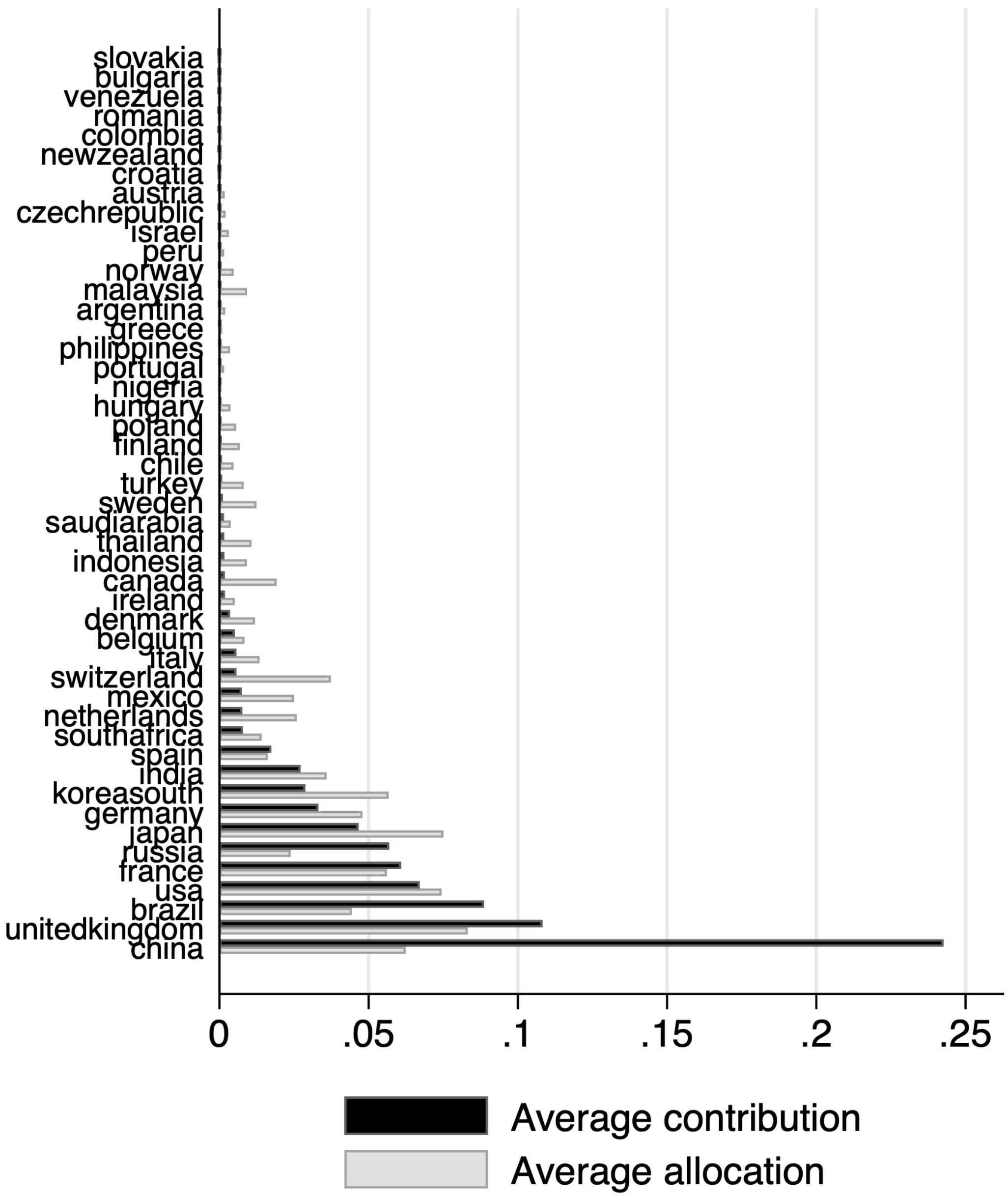
Note: The figure reports the OLS estimates of β and η coefficient under alternative sample restrictions. Markers are point estimates and whiskers are 95% confidence intervals based on standard errors clustered on investor and country. In the baseline, the sample is restricted to country-fund pairs with a mean fund allocation of 0.5% and the fund expectations are computed only if the expectation data covers at least 20% of the fund portfolio and a minimum of 6 countries. The leftmost marker in each panel reproduces the baseline estimate.

Figure E.4: Distribution of weights



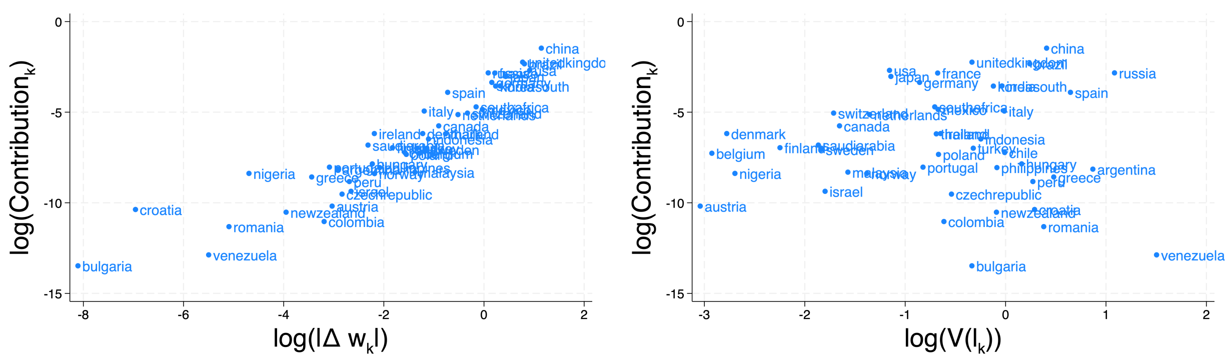
Note: The left panel represents the distribution and standard deviation of $\sigma^i_{k,t}(\Delta w^i_{k,k',t} - \Delta w_{k,k',t})$ across country pairs and investors. The right panel represents the distribution and standard deviation of $\Delta w_{k,k',t}(\sigma^i_{k,t} - 1/M)$ across country pairs and investors. The bottom panel represents the distribution and standard deviation of $\Delta w_{k,k',t}$ across country pairs.

Figure E.5: Contributors to co-ownership spillovers



Note: The figure represents the scatter plot of the average weights $w_k = \sum_{i=1}^{M} \sigma_k^i w_k^i$ against the average contributions $Contribution_k = \sum_{k'=1}^{K} \sigma_{k'} Contribution_{k',k}$.

Figure E.6: Role of weights and idiosyncratic volatility



Note: The left panel represents the scatter plot of the log of the average absolute value of co-ownership linkages $|\Delta w_k| = \sum_{k'=1}^{K} \sigma_{k'} |\Delta w_{k',k}|$ against the log of average contributions $Contribution_k = \sum_{k'=1}^{K} \sigma_{k'} Contribution_{k',k}$. The right panel represents the scatter plot of the log of the variance of country-speicifc expectations $V(l_k)$ against the log of average contributions $Contribution_k = \sum_{k'=1}^{K} \sigma_{k'} Contribution_{k',k}$.