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ABSTRACT

We introduce a novel empirical market-clearing–based decomposition of equity price growth. Using sample holdings covering only an average of 6% of market capitalization, we account for, on average, 88% of time variation in over 22,000 individual stock prices and 95% of fluctuations in 33 aggregate stock indices. Changes in portfolio weights contribute most to the variance of individual stock prices, while “safe haven” markets feature strong cross-stock substitution patterns that leave aggregate portfolio weight changes uncorrelated with aggregate indices. Equity markets are global and exchange rates play a key equilibrating role. We find that the behavior of active funds’ portfolio managers has a causal effect on stock prices by transmitting firm-specific news. Similarly, final funds’ investors play a key role in transmitting macroeconomic and risk aversion news to stock prices.

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An online appendix is available at http://www.nber.org/data-appendix/w32756

1 Introduction

One of the fundamental questions in asset pricing and macroeconomics is the role of asset demand in determining equilibrium asset prices. This paper sheds light on this topic through a novel set of facts relating equilibrium equity holdings and equity prices that are model-free and based solely on market-clearing conditions—nominal equity supply must equal nominal equity holdings.

Our methodology utilizes information about equity holdings of a subset of investors, specifically asset managers, covering the 2008–2021 period. It is founded on a minimal set of assumptions: market-clearing conditions, linearization, and most importantly, the premise that the equity holdings of our subsample of asset managers accurately reflect the behavior of all equity investors. Despite our observed asset managers' holdings covering only 6%, on average, of the market capitalization of the stocks that we consider, our reconstructed holdings-implied equity price log changes align closely with actual changes at the individual stock level for over 22,000 equities issued in 33 different currencies (our concept of "markets"). We also bridge micro stock-level facts with macro index-level facts by directly aggregating holdings to the market level. Here, our reconstructed holdings-implied stock index log changes account for, on average, 95% of monthly time-series variation of actual changes for our 33 aggregate stock markets.

The proof being in the pudding, the close correspondence between holdings-implied and actual stock price movements validates our framework and the informativeness of asset managers' holdings for aggregate investor demand and, therefore, for equity price determination. This is the central and highly surprising result of our paper. Mutual funds are "elephants" in equity markets in the sense that observing the behavior of some of them is enough to approximate the entire market.[1] As we rely on a minimal set of assumptions, the set of empirical moments that we provide is informative for any model of equity prices.

As holdings-implied price movements correspond so closely to actual price movements, it becomes informative to further examine how key components of holdings changes relate to stock price growth rates. More specifically, these components are: (i) changes in portfolio weights, (ii) final investors' inflows into and outflows from funds, (iii) reinvestment of the

[1] Though the focus of this paper is not on cross-investor comovement of holdings, our results on the representativeness of mutual fund holdings is also consistent with elephant-like herding behavior of investors.

net-of-fee fund returns, and (iv) exchange rate valuation effects. Components (i) and (ii) are the main variables of interest in the vast majority of asset pricing models, as they are often modeled as the choice variables of investors so facts about these variables are key for understanding investors' behavior. The net-of-fee return component (iii) captures wealth effects. Finally, one cannot study *global* equity prices without considering exchange rates. They are a second set of prices that helps clear equity markets as cross-country equity purchases also involve an exchange of currencies.[2] We further break down our subcomponents of equity holdings to gain insights on the behavior of holdings by investor type (e.g., index vs non-index funds and local vs foreign investors).[3]

Last but not least, we introduce a stylized model, which allows us to show the causal effect of fund's behavior on asset prices. We empirically link active funds' portfolio weight changes and final investor inflows—the components of our decomposition that contain information beyond mechanical price effects—to exogenous drivers of asset demand such as macroeconomic news, firm-level news, and risk-aversion news.[4] We do so by nesting this news-based subdecomposition of our holdings-based components within our existing framework by extending our representativeness framework, which allows us to trace how exogenous information, as captured by news, propagates to stock prices through the subcomponents of investor holdings.

The decomposition yields a set of new general facts that both inform asset pricing models and complement existing stylized facts in the literature. We summarize the main findings below.

[2]For example, a US investor purchasing a stock denominated in BRL simultaneously sells dollars for BRL and buys this stock, thereby, putting upward pressure on both prices to clear the market.

[3]The main text presents results using monthly data but the same conclusions can be drawn from quarterly data which includes additional funds that report holdings only quarterly (see the Internet Appendix). Moreover, in the Appendix we also show that the results are robust to only considering, for each stock, the holdings of funds that *changed their number of shares held over two consecutive periods*, i.e. we present an alternative version of the decomposition that captures these the so-called "marginal" investors. This is not our preferred version as the decision not to change the shares held is an endogenous decision that contains meaningful information such as the revisions in expected returns being smaller than the cost of rebalancing, for example. It is almost never the case that funds do not rebalance their portfolio with respect to any of the stocks that they hold in a single month.

[4]Papers like Doyle et al. (2006) document price responses to firm-level earnings surprises while Battalio and Mendenhall (2005) also documents that trading behavior reacts to these surprises. Effects of macroeconomic surprises on equity prices have also been found (see for example McQueen and Roley 1993 and Flannery and Protopapadakis 2002).

First, we find that *"stock picking" is alive and well.* Changes in portfolio weights are the subcomponent that covaries most strongly with individual stock price movements across all countries, with non-index ("active") funds accounting for the bulk of this covariance. Our further decomposition of active funds' portfolio rebalancing shows that firm-level news plays a central role in driving these weight changes, dominating the importance of price-based strategies such as momentum and reversal. We further find that firm-level news have causal impact on stock prices via their effect on active funds' portfolio weights changes. In addition, we uncover an important role for a common "sentiment" component across active fund investors' portfolio rebalancing that is not explained by firm fundamentals or past price movements. We construct this sentiment "shock" using a methodology analogous to that employed by Dou et al. (Forthcoming) for fund-flow shocks.

Second, *cross-stock substitution effects are quantitatively important.* At the aggregate stock market level, portfolio weight changes explain a much smaller share of price variation, reflecting strong substitution across stocks. This is captured by the covariance between portfolio weight changes for one stock and price movements of other stocks. We find that *there is important heterogeneity across countries.* These cross-asset substitution effects are strongly negative in stock markets that also have "safe haven" currencies – the US, Japanese, and Swiss markets. It is plausible that stocks in these markets lack close substitutes (particularly when one takes into consideration the unhedged exchange rate component of the investor currency return). As a result, funds rebalance *within* currency borders, explaining why portfolio weight changes at the individual stock level tend to cancel out in the aggregate, leading aggregate portfolio weight changes to be unrelated to aggregate price movements. In contrast, funds exhibit more rebalancing *across* borders for emerging market stocks.[5] Therefore, in emerging markets, the portfolio weight change subcomponent of holdings covary strongly with price changes at both the individual stock and aggregate levels. These cross-stock relationships also emerge clearly in our subdecomposition of active funds' portfolio weights changes, where demand responds not only to stock-specific news but also, importantly, to news about other large firms within the same sector. We show that such substitution patterns arise naturally within our theoretical framework.

Third, we find that while final fund inflows are positively and statistically significantly

[5]For instance, funds might move out of the Brazilian stock market to buy stocks in the Turkish stock market and not so much another stock within the Brazilian stock market.

correlated with equity price changes, they account for only a small fraction of price variation at the individual and aggregate stock levels. This is consistent with the individual-stock evidence in Koijen and Yogo (2019) and the aggregate market results in Koijen and Yogo (2020), both based on estimated structural models of asset demand. We additionally show, however, that *final fund flows are important transmitters of macroeconomic and risk-aversion news to stock prices*. "Sentiment" also plays a key role in driving final inflows, with a notable distinction between active and index funds. In particular, final inflows into active funds are more strongly influenced by macroeconomic news, risk-aversion news, and past relative fund performance than inflows into index funds, consistent with active funds' final investors being a more sophisticated group, such as fund-of-funds investors.

Fourth, some of our findings also speak to the thin but growing literature *jointly studying equity markets and exchange rates*. We find that exchange rates play an "equilibrating role" in nearly all stock markets, especially more "open" stock markets, such as emerging markets. That is, currency movements are associated with a reduction in local stock market volatility—the currency tends to appreciate when equity holdings *increase*, implying less of a local-currency equity price increase needed to clear the equity market. However, here we see another example of heterogeneity across countries with the opposite correlation of stock values falling when currencies appreciate for markets associated with safe haven currencies such as the USD, CHF, and JPY (and those pegged to the USD).[6]

The paper is organized as follows. Section 2 reviews the literature. Section 3 presents our market-clearing-based decomposition for the individual equity and aggregate stock market price growth rates. Section 4 describes the data, while Section 5 contains the empirical analysis. Section 6 presents results on exogenous drivers of the portfolio weight and fund flows subcomponents motivated by a partial equilibrium model of fund manager and investor behavior. Section 7 discusses some implications of our results for theories. Section 8 concludes.

[6]Another way to interpret this result is that, since the fluctuations of the stock market of a country and its currency tend to be positively correlated (with the exception of the safe haven currencies), foreign equity investors, who tend not to hedge currency risk (see Hacioglu-Hoke et al. 2023), take the equity risk and the foreign exchange rate risk "as a bundle" for most currencies.

2 Literature Review

Our paper closely aligns with a new class of empirical research that places equity demand and characteristics-based investing at the heart of the empirical study of asset prices.[7] One of the closest papers in the literature is Koijen and Yogo (2019) which introduces a novel framework based on models of demand from the industrial organization literature. Demand for individual US stocks is estimated using holdings of a subset of investors and used in a structural market-clearing-based decomposition of the cross-sectional variance of equity price movements.[8] Koijen and Yogo (2020) apply the method to aggregate data at the asset class level across a large number of countries.

On methodology, we also use a market-clearing-based decomposition like these papers do, but we differ importantly in taking a novel model-free, non-parametric reduced-form approach. Instead of assuming a model, we present a set of moments relating various components of holdings to asset prices in the form of a reduced-form variance decomposition—moments that can inform a wide range of structural models. Furthermore, using a single unified empirical methodology and dataset, we provide moments at both the individual stock and aggregate levels for markets associated with 33 currencies. Also in terms of exogenous variation, we focus on the propagation of news to stock prices via the rebalancing of active funds' and the investment decisions of the final fund investors, rather than estimating demand elasticities.

On implications for asset prices, these papers highlight the importance of latent demand factors that drive changes to portfolio weights, especially at the individual stock level. Gabaix et al. (2025) use the same model extended with latent characteristics and focus on estimating "asset embeddings" using machine learning and large language models. We, similarly, find a strong covariance between portfolio weights and price changes for individual stocks.

Koijen et al. (forthcoming) apply the demand-based framework to study the impact of

[7] Since the key result in our paper relies on equity investors, on average, being similar within fund types, we also follow in the footsteps of the literature that pioneered "style investing", and, in particular, the classic paper by Barberis and Shleifer (2003). There is also a large literature, less related to our work, which focuses on the performance of investment funds. For a survey, see Wermers (2011).

[8] The decomposition is structural because the characteristics-based demand function assumed for portfolio weights combined with market clearing allows equity prices to be expressed in terms of factors that are taken to be exogenous: the distribution of investors' wealth, asset supply, asset characteristics, time-varying coefficients on characteristics, and latent demand.

the increased importance of ETFs and risks related to climate change while Jiang et al. (2024) uses the methodology to explain the declining "exorbitant privilege" of the US since 2010.[9] Our finding on stock picking at the micro level are compatible with the recent study of Bertaut et al. (2023), who show, using the securities-level data underlying the US external investment positions, that international investors allocate their investment to firms at the top of the productivity distribution.

Our findings also add support to the conclusions in Gabaix and Koijen (2021), who emphasize the importance of final fund flows for explaining aggregate US stock price fluctuations, particularly because the impact of flows is vastly amplified by wealth effects. Our net-of-fee returns component directly captures such wealth effects which are ISIN or stock specific.

The empirical findings in our paper can also provide further motivation for the growing theoretical literature emphasizing the importance of asset managers for equity price determination. While existing papers focus on matching empirical facts about prices, our decomposition presents a whole new set of moments related to *quantities* that can help guide theoretical models. Some prominent papers include Basak and Pavlova (2013), who provide a model with institutional investors following benchmarks, Buffa et al. (2022) who generate novel implications from a model allowing for a continuum of active versus passive behavior by funds.[10]

By considering global investors and a large set of countries, our work is also linked to papers in the international finance literature. The empirical analysis of Maggiori et al. (2020) uses granular data on mutual funds' fixed income holdings to document an important currency bias. We document another important manifestation of the *special-ness of currencies in equity markets*: a pattern of mutual funds rebalancing within and across currency borders, with the USD, JPY, and CHF markets playing a special role. This set of empirical moments on quantities can be seen as the counterpart to existing facts about comovement of prices. The fact that investors tend to substitute across currency borders of emerging markets is consistent with the findings of Morck et al. (2000) that stock price comovements are

[9]On the fixed income side, Nenova (2023) uses granular data on bond holdings by mutual funds based in the US and the Euro area to estimate heterogeneous and time-varying elasticities of demand for bonds. She focuses on monetary policy transmission and the role of safe assets. Fang et al. (2025) studies how investor composition affects the sovereign debt market for a broad cross section of countries.

[10]Furthermore, Ozdenoren and Yuan (2017) and Kashyap et al. (2023) provide a theoretical framework to study the optimality of benchmarking in the mutual fund industry.

particularly strong in these markets and with the finding in David and Simonovska (2016) that emerging market stocks exhibit excess comovement of analysts' forecasts of firm-level fundamentals.

Our paper is also related to Hau and Rey (2006), who theoretically and empirically explore the comovements of equity prices, international portfolio equity flows, and exchange rates, and Camanho et al. (2022) who find that higher equity demand appreciates currencies using a granular instrument derived from disaggregated data on mutual fund equity flows.[11] Our evidence on USD and JPY being safe haven currencies is consistent with Stavrakeva and Tang (Forthcoming) who show that a strong information channel of US forward guidance during the global financial crisis led to higher risk aversion and a flight to safety that appreciated the USD against a number of currencies (except for the JPY). Some of our empirical findings regarding the comovement between exchange rates and stock market indices are shared by Bruno et al. (2022), who find higher local-currency stock returns to be associated with a weaker dollar. Our decomposition provides further evidence on this comovement based on the behavior of investor holdings.

Finally, the approach of decomposing equity price movements into subcomponents with clear economic interpretations is an approach also taken in the well-known Campbell and Shiller (1988) decomposition linking equity price movements to revisions in expectations over discount rates, equity risk premia and dividend growth. Instead, we leverage another important relationship that features equity prices—namely the market-clearing condition—to link equity prices to equilibrium equity holdings and its subcomponents.[12]

3 Market-Clearing Decomposition

This section presents the theoretical underpinnings of our equity price decomposition.

[11] Tesar and Werner (1995) study international flows and home bias and Froot and Ramadorai (2005) the links between institutional flows and temporary and permanent currency returns.

[12] Our decomposition relies on a milder set of assumptions than the Campbell-Shiller decomposition, which requires assumptions on how the marginal trader forms her beliefs.

3.1 Individual Equity Price Growth Rate Decomposition

We start with the market-clearing condition for a single stock j, defined by an ISIN:

$$\sum_{i \in I} \omega_t^{i,j} W_t^i S_t^{l/c^i} = P_t^j Q_t^j \text{ where } c^j = l. \tag{1}$$

W_t^i is the total invested wealth of investor i (assets under management for mutual funds), denominated in the investor's currency, which is the currency of the investor's main region of operation (region of sale (ROS) for mutual funds), which is denoted as c^i. c^j is the currency of issuance of ISIN j, which for this particular ISIN is l, and $\omega_t^{i,j}$ is the share of assets under management of investor i invested in ISIN j. Furthermore, I is the universe of investors that hold asset j. S_t^{l/c^i} is the nominal exchange rate defined as units of currency l needed to purchase one unit of currency c^i. Finally, P_t^j is the price of ISIN j denominated in currency c^j and Q_t^j is the outstanding shares of ISIN j. Based on these variable definitions, $\sum_{i \in I} \omega_t^{i,j} W_t^i S_t^{l/c^i}$ is the total nominal holdings for ISIN j denominated in currency c^j while $P_t^j Q_t^j$ is the nominal value of the supply of ISIN j, i.e., the market capitalization of stock j.

We linearize market-clearing condition (1) with respect to $\omega_t^{i,j}$ and log-linearize with respect to W_t^i, S_t^{l/c^i}, and P_t^j around some constant values:

$$\underbrace{\sum_{i \in I} \widehat{W}^i \widehat{S}^{l/c^i} \left(\Delta\omega_t^{i,j} + \widehat{\omega}^{i,j} \Delta s_t^{l/c^i} + \widehat{\omega}^{i,j} \Delta w_t^i \right)}_{\Delta H_t^j} = \underbrace{\widehat{P^j Q^j} \left(\Delta p_t^j + \Delta q_t^j \right)}_{\Delta MC_t^j}, \tag{2}$$

where lowercase letters denote logs and hats denote the values around which we linearize. In our empirical application, we use sample averages for these points of approximation.

Equation (2) implies that the change in total holdings for ISIN j, ΔH_t^j, can be decomposed into three components. The first component captures the changes of the portfolio weights for asset j, $\sum_{i \in I} \widehat{W}^i \widehat{S}^{l/c^i} \Delta\omega_t^{i,j}$. This is the component of equity holdings that investors directly control. In most models of optimal equity demand, it would be determined by the portfolio optimization condition with respect to asset j (i.e., the Euler equation). The next component is associated with valuation effects due to exchange rate movements, $\sum_{i \in I} \widehat{W}^i \widehat{S}^{l/c^i} \widehat{\omega}^{i,j} \Delta s_t^{l/c^i}$. It will be particularly important for stocks that receive a large amount of demand from "foreign" investors (i.e., from investors whose currency, c^i, differs from c^j). This component captures the fact that the investors need to convert their holdings denominated in their investors' currencies into the currency of issuance of stock j. The last component of the change in total holdings is associated with the growth rate of the investor's wealth, $\sum_{i\in I} \widehat{W}^i \widehat{S}^{l/c^i} \widehat{\omega}^{i,j} \Delta w_t^i$. We decompose Δw_t^i further into components associated with the net-of-fee portfolio returns of investor i, $R_t^{i,NF}$, and the net inflows/outflows into the investment fund, $Flow_t^i$ using the law of motion of the assets under management of investor i, an accounting identity given by:

$$W_t^i = R_t^{i,NF} W_{t-1}^i + Flow_t^i,$$

which implies the following expression for the growth rate of wealth of investor i:

$$\Delta w_t^i = \frac{W_t^i - W_{t-1}^i}{W_{t-1}^i} = \underbrace{\left(R_t^{i,NF} - 1\right)}_{r_t^{i,NF}} + \underbrace{\frac{Flow_t^i}{W_{t-1}^i}}_{flow_t^i}. \tag{3}$$

Substituting expression (3) into equation (2) implies:

$$\begin{aligned} \Delta p_t^j &= \sum_{i\in I} \frac{\mu^{i,j}}{\widehat{P^j Q^j}} \left(\Delta s_t^{l/c^i} + \frac{\Delta \omega_t^{i,j}}{\widehat{\omega}^{i,j}} + r_t^{i,NF} + flow_t^i\right) - \Delta q_t^j \qquad (4) \\ \text{where } \mu^{i,j} &= \widehat{W}^i \widehat{S}^{l/c^i} \widehat{\omega}^{i,j}. \end{aligned}$$

$\mu^{i,j}$ is the sample average holdings of ISIN j by investor i, denominated in currency $c^j = l$ and $\frac{\mu^{i,j}}{\widehat{P^j Q^j}}$ captures the share of ISIN j's market capitalization held by investor i.

Equation (4) provides a *micro-level* decomposition of the growth rate of the price of ISIN j, Δp_t^j, as a function of four subcomponents of the change in holdings and the change in ISIN-level supply due to certain corporate actions such as stock issuances or buy-backs.[13]

To summarize, the change in the total equity holdings of stock j is decomposed into four subcomponents, reflecting changes due to: (i) exchange rate movements, which matter due to the presence of foreign investors, (ii) scaled changes in the portfolio weights of the investors holding stock j, (iii) reinvestment of net-of-fee portfolio returns, measured in the investors' currency, which acts as an amplification mechanism, and, finally, (iv) inflows into fund i, when considering asset managers (or into the invested wealth of investor i more generally),

[13] We use a stock price adjusting for stock splits and, more broadly, for mechanical structural breaks in the price series and, as a result, our ISIN-level supply series are also adjusted for these events. Since new equity of a firm is often issued under a new ISIN, and since our analysis is at the ISIN-level, Δq_t^j captures mostly buy-backs.

measured in the investors' currency.

3.1.1 Empirical Methodology

Constructing the subcomponents of equity holdings in equation (4) requires data on the holdings of every single investor who owns stock j, which is unrealistic, even with the best available data. In order to circumvent this obstacle, we will scale our observed asset managers' holdings, as if they comprise a representative sample of investors that own asset j. We do that in two steps.

In step one, we decompose our portfolio weight changes, net-of-fee returns and final flows subcomponents into averages and residuals, within narrowly-defined types of investors. In step two, we impose two assumptions related to the representativeness of our sample of equity holdings. One is a representativeness assumption that the *population* averages of the portfolio weight changes, net-of-fee returns and final flows, within an investor type, can be well approximated by our equivalent *sample* averages. The other assumption is that we have *"representative holdings ratios"* in our sample across investor types and for each ISIN. Effectively, this means assuming that the ratio of average-over-time *sample* holdings of ISIN j relative to the average-over-time *population* holdings of ISIN j, for a given investor type, is the same across all types of investors, for a given ISIN j.

These two assumptions imply that we can scale up the *averages* of our observed equilibrium holdings subcomponents, appropriately scaled by the share that each fund type holds of the market value of ISIN j, by the inverse of the coverage ratio, to obtain what we call the *"common" subcomponents of equity holdings* of our market-clearing decomposition. As we will show in the results section, the common subcomponents of equity holdings that we construct from *observable* mutual fund holdings have a close correspondence with actual equity price growth variation, thus validating this approach, despite the low sample coverage. Note importantly, that by using only sample averages, this methodology reconstructs equity holdings for the universe of investors without assuming a model of investor behavior and without estimating any model parameters. While the model-free nature of the exercise prevents us from making *structural or causal* statements about exogenous drivers of asset prices, we are able to provide a set of empirical moments that are universal to all models.

In what follows, we explain the exact assumptions that allow us to re-express and reconstruct the terms in the accounting identity in equation (4).

Fund Types We decompose the portfolio weight change, associated with stock j and investor i, into a common component, which is the *arithmetic* average of portfolio weight changes within a narrowly defined group of investors, for a given stock j, and an idiosyncratic residual term, $\varepsilon_t^{\omega,i,j}$:

$$\frac{\Delta\omega_t^{i,j}}{\widehat{\omega}^{i,j}} = \sum_{k\in\tau_i'} \frac{1}{|\tau_i'|} \frac{\Delta\omega_t^{k,j}}{\widehat{\omega}^{k,j}} + \varepsilon_t^{\omega,i,j}. \tag{5}$$

We do not need to impose any assumptions on the correlation structure or the distributions of the residual terms. The investor type is represented by $\tau' \in \Upsilon'$, where $\Upsilon' = \mathit{Active} \times \mathit{Broad\ Strategy} \times \mathit{Freq\ Rebalance} \times \mathit{ROS\ Local\ Currency}$ and $\tau_i' = \{k \in \tau' | i \in \tau'\}$ is the set of all investors that are the same type as investor i. Finally, $|\tau_i'|$ is the number of elements in the set τ_i'.

The "Active" category conditions on whether an investor is an index fund or not. Within non-index funds, we further split the investors into more or less active types. To implement this for mutual funds, we split them based on above or below median average tracking errors. We measure tracking errors as the average absolute deviation of realized fund returns from the average returns of all funds with the same prospectus benchmark index. The "Broad Strategy" category conditions on investor specialization. For our funds, this is based on the reported specialization which can be "Equity", "Mixed Allocation", "Fixed Income" or "Other". The "Freq Rebalance" category conditions on above or below median frequency of portfolio share re-balancing. In our observed sample, this frequency of portfolio share re-balancing is computed at the fund level as the average over time of the fraction of ISINs, out of all ISINs held, at each date for which the fund changed the number of shares held. The "ROS Local Currency" category splits the investors into those whose investor's currency is or is not the same as the currency of issuance of the ISIN.[14] For mutual funds, the investor's currency is the predominant currency in which the fund sells shares to its final investors (i.e., the ROS currency).

[14] Abusing the notation slightly, as the sets need to be specific to investors and not ISINs, in the "ROS Local Currency" set we include an exhaustive list of all 33 investor currencies, which also correspond to the ISIN currencies, and a residual investor set.

Similarly to the portfolio weight change subcomponent, we express the flows and the net-of-fee returns for each investor as an arithmetic average within each investor type plus investor-specific residuals as follows:

$$flow_t^i = \sum_{k\in\tau_i} \frac{flow_t^k}{|\tau_i|} + \varepsilon_t^{f,i} \tag{6}$$

$$r_t^{i,NF} = \sum_{k\in\tau_i} \frac{r_t^{k,NF}}{|\tau_i|} + \varepsilon_t^{r,i}, \tag{7}$$

where $\varepsilon_t^{f,i}$ and $\varepsilon_t^{r,i}$ are the residuals and, once again, we do not need to impose any assumptions regarding their distributions or correlation structures. For the construction of these averages, which are not ISIN-specific, we can use an even more granular grouping of investors, captured by $\tau \in \Upsilon$, where $\Upsilon = Active \times Size \times Broad\ Strategy \times Narrow\ Strategy \times Freq\ Rebalance \times ROS\ Currency$ and $\tau_i = \{k \in \tau | i \in \tau\}$ is the set of all investors of the same type as investor i. The three new subcategories are "ROS Currency", "Size" and "Narrow Strategy".[15] "ROS Currency" is each investor's currency. We have three investor "Size" categories: " $\leq$ \$100 mil", " $>$ \$100 mil and $\leq$ \$1 bil" and "$>$ \$1 bil". The "Narrow Strategy" category further disaggregates USD, EUR, and GBP investors, the vast majority of funds in our sample, by more narrowly-defined strategies such as: "Global Emerging Markets Equity", "Europe Equity Large Cap", "US Equity Large Cap Value", and many others. The way we define the investor groups ensures that it is always the case that $\tau \subseteq \tau'$, which we will use later on in the aggregation.

Scaling Up We define the coverage ratios $\widehat{H}_{\tilde{I}}^{j,\tau} \equiv \sum_{i\in\tau\cap\tilde{I}} \frac{\mu^{i,j}}{\widehat{P^jQ^j}}$ and $\widehat{H}_{\tilde{I}^{miss}}^{j,\tau} \equiv \sum_{\{i|\ i\in\tilde{I}^{miss}\cap i\in\tau\}} \frac{\mu^{i,j}}{\widehat{P^jQ^j}}$, where $\tilde{I}$ is the set of funds we observe in our sample that hold ISIN j and $\tilde{I}^{miss} \equiv I \setminus \tilde{I}$ is the set of investors we do not observe. Intuitively, $\widehat{H}_{\tilde{I}}^{j,\tau}$ is the sample average holdings of ISIN j by all funds of type τ in our sample, as a fraction of the sample average market capitalization of this ISIN. $\widehat{H}_{\tilde{I}^{miss}}^{j,\tau}$ is the same variable but summed across the investors that we do not observe in our sample. Similarly, we define $\widehat{H}_{\tilde{I}}^{j,m} \equiv \sum_{\{i|\ i\in\tilde{I}\cap c^i=m\}} \frac{\mu^{i,j}}{\widehat{P^jQ^j}}$ and $\widehat{H}_{\tilde{I}^{miss}}^{j,m} \equiv \sum_{\{i|\ i\in\tilde{I}^{miss}\cap c^i=m\}} \frac{\mu^{i,j}}{\widehat{P^jQ^j}}$. $\widehat{H}_{\tilde{I}}^{j,m}$ is the sample average holdings of ISIN j by all funds

[15] The reason why we cannot construct average portfolio weight changes using as fine of a grouping is because we observe weights at the ISIN×fund level and our grouping of funds within ISINs is limited by the, sometimes small, number of funds holding each ISIN.

in our sample with a ROS currency m, as a fraction of the sample average market capitalization of stock j. $\widehat{H}^{j,m}_{\tilde{I}^{miss}}$ has a similar interpretation but we sum over the investors whose holdings we do not observe. Substituting equations (5), (6), and (7) into equation (4) and utilizing the definitions of our coverage ratios, one obtains the following expression:

$$\begin{aligned}\Delta p^j_t = \quad & \sum_m \left(\widehat{H}^{j,m}_{\tilde{I}} + \widehat{H}^{j,m}_{\tilde{I}^{miss}}\right)\left(\Delta s^{l/m}_t\right) \\ & + \sum_{\tau\in\Upsilon} \left(\widehat{H}^{j,\tau}_{\tilde{I}} + \widehat{H}^{j,\tau}_{\tilde{I}^{miss}}\right)\left(\alpha^{f,\tau}_t + \alpha^{\omega,\tau,j}_t + \bar{r}^{NF,\tau}_t\right) \\ & + \sum_{i\in I} \frac{\mu^{i,j}}{\widehat{P^jQ^j}}\left(\varepsilon^{r,i}_t + \varepsilon^{f,i}_t + \varepsilon^{\omega,i,j}_t\right) - \Delta q^j_t,\end{aligned} \tag{8}$$

where

$$\begin{aligned}\alpha^{f,\tau}_t = \quad & \sum_{k\in\tau} \frac{flow^k_t}{|\tau|}, \\ \alpha^{\omega,\tau,j}_t = \quad & \sum_{k\in\tau'} \frac{1}{|\tau'|}\frac{\Delta\omega^{k,j}_t}{\widehat{\omega}^{k,j}} \textit{ for all } \tau \subseteq \tau', \\ \bar{r}^{NF,\tau}_t = \quad & \sum_{k\in\tau} \frac{r^{k,NF}_t}{|\tau|}.\end{aligned}$$

We then impose our second assumption:

Assumption 1 (Representative Holdings Ratio)**.** *The ratio of average-over-time sample holdings of ISIN j relative to the average-over-time population holdings of ISIN j, for a given investor type, is the same across all types of investors, for a given ISIN j:*

$$\widehat{H}^{j,\tau}_{\tilde{I}^{miss}} = \kappa^j \widehat{H}^{j,\tau}_{\tilde{I}}, \tag{9}$$

where the scaling parameter κ^j is specific to the ISIN but not to the investor type.

Note that, given that the set τ conditions on the ROS currency of the fund, equation (9) also implies $\widehat{H}^{j,m}_{\tilde{I}^{miss}} = \kappa^j \widehat{H}^{j,m}_{\tilde{I}}$.

Equation (9) allows us to define precisely *representative holdings ratios* for ISIN j as:

$$\frac{1}{1+\kappa^j} = \frac{\sum_{i\in\tau\cap\tilde{I}} \mu^{i,j}}{\sum_{\{i|\ i\in I\cap i\in\tau\}} \mu^{i,j}} \text{ for every } \tau.$$

Since total equity holdings must equal the total market capitalization of ISIN j, after imposing Assumption 1, given by equation (9), one can solve out for $1+\kappa^j$ as a function of observable variables as follows:

$$\sum_{\tau\in\Upsilon}\left(\widehat{H}^{j,\tau}_{\tilde{I}}+\widehat{H}^{j,\tau}_{\tilde{I}^{miss}}\right)=\left(1+\kappa^j\right)\sum_{\tau\in\Upsilon}\widehat{H}^{j,\tau}_{\tilde{I}}=1,$$

which implies

$$1+\kappa^j=\frac{1}{\sum_{\tau\in\Upsilon}\left(\widehat{H}^{j,\tau}_{\tilde{I}}\right)}=\frac{\widehat{P^jQ^j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}. \tag{10}$$

Therefore, Assumption 1, combined with equation (10), implies that we can re-write equation (8) as:

$$\Delta p^j_t = \underbrace{\Delta d^{s,j}_t+\underbrace{\Delta d^{f,j}_t+\Delta d^{\omega,j}_t+\Delta d^{r^{NF},j}_t}_{\Delta d^{ROS,j}_t}}_{\Delta d^j_t}+d^{Resid,j}_t-\Delta q^j_t \tag{11}$$

where

$$\begin{aligned}
\Delta d^{s,j}_t &= \sum_m\frac{\sum_{\left\{i:\, i\in\tilde{I}\cap c^i=m\right\}}\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\Delta s^{l/m}_t,\\
\Delta d^{f,j}_t &= \sum_{\tau\in\Upsilon}\frac{\sum_{i\in\tau\cap\tilde{I}}\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\alpha^{f,\tau}_t,\\
\Delta d^{\omega,j}_t &= \sum_{\tau\in\Upsilon}\frac{\sum_{i\in\tau\cap\tilde{I}}\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\alpha^{\omega,\tau,j}_t,\\
\Delta d^{r^{NF},j}_t &= \sum_{\tau\in\Upsilon}\frac{\sum_{i\in\tau\cap\tilde{I}}\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\bar{r}^{NF,\tau}_t,\\
d^{Resid,j}_t &= \sum_{i\in I}\frac{\mu^{i,j}}{\widehat{P^jQ^j}}\left(\varepsilon^{r,i}_t+\varepsilon^{f,i}_t+\varepsilon^{\omega,i,j}_t\right).
\end{aligned}$$

Our second assumption is that we can proxy the population average net-of-fee returns, flows, and portfolio weight change terms, for each fund type, using sample averages:

Assumption 2 (Representative Averages)**.** *Population averages of the portfolio weight changes, net-of-fee returns and final flows, within an investor type, are well approximated by type-*

specific sample averages:

$$\alpha_t^{f,\tau} = \sum_{k\in\tau} \frac{flow_t^k}{|\tau|} \approx \sum_{k\in\tau\cap\tilde{I}} \frac{flow_t^k}{|\tau|},$$

$$\alpha_t^{\omega,\tau,j} = \sum_{k\in\tau'} \frac{1}{|\tau'|}\frac{\Delta\omega_t^{k,j}}{\widehat{\omega}^{k,j}} \approx \sum_{k\in\tau'\cap\tilde{I}} \frac{1}{|\tau'|}\frac{\Delta\omega_t^{k,j}}{\widehat{\omega}^{k,j}} \text{ for all } \tau \subseteq \tau',$$

$$\bar{r}_t^{NF,\tau} = \sum_{k\in\tau} \frac{r_t^{k,NF}}{|\tau|} \approx \sum_{k\in\tau\cap\tilde{I}} \frac{r_t^{k,NF}}{|\tau|}.$$

Thus, the common subcomponents of ISIN j holdings, by fund type τ, are within-fund-type sample averages of portfolio weight changes, net-of-fee returns and final flows scaled up by $\frac{\sum_{i\in\tau\cap\tilde{I}}\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}$. This factor captures the sample average holdings of stock j by funds of type τ relative to the total sample average holdings of stock j.

We then further sum up these fund-type-specific common subcomponents of ISIN j holdings, across fund types, in order to obtain what we refer to as the *common subcomponents of equity holdings*, which enter the equity price growth rate decomposition given by equation (11): $\Delta d_t^{r^{NF},j}$, $\Delta d_t^{\omega,j}$, and $\Delta d_t^{f,j}$. Notice that the exchange rate common subcomponent, $\Delta d_t^{s,j}$, is analogously defined. The only difference is that we directly observe the exchange rate change relevant for all investors. Moreover, for the exchange rate common subcomponent, the only relevant fund type is the currency of ROS of the fund.

We refer to the sum of all common subcomponents as the *total common component of equity holdings* and denote it with Δd_t^j. Within this overall total, $\Delta d_t^{ROS,j}$ captures the total common component of equity holdings, denominated in the currencies of ROS of the final investors. Finally, $d_t^{Resid,j}$ is an unobservable residual capturing the idiosyncratic portfolio weight changes, net-of-fee returns, and final flows, in addition to measurement error.

In what follows, we discuss the economic interpretation of the most important terms in equation (11). There are two common subcomponents of equity holdings that relate to valuation effects. The first one refers to the fact that nominal equity holdings are impacted by the overall performance/net-of-fee returns of investors, $\Delta d_t^{r^{NF},j}$. Holding the other subcomponents of common equity holdings and equity supply constant, higher net-of-fee portfolio returns get reinvested, which, in turn, increases the nominal holdings of equities and increases stock prices. This is akin to a *wealth effect.*

The second valuation subcomponent of common equity holdings, $\Delta d_t^{s,j}$, captures the fact that equity prices and exchange rates are jointly determined in equilibrium. Based on equation (11), *conditional* on equity holdings denominated in the currencies of the investors, $\Delta d_t^{ROS,j}$, local currency depreciation implies higher *local currency* equity holdings, which can increase the equilibrium local-currency stock market price.

That said, for most ISINs, we would expect the opposite *unconditional* relationship; i.e., local currency *appreciation* would be associated with a local-currency stock market price increase as higher equity holdings, measured in the investors' currencies, will increase both prices (i.e., $Cov(\Delta d_t^{s,j}, \Delta d_t^{ROS,j}) < 0$). Moreover, if the exchange rate between the local ISIN currency and the investor currency, is fixed, for example as in the case of the HKD against the USD, the exchange rate equilibrating mechanism is not present and higher equity holdings by investors have to be entirely absorbed by an increase of the local-currency stock market price.

The last two subcomponents of common equity holdings relate to the portfolio weight changes with respect to ISIN j, $\Delta d_t^{\omega,j}$, and to the decisions of the final investors regarding how much to save in funds that invest in equities, $\Delta d_t^{f,j}$. In our decomposition, a higher weight placed by portfolio managers on ISIN j or more inflows into equity funds that are long ISIN j will both increase the price of ISIN j, all else constant.

3.2 Aggregate Stock Market Price Growth Rate Decomposition

To study how holdings relate to *aggregate* stock market price growth, we directly aggregate equation (11) across ISINs, by constructing a weighted average of the equity price growth rates and its subcomponents. The weights are the sample average market capitalization of each ISIN relative to the total market capitalization of all ISINs in the stock market associated with currency l, $\nu^{j,l} = \frac{\widehat{P^jQ^j}}{\sum_{\{j:c^j=l\}} \widehat{P^jQ^j}}$. We can express this weighted sum as:

$$\Delta p_t^{SM,l} = \underbrace{\Delta D_t^{s,l} + \underbrace{\Delta D_t^{f,l} + \Delta D_t^{\omega,l} + \Delta D_t^{r^{NF},l}}_{\Delta D_t^{ROS,l}}}_{\Delta D_t^{l}} + D_t^{Resid,l} - \sum_{\{j:c^j=l\}} \nu^{j,l} \Delta q_t^j \tag{12}$$

where $\Delta p_t^{SM,l} = \sum_{\{j:c^j=l\}} \nu^{j,l} \Delta p_t^j$ and $\Delta D_t^{x,l} = \sum_{\{j:c^j=l\}} \nu^{j,l} \Delta d_t^{x,j}$. $D_t^{Resid,l}$ is once again backed out as a residual.

We construct the subcomponents of decompositions (11) and (12) at a monthly frequency and report two robustness checks in the Internet Appendix. The first uses quarterly data, incorporating additional funds that report holdings only at a quarterly frequency. The second considers an alternative decomposition that restricts attention to "marginal" funds, defined as those that change the number of shares held of a given stock over the month. This is not our preferred specification, as an absence of share changes may reflect an active decision not to rebalance in response to limited ISIN-specific news rather than an institutional constraint. Consistent with this interpretation, most funds adjust at least some positions every month, even if they do not change their holdings of every asset, suggesting that broad constraints on portfolio rebalancing—such as restrictions to quarter-end trading—are unlikely to be driving our results.

4 Data Description and Summary Statistics

We use equity mutual fund data from Morningstar, comprising over 80,000 self-reporting funds in the Morningstar Direct database. Of these, more than 31,000 are Equity funds and more than 18,000 are Allocation funds. The remainder are classified as Fixed Income or Other, with Money Market Funds comprising the majority of the latter. Almost all of equity holdings are held by Equity funds and, hence, the results will be primarily driven by Equity funds. The vast majority of the funds are domiciled in the US, Eurozone, and UK but we also have a number of large funds domiciled in other jurisdictions. We have fund-level and share-class-level information including ISIN-level positions (portfolio weights, shares held, and market values of holdings), assets under management, net-of-fee portfolio returns, fund flows, Region of Sale (constructed based on the currency of issuance of the share class) and Fund Type. For each asset at an ISIN/CUSIP level, we obtain data from Refinitiv/Eikon on prices, market capitalization, and characteristics, including the type of the asset (fixed income vs equity etc.), industry of the issuing firm, currency of issuance, and main region of operation of the issuer. The number of shares outstanding is calculated from the market capitalization and the equity price. See the Data Appendix for more details.

In Figures 1–2, we show the time series of AUM in USD of our funds by group for our monthly data.[16] Total assets under management peaks at about 26 trillion USD (a little over 13 trillion for Equity funds) towards the end of the sample. From Figure 1, one can see the distribution of the AUM in terms of ROS currency. For equity funds, in particular, the vast majority of AUM are in USD funds. Figure 2 reports the AUM split into active funds and index funds. One can see that index funds have grown in importance among Equity funds, in particular, but the AUM of active funds dominates.

Our data includes 24194 individual equity ISINs after restricting the sample to ISINs which appear in the sample for at least a year. The set of ISINs spans stock markets associated with the following 33 currencies: AUD, BRL, CAD, CHF, CLP, COP, CZK, CNH, DKK, EGP, EUR, GBP, HKD, HUF, IDR, ILS, INR, JPY, KRW, MXN, MYR, NOK, NZD, PHP, PLN, RUB, SEK, SGD, THB, TRY, TWD, USD, and ZAR. To simplify notation, we will denote a given stock market by its currency. We focus on the Jan 2008–Dec 2021 period.[17] Since we will also examine aggregate stock-market-level results, we limit our analysis to ISINs issued in the currency of the main region of operation of the issuing firm, to capture local stock markets rather than, for example, non-US firms issuing in USD.[18]

As an external validity check of the quality of our data, at the total stock market level, we compare our monthly stock market price growth rates, constructed using ISIN-level prices, $\sum_{\{j:c^j=l\}} \nu^{j,l} \Delta p_t^j$, to the growth rate of commonly used stock market indices, obtained from Global Financial Data.[19] The average correlation across all stock markets is 94 percent, with the respective numbers for the US, Eurozone and UK stock markets being 99, 99 and 99 percent (see Figure F.31 in the Internet Appendix).

Table 1 reports weighted-average coverage ratios of our observed holdings for the various stock markets, where we use the same weights as the ones used to construct our size-weighted stock market price growth rates. The weighted-average coverage ratios range from 1% to 23% at the end of our monthly sample with the coverage being the highest for the US, Eurozone, UK, and other advanced economies.[20]

Table 1 also reports the number of ISINs per stock market that we use to construct our

[16]Figure F.30 in the Internet Appendix present the total AUM across all funds. Equivalent graphs for the quarterly data are presented in the Internet Appendix in Figures G.48–G.49.

[17]The samples for MXN, CNH and COP start in Jan 2009, Jan 2014 and Jan 2012, respectively.

[18]We do not include depository receipts in our sample.

[19]The list of stockmarket indices is reported in the Data Appendix.

[20]The respective range for the quarterly data is 4–35% (see Table G.8 in the Internet Appendix).

stock market price indices, which ranges from as few as 5 ISINs for the CZK to 5,824 ISINs for the USD. The currencies of the largest stock markets in terms of both number of ISINs and market capitalization are: USD, EUR, CNH, JPY, INR, GBP, CHF, CAD, TWD and KRW.

Finally, the number of fund types we use to construct the common flow and net-of-fee returns subcomponents of equity holdings is 1,445. Of this number, 491 fund types are those with a "Broad Strategy" classification of "Equity", a category that comprises the bulk of equity holdings (see Figure F.32 in the Internet Appendix for the distribution of the number of funds per type). Across ISINs, the maximum number of fund types we use to compute the portfolio weight change common subcomponent of equity holdings at an ISIN level is 57.

5 Results

In this section, we use our empirical methodology to construct total equity holdings and their subcomponents. We document many novel facts related to the relationships between various dimensions of equity holdings and equity price growth movements at the individual and aggregate stock market levels and interesting heterogeneity across ISINs and countries.

It is important to re-emphasize that many of the results presented in this section are also reproduced in the Internet Appendix under two alternative specifications of the decomposition. The first uses quarterly data and includes additional funds that report holdings only at a quarterly frequency. The second restricts attention, for each stock, to the holdings of funds that *change the number of shares held over two consecutive periods*, thereby isolating the behavior of so-called "marginal" investors. Our results are robust to both alternative specifications.

Before we discuss the fit of our decomposition, which is a metric of the appropriateness of our representativeness assumptions, we present a few figures illustrating properties of the average and idiosyncratic residual components of equations (5), (6) and (7). Figures 3–4 showcase, for two types of funds, fund level flows and net-of-fee returns, as well as the averages within each fund type.[21] It is clear that there is significant heterogeneity of both

[21] Figures F.33–F.34 in an Internet Appendix present the same information for two more fund types as examples.

flows within fund types and average flows across fund types, but not so much for net-of-fee returns. The latter result is to be expected, as the high comovement of stock prices implies high correlations of net-of-fee portfolio returns, particularly across funds with the same "Narrow Strategy".

We also present, in Figure 5, the raw data on the portfolio weight change for a set of ISINs: Apple, LVMH, and the Industrial and Commercial Bank of China. Figure F.35 in the Internet Appendix presents the same information for HSBC, Sberbank Rossii, Petrobras, Rosneft, and Tesla. We separate the fund-level data points by index funds vs active funds and include the averages within these categories. The average portfolio weight changes across index funds and active funds are very similar. This result could be rationalized if stock prices respond strongly to the active funds' average portfolio weight changes. More specifically, if, within the same benchmark, the price of ISIN j increases relative to the price of ISIN k due to active funds' rebalancing into ISIN j and out of ISIN k, then we would observe the automatic portfolio weight change of index funds in a direction consistent with the active funds.

Last but not least, another key observation that stands out is the very large volatility of the idiosyncratic residuals, $\varepsilon_t^{\omega,i,j}$, $\varepsilon_t^{f,i}$ and $\varepsilon_t^{r,i}$, or the differences between the fund level points in each figure and the average lines. In order for our total common equity holdings component to explain a sizable fraction of stock price movements, it has to be the case that these very volatile residuals, even when aggregated using *weighted* sums, and any measurement errors resulting from our method, largely cancel out. In other words, $d^{Resid,j}$ must not be strongly related with equity price changes.

5.1 Individual Equity Price Growth Rates

This subsection examines relationships between our common components of equity holdings and actual equity price growth rates. Since total holdings must equal total asset supply to clear markets, the correspondence between total common components of holdings and prices is jointly informative of the appropriateness of our representativeness assumptions and the importance of the *common* aspects of holdings for movements in aggregate holdings. We then also examine the relationships between subcomponents of holdings and price changes.

A compact way to quantitatively assess these relationship is the following variance covariance decomposition:

$$1 = \sum_{y \in \left\{\Delta d^{s,j}, \Delta d^{f,j}, \Delta d^{\omega,j}, \Delta d^{r^{NF},j}, d^{Resid,j}\right\}} \beta^{p,y} - \beta^{p,\Delta q^j}, \text{ where } \beta^{p,y} = \frac{Cov\left(y_t, \Delta p_t^j\right)}{Var\left(\Delta p_t^j\right)}.$$

This identity says that the covariances of the different components of prices, expressed in equation (11), scaled by the variance of equity price changes must sum to 1, recalling that we compute $d^{Resid,j}$ as a residual. We estimate $\beta^{p,x}$ by regressing x_t on Δp_t^j at the ISIN level. We also report the variance contributed by the total common equity holdings component, defined as: $\beta^{p,\Delta d^j} = \frac{Cov\left(\Delta d^j, \Delta p_t^j\right)}{Var\left(\Delta p_t^j\right)}$.

This variance covariance decomposition should make it clear that, throughout the paper, when we use terms like "importance" or describe contributions to the variance, it is purely in a reduced-form statistical sense to be interpreted as an unconditional empirical moment, and not in a structural or causal sense.

Total Common Equity Holdings Component The left panel of Figure 6 reports the distribution of $\beta^{p,\Delta d^j}$ across ISINs. We can see that the total common component of equity holdings has tight time-series correspondences with changes in log equity prices, with a large part of the distribution of $\beta^{p,\Delta d^j}$ being close to 1. As a matter of fact, out of the 24194 ISINs that we start with, $\frac{Cov\left(\Delta d^j, \Delta p_t^j\right)}{Var\left(\Delta p_t^j\right)}$ is between 0.5 and 1.5 for 22357 ISINs. From now on, we focus only on the subset of ISINs for which $\frac{Cov\left(\Delta d^j, \Delta p_t^j\right)}{Var\left(\Delta p_t^j\right)}$ is between 0.5 and 1.5, which captures almost all ISINs we started with. Within that subset of ISINs, the average scaled covariance is very high at 88%. In summary, the total common component of equity holdings, constructed from *observed* data on a subset of holdings, net-of-fee returns, flows of equity mutual funds, and exchange rate data, tracks remarkably closely the changes in stock prices for the vast majority of ISINs.

The first column of Table 2 presents panel regressions of Δd^j on Δp_t^j within each stock market (as denoted by the currency associated with that stock market). We account for ISIN-level fixed effects and for heteroskedasticity-consistent standard errors, clustered by ISIN. The estimated panel regression coefficients range from 0.76 to 1.00, with a mean of 0.85, and are all highly statistically significant. One can see that our common equity holdings components can indeed explain the vast majority of the variation of equity price growth rates across all stock markets, not just a few. Moreover, it further implies that changes in common (or average) holdings play a more important role than idiosyncratic changes in holdings. The remarkably close fit for a large number of stocks also validates our aggregation methodology by revealing that, although we only observe holdings of a small subset of the investors that invest in those stocks, there is a remarkably high degree of similarity in the *average* holdings between the asset managers in our data and the investors that we do not observe.

As expected, the fit improves when we have a larger number of funds holding a given stock. Figure 7a plots $|1 - \beta^{p,\Delta d^j}|$ against the average number of funds holding the ISIN per month. The closer to zero $|1 - \beta^{p,\Delta d^j}|$ is, the better the fit of our decomposition is. It is fairly rare for an ISIN to be held on average by 200 or more funds per month and to have $|1 - \beta^{p,\Delta d^j}|$ greater than 0.2 (a fit smaller than 80% or larger than 120%). The fit also improves with coverage defined as the percentage of the supply of a given stock that is held by the funds in our sample (see Figure 7b which plots $|1 - \beta^{p,\Delta d^j}|$ against the median over time coverage per ISIN). That said, we do see that the total common component of equity holdings still almost perfectly comoves with stock price growth for some ISINs for which we do not have much data coverage, suggesting that our two representativeness assumptions, discussed in section 3.1.1, may be strongly satisfied in these cases.

We next present plots of the stock price growth rate against the common component of equity holdings for a set of ISINs. For some of these ISINs, we have close to a perfect fit (for example, Apple, LVMH, Toyota, and HSBC as shown in Figures 8 and 9, and Figures F.36 and F.37 in the Internet Appendix). For others, the fit is poor at the beginning of the sample but then improves dramatically towards the end of the sample as more funds hold these stocks, perhaps because of the inclusion in some emerging market index (for example, Industrial and Commercial Bank of China Ltd, Petrobras, Rosneft, and Sberbank as shown in Figure 10 and Figures F.38–F.40 in the Internet Appendix).

When the fit is poor in the beginning of the sample, it is clear we have very few funds (and for some even very poor coverage with an average coverage for the Industrial and Commercial Bank of China Ltd as low as 0.1%), which can be seen in the scatter plots we already discussed (see, for example, Figure 5c for the Industrial and Commercial Bank of China Ltd. and, even more strikingly, see also Figure F.35b in the Internet Appendix for Sberbank). Moreover, for certain firms like Tesla that attract "fan" type of investors, despite the significant coverage and large number of funds holding the ISIN, the fit isn't as tight as for other ISINs with large market cap (see Figures F.35e and F.41), albeit still very good.

New Issuance/Buybacks The second panel of Figure 6 shows the importance of new issuance/buybacks as a contributor to the variance of the stock price growth rate by presenting the histogram for $\frac{Cov\left(\Delta q_t^j, \Delta p_t^j\right)}{Var\left(\Delta p_t^j\right)}$. The scaled covariance peaks at zero and equity buybacks and new ISIN-level issuance appear to be second-order contributors to the variance of equity prices. The last column of Table 2 presents panel regressions of Δq_t^j on Δp_t^j by stock market. The estimated coefficient is negative, on average -0.01, for almost all stock markets and also significant for about half of the stock markets, including the US and the Eurozone, as the theory would predict, as stock buybacks increase the stock price. However, for the vast majority of ISINs, the estimated contribution is very close to zero.

Idiosyncratic Equity Holdings Table 2 also reports the importance of the idiosyncratic residual equity holdings component in the panel regressions of $d^{Resid,j}$ on Δp_t^j. As a reminder, $d^{Resid,j}$ is backed out as a residual from equation (11). On average, the scaled covariance explains 0.13 of the equity price growth rates across our panel regressions with estimated coefficients being statistically significant for most countries.

We are seeing market-clearing in action. Given the large volatility of the idiosyncratic components of portfolio weight changes, net-of-fee returns and fund flows, the fact that it is the total common component of equity holdings, calculated from the far-less-volatile averages of these same variables, that contribute most to the variance of equity price growth rates is particularly striking. Notice that the idiosyncratic equity holdings of large funds that hold more of a ISIN receive a higher weight in $d^{Resid,j}$ than the idiosyncratic equity holdings of smaller funds. As a result, the fact that $d^{Resid,j}$ does not explain a large fraction of the variance of equity price growth rates is not obvious.

5.1.1 Subcomponents of Common Equity Holdings

Next, we discuss the relative importance of the various components of common equity holdings. Figure 11 presents the histograms of ISIN-level estimates of $\beta^{p,x}$ for $x = \left\{\Delta d^{s,j}, \Delta d^{f,j}, \Delta d^{\omega,j}, \Delta d^{r^{NF},j}\right\}$. Figure 12 and Table 2 present estimates from panel regressions of all subcomponents on Δp_t^j by stock market. We also examine the importance of different types of funds for the covariances between equity price changes and the portfolio weight change and final fund flow subcomponents of holdings. In particular, we separate these common equity holdings subcomponents by *index funds vs active funds* and local currency vs other currency investors. The panel regression results are presented in Tables 3 and 4.[22] The sum of the index funds' and active funds' subcomponents might not add up to the total estimated contribution as for some stocks, there are no index fund holdings and, thus, we have sample differences across the regressions.[23]

Portfolio Weights From the panel regressions, it is clear that the portfolio weight change common subcomponent contribute the lion's share to variance of stock price growth (on average, 69%, and between 58% for the ILS and 88% for the COP), where all the estimated covariances are also highly statistically significant. Changes in portfolio weights account for 63% of the variance of the stock market associated with the Euro, 66% for the JPY, 63% for the GBP and 76% for the CNH. The variance contributed by portfolio weight changes tends to be even higher for emerging markets (it is 71% or above for 14 emerging markets). Active funds' changes in weights explain most of the variance while passive changes in weights by index funds are of lower importance and act as an amplifier. There are only two currencies for which the change in weights of index funds is almost as important as the rebalancing of non-index funds: JPY and CNH.

Another important finding is that, for a number of stock markets, we see a sort of home bias in the portfolio weight change common subcomponent of equity holdings. For example, Table 4 shows that, for the US, almost all of the variation in the change in the portfolio weight change common subcomponent reflects the behavior of investors whose ROS currency is the USD. Currency home bias is also important, but to a lesser degree, for the GBP, and the CHF stock markets. This stands in stark contrast to stock prices in some other markets like those of Canada, China, Hong Kong, Singapore, and some emerging markets where ISIN-level prices are almost completely uncorrelated with portfolio weight shifts of local currency funds but are strongly related to those of foreign currency funds.

[22]The same results are presented visually in Figures F.42–F.45 in the Internet Appendix.

[23]We also break down the importance of the equity holdings subcomponents for select individual ISINs in Figures 8–10 and Figures F.36–F.41 presented in the Internet Appendix.

Flows Flows enter significantly and positively in the variance covariance decomposition, but explain a much smaller share of the overall stock price variance: on average only 2%. For the vast majority of currencies, both flows into index funds and active funds or into local and other currency funds contribute positively and statistically significantly to the variance of equity price growth rates.

Net-of-Fee Returns The portfolio weight changes and flows into mutual funds components are ones that are typically modeled as containing exogenous drivers of the behavior of portfolio managers and final investors. The net-of-fee returns subcomponent of equity holdings, in contrast, can typically be understood as an endogenous, amplifying wealth effect. It enters positively and significantly and explains a non-trivial share of the variance (on average, 19%, and between 12% for the AUD and 31% for the CZK).

Exchange Rates The exchange rate subcomponent, $\Delta d^{s,j}$, enters significantly and negatively for most currencies, indicating that exchange rates tend to appreciate when stock prices go up, unconditionally. The estimated average coefficient in the panel regressions is -0.04. Following the classic intuition of portfolio balance models (Kouri 1976), when foreign demand increases for an asset, there are two ways to clear the market: the asset price goes up or the exchange rate appreciates. This is consistent with the empirical findings of Bruno et al. (2022) who show that local currencies tend to appreciate with aggregate stock market gains. This is also consistent with Camanho et al. (2022), who use a granular instrument to show that international net equity flows of mutual funds into a stock market *causally* appreciates the currency of that stock market.[24]

Very interestingly, however, there are five currencies that exhibit an opposite comovement of exchange rates and stock prices, i.e., the currency depreciates when individual stock prices go up: the USD, JPY, CHF, HKD, and EGP. The first three currencies are safe haven

[24]They estimate the elasticity of the currency supply using idiosyncratic shocks to large mutual equity funds and provide a partial equilibrium model that jointly determines equity price growth rates and exchange rates. Conditional on a positive shock on US equity returns—effectively, a positive wealth shock—mean-variance investors rebalance out of the US into foreign stock markets, appreciating the foreign currency relative to the USD and increasing the foreign stock price. In a world in which most of the wealth is concentrated in USD assets, this channel generates comovements consistent with our findings, including the negative USD comovement described below.

currencies and the last two are pegged to the USD.[25]

For these currencies, these unconditional comovements are likely dominated by flight-to-safety episodes where stock prices decrease and investors seek refuge in, for example, USD and JPY fixed income markets. This touches upon a fundamental difference between international equity investments, which are diversified across many markets and currencies, and fixed income markets, which tend to be much more concentrated in a few currencies (see Maggiori et al. 2020), some of which are safe haven currencies. Very interestingly, the EUR does not exhibit this type of safe haven negative comovement between the values of the local currency and stocks.[26]

5.2 Aggregate Stock Market

Having established the very good fit of our total common equity holdings component with respect to stock price growth rates and analyzed the relative importance of each subcomponent of our equity stock price decomposition at the micro level, for each individual ISIN, we proceed to analyze the macro stock market level. Again, we define the stock market to be all ISINs issued in the same currency as the main region of operation of the company.

Many existing theoretical models focus on modeling only the country's aggregate stock market, abstracting from any heterogeneity across different equities. Thus, understanding relationships between key variables and overall stock market price growth is informative for existing theories. Models of the aggregate stock market that are well-informed by the data are, in turn, key for policymakers as they help further the understanding of impacts of policies on aggregate stock market fluctuations, which can further transmit to the real economy through consumer wealth effects.

We are going to once again perform a variance covariance decomposition but, this time,

[25] In the quarterly results, the estimated CHF coefficient becomes negative, implying that the safe haven properties, by this metric, are only present at the monthly frequency for the CHF.

[26] This is consistent with Stavrakeva and Tang (Forthcoming) who also do not find the EUR to be a safe haven currency, as measured by the covariance of the US stock market and the EUR/USD exchange rate. Additionally, estimating time-varying own- and cross-elasticities of substitution across bonds using granular data on US and euro area bond funds, Nenova (2023) shows that US Treasuries are global safe assets while German Bunds are regional safe assets.

focusing on the aggregate stock market and using the variables defined in equation (12):

$$1 \approx \sum_{x \in \left\{\Delta D_t^{s,l}, \Delta D_t^{f,l}, \Delta D_t^{\omega,l}, \Delta D_t^{r^{NF},l}, D_t^{Resid,l}\right\}} \beta^{p,x},$$

$$\text{where } \beta^{p,x} = \frac{Cov\left(x_t, p_t^{SM,l}\right)}{Var\left(\Delta p_t^{SM,l}\right)} \text{ and } \Delta p_t^{SM,l} = \sum_{\{j:c^j=l\}} \nu^{j,l} \Delta p_t^j.$$

We abstract from $\sum_{\{j:c^j=l\}} \nu^{j,l} \Delta q_t^j$ since, as we showed, new issuance and buybacks explain close to none of the variation of individual stock market price growth rates. We again construct $D_t^{Resid,l}$ as a residual from equation (12). We also report the variance contributed by the total common equity holdings component, defined as: $\beta^{p,\Delta D^l} = \frac{Cov\left(\Delta D_t^l, p_t^{SM,l}\right)}{Var\left(\Delta p_t^{SM,l}\right)}$.

We present $\beta^{p,\Delta D^l}$ in Figure 13 and Table 5. The average explanatory power of our total common equity holdings component is 0.95 with the smallest and largest scaled covariances being 0.67 for CNH and 1.08 for the THB. The numbers for the USD, EUR, GBP and JPY are 0.96, 0.96, 0.95 and 0.98 respectively.

To visually explore the fit, Figure 15 and Figure F.46 in the Internet Appendix plot our measures of the common equity holdings component, ΔD_t^l, against the stock market price growth rate. The difference between the two series represents idiosyncratic equity holdings, new issuance/buybacks, and measurement error. The fit between the two series is almost perfect, reflecting the fact that $\beta^{p,\Delta D^l}$ is very close to one for almost all stock markets. This is true for advanced economies, emerging markets, carry trade economies, countries with safe haven currencies, etc. As surprising as it may sound, we are able to build international equity holdings, incorporating exchange rate valuation effects, from the ISIN level up for 33 aggregate country/currency-level stock markets with an almost perfect fit in each case. This is done without estimating any parameters and using only data from mutual funds, where we rely solely on a linearized market-clearing conditions and assumptions about the representativeness of our sample of funds.

In what follows, we study the relative contributions of the equity holdings common subcomponents to variation in overall stock price growth rates. The scaled covariances for the subcomponents are presented in Figure 14 and Table 5 where we also present the adjusted

R^2 from regressing the respective subcomponent on the aggregate stock price growth rate.[27] The key result is a dramatic change between the micro level and the macro level, which we carefully dissect in the next subsections. *Aggregation matters.*

Portfolio Weights: "Micro is not like Macro"

The main finding is that the importance of the portfolio weight change common subcomponent falls dramatically at the aggregate level. Portfolio weight changes still explain a high fraction of stock price change variance for emerging markets—BRL (49%), CLP (43%), IDR (54%), TRY (65%) and ZAR (59%) among many others. However, their contribution decreases significantly for advanced economies and even turns slightly negative for USD, JPY and CHF. The portfolio weight change common subcomponent is always statistically significantly correlated with the stock price growth rate, with the exception of CNH, USD, JPY, CHF, and MYR.

The question emerges of how can we explain the dramatic difference between the *micro* level and *macro* level results? In order to understand why the portfolio weight change components covary less with stock price changes when we aggregate, for some stock markets, we decompose this covariance at the aggregate level into parts associated with *own* versus *cross* comovements between portfolio weight changes and equity price growth rates at the individual stock level. Specifically, we can re-write $\frac{Cov\left(\Delta D_t^{\omega,l}, \Delta p_t^{SM,l}\right)}{Var\left(\Delta p_t^{SM,l}\right)}$ as:

$$\frac{\mathrm{Cov}\left(\sum_j \nu^{j,l}\Delta p_t^j, \sum_j \nu^{j,l}\Delta d_t^{\omega,j}\right)}{\mathrm{Var}\left(\sum_j \nu^{j,l}\Delta p_t^j\right)} = \underbrace{\sum_j \left(\nu^{j,l}\right)^2 \frac{\mathrm{Var}\left(\Delta p_t^j\right)}{\mathrm{Var}\left(\sum_j \nu^{j,l}\Delta p_t^j\right)} \frac{\mathrm{Cov}\left(\Delta p_t^j, \Delta d_t^{\omega,j}\right)}{\mathrm{Var}(\Delta p_t^j)}}_{\beta^{\omega}_{\text{OwnCov}}} + \underbrace{\sum_j \sum_{k\neq j} \nu^{j,l}\nu^{k,l} \frac{\mathrm{Cov}\left(\Delta p_t^k, \Delta d_t^{\omega,j}\right)}{\mathrm{Var}(\Delta p_t^k)} \frac{\mathrm{Var}(\Delta p_t^k)}{\mathrm{Var}\left(\sum_j \nu^{j,l}\Delta p_t^j\right)}}_{\beta^{\omega}_{\text{CrossCov}}}, \quad (13)$$

where we are summing over all stocks j such that $c^j = l$. The first term on the right hand side of the equation above, β^{ω}_{OwnCov}, captures how much of the overall stock price movement

[27] Because these are univariate regressions, these adjusted R^2s are also those that would be given by the reverse regression of aggregate stock price growth on each subcomponent. Therefore, we can also interpret these R^2s in terms of explanatory power of each subcomponent for aggregate stock price growth.

is explained by the ISIN-level comovement of the portfolio weight change with respect to the own-ISIN price, scaled appropriately, while $\beta^{\omega}_{CrossCov}$ captures the explanatory power of the ISIN level comovement of the portfolio weight change with respect to the cross-ISIN price, scaled appropriately. The scaling adds an influence of the size of the market to the terms β^{ω}_{OwnCov} and $\beta^{\omega}_{CrossCov}$. Markets with more ISINs have lower $(\nu^{j,l})^2$ and more cross covariance terms, implying a relatively more important role for the cross covariance terms.

Figure 16 presents the results for β^{ω}_{OwnCov} and $\beta^{\omega}_{CrossCov}$. For exactly the three countries for which the comovement of the common portfolio weight change subcomponent of equity holdings with the aggregate stock market price is negative (i.e., USD, JPY, and CHF), $\beta^{\omega}_{CrossCov}$ is negative. This is consistent with increases of portfolio weight exposure with respect to one US stock often being associated with decreasing the weight exposure with respect to another US stock. In other words, investors rebalance within the US stock or currency borders, leading to the importance of portfolio weight changes in the micro data to disappear at the macro level. β^{ω}_{OwnCov} is positive but very small, as the US stock market has over 5,000 ISINs which dampens the importance of the own-ISIN covariances for the aggregate stock market movement relative to the cross-ISIN covariances.

A similar phenomenon seems to occur within the borders of the stock markets of the CHF and JPY, which are also perceived as safe haven currencies and, apparently, also stock markets that are not easily substitutable. But remarkably, we do not observe negative $\beta^{\omega}_{CrossCov}$ anywhere else, with the exception of NOK where portfolio weight changes remain important in the aggregate due to a very large own-ISIN covariance term. In particular, for emerging markets, the weights fund managers place on individual stocks with the market are very strongly correlated—funds tend to entirely go in and out of the currency borders rather than reallocate within the borders. Investors take the Brazilian equity and the Brazilian Real currency risk jointly or they exit it altogether and substitute into another equity/currency, for example, Turkish equities and Turkish Lira. The cross-covariance term tends to be very positive for emerging markets, in particular, explaining why portfolio weight changes continue to strongly covary with stock market fluctuations at the aggregate level for these markets.

Flows

The final fund flows common subcomponent of equity holdings has gained some importance in the aggregate variance covariance decomposition.[28] This subcomponent always comoves positively with the stock market price in a statistically significant way for 28 out of 33 stock markets. The average fraction of aggregate stock price movements explained by the final flows common subcomponent is 6% and the maximum is 20% for ILS, followed by 15% for both CNH and CLP. The numbers for the USD, EUR and GBP are 5%, 7% and 3% and all are statistically significant at one percent.

Net-of-Fee Returns

The complement to the "micro-to-macro puzzle" we documented for the portfolio weight change common subcomponent is the large increase in the explanatory power of the net-of-fees return component, which reflects wealth effects. As anticipated with our discussion on the "wealth multiplier", any reinvestment of net-of-fee returns that increase due to higher stock prices would further increase prices. The amplification effect would be even stronger for stock markets that are close to "autarky" such as the USD stock market. We do find that the common net-of-fee return component contributes close to 90% or more of the variance in aggregate stock price changes in the USD, CHF, and GBP stock markets, in which many of the equities are indeed held by local-currency funds, as well as for the CAD, which is very integrated with the USD and which has a stock market very correlated with the US stock market. However, the net-of-fee returns component is overall much more important for all stock markets at the aggregate level compared to the individual stock level, which would reflect the high correlation across aggregate stock prices globally.

We perform a micro-to-macro decomposition of $\frac{Cov\left(\Delta D_t^{r^{NF},l},\Delta p_t^{SM,l}\right)}{Var\left(\Delta p_t^{SM,l}\right)}$, similar to the one for portfolio weight changes, based on own- and cross-asset comovements between net-of-fee fund returns and equity price growth rates. Figure 17 presents the results. It is clear the overall covariance is almost entirely explained by the large and positive component capturing the unconditional covariance between an increase in the price of ISIN j and the net-of-fee return component attributable to ISIN k (i.e., the cross-asset terms). This reflects the very high correlation across the returns of asset managers' portfolios and across equity price growth rates more broadly.

[28]Similarly, Koijen and Yogo (2020) find, from estimates of a structural model of asset demand, a larger role for portfolio flows in driving aggregate stock market variation relative to the role found at the individual stock level in Koijen and Yogo (2019) using an analogous model.

The Importance of Exchange Rates For Aggregate Stock Market Fluctuations

Last, but not least, we examine the explanatory power of our exchange rate valuation subcomponent. As in our ISIN-level equity price growth rate decompositions, we again observe that the exchange rate subcomponent dampens the volatility of local stock markets for all stock markets, but the CHF, JPY, USD, HKD, and EGP, for which exchange rate movements actually amplify aggregate stock market volatility.[29] The contribution of the exchange rate subcomponent tends to be the most negative for emerging market economies and can be as negative as -47% for ZAR, -32% for MXN and -31% for BRL. The respective numbers for the USD, JPY and CHF are 2%, 26% and 8%.[30] The average scaled covariance is -14%. The exchange rate subcomponent of equity holdings is statistically significant in all cases but DKK.

6 Drivers of Equity Prices

So far, we have been agnostic about the sources of variation of our common components. In this section, we introduce a framework clarifying which components of our decomposition can affect stock prices through channels other than purely mechanical price effects.

First, using a stylized model, in our decomposition of stock price changes, we show that there are two terms which do not entirely depend mechanically on prices themselves: final customer inflows into funds and the change in weights by active funds.

Second, we show how these two components are driven by macroeconomic news, risk aversion news, firm specific news and past prices. News are not structural shocks but they are perceived as exogenous from the point of view of funds' managers and the final fund investors.

Third, we nest this subdecomposition based on exogenous drivers in our existing framework by generalizing our representativeness model. This allows us to document how news transmit to stock prices via the subcomponents of our decomposition. We find that the be-

[29] Again, the HKD and the EGP are pegged to the USD. We note that the CNH and the SGD do not follow the same pattern as the HKD possibly because they are not strict pegs to the dollar, but rather stabilized within some bands vis-à-vis a currency basket.

[30] The smaller explanatory power of the exchange rate subcomponent for the USD stock market, in absolute value, may simply reflect the very large home bias for USD stocks where exchange rates are a less important equilibrating mechanism for US stocks.

havior of active funds' portfolio managers has a causal effect on stock prices by transmitting firm-specific news. Similarly, final funds' investors play a role in transmitting macroeconomic and risk aversion news to stock prices.

6.1 Partial Equilibrium Model

Consider a model with only USD-denominated funds whose investment universe is a fixed set (no entry or exit) of equities in C different countries, indexed by $c \in \{1, ...C\}$, each with N^c stocks. The stocks also belong to Z different industries, indexed by $z \in \{1, ...Z\}$, each with N^z stocks. Funds consist of active and index country funds. We start by describing the behavior of each of these fund types. We further assume that the set of active funds is I^A with the number of active funds being given by the norm $|I^A|$. There is a representative index fund for each country's stock market. Detailed derivations can be found in Section H of the Internet Appendix.

Active Funds

Each active fund i maximizes expected return, where fund-specific expectations, E_t^i, are the only source of heterogeneity across funds. Each fund is myopic, maximizing the expected fees earned only in the next period, which are a fraction c^p of next period's expected return. We also assume an exogenous diversification motive across stocks, industries, and countries, modeled with quadratic losses from larger portfolio shares. That is, fund i solves:

$$\max_{\{\omega_t^{i,j,A}\}} c^p \left(\sum_{c=1}^{C} \sum_{j \in J^c} \omega_t^{i,j,A} E_t^i \frac{P_{t+1}^{j,USD}}{P_t^{j,USD}} \right) - \sum_{c=1}^{C} \sum_{j \in J^c} \frac{\varphi}{2} \left(\omega_t^{i,j,A} \right)^2 - \sum_{z=1}^{Z} \frac{\mu^z}{2} \left(\sum_{j \in J^z} \omega_t^{i,j,A} \right)^2 - \sum_{c=1}^{C} \frac{\mu^c}{2} \left(\sum_{j \in J^c} \omega_t^{i,j,A} \right)^2,$$

$$\text{subject to } \sum_{c=1}^{C} \sum_{j \in J^c} \omega_t^{i,j,A} \leq 1,$$

where J^z is the set of stocks (across all countries) that belong to industry z and J^c is the set of stocks (across all industries) that belong to country c. Higher values of φ, μ^z, and μ^c represent greater preference for diversification across individual stocks, industries, and countries, respectively. To simplify exposition, we assume that the following are homogeneous constants across industries z's and countries c's: the numbers of stocks in each country $N^c \equiv |J^c|$ and in each industry $N^z \equiv |J^z|$ as well as μ^c and μ^z. We also assume a uniform firm distribution, with the same number of $\frac{N^c}{Z} = \frac{N^z}{C}$ stocks in each country-industry cell.

The first-order-condition allows us to express asset j's optimal portfolio weight in terms of its expected return and the total weights on the assets in its industry and its country, with λ_t^A being the Lagrange multiplier on the summing-up constraint:

$$\varphi\omega_t^{i,j,A} = c^p \left(E_t^i \frac{P_{t+1}^{j,USD}}{P_t^{j,USD}} \right) - \mu^z \left(\sum_{j \in J^z} \omega_t^{i,j,A} \right) - \mu^c \left(\sum_{j \in J^c} \omega_t^{i,j,A} \right) - \lambda_t^A. \tag{14}$$

We then sum this expression across different groups of assets to solve out for these total industry and total country weights as well as for the λ_t^A Lagrange multiplier (using the summing-up condition). The resulting solution for optimal weights on individual assets is:

$$\begin{aligned}
\omega_t^{i,j,A} &= \frac{c^p E_t^i \left[\frac{P_{t+1}^{j,USD}}{P_t^{j,USD}} - \tilde{R}_{t+1}^{c,z} \right]}{\varphi} + \frac{1}{CN^c}, \qquad (15)\\
\text{where } \tilde{R}_{t+1}^{c,z} &\equiv \frac{1 - \tilde{\mu}^z - \tilde{\mu}^c}{CN^c} \sum_{c=1}^{C} \sum_{j \in J^c} \frac{P_{t+1}^{j,USD}}{P_t^{j,USD}} + \frac{\tilde{\mu}^z}{N^z} \sum_{j \in J^z} \frac{P_{t+1}^{j,USD}}{P_t^{j,USD}} + \frac{\tilde{\mu}^c}{N^c} \sum_{j \in J^c} \frac{P_{t+1}^{j,USD}}{P_t^{j,USD}},\\
\tilde{\mu}^c &\equiv \frac{\mu^c}{\mu^c + \frac{\varphi}{N^c}} \text{ and } \tilde{\mu}^z \equiv \frac{\mu^z}{\mu^z + \frac{\varphi}{N^z}}.
\end{aligned}$$

The optimal portfolio weight admits a clear interpretation: it corresponds to a uniform asset weight tilted toward the expected return of asset j relative to a linear combination of the unweighted average returns of all global assets, other firms in the same industry, and other firms in the same country. The coefficients on each component of this linear combination increase with the strength of the corresponding diversification motive across stocks, industries, and countries. The overall importance of the expected relative return of asset j rises with the fund fee rate and declines with the motive to diversify across individual stocks (φ).[31]

With these weights, the law of motion of the AUM of an active fund i is given by:

$$W_{t+1}^{i,A} = (1 - c^p)\, W_t^{i,A} \underbrace{\sum_{c=1}^{C} \sum_{j \in J^c} \omega_t^{i,j,A} \frac{P_{t+1}^{j,USD}}{P_t^{j,USD}}}_{R_{t+1}^{i,A}} + Flow_{t+1}^{i,A}.$$

[31] See Section H.1 in the Internet Appendix for additional details on the derivation.

Index Funds

A set of representative index funds holds the stock indices of each country. Thus, a country c index fund's weight on any asset $j \in J^c$ is that asset's share of the market:

$$\omega_t^{j,I^c} = \frac{P_t^{j,USD} Q^j}{\sum_{k=1}^{J^c} P_t^{k,USD} Q^k}.$$

This weight changes if one stock's market cap changes relative to the total market's value due to price changes (assuming supply is fixed). With this portfolio, the index fund's AUM evolves as:

$$W_{t+1}^{I^c} = \left(1 - c^{p,I}\right) W_t^{I^c} \underbrace{\sum_{j \in J^c} \omega_t^{j,I^c} \frac{P_{t+1}^{j,USD}}{P_t^{j,USD}}}_{R_{t+1}^{c,index}} + Flow_{t+1}^{I^c}.$$

where $c^{p,I}$ is the fraction of the AUM that is allocated to fund fees each period.[32]

Market Clearing for Stock j

The market clearing condition for stock j is that the sum of nominal holdings of active and index funds must equal the nominal asset supply:

$$\sum_{i \in I^A} \omega_t^{i,j,A} S_t^{c^j/USD} W_t^{i,A} + \omega_t^{j,I^c} S_t^{c^j/USD} W_t^{I^c} = P_t^j Q^j,$$

.

Since we assume that there are only USD investors, we can rewrite the market clearing condition above with asset j's price expressed in USD instead of local currency c^j:

$$\sum_{i \in I^A} \omega_t^{i,j,A} W_t^{i,A} + \omega_t^{j,I^c} W_t^{I^c} = P_t^{j,USD} Q^j, \quad \text{where } P_t^{j,USD} \equiv S_t^{USD/c^j} P_t^j.$$

[32] Assuming that index fund fees are small ($c^{p,I} \approx 0$), then the shares held by index funds, equal to $q_t^{I^c} = \frac{\omega_t^{j,I^c} W_t^{I^c}}{P_t^{j,USD}} = \frac{W_t^{I^c} Q^j}{\sum_{k=1}^{J^c} P_t^{k,USD} Q^k}$, will change only if there are inflows or outflows from the fund in this model:

$$q_{t+1}^{I^c} - q_t^{I^c} = \frac{W_{t+1}^{I^c} Q^j}{\sum_{k=1}^{J^c} P_{t+1}^{k,USD} Q^k} - \frac{W_t^{I^c} Q^j}{\sum_{k=1}^{J^c} P_t^{k,USD} Q^k} = \frac{Flow_{t+1}^{I^c} Q^j}{\sum_{k=1}^{J^c} P_{t+1}^{k,USD} Q^k}.$$

For USD stocks, the exchange rate does not play a role as $P_t^{j,USD} = P_t^j$.

Combining the linearized expressions for portfolio weights and the laws of motion for fund assets under management—both for index and active funds—with the linearized market-clearing condition yields a matrix equation that characterizes equilibrium prices. This formulation allows us to solve for net-of-fee fund returns and index funds' portfolio weight changes as linear combinations of price growth rates, and to express price changes as functions of active funds' portfolio weight changes and final fund inflows:

$$\begin{aligned}
\mathbf{\Delta P}_t^{USD} &= \mathbf{\Phi}^{-1}\left[\mathbf{\Delta}\ln\boldsymbol{\omega}_t^{j,A} + \mathbf{flow}_t^A + \mathbf{flow}_t^{I^c}\right], \\
\text{where} \quad \mathbf{\Delta P}_t^{USD} &= \left[\Delta p_t^{1,USD} \ \ldots \ \Delta p_t^{CN^c,USD}\right]', \\
\mathbf{\Delta}\ln\boldsymbol{\omega}_t^{A} &= \left[\sum_{i\in I^A}\mu^{i,1,A}\Delta\ln\omega_t^{i,1,A} \ \ldots \ \sum_{i\in I^A}\mu^{i,CN^c,A}\Delta\ln\omega_t^{i,CN^c,A}\right]', \\
\mathbf{flow}_t^A &= \left[\sum_{i\in I^A}\mu^{i,1,A} flow_t^{i,A} \ \ldots \ \sum_{i\in I^A}\mu^{i,CN^c,A} flow_t^{i,A}\right]', \\
\text{and} \quad \mathbf{flow}_t^{I^c} &= \left[\mu^{1,I^c} flow_t^{I^c} \ \ldots \ \mu^{CN^c,I^c} flow_t^{I^c}\right]',
\end{aligned}$$

Importantly, with non-zero off-diagonal elements of $\mathbf{\Phi}$, this shows cross-asset unconditional relationships between equity prices and portfolio weights and fund flows.

Effectively, this simple model shows that because all exogenous drivers of asset demand are transmitted through the active funds' portfolio weight changes and the final-flow subcomponents, the price growth rate can be expressed solely as a function of these three subcomponents: changes in active funds' portfolio weights and flows into active and index funds. The net-of-fund returns term and the portfolio weight changes of the index funds only serve to amplify the effects of the exogenous drivers. However, the growth rate of stock j's price depends on the active funds' portfolio weight change and final-flow subcomponents of *all* other stocks, making this version of the decomposition impractical to implement empirically.

An important caveat is that this is a highly stylized model and does not capture all exogenous variation in the full empirical model. In particular, it shuts down the exchange rate channel by assuming only U.S. investors and by focusing exclusively on drivers of dollar-denominated prices rather than of local-currency prices—a key distinction relative to the preceding general framework. It also assumes that only equity funds exist. For example, allocation funds are omitted, even though in reality they transmit shocks from fixed income markets to equity prices through substitution effects (e.g., when allocation funds rebalance toward fixed income, they may need to sell equities). A model with allocation funds would result in a solution that contains both fixed-income and equity prices.

Finally, the model abstracts from dividend payments, which affect net-of-fee returns, and from supply-side shocks such as share buybacks. While this simplified setup is useful for clarifying which components transmit exogenous variation to equity prices—and we will rely on it to further decompose the active-fund weight changes and final inflows into exogenous drivers—the empirical decomposition presented earlier remains far more general and practical to implement.

6.2 Empirical Model of Active Funds' Portfolio Weight Changes and Final Inflows

Next, we introduce an alternative decomposition that imposes additional structure on the drivers of $\Delta \ln \omega_t^{i,j,A}$, $flow_t^{i,A}$, and $flow_t^{I^{US}}$. Rather than assuming that funds of a given type share the same average portfolio weight change, we estimate an empirical model of this average behavior, guided by the stylized model developed above.

Specifically, recall from equation (15) that the optimal portfolio weight of active fund i on asset j depends on the expected return (capital gain) of asset j, as well as on the unweighted average returns of assets in the same country, the same industry, and the global market.

In the empirical implementation, we posit that return expectations are shaped by firm-level news, which we measure using scaled IBES surprises of quarterly firm-level fundamentals. Due to data availability, we restrict attention to U.S. stocks and, for simplicity, assume that funds investing in U.S. equities specialize in the U.S. market, which is equivalent to assuming a single-country setting. Under these assumptions, changes in fund i's portfolio weight on asset j take the following functional form:

$$\Delta \ln \omega_t^{i,j,A} = \alpha^{i,j,Own}(E_t^i \Delta p_{t+1}^{j,USD} - E_{t-1}^i \Delta p_t^{j,USD}) - \alpha^{i,j,z}(E_t^i \Delta p_{t+1}^{z,avg} - E_{t-1}^i \Delta p_t^{z,avg})$$
$$-\alpha^{i,j,c}(E_t^i \Delta p_{t+1}^{USD,avg} - E_t^i \Delta p_{t+1}^{USD,avg}). \quad (16)$$

where $\Delta p_{t+1}^{z,avg}$ and $\Delta p_{t+1}^{USD,avg}$ are unweighted averages of log price changes within the same industry z as asset j and within the US, respectively.

We will empirically model active funds' expectations about the capital gain of stock j as depending on current news about the firm, recent past prices that may predict price reversals, and momentum related to further-lagged longer-horizon price movements, the latter two capturing prevalent strategies in financial markets. That is, changes in these expectations are modeled as:

$$E_t^i \Delta p_{t+1}^{j,USD} = \beta^{i,j} f\left(news_t^{firm,j}\right) + (1-\beta^{i,j})\left(\sum_{l=1}^2 \gamma^{i,l} \Delta p_{t-l}^{j,USD} + \gamma^{i,mom} \frac{\sum_{l=3}^{12} \Delta p_{t-l}^{j,USD}}{10}\right) + \varepsilon_t^{i,j}, \quad (17)$$

where $news_t^{firm,j}$ stands for firm-specific IBES surprises (realization minus latest average forecasters' expectation before the quarterly statement scaled by cross-sectional forecast dispersion). These surprises are available for a number of measures like earnings per share, firm sales, etc. Further details on these surprises are in Section D of the Internet Appendix.

Substituting equation (17) into equation (16) makes clear that the active funds rebalancing is a function not only of firm j specific news but also aggregate industry news and country-specific news. Similarly, for the reversal and momentum components of beliefs, past capital gains relative to industry- and country-specific average capital gains drive rebalancing. Average sentiment across funds (including animal spirits) that are not accounted for by firm-level fundamentals and past price movements are captured by $\sum_{i \in I^A} \Delta \varepsilon_t^{i,j}$.

For the final flows of each fund i, we exogenously assume dependence on country-specific macro news, $surp_t^{macro,US}$, risk aversion news, $\rho_t^{i,A}$, lagged fund performance as captured by the fund's net of fee returns, $R_{t-l}^{i,A}$, and country-level fund performance as captured by the

US stock market performance:[33]

$$flow_t^{i,A} = g^{i,A}\left(surp_t^{macro,US}, \rho_t^{i,A}\right) + \sum_{l=1}^{6} (1-c^p)\, \mu_l^{i,A,R} R_{t-l}^{i,A} + \sum_{l=1}^{6} \mu_l^{i,A,US} \sum_{j \in J^{US}} \Delta p_{t-l}^{j,USD} + \varepsilon_t^{i,A,flow}. \tag{18}$$

An analogous functional form is also assumed for flows into the representative index fund.

This functional form can be microfounded via an optimal portfolio allocation problem of a risk-averse final investor into active and index funds.

6.2.1 Implementation

This section describes the empirical implementation of the subdecomposition introduced in the previous section of active funds' portfolio weight changes and final inflows and explains how we embed it in our representativeness framework. Full estimation details are provided in the Internet Appendix in Section H.3; here we summarize the main steps.

Flows To assess the drivers of final fund inflows, we amend the representativeness framework of Section 3 and focus on the marginal-trader decomposition (Internet Appendix Section E), which isolates portfolio adjustments associated with changes in shares held.

We decompose the common component of final fund flows, $\alpha_t^{f,\tau}$, into macroeconomic news, risk-aversion news, lagged performance effects, and a residual sentiment component:

$$\alpha_t^{f,\tau} = \alpha_t^{f,macro,\tau} + \alpha_t^{f,risk,\tau} + \alpha_t^{f,perform,\tau} + \alpha_t^{f,sentiment,\tau}. \tag{19}$$

These components are obtained from panel regressions of fund-level flows on a contemporaneous U.S. macro news index, a risk-aversion news index orthogonal to US macroeconomic surprises, lagged net-of-fee fund returns, and lagged stock market performance at the U.S. (and ROS levels) as in equation (18) (for details on how the news indices are constructed see Appendix and Rey and Stavrakeva (2024)). Investor types are defined by $\{Index \times Broad\ Strategy \times ROS\ Currency\}$ to ensure sufficient observations where Index

[33]If the final investor's ROS currency is not the US, we include the local stock market performance as well.

takes the value of one if the fund is an index fund and zero if non index fund. The fitted values from these regressions are then averaged within fund type to construct the common flow subcomponents. The residual captures time-varying flow sentiment, analogous to the common flow shocks in Dou et al. (Forthcoming).

Portfolio Weights We next decompose the common component of active funds' portfolio weight changes, $\alpha_t^{\omega,\tau',j}$, into lagged price effects, firm-level news, and sentiment:

$$\alpha_t^{\omega,\tau',j} = \alpha_t^{\omega,\tau',prices,j} + \alpha_t^{\omega,\tau',firm\ news,j} + \alpha_t^{\omega,\tau',sentiment,j}, \tag{20}$$

where investor types are defined by $\{Index \times Broad\ Strategy \times ROS\ Local\ Currency\}$.

The decomposition is based on the regression specification obtained by combining equations (16) and (17), but is implemented in two stages using marginal funds only. First, portfolio weight changes are regressed on lagged relative price movements at the firm, industry, and market levels, capturing momentum and reversal strategies. Second, the residual weight changes are regressed on principal components of IBES firm-level surprises for the firm itself and for the largest firms in the same industry, allowing for cross-stock substitution effects as required by the theory. The remaining residual defines a "sentiment" component.[34]

To accommodate the mixed frequency of quarterly earnings announcements and monthly holdings data, we estimate these regressions separately by event time relative to earnings releases. This flexible specification allows the importance of price-based strategies to vary around announcement months.

Aggregation Finally, the estimated subcomponents of flows and active funds' portfolio weight changes by fund type are aggregated to the ISIN level. By construction, the sum of the new subcomponents of the active funds' portfolio weight changes exactly coincides with its counterpart in the "marginal" decomposition presented in the Appendix in Section E as we do not utilize fund specific regressors when constructing the subcomponents. In contrast, the summed final-flow new subcomponents—further decomposed into index and active fund inflows—may differ slightly from the corresponding terms in the marginal decomposition, as the panel regressions used to construct these flow subcomponents rely on

[34]The details of the implementation and the measures used are in the Internet Appendix.

fund-level regressors. Importantly, the overall fit of the new summed common components to the total stock price growth rate remains almost identical to that obtained under the marginal decomposition reported in Section E of the Appendix.

To provide illustrative examples of the subcomponents discussed above, Figures 18 and 19 in the Appendix plot the corresponding decompositions for Coca-Cola and Apple, respectively. For clarity, the "sentiment" subcomponents are not shown, as they are constructed as residuals obtained by subtracting the lagged price effects and firm-level news components from the active portfolio weight change component. The same convention is applied to the final flow decompositions for both index and non-index funds.

6.3 Results

We implement the alternative subdecomposition for U.S. stocks with average market capitalization above $10 billion for which IBES data are available. The resulting sample includes 286 stocks, for which the sum of all common components accounts for between 0.85 and 1.15 of the time-series variance of stock price growth rates.

Our analysis proceeds in two steps. First, we quantify the contribution of each exogenous driver and the price-driven subcomponents to the variation in the common components of active funds' portfolio-weight changes and final fund inflows. Second, we examine how these subcomponents transmit to stock prices.

Decomposition of Common Components To evaluate the relative importance of the drivers, we estimate ISIN-level variance decompositions of the common components. For active funds' portfolio weight changes, we estimate

$$\Delta \tilde{d}_t^{\omega,m,j,NonIndex} = \widehat{\alpha}_1^j + \widehat{\beta}_1^j \Delta \tilde{d}_t^{\omega,j,NonIndex} + \varepsilon_{t,1}^{p,j},$$

where $m \in \{\text{prices}, \text{firm news}, \text{sentiment}\}$. For final fund inflows, we estimate

$$\Delta \tilde{d}_t^{f,z,j,k} = \widehat{\alpha}_2^j + \widehat{\beta}_2^j \Delta \tilde{d}_t^{f,j,k} + \varepsilon_{t,2}^{j},$$

where $k \in \{\text{Index}, \text{NonIndex}\}$ and $z \in \{\text{macro}, \text{risk}, \text{perform}, \text{sentiment}\}$. As in the baseline representativeness-based decomposition, the estimated coefficients can be interpreted as variance shares of the corresponding common components.

Transmission to Prices We then estimate, for each ISIN j,

$$\Delta p_t^j = \widehat{\alpha}_3^j + \widehat{\beta}_3^j x_t + \varepsilon_{t,3}^j,$$

where x_t is one of the subcomponents of portfolio weights or flows. Since these regressors are fitted values from first-stage decomposition regressions, the estimated coefficients are similar to 2SLS estimates, with exogenous drivers serving as instruments for changes in investor demand.

Figures 20–25 report the distributions of estimated coefficients, along with means, medians, and the fraction significant at the 10% level.

Active Funds' Portfolio Weights Figure 20 decomposes variation in the active funds' common portfolio weight change component, $\Delta \tilde{d}_t^{\omega,j,NonIndex}$. On average, active portfolio rebalancing accounts for 31% of the variation in stock price growth rates. Firm-level news explains 35% of the variation in $\Delta \tilde{d}_t^{\omega,j,NonIndex}$, where most of the explanatory power comes from accounting also for the news of the largest companies in the industry due to the cross substitution effects we discussed. More specifically, own firm level news explain 5.7%, on average, of the variation of the active funds' portfolio rebalancing component while news related to the largest 5 firms in the industry account for 29% of the variation. Sentiment and lagged price effects account for 47.6% and 17%, respectively.

Figure 21 shows the price impact of active portfolio rebalancing. Regressing prices on the total active funds' portfolio weight change component yields an average coefficient of 1.3, with 97% of estimates statistically significant. Firm-news-driven rebalancing generates a price response of 1.3 percentage points per one-percentage-point increase in portfolio weights (96% significant). Sentiment-driven rebalancing produces an average price impact of 1.05 percentage points (92% significant), while momentum- and reversal-driven rebalancing is associated with an increase in the stock price growth rate of 1.16 percentage points, on average).

Final Flows of Active and Index Funds Figures 22 and 23 show that final inflows into active and index funds explain, on average, 1% and 1.76% of stock price variation, respectively. Decomposing flows reveals that macroeconomic news, risk-aversion news, and past performance explain a larger share of active fund inflows (5.4%, 1.9%, and 25%) than index fund inflows (3%, 1.6%, and 17%). Sentiment accounts for the majority of flow variation—67.7% for active funds and 78% for index funds. The fact that macro news, risk aversion news, and past fund performance seem to matter more for flows into active funds while index fund flows are less dependent on these drivers is consistent with active funds having a disproportionally larger share of more sophisticated final investors (such as funds of funds).[35]

Figures 24 and 25 report the price effects of the final inflow components. The average price impact of total final inflows is 7.4 for active funds and 3.1 for index funds, with the estimated coefficients statistically significant for 81% and 75% of stocks, respectively. Macro-news-driven inflows generate large and statistically significant price responses—26 percentage points for index funds and 46 percentage points for active funds—with significance for 89% and 91% of stocks. Risk-aversion-driven inflows have even stronger effects: a one-percentage-point increase in this component is associated with price increases of 61 percentage points for active funds and 24.8 percentage points for index funds, with coefficients significant for 94% of stocks in both cases. By contrast, performance-driven inflows, while accounting for a sizable share of variation in flows, generally do not exhibit statistically significant price effects. Finally, sentiment-driven inflows raise prices by 6.7 percentage points for active funds and 2.4 percentage points for index funds, with the corresponding coefficients significant for 72% and 51.7% of stocks.

Overall, the results indicate that active funds' portfolio rebalancing transmits firm-specific information to equity prices, while final inflows into both active and index funds serve as key channels through which U.S. macroeconomic and risk-aversion news affect stock prices. Cross-stock substitution effects are central: news about large firms within an industry significantly influences the prices of other firms in the same sector, consistent with the portfolio choice mechanisms emphasized in the model.

7 Implications for Asset Pricing Theories

In this section, we synthesize the main stylized facts that we document using our novel decomposition of individual equity price changes and aggregate stock market price growth

[35]In unreported results, we verified that macroeconomic and risk aversion news, which is important for final flows, are not broadly significant drivers of portfolio weight changes.

rates. In addition to providing *quantitative* moments that can inform existing models, we also emphasize a number of important *qualitative* results and their relation to theories below.

Starting with the portfolio weight changes, our results show large heterogeneity in weight changes across funds for a given stock. This heterogeneity is consistent with the finding in Koijen and Yogo (2019) of large cross-investor variation in latent demand, particular among mutual funds, which matters for explaining *cross-sectional* variation of stock returns. However, we find that even at the individual stock level, much of that heterogeneity appears to cancel out. In other words, the cross-fund variation in portfolio weights is vastly greater than the time variation of the common component alone. Thus, for explaining *time* variation of stock prices, even at the individual level, the much less volatile *common*, as opposed to idiosyncratic, component of weight changes is most important.

Furthermore, we find evidence of important cross-stock substitution patterns in the relationships between the portfolio weight allocated to one stock and the price of another, particularly within equity markets associated with safe haven currencies. We further find cross-stock relationships in the way that portfolio weight changes respond to firm news with portfolio weights of one firm being significantly affected by news for the other large firms in the same industry. This *fund holdings*-based evidence is consistent with evidence of cross-stock *price* comovement (see Barberis and Shleifer 2003, Morck et al. 2000, and David and Simonovska (2016), for example). Our results thus indicate that such cross-stock relationships, which have not yet been the focus of structural models of asset demand, are an important area for future theoretical and empirical work.

Lastly, our results suggest that theories should take heterogeneity across countries more seriously. We find important heterogeneity in both how exchange rates comove with local stock market prices and the aforementioned cross-stock substitution patterns. Importantly, for equity markets that are associated with safe haven currencies, investors tend to substitute among stocks *within* the market, which results in relatively small aggregate portfolio weight changes that are broadly unrelated to aggregate stock price movements. But we see the opposite in other countries, particularly emerging markets. There, investors tend to substitute *across* markets, resulting in aggregate portfolio weight changes being still strongly related to aggregate stock price movements. Thus, a microfoundation of why investors rebalance within certain markets but not others may be crucial for understanding the “specialness” of these safe haven currencies and markets.

8 Conclusion

Data on mutual funds' holdings, which cover, on average, 6% of ISIN-level equity market capitalization are sufficient to reconstruct total common equilibrium equity holdings that correspond closely to individual equity and aggregate stock market log price changes. *This is the central and highly surprising result of the paper.* Based on this novel decomposition of individual equity price growth rates and stock market price growth rates, we document numerous stylized facts that are informative for all asset pricing theories, given the minimal set of assumptions we impose to arrive at these empirical results.

With this decomposition, we find several key results. There is a strong relationship between common components of portfolio weight changes and equity prices at the individual stock level. Such portfolio weight changes transmit firm-level news to equity prices. However, for some countries, especially those with safe haven currencies, this relationship disappears at the aggregate market level. This is due to strong cross-stock substitution patterns within these markets—patterns that we also see in the form of portfolio weights allocated to one stock reacting to other firms' earnings report news.

We also find that final fund flows are transmitters of macro and risk aversion news to equity prices although they account for less of the overall variation of equity prices.

Finally, we emphasize the importance of studying exchange rates and equity markets jointly. We further explore the link between exchange rates and equity markets in Rey and Stavrakeva (2024), where we show that the same market-clearing conditions for equities can be used to express exchange rates as a function of the net equity-related supply of currencies and observed elasticities that are linked to the centrality of a currency for equity markets.

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9 Tables and Figures

Figure 1: AUM by Investment Type and ROS Currency (Monthly Sample, USD Trillions)

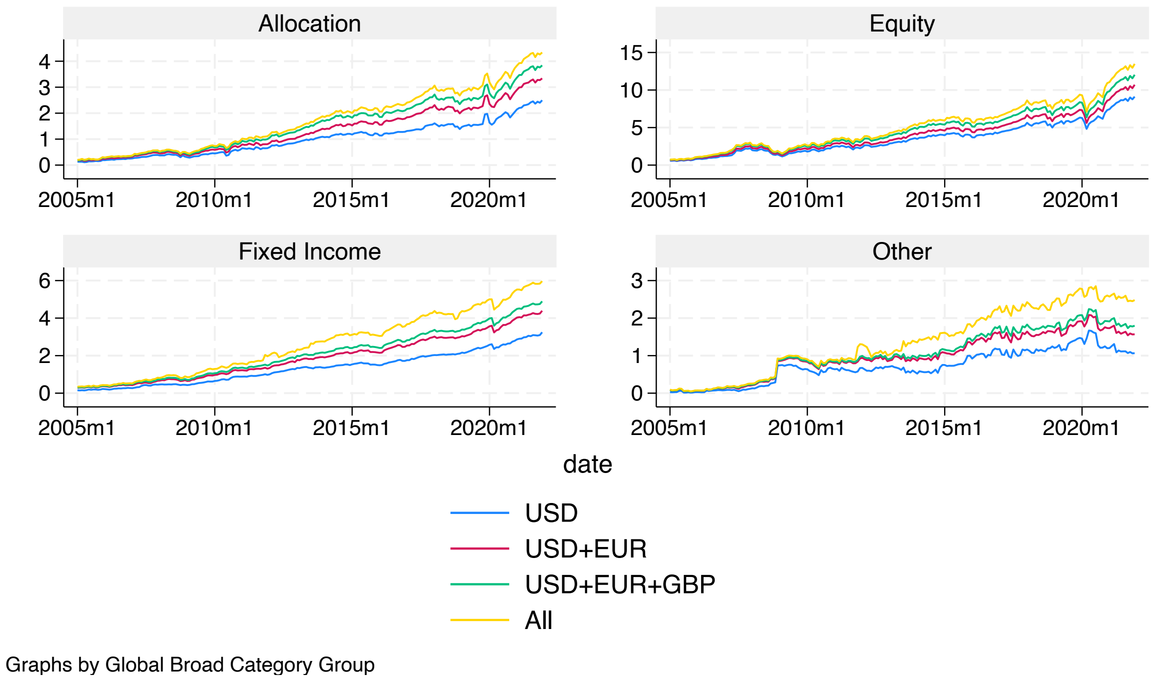


Figure 2: AUM by Investment Type and Index Funds/Active Funds (Monthly, USD Trillions)

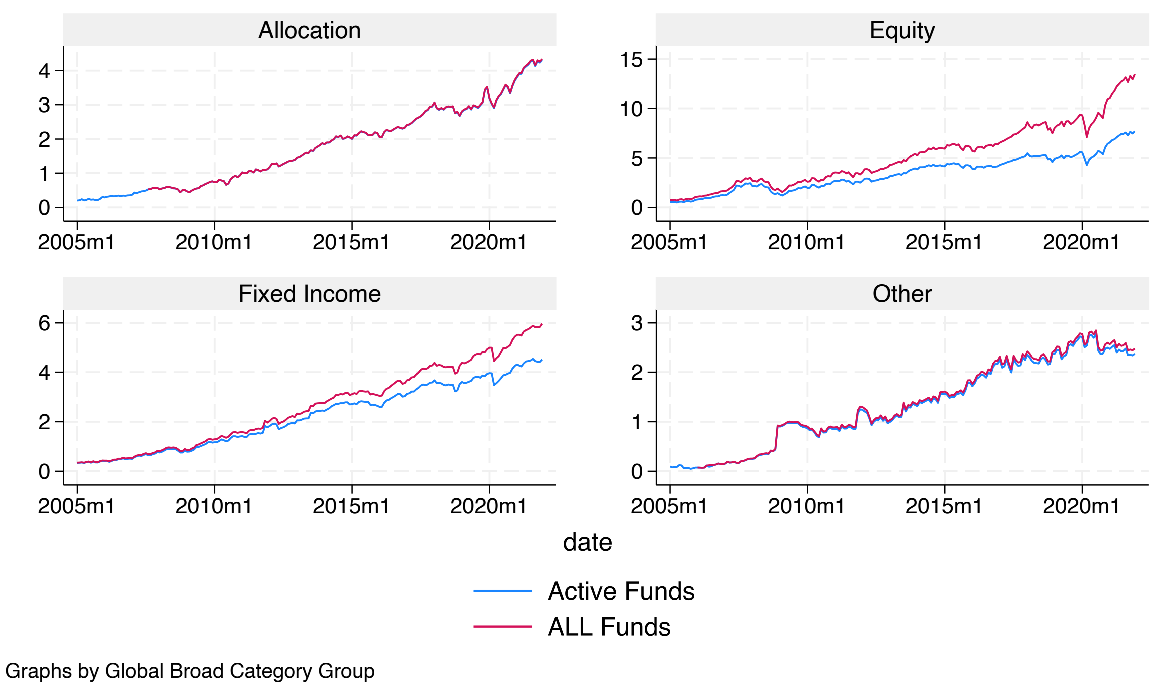
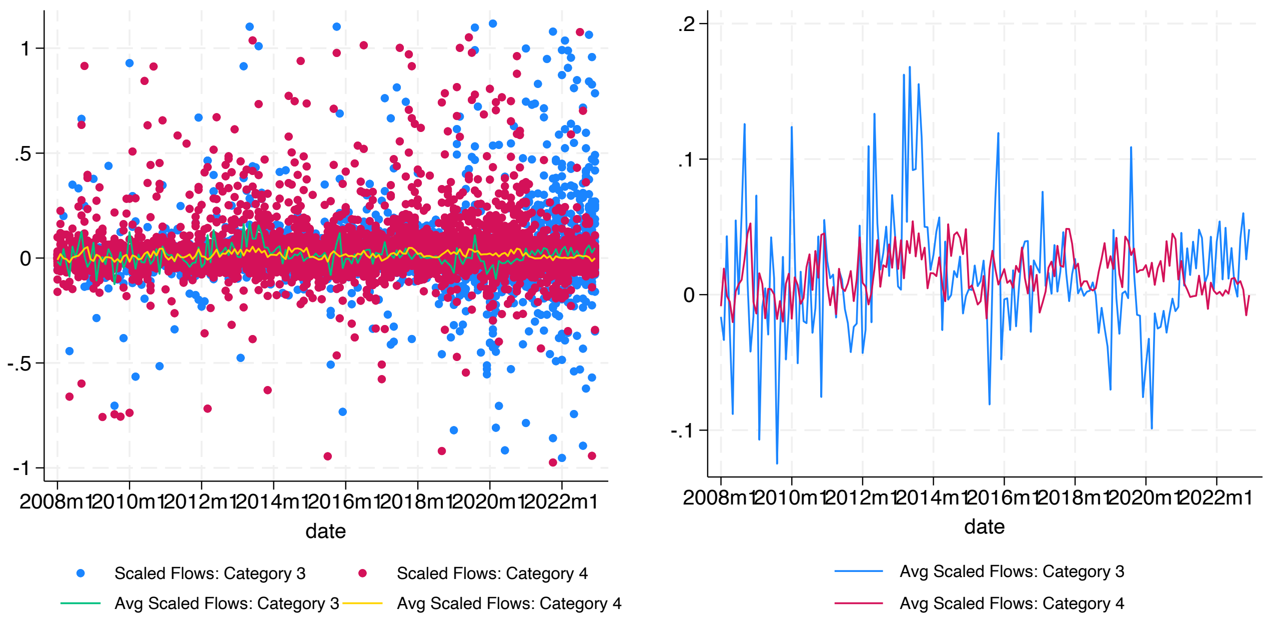


Table 1: Coverage and Market Capitalization (Monthly Sample)

Currency	*AvgCoverage*	*CoverageStart*	*CoverageEnd*	*AvgMarketCapUSDbil*	*MarketCapStartUSDbil*	*MarketCapEndUSDbil*	*ISINs*
AUD	0.07	0.06	0.11	1006.94	759.53	1449.23	691.00
BRL	0.07	0.02	0.13	806.26	746.86	714.29	298.00
CAD	0.05	0.04	0.09	1389.11	1060.12	2157.50	658.00
CHF	0.10	0.04	0.17	1209.37	885.53	1978.08	239.00
CLP	0.02	0.00	0.04	176.15	139.78	110.50	76.00
CNH	0.00	0.00	0.01	3783.26	274.35	10015.30	1419.00
COP	0.02	0.00	0.03	112.55	82.48	77.38	27.00
CZK	0.05	0.04	0.03	28.19	51.94	32.10	5.00
DKK	0.07	0.02	0.14	219.10	115.30	494.98	101.00
EGP	0.02	0.02	0.03	32.92	63.92	28.51	49.00
EUR	0.08	0.04	0.13	6081.11	5759.58	9594.51	1851.00
GBP	0.14	0.05	0.23	2714.75	2604.17	3265.72	1274.00
HKD	0.06	0.04	0.08	904.81	608.97	1056.82	493.00
HUF	0.10	0.05	0.13	16.74	19.43	27.60	12.00
IDR	0.04	0.02	0.05	314.74	122.53	409.74	214.00
ILS	0.03	0.02	0.05	151.27	128.22	282.40	267.00
INR	0.07	0.03	0.12	1388.59	847.34	3245.23	982.00
JPY	0.06	0.02	0.10	4544.64	3521.54	6562.13	2886.00
KRW	0.07	0.03	0.10	1158.36	772.82	1982.80	1606.00
MXN	0.07	0.03	0.08	309.78	207.91	379.50	124.00
MYR	0.03	0.03	0.03	361.88	265.77	373.81	388.00
NOK	0.07	0.02	0.13	228.78	224.12	372.16	182.00
NZD	0.06	0.03	0.10	53.68	21.87	114.10	81.00
PHP	0.03	0.03	0.03	172.29	55.09	234.66	104.00
PLN	0.03	0.02	0.05	126.95	103.89	160.94	129.00
RUB	0.01	0.00	0.02	410.73	248.29	609.20	67.00
SEK	0.06	0.02	0.13	444.65	314.00	1012.06	370.00
SGD	0.05	0.04	0.07	317.24	286.48	329.19	220.00
THB	0.02	0.02	0.01	450.02	191.72	686.98	284.00
TRY	0.04	0.04	0.03	188.11	191.38	129.57	183.00
TWD	0.06	0.03	0.09	909.42	534.52	2108.08	1054.00
USD	0.12	0.08	0.16	22199.78	13946.97	47654.68	5824.00
ZAR	0.06	0.05	0.07	330.57	281.31	340.58	199.00

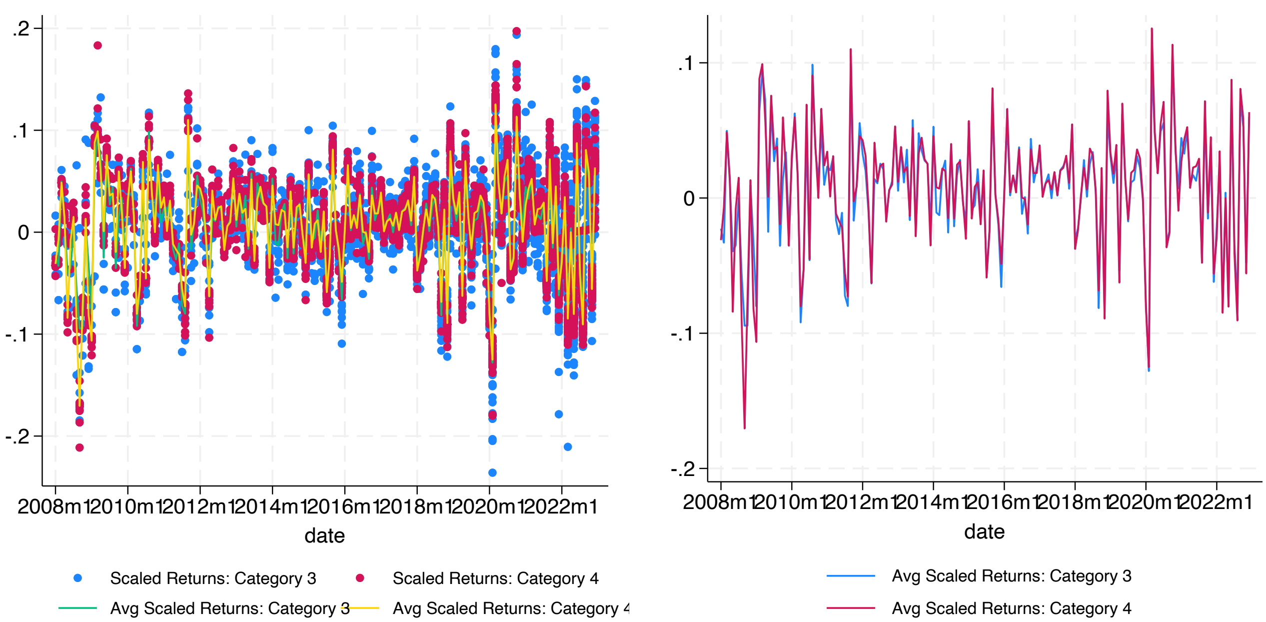
This table presents the sample average, starting date and ending date coverage ratios, weighted by the market capitalization of the ISIN. The coverage ratio for an ISIN is defined as total observed holdings of this ISIN in our data set over the market capitalization of the ISIN, translated in the same currency. It also reports the sample average, starting and ending date market capitalization for all ISINs issued in a given currency and the number of ISINs in our sample. We have kept only firms for which the currency of issuance is the same as the main region of operation.

Figure 3: Examples of Fund-level and Average Scaled Flows For Select Categories



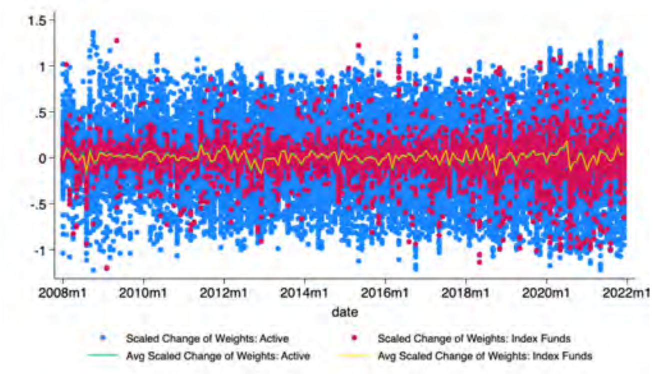
Equity Funds; USD ROS currency;
Category 3 : Active: more active; Freq Rebalance: re-balancing frequently; size of fund: <=100mil; GlobalCategory: US Equity Large Cap Blend
Category 4: Active: Index Funds; Freq Rebalance: re-balancing frequently; size of fund: >1bil; GlobalCategory: US Equity Large Cap Blend

Figure 4: Examples of Fund-level and Average Net-of-Fee Returns For Select Categories

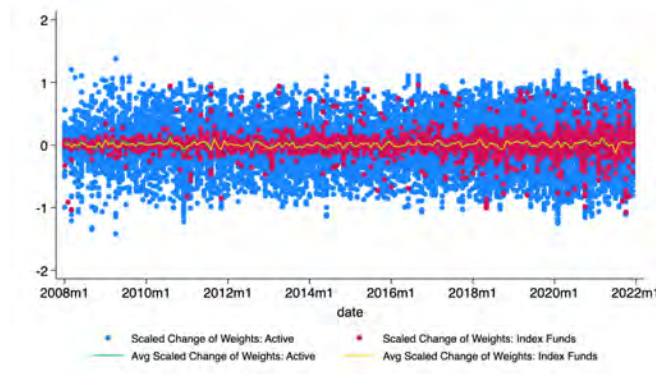


Equity Funds; USD ROS currency;
Category 3 : Active: more active; Freq Rebalance: re-balancing frequently; size of fund: <=100mil; GlobalCategory: US Equity Large Cap Blend
Category 4: Active: Index Funds; Freq Rebalance: re-balancing frequently; size of fund: >1bil; GlobalCategory: US Equity Large Cap Blend

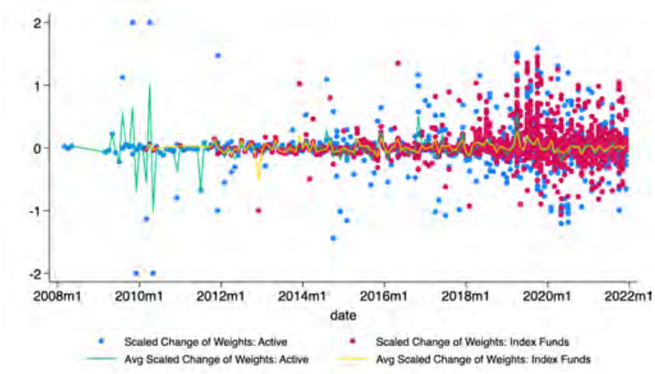
Figure 5: Portfolio Weight Change for Select Stocks



(a) Apple

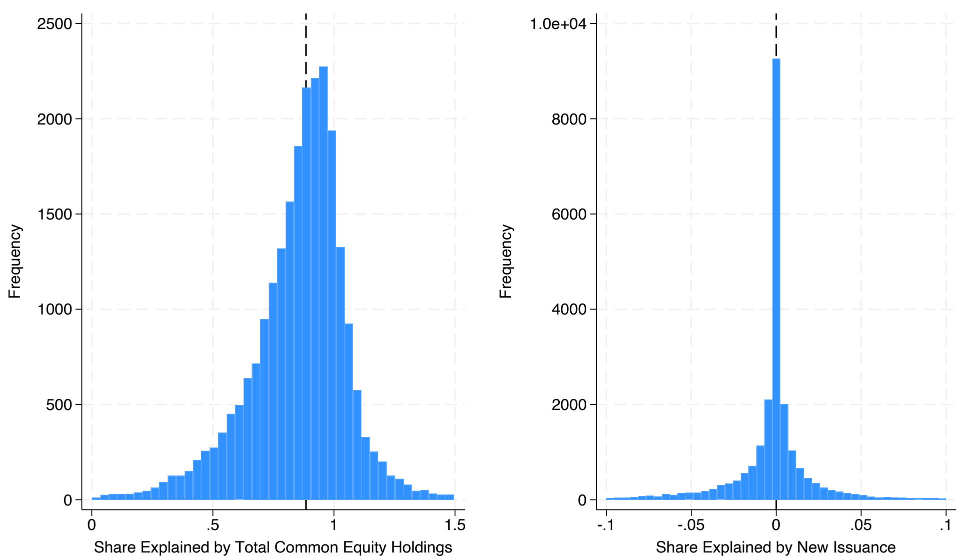


(b) LVMH



(c) Industrial and Commercial Bank of China Ltd

Figure 6: ISIN-Level Equity Price Growth Rate Decomposition: Histograms



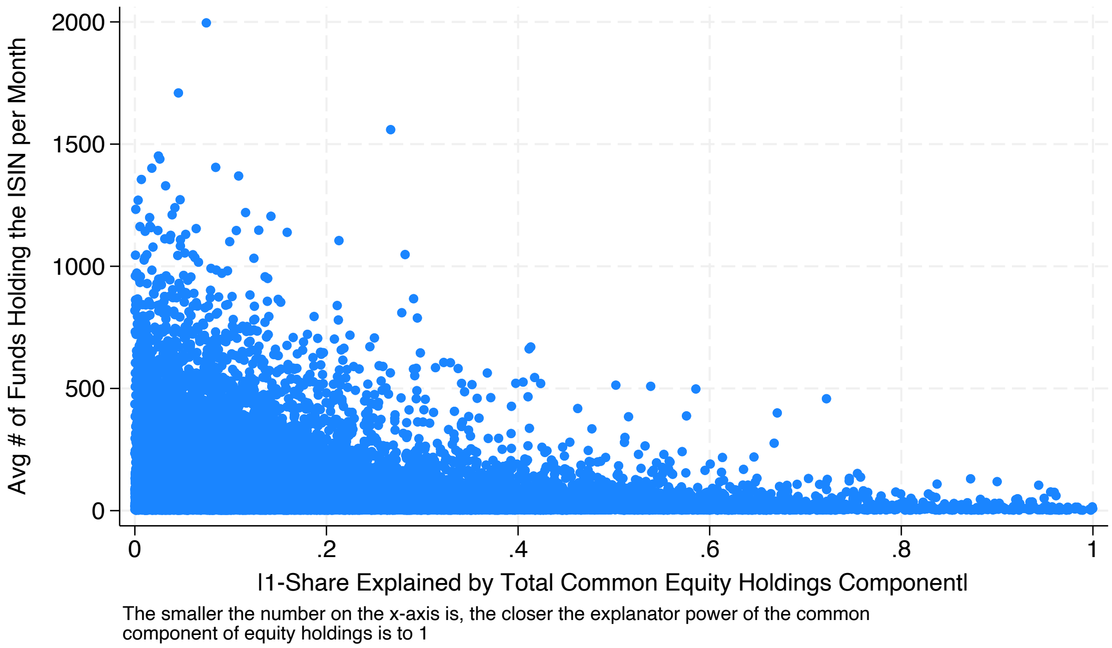
We plot only the set of ISINs for which $\frac{Cov\left(\Delta d^j, \Delta p_t^j\right)}{Var\left(\Delta p_t^j\right)}$ is between 0 and 1.5.

Table 2: ISIN-Level Equity Price Growth Rate Decomposition: Panel Regressions

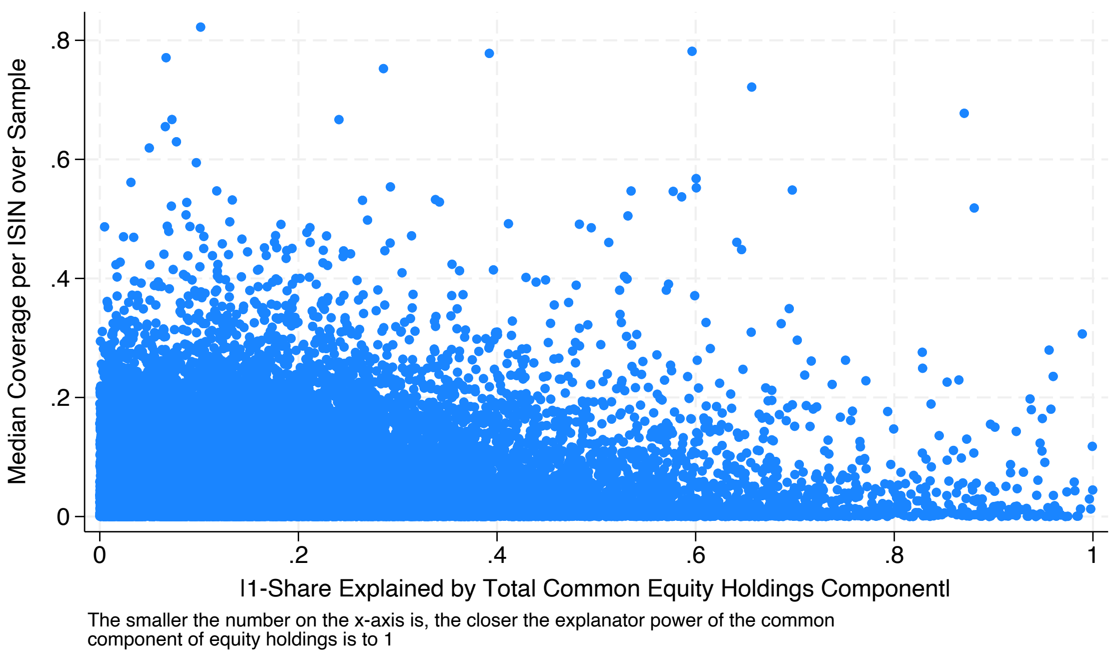
Currency	Δd_t^j	$\Delta d_t^{\omega,j}$	$\Delta d_t^{s,j}$	$\Delta d_t^{f,j}$	$\Delta d_t^{r^{NF},j}$	$\Delta d_t^{Resid,j}$	Δq_t^j
AUD	0.756***	0.674***	-0.042***	0.006***	0.119***	0.228***	-0.014***
BRL	0.806***	0.702***	-0.065***	0.016***	0.153***	0.190***	-0.003
CAD	0.774***	0.674***	-0.048***	0.010***	0.138***	0.220***	-0.002
CHF	0.861***	0.636***	0.004***	0.005***	0.217***	0.134***	-0.005
CLP	0.868***	0.681***	-0.070***	0.051***	0.206***	0.124***	-0.002
CNH	0.910***	0.755***	-0.013***	0.031***	0.136***	0.089***	-0.000
COP	0.905***	0.877***	-0.183***	0.021***	0.189***	0.073*	-0.006
CZK	1.001***	0.771***	-0.102**	0.017	0.315***	0.002	0.003
DKK	0.856***	0.658***	-0.011***	0.016***	0.193***	0.128***	-0.010**
EGP	0.909***	0.665***	0.058***	0.015***	0.172***	0.065***	-0.022***
EUR	0.839***	0.626***	-0.021***	0.022***	0.212***	0.152***	-0.008***
GBP	0.790***	0.632***	-0.006***	0.006***	0.159***	0.196***	-0.010***
HKD	0.888***	0.674***	0.013***	0.018***	0.184***	0.106***	-0.005**
HUF	0.903***	0.734***	-0.122***	0.014**	0.277***	0.099	0.002
IDR	0.851***	0.758***	-0.061***	0.014***	0.139***	0.148***	0.000
ILS	0.813***	0.579***	-0.006***	0.081***	0.159***	0.168***	-0.018***
INR	0.799***	0.646***	-0.025***	0.001**	0.176***	0.203***	0.001
JPY	0.925***	0.662***	0.057***	0.007***	0.198***	0.074***	-0.002**
KRW	0.904***	0.782***	-0.032***	-0.002***	0.156***	0.090***	-0.005***
MXN	0.779***	0.691***	-0.078***	0.019***	0.148***	0.217***	-0.003
MYR	0.851***	0.657***	-0.043***	0.019***	0.219***	0.139***	-0.008*
NOK	0.771***	0.642***	-0.030***	0.015***	0.143***	0.226***	-0.003
NZD	0.839***	0.699***	-0.037***	0.008***	0.168***	0.156***	-0.002
PHP	0.901***	0.718***	-0.024***	0.016***	0.191***	0.095***	-0.001
PLN	0.821***	0.721***	-0.094***	0.009***	0.184***	0.178***	-0.001
RUB	0.872***	0.762***	-0.090***	0.016***	0.184***	0.131***	0.003
SEK	0.871***	0.679***	-0.025***	0.027***	0.190***	0.131***	0.003
SGD	0.885***	0.650***	-0.045***	0.023***	0.256***	0.112***	-0.004
THB	0.900***	0.692***	-0.049***	0.027***	0.231***	-0.148***	-0.244***
TRY	0.897***	0.766***	-0.082***	0.019***	0.194***	0.105***	0.002
TWD	0.919***	0.710***	-0.028***	0.010***	0.228***	0.079***	-0.001*
USD	0.803***	0.599***	0.002***	0.009***	0.193***	0.186***	-0.006***
ZAR	0.796***	0.712***	-0.090***	0.015***	0.159***	0.194***	-0.009*

Note: This table reports the coefficients from panel regressions of the total common component of equity holdings, Δd_t^j, and its subcomponents on Δp_t^j by stock market (as denoted by the currency associated with that stock market). The subcomponents are the portfolio weight changes "common" subcomponent, $\Delta d_t^{\omega,j}$; the exchange rate "common" subcomponent, $\Delta d_t^{s,j}$; the final flows "common" subcomponent, $\Delta d_t^{f,j}$; and the net-of-fee returns "common" subcomponent, $\Delta d_t^{r^{NF},j}$. We also report regressions for the residual (unobservable) subcomponent, $\Delta d_t^{Resid,j}$, and for the change in shares outstanding, Δq_t^j. We allow for ISIN-level fixed effects and cluster the standard errors by ISIN. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%.

Figure 7: ISIN Level Fit

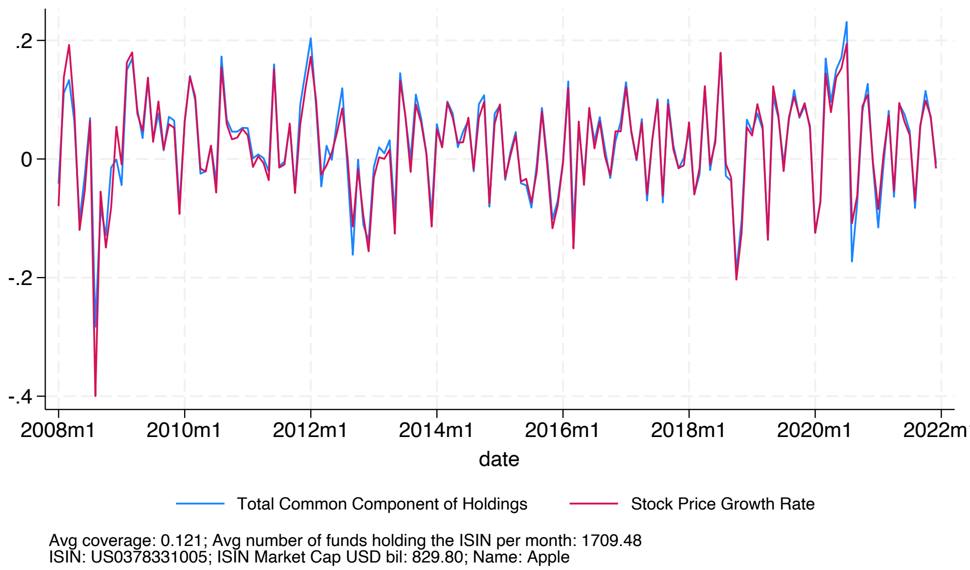


(a) Against Average Number of Funds

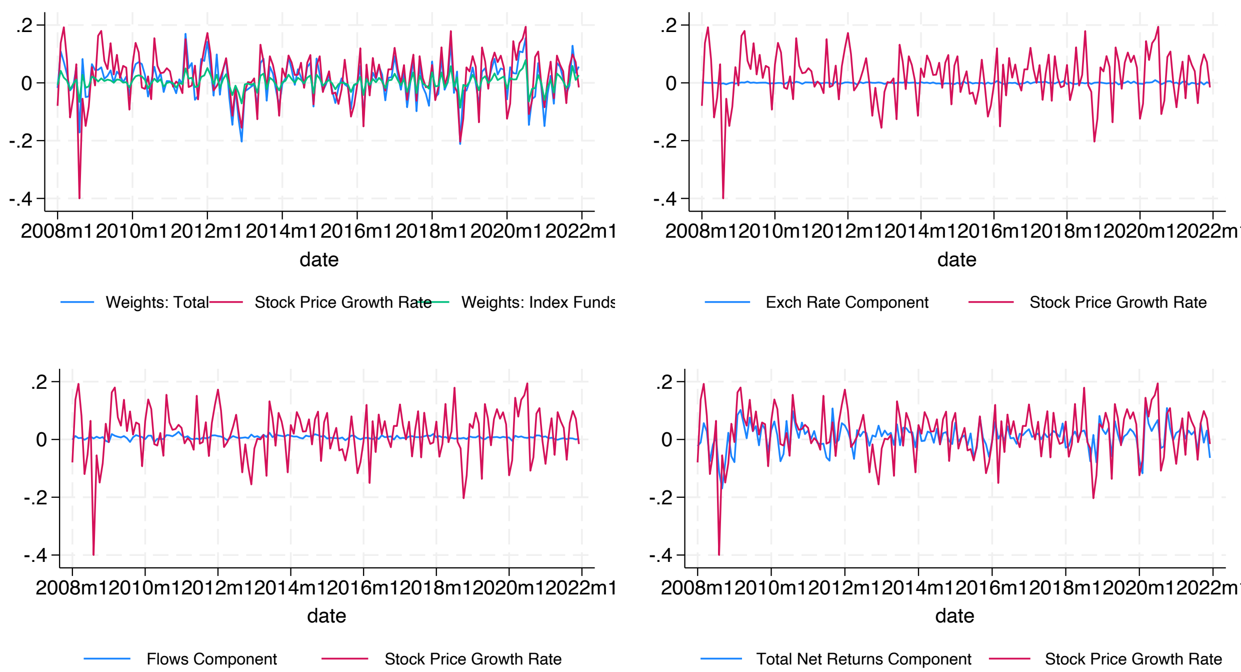


(b) Against Coverage

Figure 8: Common Equity Holdings Components: Apple

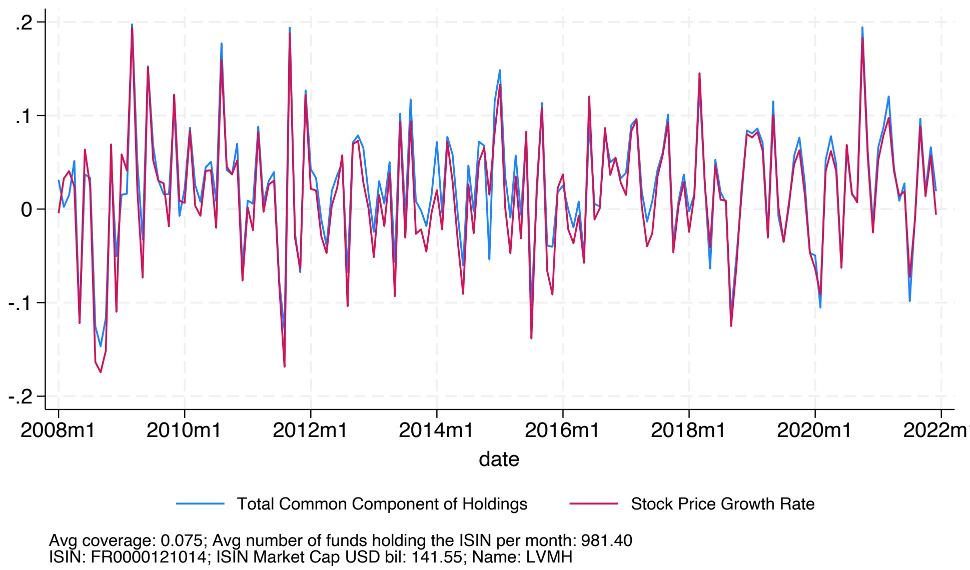


(a) Total

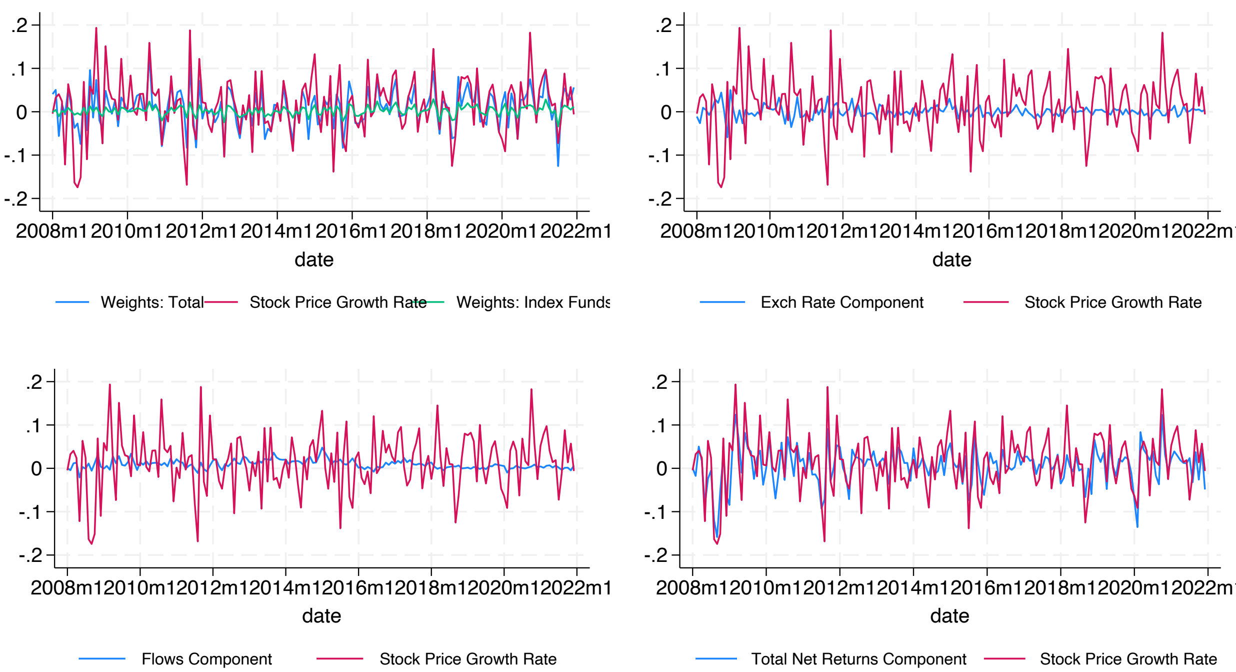


(b) subcomponents

Figure 9: Common Equity Holdings Components: LVMH

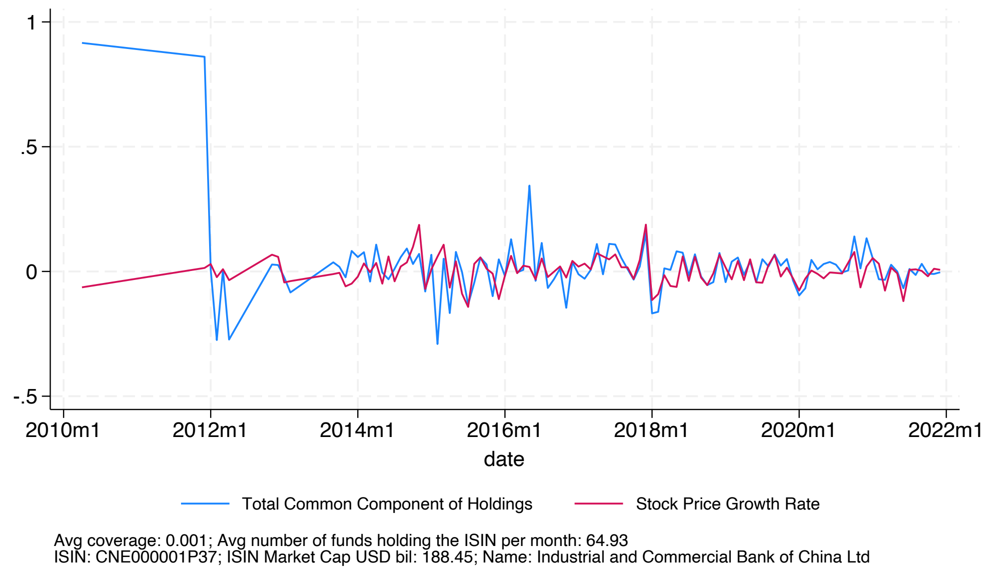


(a) Total

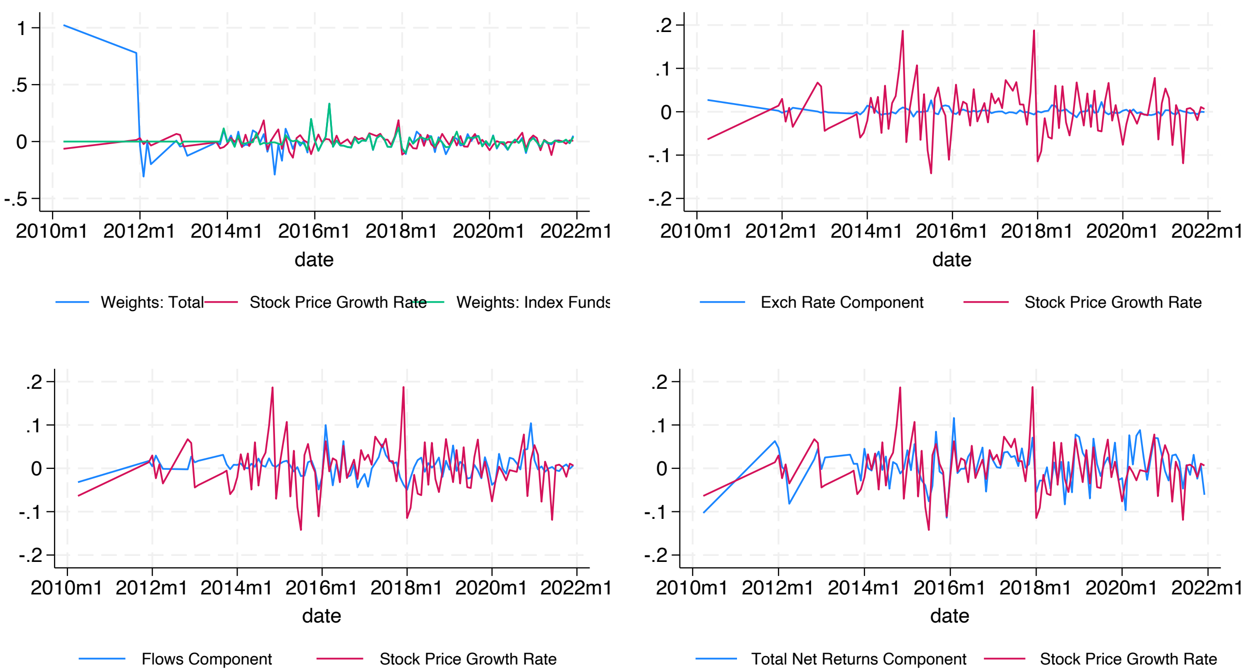


(b) subcomponents

Figure 10: Common Equity Holdings Components: Industrial and Commercial Bank of China Ltd

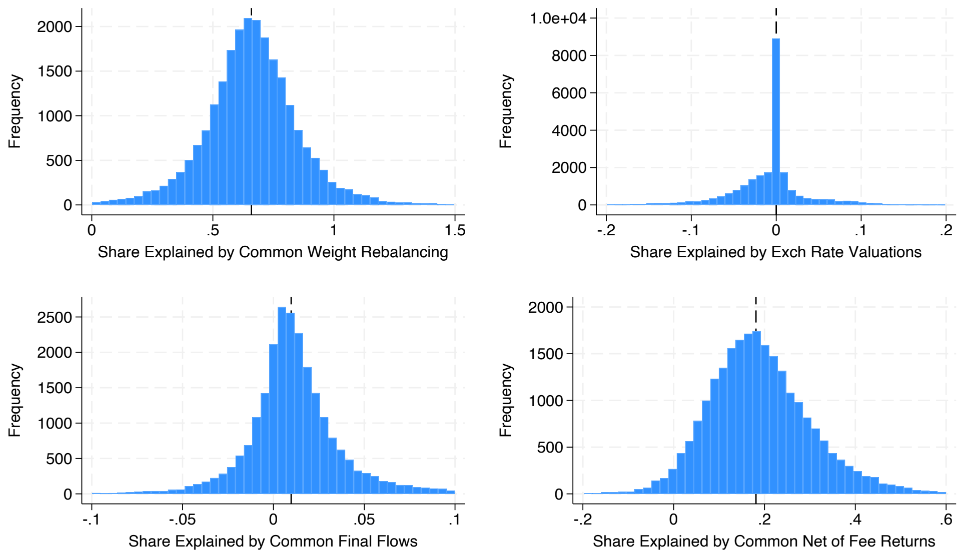


(a) Total



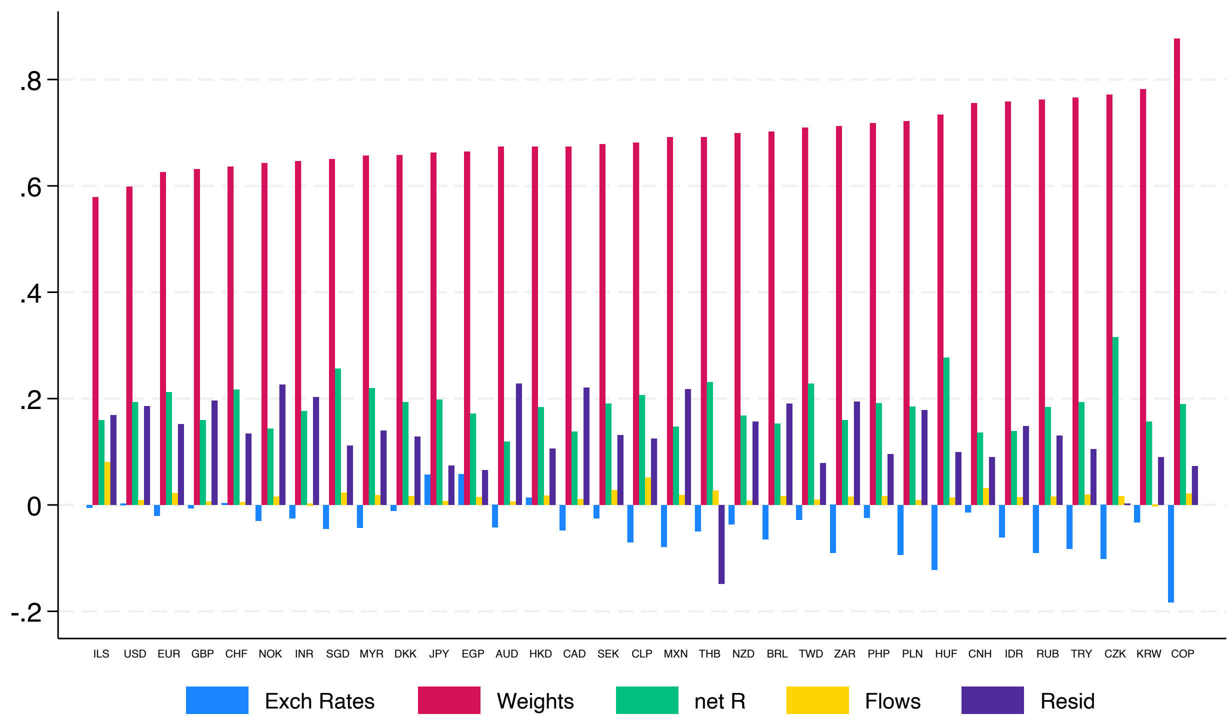
(b) subcomponents

Figure 11: ISIN-Level Equity Price Growth Rate Decomposition: Equity Holdings subcomponents



We plot only the set of ISINs for which $\frac{Cov\left(\Delta d^j, \Delta p_t^j\right)}{Var\left(\Delta p_t^j\right)}$ is between 0 and 1.5.

Figure 12: ISIN-Level Equity Price Growth Rate Decomposition: Panel Regression Estimates



Notes: This figure presents the coefficients from panel regressions of the equity holdings subcomponents on Δp_t^j by stock market (as denoted by the currency associated with that stock market). "Exch Rates" is the exchange rate "common" subcomponent, $\Delta d_t^{s,j}$; "Weights" is the portfolio weight changes "common" subcomponent, $\Delta d_t^{\omega,j}$; "net R" is the net-of-fee returns "common" subcomponent, $\Delta d_t^{r^{NF},j}$; "Flows" is the final flows "common" subcomponent, $\Delta d_t^{f,j}$; and "Resid" is the residual (unobservable) subcomponent, $\Delta d_t^{Resid,j}$. We allow for ISIN-level fixed effects.

Table 3: ISIN-Level Equity Price Growth Rate Decomposition: Index Funds vs Active Funds Portfolio Weight Changes and Flows: Panel Regressions

Currency	$\Delta d^{\omega,j}_{Index}$	$\Delta d^{\omega,j}_{Active}$	$\Delta d^{f,j}_{Index}$	$\Delta d^{f,j}_{Active}$
AUD	0.144***	0.595***	0.001	0.007***
BRL	0.117***	0.618***	0.003***	0.014***
CAD	0.160***	0.580***	0.005***	0.009***
CHF	0.213***	0.434***	-0.004***	0.010***
CLP	0.192***	0.553***	0.016***	0.042***
CNH	0.466***	0.420***	0.032***	-0.001
COP	0.393***	0.544***	0.022***	0.005**
CZK	0.190***	0.632***	0.004	0.014**
DKK	0.094***	0.600***	0.002***	0.015***
EGP	0.172***	0.481***	0.011***	0.007***
EUR	0.107***	0.559***	0.005***	0.019***
GBP	0.117***	0.559***	0.001***	0.005***
HKD	0.140***	0.594***	0.006***	0.015***
HUF	0.257***	0.665***	0.005	0.009**
IDR	0.177***	0.654***	0.006***	0.012***
ILS	0.106***	0.508***	0.012***	0.072***
INR	0.075***	0.607***	0.001***	0.004***
JPY	0.269***	0.451***	-0.004***	0.011***
KRW	0.341***	0.596***	-0.008***	0.005***
MXN	0.186***	0.550***	-0.002	0.021***
MYR	0.177***	0.579***	0.009***	0.015***
NOK	0.115***	0.561***	-0.001	0.016***
NZD	0.113***	0.627***	0.002	0.007***
PHP	0.164***	0.617***	0.008***	0.012***
PLN	0.162***	0.626***	0.007***	0.005***
RUB	0.326***	0.590***	0.010***	0.011***
SEK	0.258***	0.459***	0.016***	0.013***
SGD	0.128***	0.592***	0.004***	0.021***
THB	0.290***	0.517***	0.025***	0.012***
TRY	0.173***	0.654***	0.007***	0.015***
TWD	0.177***	0.614***	0.008***	0.007***
USD	0.207***	0.406***	0.006***	0.004***
ZAR	0.190***	0.569***	0.010***	0.008***

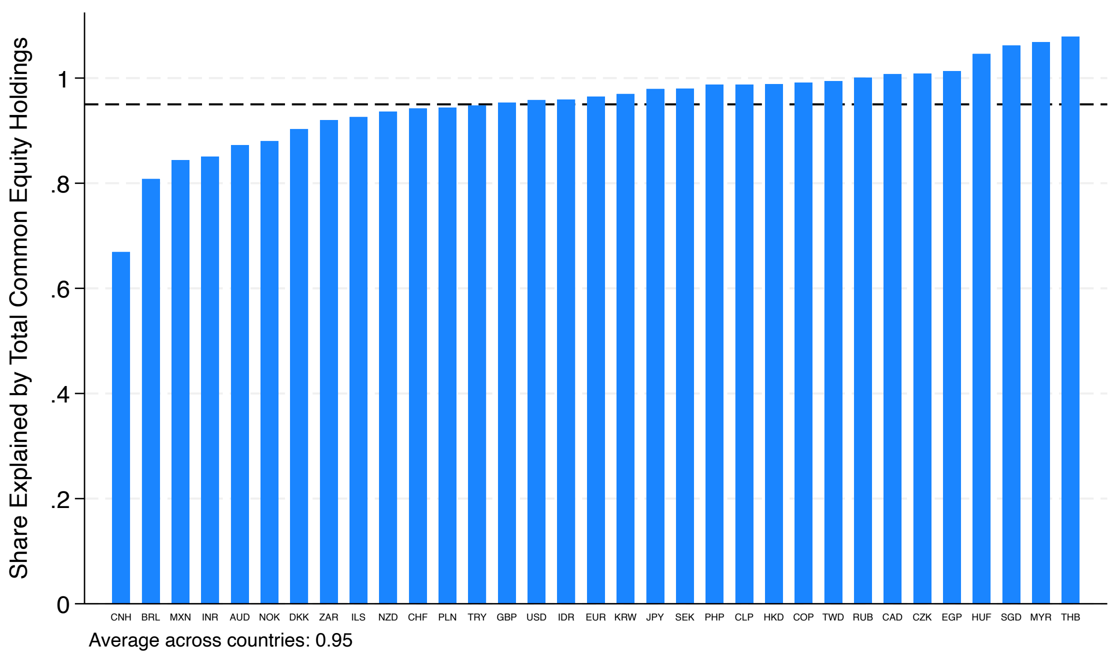
Note: This table reports coefficients from panel regressions of the portfolio weight changes and final flows "common" subcomponents, broken down by index and active funds, on Δp^j_t by stock market (as denoted by the currency associated with that market). Specifically, $\Delta d^{\omega,j}_{Index}$ and $\Delta d^{\omega,j}_{Active}$ denote the portfolio weight changes "common" subcomponents of index and active funds, respectively, while $\Delta d^{f,j}_{Index}$ and $\Delta d^{f,j}_{Active}$ denote the final flows "common" subcomponents of index and active funds, respectively. We allow for ISIN-level fixed effects and cluster the standard errors by ISIN. * significant at 10%; ** at 5%; *** at 1%.

Table 4: ISIN-Level Equity Price Growth Rate Decomposition: Local vs Other Currency Investors Portfolio Weight Changes and Flows: Panel Regressions

Currency	$\Delta d^{\omega,j}_{LocalCurr}$	$\Delta d^{\omega,j}_{OtherCurr}$	$\Delta d^{f,j}_{LocalCurr}$	$\Delta d^{f,j}_{OtherCurr}$
AUD	0.273***	0.431***	0.000	0.006***
BRL	0.407***	0.393***	0.008***	0.010***
CAD	0.010***	0.672***	0.001***	0.011***
CHF	0.404***	0.260***	-0.002**	0.008***
CLP	0.224***	0.520***	0.040***	0.020***
CNH	0.018***	0.746***	0.001***	0.031***
COP	.	0.883***	.	0.023***
CZK	.	0.807***	.	0.016
DKK	0.141***	0.554***	-0.002*	0.018***
EGP	.	0.610***	.	0.016***
EUR	0.321***	0.349***	0.013***	0.010***
GBP	0.511***	0.156***	0.003***	0.004***
HKD	0.001***	0.671***	0.000***	0.018***
HUF	.	0.795***	.	0.012**
IDR	.	0.759***	.	0.015***
ILS	0.463***	0.196***	0.078***	0.004***
INR	0.387***	0.358***	-0.003***	0.006***
JPY	0.214***	0.495***	-0.003***	0.010***
KRW	0.276***	0.658***	-0.011***	0.006***
MXN	0.272***	0.432***	0.006*	0.013***
MYR	.	0.657***	.	0.019***
NOK	0.361***	0.318***	0.009***	0.007***
NZD	0.328***	0.459***	0.003	0.006***
PHP	.	0.716***	.	0.016***
PLN	.	0.724***	.	0.009***
RUB	.	0.763***	.	0.016***
SEK	0.248***	0.495***	0.017***	0.013***
SGD	0.003	0.654***	0.000	0.023***
THB	.	0.692***	.	0.029***
TRY	0.003*	0.767***	0.002	0.018***
TWD	.	0.710***	.	0.011***
USD	0.573***	0.030***	0.009***	0.000***
ZAR	0.083***	0.683***	0.001*	0.015***

Note: This table reports coefficients from panel regressions of the portfolio weight changes and final flows "common" subcomponents, broken down by local-currency and foreign-currency investors, on Δp^j_t by stock market (as denoted by the currency associated with that market). Specifically, $\Delta d^{\omega,j}_{LocalCurr}$ and $\Delta d^{\omega,j}_{OtherCurr}$ denote the portfolio weight changes "common" subcomponents of local-currency and foreign-currency investors, respectively, while $\Delta d^{f,j}_{LocalCurr}$ and $\Delta d^{f,j}_{OtherCurr}$ denote the final flows "common" subcomponents of local-currency and foreign-currency investors, respectively. We allow for ISIN-level fixed effects and cluster the standard errors by ISIN. * significant at 10%; ** at 5%; *** at 1%.

Figure 13: Aggregate Stock Market Price Growth Rate Decomposition: Common Component of Equity Holdings



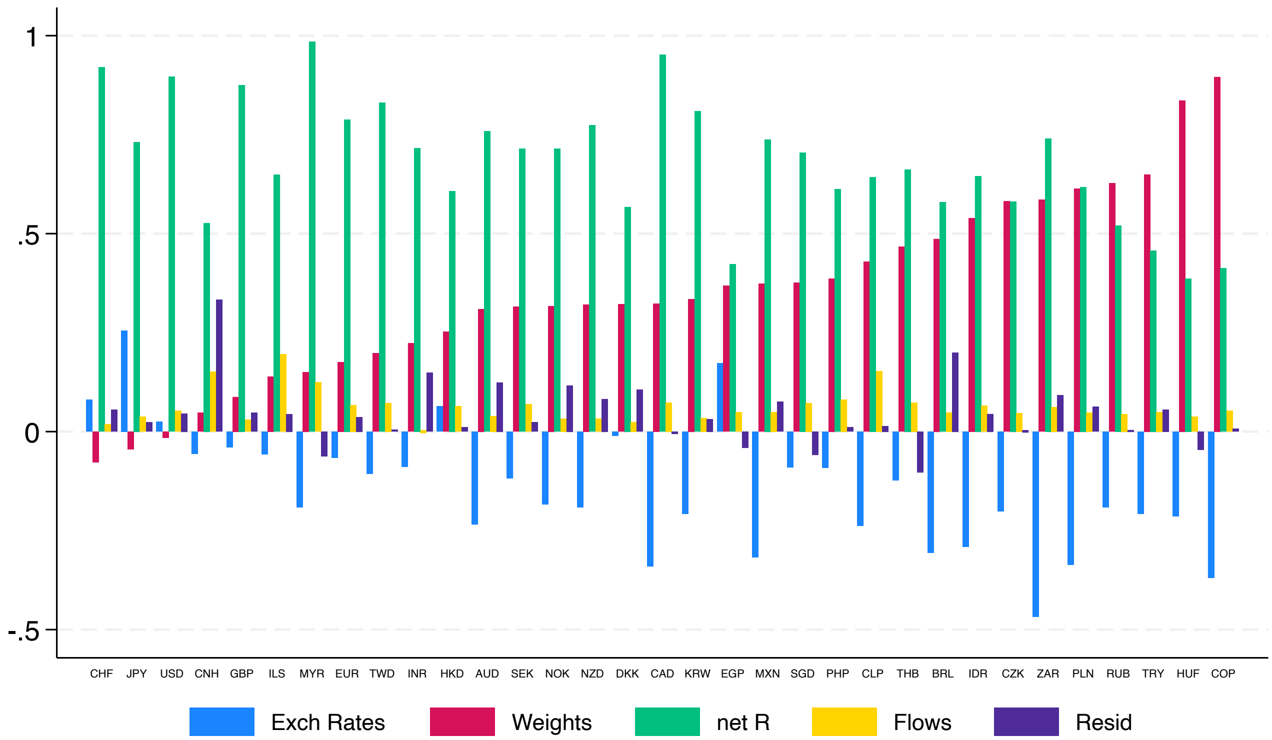
Notes: This figure presents OLS coefficients from regressions of the total "common" equity holdings component, ΔD_t^l, on the aggregate stock market price growth rate, $\Delta p_t^{SM,l}$ (where the stock market is denoted by the currency associated with that market) (i.e., $\beta^{p,\Delta D^l} = \frac{Cov\left(\Delta D_t^l, p_t^{SM,l}\right)}{Var\left(\Delta p_t^{SM,l}\right)}$).

Table 5: Aggregate Stock Market Price Growth Rate Decomposition

Currency	ΔD^l	R^2	$\Delta D^{s,l}$	R^2	$\Delta D^{\omega,l}$	R^2	$\Delta D^{r^{NF},l}$	R^2	$\Delta D^{f,l}$	R^2	$\Delta D^{Resid,l}$	R^2
AUD	0.87***	0.93	-0.23***	0.21	0.31***	0.42	0.76***	0.73	0.04***	0.05	0.12***	0.17
BRL	0.81***	0.87	-0.31***	0.40	0.49***	0.54	0.58***	0.70	0.05***	0.06	0.20***	0.29
CAD	1.01***	0.91	-0.34***	0.33	0.32***	0.26	0.95***	0.73	0.07***	0.15	-0.01	-0.01
CHF	0.94***	0.91	0.08**	0.03	-0.08	0.02	0.92***	0.78	0.02	0.01	0.05**	0.03
CLP	0.99***	0.79	-0.24***	0.15	0.43***	0.21	0.64***	0.41	0.15***	0.23	0.01	-0.01
CNH	0.67***	0.50	-0.06***	0.10	0.05	-0.00	0.53***	0.52	0.15***	0.23	0.33***	0.19
COP	0.99***	0.87	-0.37***	0.34	0.90***	0.74	0.41***	0.39	0.05***	0.06	0.01	-0.01
CZK	1.01***	0.84	-0.20***	0.14	0.58***	0.35	0.58***	0.45	0.05***	0.05	0.00	-0.01
DKK	0.90***	0.90	-0.01	-0.00	0.32***	0.36	0.57***	0.68	0.02*	0.03	0.11***	0.10
EGP	1.01***	0.76	0.17*	0.04	0.37***	0.20	0.42***	0.36	0.05***	0.09	-0.04	-0.00
EUR	0.96***	0.96	-0.07***	0.06	0.18***	0.36	0.79***	0.93	0.07***	0.13	0.04*	0.03
GBP	0.95***	0.95	-0.04**	0.03	0.09***	0.08	0.88***	0.90	0.03***	0.04	0.05*	0.03
HKD	0.99***	0.96	0.06***	0.38	0.25***	0.28	0.61***	0.75	0.06***	0.27	0.01	-0.00
HUF	1.05***	0.57	-0.21***	0.22	0.84***	0.42	0.39***	0.37	0.04***	0.06	-0.05	-0.00
IDR	0.96***	0.88	-0.29***	0.41	0.54***	0.41	0.65***	0.56	0.07***	0.14	0.04	0.01
ILS	0.93***	0.84	-0.06**	0.05	0.14**	0.07	0.65***	0.62	0.20***	0.26	0.04	0.00
INR	0.85***	0.89	-0.09***	0.28	0.22***	0.35	0.72***	0.88	0.00	-0.01	0.15***	0.19
JPY	0.98***	0.93	0.26***	0.42	-0.04	0.01	0.73***	0.77	0.04**	0.02	0.02	0.00
KRW	0.97***	0.93	-0.21***	0.18	0.33***	0.39	0.81***	0.74	0.03	0.02	0.03	0.01
MXN	0.84***	0.75	-0.32***	0.35	0.37***	0.33	0.74***	0.68	0.05	0.01	0.08*	0.02
MYR	1.07***	0.86	-0.19***	0.13	0.15	0.02	0.98***	0.53	0.12***	0.14	-0.06*	0.01
NOK	0.88***	0.75	-0.18***	0.36	0.32***	0.20	0.71***	0.79	0.03**	0.03	0.12**	0.05
NZD	0.94***	0.79	-0.19***	0.07	0.32***	0.18	0.77***	0.49	0.03	0.01	0.08*	0.02
PHP	0.99***	0.92	-0.09***	0.12	0.39***	0.27	0.61***	0.48	0.08***	0.16	0.01	-0.00
PLN	0.94***	0.89	-0.34***	0.38	0.61***	0.52	0.62***	0.58	0.05***	0.07	0.06*	0.03
RUB	1.00***	0.69	-0.19***	0.08	0.63***	0.38	0.52***	0.50	0.04***	0.04	0.00	-0.01
SEK	0.98***	0.93	-0.12***	0.14	0.32***	0.44	0.71***	0.84	0.07***	0.14	0.02	0.00
SGD	1.06***	0.95	-0.09***	0.15	0.38***	0.41	0.70***	0.76	0.07***	0.22	-0.06	0.05
THB	1.08***	0.81	-0.12***	0.22	0.47***	0.29	0.66***	0.58	0.07***	0.07	-0.10**	0.03
TRY	0.95***	0.93	-0.21**	0.10	0.65***	0.54	0.46***	0.48	0.05***	0.12	0.06**	0.04
TWD	0.99***	0.91	-0.11***	0.18	0.20***	0.11	0.83***	0.68	0.07***	0.10	0.00	-0.01
USD	0.96***	0.98	0.02***	0.23	-0.02	0.01	0.90***	0.98	0.05***	0.23	0.05**	0.09
ZAR	0.92***	0.87	-0.47***	0.28	0.59***	0.41	0.74***	0.50	0.06***	0.06	0.09**	0.05

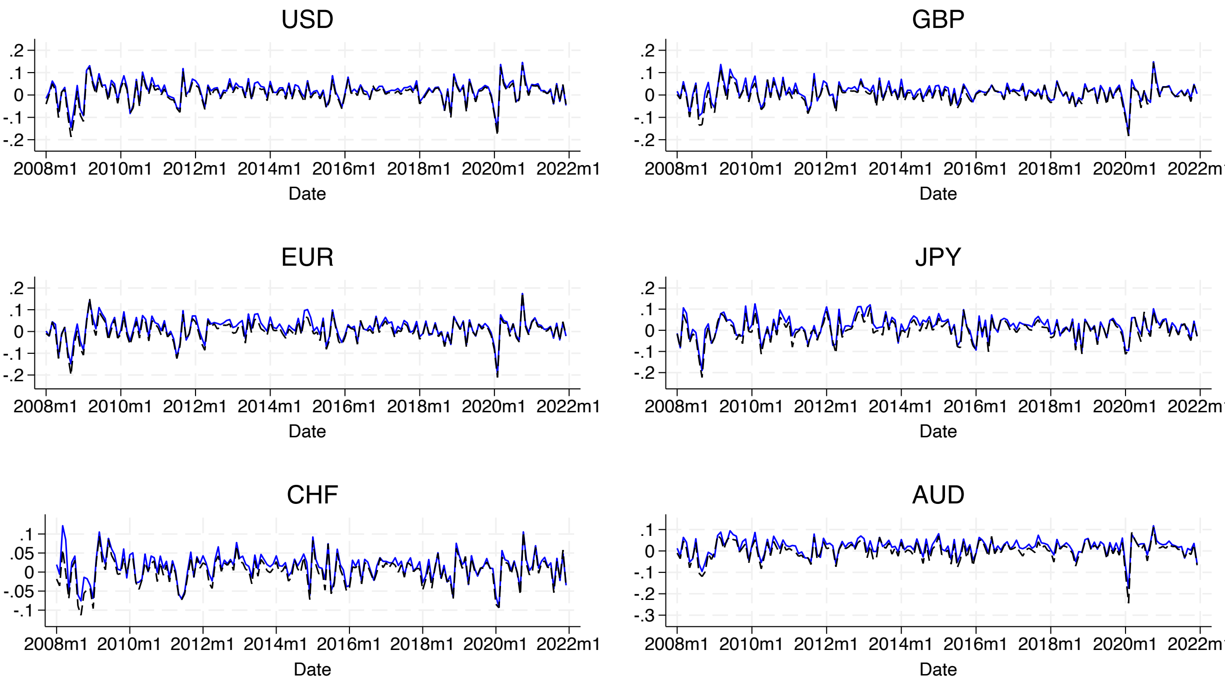
Note: This table reports OLS coefficients from regressions of the total "common" component of equity holdings, ΔD^l, and its subcomponents on the aggregate stock market price growth rate (where the stock market is denoted by the currency associated with that market). The subcomponents are the exchange rate "common" subcomponent, $\Delta D^{s,l}$; the portfolio weight changes "common" subcomponent, $\Delta D^{\omega,l}$; the net-of-fee returns "common" subcomponent, $\Delta D^{r^{NF},l}$; and the final flows "common" subcomponent, $\Delta D^{f,l}$. We also report results for the residual (unobservable) subcomponent, $\Delta D^{Resid,l}$. The table also presents the corresponding R^2 values next to each component. Robust standard errors. * significant at 10%; ** at 5%; *** at 1%.

Figure 14: Aggregate Stock Market Price Growth Rate Decomposition



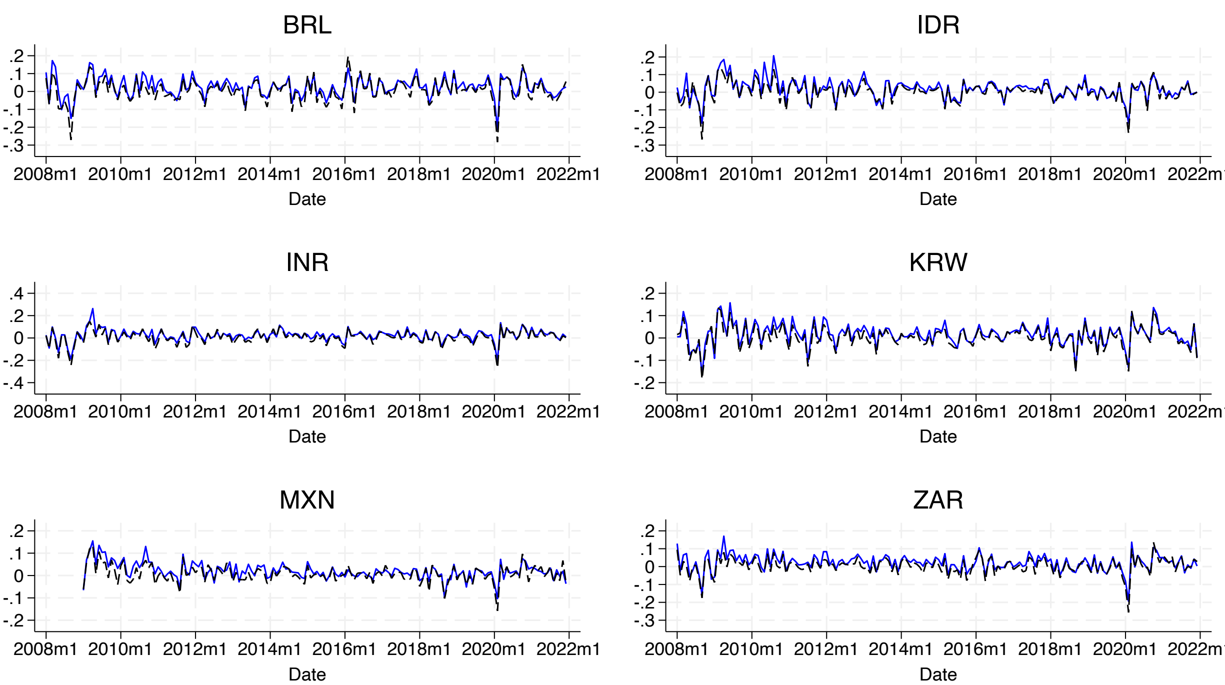
Notes: This figure presents OLS coefficients from regressions of the equity holdings subcomponents on the aggregate stock market price growth rate, $\Delta p_t^{SM,l}$ (where the stock market is denoted by the currency associated with that market). "Exch Rates" is the exchange rate "common" subcomponent, $\Delta D_t^{s,l}$; "Weights" is the portfolio weight changes "common" subcomponent, $\Delta D_t^{\omega,l}$; "net R" is the net-of-fee returns "common" subcomponent, $\Delta D_t^{r^{NF},l}$; "Flows" is the final flows "common" subcomponent, $\Delta D_t^{f,l}$; and "Resid" is the residual (unobservable) subcomponent, $\Delta D_t^{Resid,l}$.

Figure 15: Aggregate Stock Market Price Growth Rate vs Total Common Component of Equilibrium Holdings



The black dashed line represents the stock price growth rate and the solid blue line is the change in total common equity holdings.

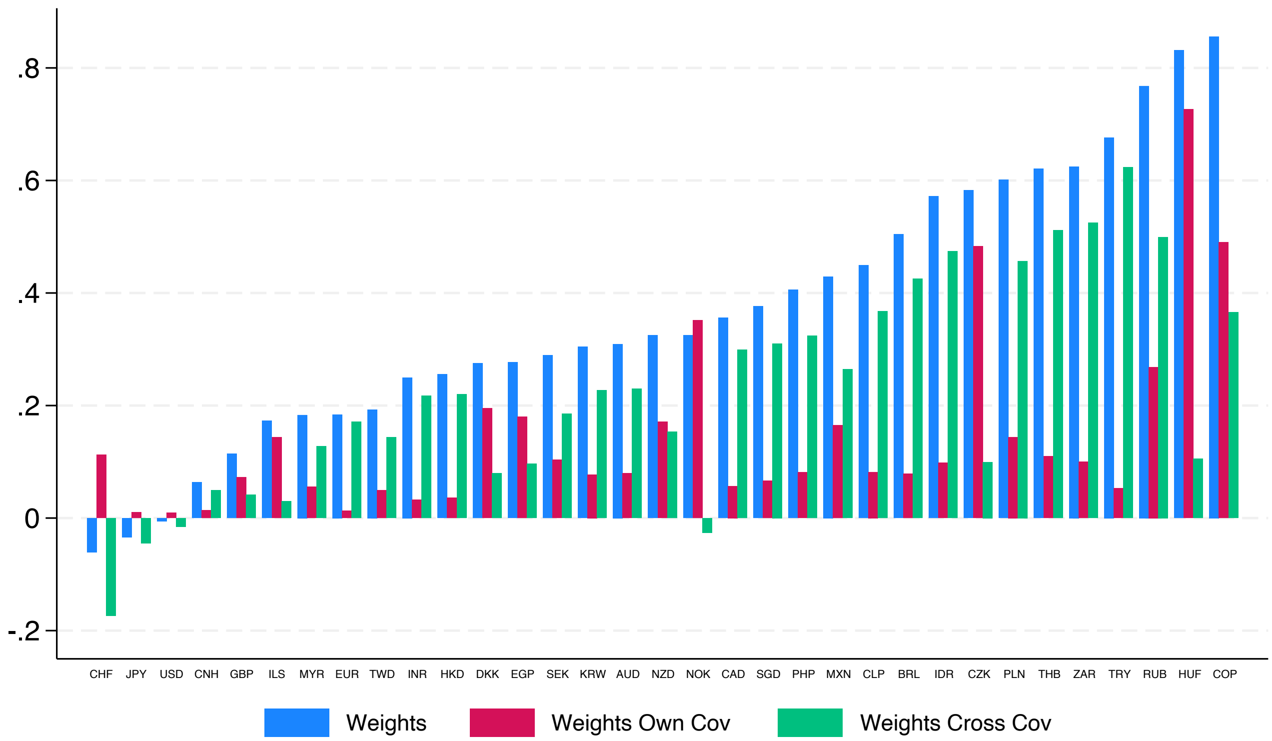
(a) Select Advanced Economies



The black dashed line represents the stock price growth rate and the solid blue line is the change in total common equity holdings.

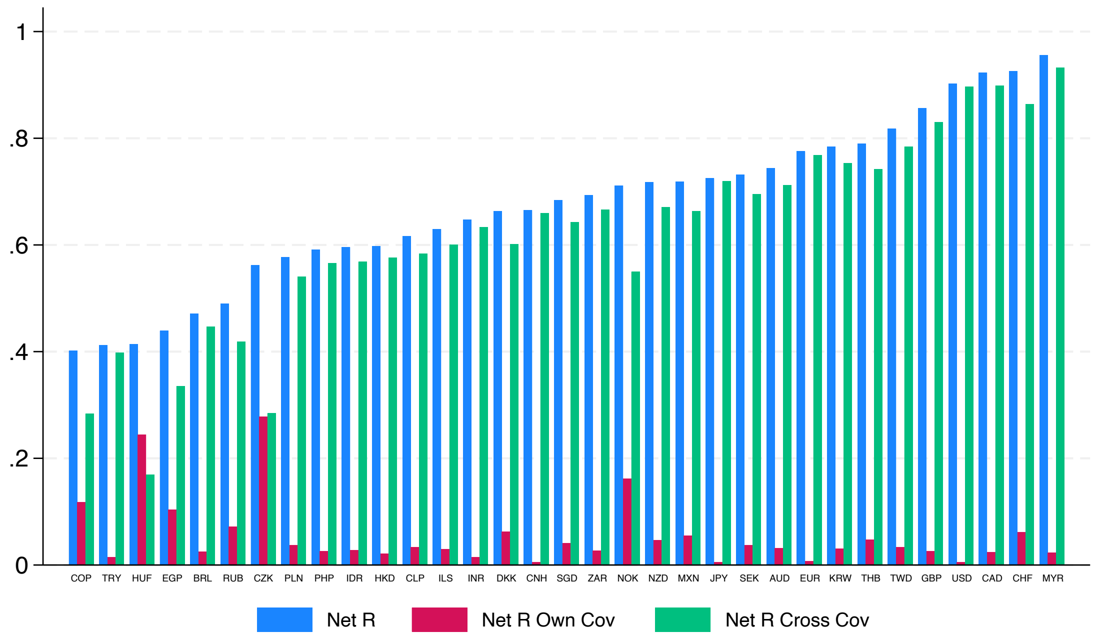
(b) Select Emerging Markets

Figure 16: The Importance of Own vs Cross-Covariance Subcomponents: Portfolio Weight Changes



Notes: This figure presents coefficients from panel regressions of the portfolio weight changes "common" subcomponent, $\Delta D_t^{\omega,l}$, on $\Delta p_t^{SM,l}$ by stock market (as denoted by the currency associated with that market). The estimates are further decomposed into parts associated with *own* and *cross* comovements between portfolio weight changes and equity price growth rates. "Weight" refers to the total portfolio weight changes "common" subcomponent, $\Delta D_t^{\omega,l}$. "Weights Own Cov" corresponds to β^{ω}_{OwnCov}, defined in (13), and captures how much of the overall stock price movement is explained by the ISIN-level comovement of portfolio weight changes with their own-ISIN prices, scaled appropriately. "Weights Cross Cov" corresponds to $\beta^{\omega}_{CrossCov}$, also defined in (13), and measures the contribution of ISIN-level comovement between portfolio weight changes and cross-ISIN prices, scaled appropriately.

Figure 17: The Importance of Own vs Cross-Covariance Subcomponents: Net-of-Fee Returns



Notes: This figure presents coefficients from panel regressions of the net-of-fee returns "common" subcomponent, $\Delta D_t^{r^{NF},l}$ on $\Delta p_t^{SM,l}$ by stock market (as denoted by the currency associated with that market). The estimates are further decomposed into parts associated with *own* and *cross* comovements between net-of-fee returns and equity price growth rates. "Net R" refers to the total net-of-fee returns "common" subcomponent, $\Delta D_t^{r^{NF},l}$. "Net R Own Cov" corresponds to $\beta_{OwnCov}^{r^{NF}} = \sum_j \left(\nu^{j,l}\right)^2 \frac{\text{Var}\left(\Delta p_t^j\right)}{\text{Var}\left(\sum_j \nu^{j,l} \Delta p_t^j\right)} \frac{\text{Cov}\left(\Delta p_t^j, \Delta d_t^{j,r^{NF}}\right)}{\text{Var}(\Delta p_t^j)}$, and captures how much of the overall stock price movement is explained by the ISIN-level comovement of net-of-fee returns with their own-ISIN prices, scaled appropriately. "Net R Cross Cov" corresponds to $\beta_{CrossCov}^{r^{NF}} = \sum_j \sum_{k \neq j} \nu^{j,l} \nu^{k,l} \frac{\text{Cov}\left(\Delta d_t^{j,r^{NF}}, \Delta p_t^k\right)}{\text{Var}(\Delta p_t^k)} \frac{\text{Var}(\Delta p_t^k)}{\text{Var}\left(\sum_j \nu^{j,l} \Delta p_t^j\right)}$, and measures the contribution of ISIN-level comovement between net-of-fee returns and cross-ISIN prices, scaled appropriately.

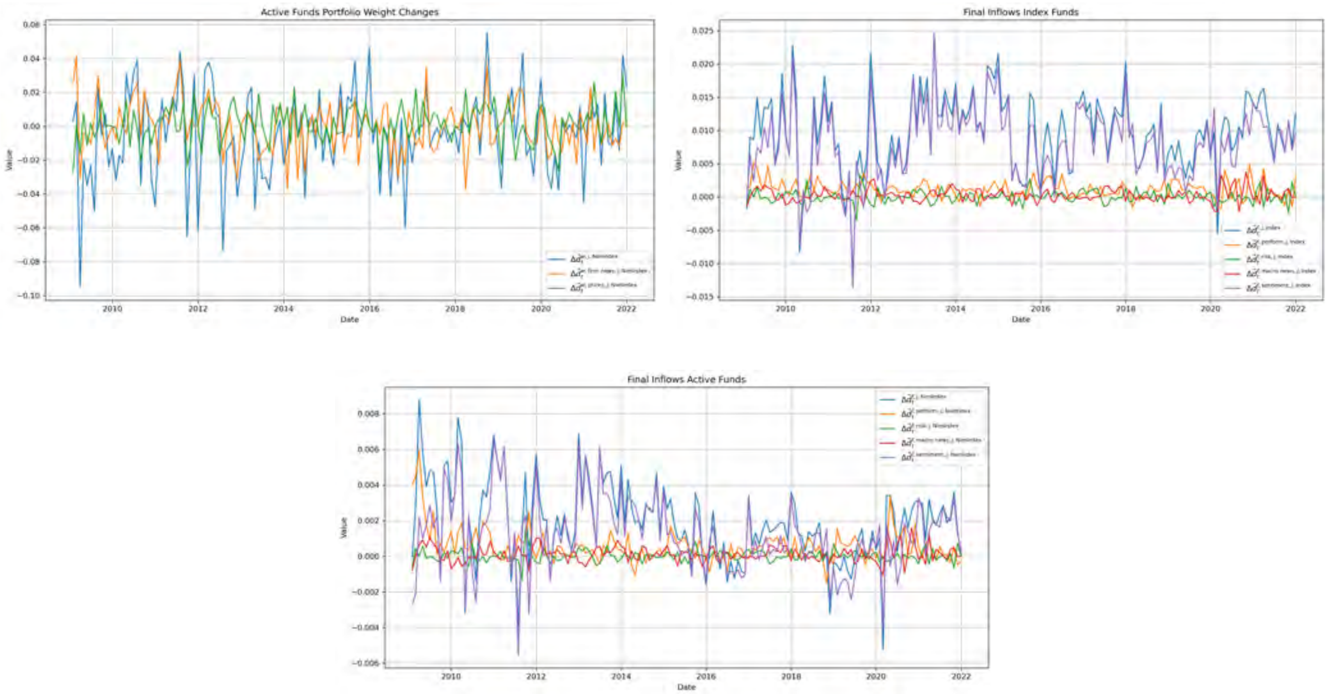


Figure 18: Coca Cola: Exogenous Drivers of Active Weight Changes and Final Flows

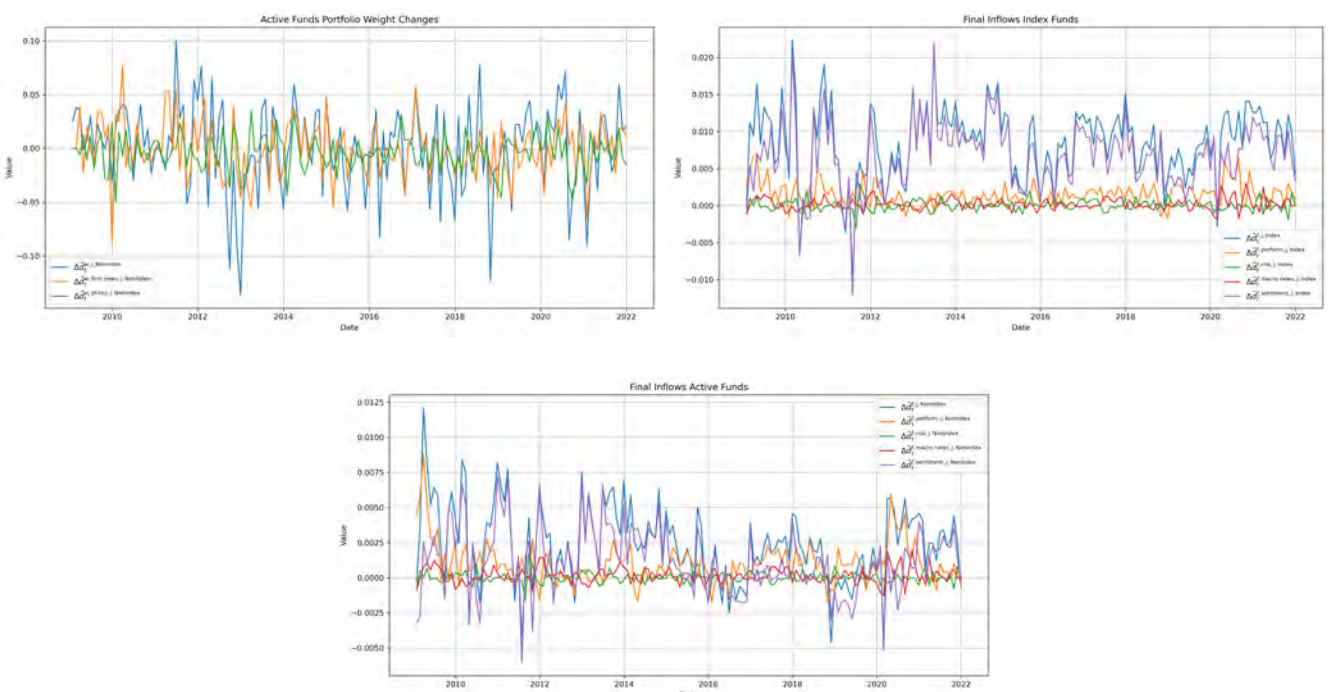
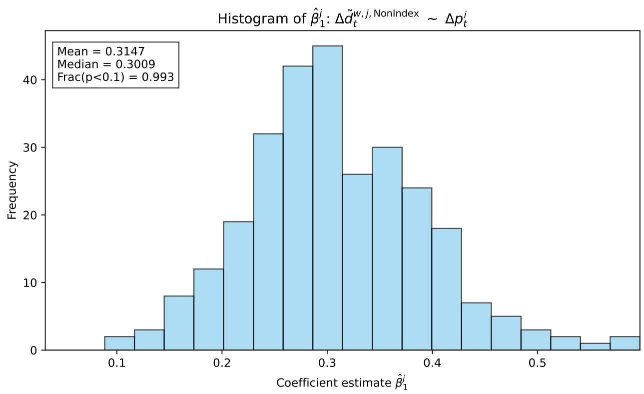
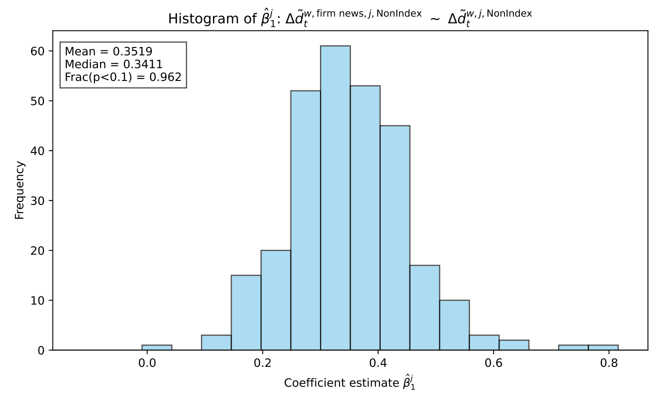


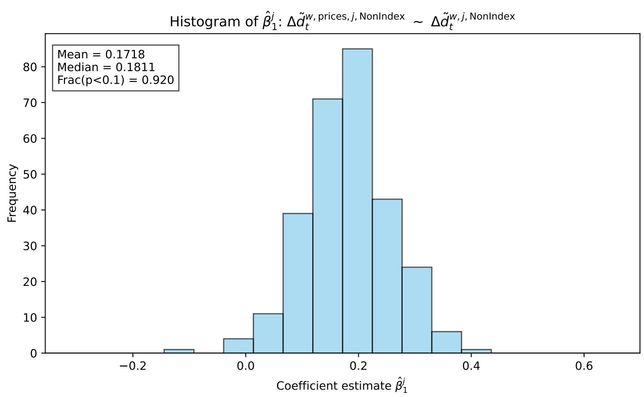
Figure 19: Apple : Exogenous Drivers of Active Weight Changes and Final Flows



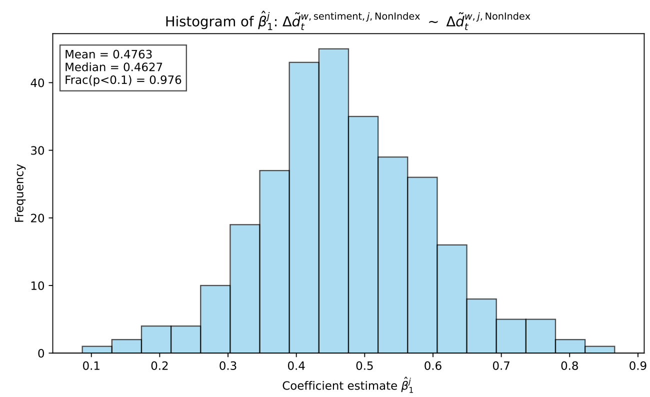
(a) $\widehat{\beta}_1^j$: $\Delta\tilde{d}_t^{\,w,j,\mathrm{NonIndex}}$ on Δp_t^j



(b) $\widehat{\beta}_1^j$: $\Delta\tilde{d}_t^{\,w,\text{firm news},j,\mathrm{NonIndex}}$ on $\Delta\tilde{d}_t^{\,w,j,\mathrm{NonIndex}}$



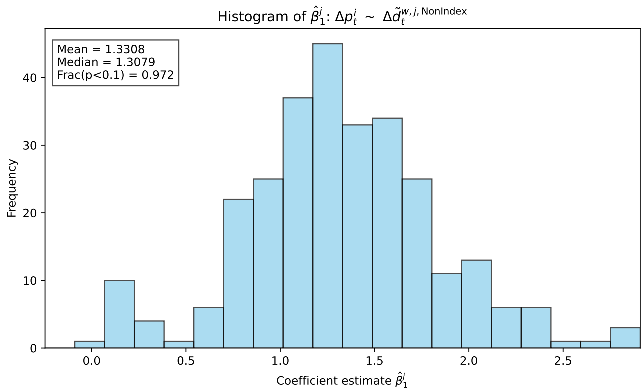
(c) $\widehat{\beta}_1^j$: $\Delta\tilde{d}_t^{\,w,\text{prices},j,\mathrm{NonIndex}}$ on $\Delta\tilde{d}_t^{\,w,j,\mathrm{NonIndex}}$



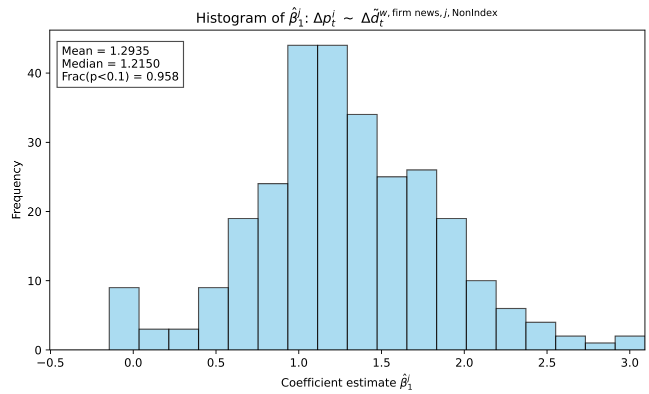
(d) $\widehat{\beta}_1^j$: $\Delta\tilde{d}_t^{\,w,\text{sentiment},j,\mathrm{NonIndex}}$ on $\Delta\tilde{d}_t^{\,w,j,\mathrm{NonIndex}}$

Figure 20: Variance–Covariance Decomposition of Non-Index Funds' Portfolio Weight Changes

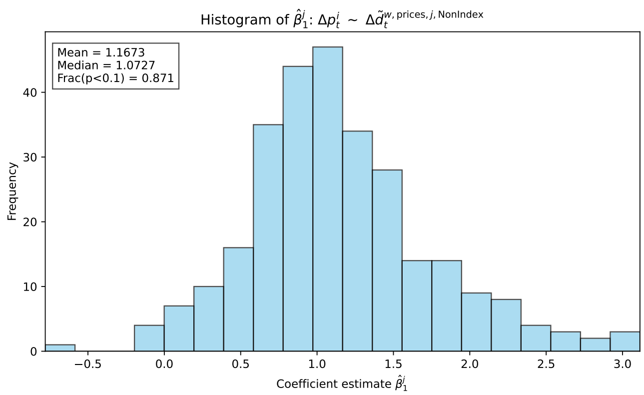
Notes: This figure reports a variance–covariance analysis of the drivers of changes in the portfolio weights of marginal non-index funds, $\Delta\tilde{d}_t^{\omega,j,\mathrm{NonIndex}}$. For each panel, we estimate separate firm-level regressions and plot the cross-sectional histogram of the resulting slope coefficients, reporting also their mean, median, and the fraction of estimates that are significantly different from zero at the 10% level (based on heteroskedasticity-consistent standard errors). As a benchmark, Panel a reports coefficients from regressions of $\Delta\tilde{d}_t^{\omega,j,\mathrm{NonIndex}}$ on Δp_t^j. These coefficients summarize the fraction of the variation in the price growth rate that is associated with active funds' portfolio rebalancing. Panel b reports coefficients from regressions of $\Delta\tilde{d}_t^{\omega,\text{firm news},j,\mathrm{NonIndex}}$ on $\Delta\tilde{d}_t^{\omega,j,\mathrm{NonIndex}}$, measuring the fraction of the variation in $\Delta\tilde{d}_t^{\omega,j,\mathrm{NonIndex}}$ accounted for by firm news. Panel c reports coefficients from regressions of $\Delta\tilde{d}_t^{\omega,\text{prices},j,\mathrm{NonIndex}}$ on $\Delta\tilde{d}_t^{\omega,j,\mathrm{NonIndex}}$, capturing the contribution of lagged price effects. Panel d reports coefficients from regressions of $\Delta\tilde{d}_t^{\omega,\text{sentiment},j,\mathrm{NonIndex}}$ on $\Delta\tilde{d}_t^{\omega,j,\mathrm{NonIndex}}$, capturing the contribution of sentiment. The sample consists of U.S. stocks with an average market capitalization above 10 billion USD and available IBES data (286 firms).



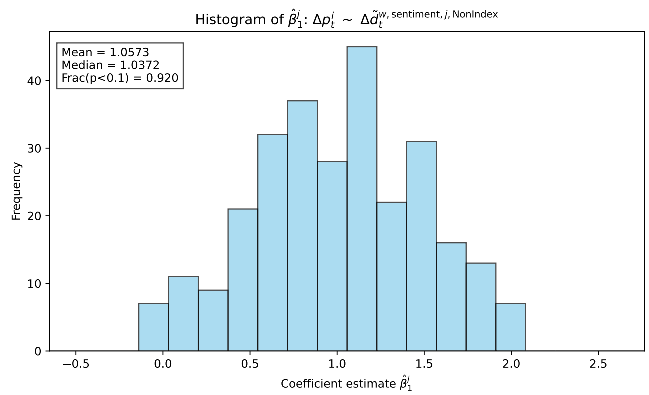
(a) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta \tilde{d}_t^{w,j,\text{NonIndex}}$



(b) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta \tilde{d}_t^{w,\text{firm news},j,\text{NonIndex}}$



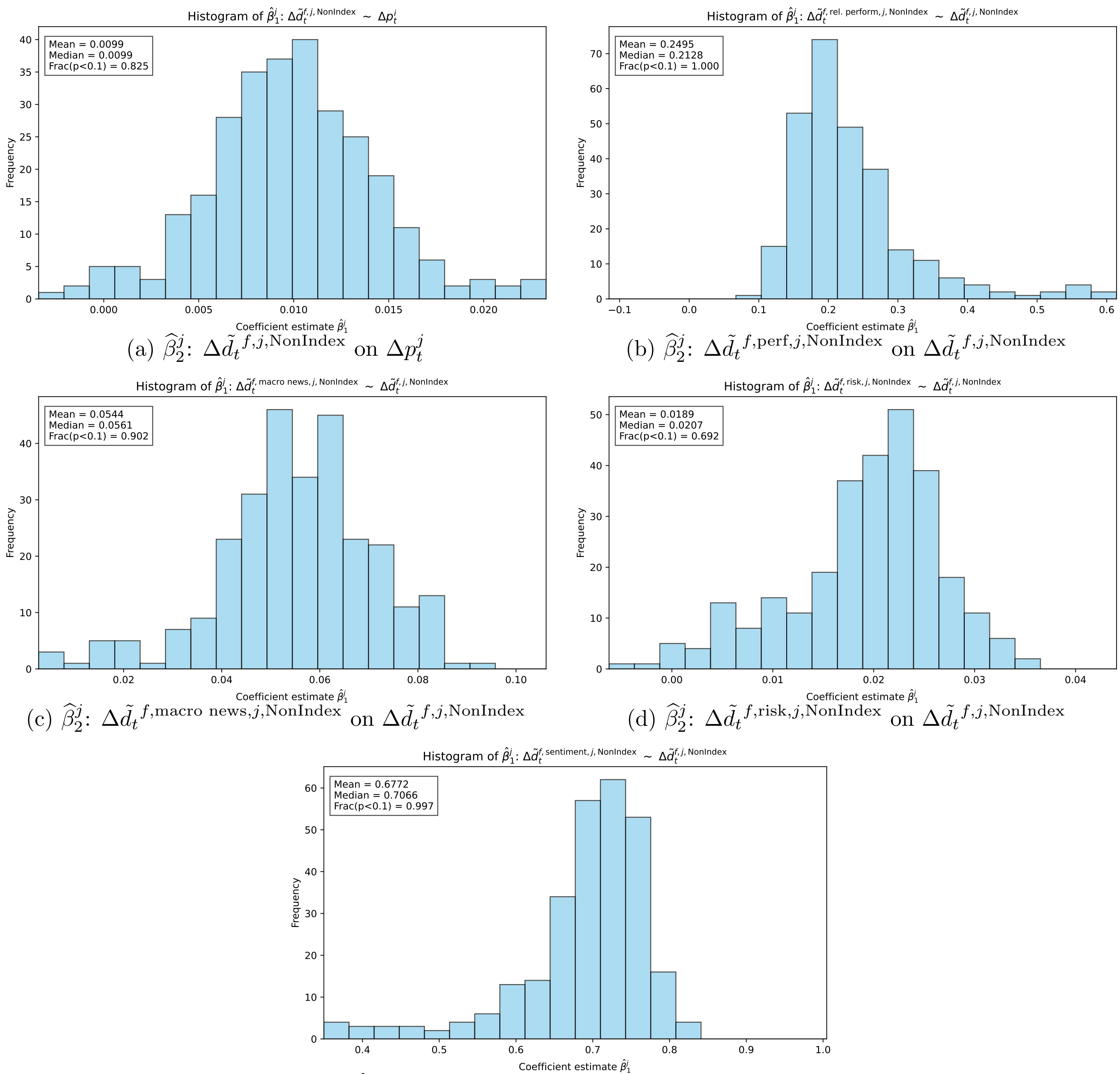
(c) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta \tilde{d}_t^{w,\text{prices},j,\text{NonIndex}}$



(d) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta \tilde{d}_t^{w,\text{sentiment},j,\text{NonIndex}}$

Figure 21: Sensitivity of Equity Price Growth to Non-Index Funds' Portfolio Weight Rebalancing

Notes: This figure reports firm-level estimates of the sensitivity of the equity price growth rate, Δp_t^j, to non-index funds' portfolio weight rebalancing and its underlying drivers. For each panel, we estimate separate firm-level regressions of Δp_t^j on different components of $\Delta\tilde{d}_t^{\omega,j,\text{NonIndex}}$ and plot the cross-sectional histogram of the resulting slope coefficients, reporting also their mean, median, and the fraction of estimates that are significantly different from zero at the 10% level (based on heteroskedasticity-consistent standard errors). Panel a reports coefficients from regressions of Δp_t^j on $\Delta\tilde{d}_t^{\omega,j,\text{NonIndex}}$. Panel b reports coefficients from regressions of p_t^j on $\Delta\tilde{d}_t^{\omega,\text{firm news},j,\text{NonIndex}}$, the component of non-index portfolio-weight rebalancing driven by firm- or industry-specific news. Panel c reports coefficients from regressions of Δp_t^j on $\Delta\tilde{d}_t^{\omega,\text{prices},j,\text{NonIndex}}$, the component driven by lagged prices (momentum or reversal strategies). Panel d reports coefficients from regressions of Δp_t^j on $\Delta\tilde{d}_t^{\omega,\text{sentiment},j,\text{NonIndex}}$, the residual sentiment component of non-index funds' rebalancing not explained by firm news or lagged prices. The sample consists of U.S. stocks with an average market capitalization above 10 billion USD and available IBES data (286 firms).



(a) $\widehat{\beta}_2^j$: $\Delta\tilde{d}_t{}^{f,j,\text{NonIndex}}$ on Δp_t^j

(b) $\widehat{\beta}_2^j$: $\Delta\tilde{d}_t{}^{f,\text{perf},j,\text{NonIndex}}$ on $\Delta\tilde{d}_t{}^{f,j,\text{NonIndex}}$

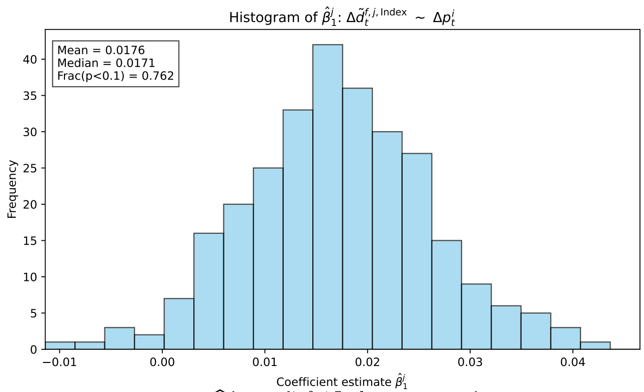
(c) $\widehat{\beta}_2^j$: $\Delta\tilde{d}_t{}^{f,\text{macro news},j,\text{NonIndex}}$ on $\Delta\tilde{d}_t{}^{f,j,\text{NonIndex}}$

(d) $\widehat{\beta}_2^j$: $\Delta\tilde{d}_t{}^{f,\text{risk},j,\text{NonIndex}}$ on $\Delta\tilde{d}_t{}^{f,j,\text{NonIndex}}$

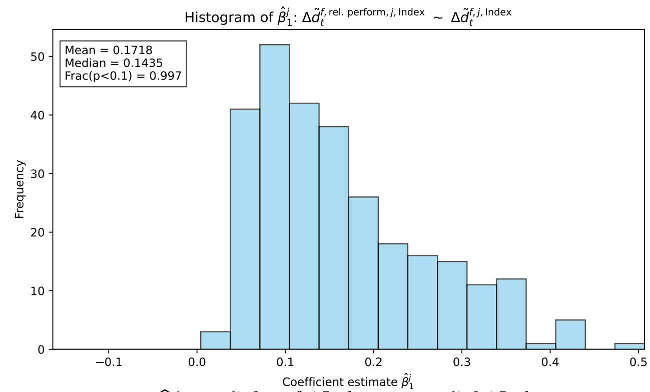
(e) $\widehat{\beta}_2^j$: $\Delta\tilde{d}_t{}^{f,\text{sentiment},j,\text{NonIndex}}$ on $\Delta\tilde{d}_t{}^{f,j,\text{NonIndex}}$

Figure 22: Variance–Covariance Decomposition of the Final Inflows of Marginal Non-Index Funds

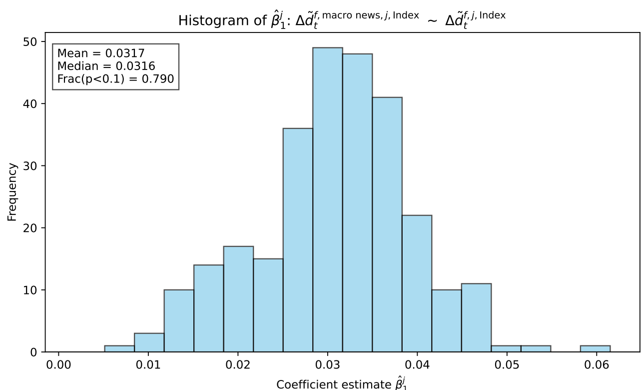
Notes: This figure reports a variance–covariance analysis of the drivers of changes in the final inflows of marginal non-index funds, $\Delta\tilde{d}_t^{f,j,\text{NonIndex}}$. For each panel, we estimate separate firm-level regressions and plot the cross-sectional histogram of the slope coefficients, reporting also their mean, median, and the fraction that are significantly different from zero at the 10% level (based on heteroskedasticity-consistent standard errors). Panel a reports coefficients from regressions of Δp_t^j on $\Delta\tilde{d}_t^{f,j,\text{NonIndex}}$, summarizing the fraction of the variation in the price growth rate associated with non-index funds' final inflows. Panel b reports coefficients from regressions of the past-performance component $\Delta\tilde{d}_t^{f,\text{perf},j,\text{NonIndex}}$ on $\Delta\tilde{d}_t^{f,j,\text{NonIndex}}$. Panel c reports coefficients for the macro-news component $\Delta\tilde{d}_t^{f,\text{macro news},j,\text{NonIndex}}$, Panel d for the risk-aversion component $\Delta\tilde{d}_t^{f,\text{risk},j,\text{NonIndex}}$, and Panel e for the residual sentiment component $\Delta\tilde{d}_t^{f,\text{sentiment},j,\text{NonIndex}}$, each regressed on $\Delta\tilde{d}_t^{f,j,\text{NonIndex}}$. The sample consists of U.S. stocks with an average market capitalization above 10 billion USD and available IBES data (286 firms).



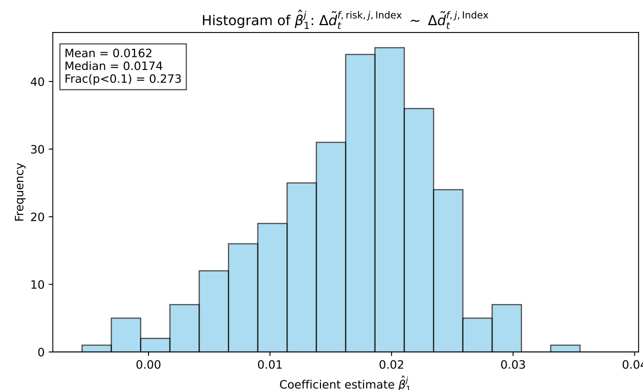
(a) $\widehat{\beta}_2^j$: $\Delta\tilde{d}_t^{f,j,\text{Index}}$ on Δp_t^j



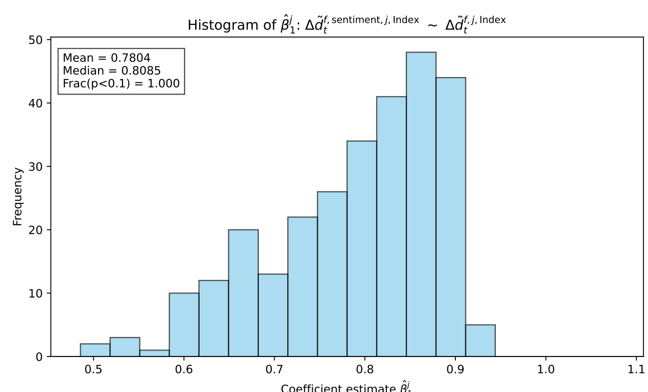
(b) $\widehat{\beta}_2^j$: $\Delta\tilde{d}_t^{f,\text{perf},j,\text{Index}}$ on $\Delta\tilde{d}_t^{f,j,\text{Index}}$



(c) $\widehat{\beta}_2^j$: $\Delta\tilde{d}_t^{f,\text{macro news},j,\text{Index}}$ on $\Delta\tilde{d}_t^{f,j,\text{Index}}$



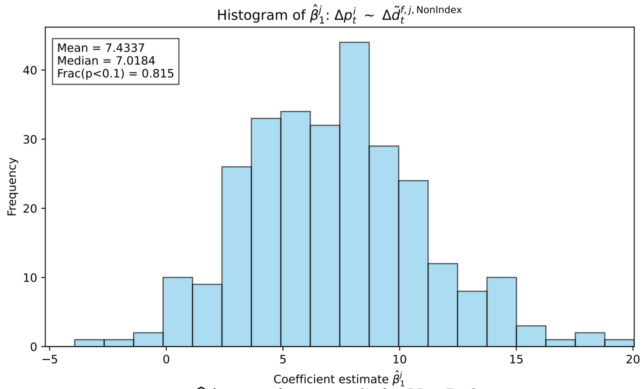
(d) $\widehat{\beta}_2^j$: $\Delta\tilde{d}_t^{f,\text{risk},j,\text{Index}}$ on $\Delta\tilde{d}_t^{f,j,\text{Index}}$



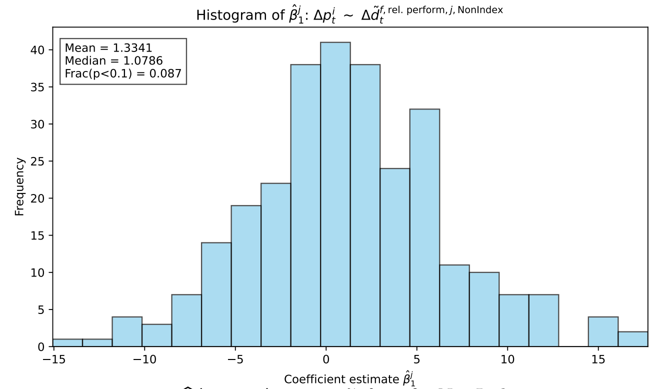
(e) $\widehat{\beta}_2^j$: $\Delta\tilde{d}_t^{f,\text{sentiment},j,\text{Index}}$ on $\Delta\tilde{d}_t^{f,j,\text{Index}}$

Figure 23: Variance–Covariance Decomposition of the Final Inflows of Marginal Index Funds

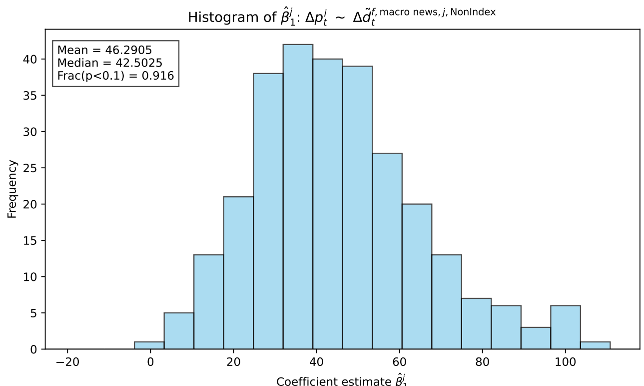
Notes: This figure reports a variance–covariance analysis of the drivers of changes in the final inflows of marginal index funds, $\Delta\tilde{d}_t^{f,j,\text{Index}}$. For each panel, we estimate separate firm-level regressions and plot the cross-sectional histogram of the slope coefficients, reporting also their mean, median, and the fraction that are significantly different from zero at the 10% level (based on heteroskedasticity-consistent standard errors). Panel a reports coefficients from regressions of Δp_t^j on $\Delta\tilde{d}_t^{f,j,\text{Index}}$, summarizing the fraction of the variation in the price growth rate associated with index funds' final inflows. Panel b reports coefficients from regressions of the past-performance component $\Delta\tilde{d}_t^{f,\text{perf},j,\text{Index}}$ on $\Delta\tilde{d}_t^{f,j,\text{Index}}$. Panel c reports coefficients for the macro-news component $\Delta\tilde{d}_t^{f,\text{macro news},j,\text{Index}}$, Panel d for the risk-aversion component $\Delta\tilde{d}_t^{f,\text{risk},j,\text{Index}}$, and Panel e for the residual sentiment component $\Delta\tilde{d}_t^{f,\text{sentiment},j,\text{Index}}$, each regressed on $\Delta\tilde{d}_t^{f,j,\text{Index}}$. The sample consists of U.S. stocks with an average market capitalization above 10 billion USD and available IBES data (286 firms).



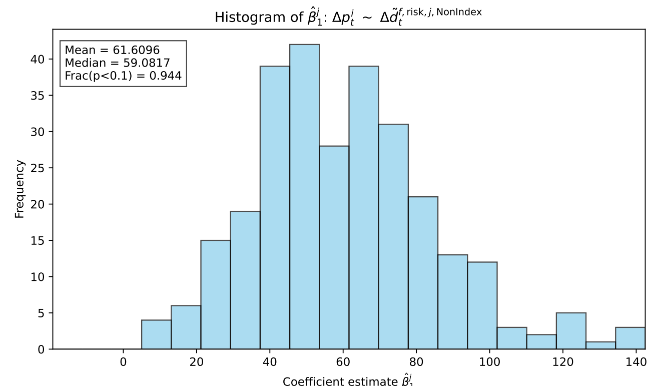
(a) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta \tilde{d}_t^{f,j,\text{NonIndex}}$



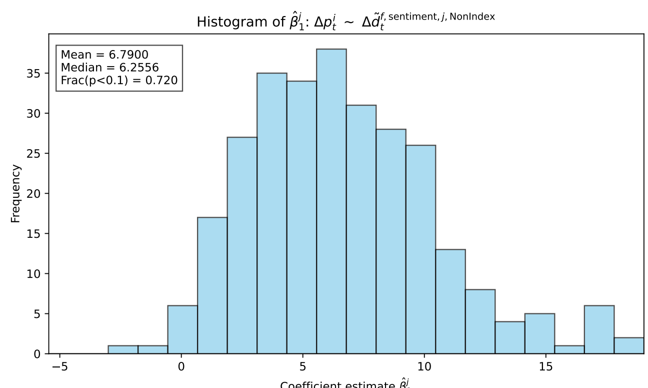
(b) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta \tilde{d}_t^{f,\text{perf},j,\text{NonIndex}}$



(c) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta \tilde{d}_t^{f,\text{macro news},j,\text{NonIndex}}$



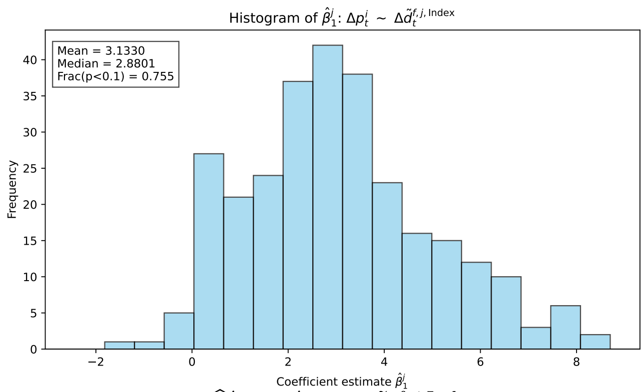
(d) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta \tilde{d}_t^{f,\text{risk},j,\text{NonIndex}}$



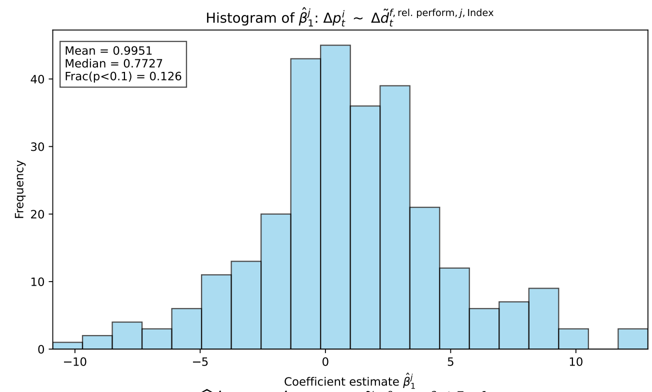
(e) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta \tilde{d}_t^{f,\text{sentiment},j,\text{NonIndex}}$

Figure 24: Sensitivity of Equity Price Growth to Marginal Non-Index Funds' Final Inflows

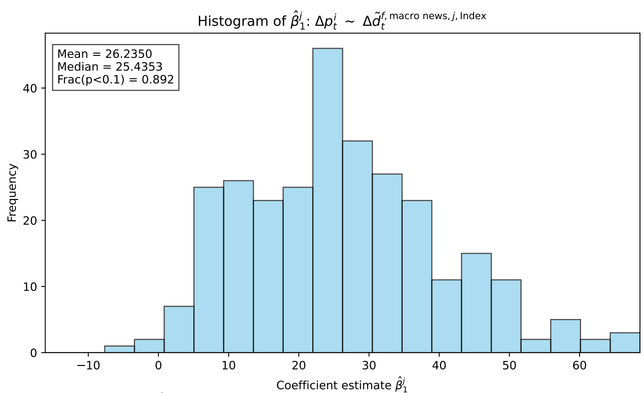
Notes: This figure reports firm-level estimates of the sensitivity of the equity price growth rate, Δp_t^j, to marginal non-index funds' final inflows and their underlying drivers. For each panel, we estimate separate firm-level regressions of Δp_t^j on different components of $\Delta\tilde{d}_t^{f,j,\text{NonIndex}}$ and plot the cross-sectional histogram of the resulting slope coefficients, reporting also their mean, median, and the fraction of estimates that are significantly different from zero at the 10% level (based on heteroskedasticity-consistent standard errors). Panel a reports coefficients from regressions of Δp_t^j on marginal non-index funds' final inflows, $\Delta\tilde{d}_t^{f,j,\text{NonIndex}}$. Panels b–e report coefficients from regressions of Δp_t^j on the past-performance ($\Delta\tilde{d}_t^{f,\text{perf},j,\text{NonIndex}}$), macro-news ($\Delta\tilde{d}_t^{f,\text{macro news},j,\text{NonIndex}}$), risk-aversion ($\Delta\tilde{d}_t^{f,\text{risk},j,\text{NonIndex}}$), and residual sentiment ($\Delta\tilde{d}_t^{f,\text{sentiment},j,\text{NonIndex}}$) components of funds' final inflows, respectively. The sample consists of U.S. stocks with an average market capitalization above 10 billion USD and available IBES data (286 firms).



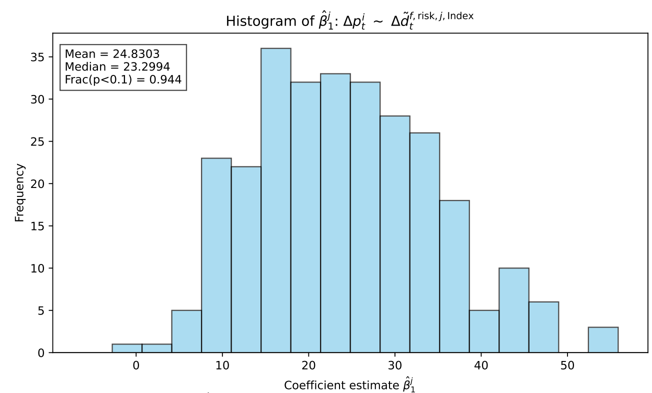
(a) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta\tilde{d}_t^{f,j,\text{Index}}$



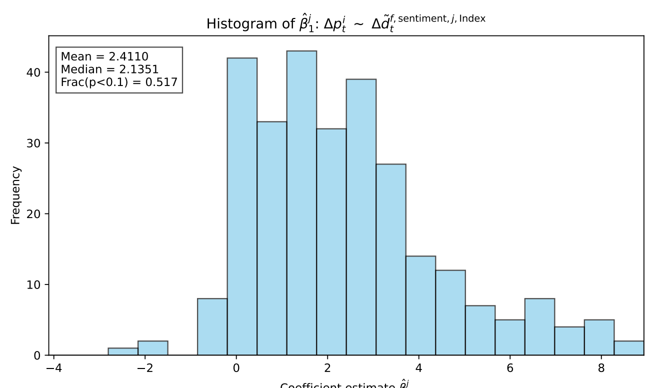
(b) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta\tilde{d}_t^{f,\text{perf},j,\text{Index}}$



(c) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta\tilde{d}_t^{f,\text{macro news},j,\text{Index}}$



(d) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta\tilde{d}_t^{f,\text{risk},j,\text{Index}}$



(e) $\widehat{\beta}_3^j$: Δp_t^j on $\Delta\tilde{d}_t^{f,\text{sentiment},j,\text{Index}}$

Figure 25: Sensitivity of Equity Price Growth to Marginal Index Funds' Final Inflows

Notes: This figure reports firm-level estimates of the sensitivity of the equity price growth rate, Δp_t^j, to marginal index funds' final inflows and their underlying drivers. For each panel, we estimate separate firm-level regressions of Δp_t^j on different components of $\Delta\tilde{d}_t^{f,j,\text{Index}}$ and plot the cross-sectional histogram of the resulting slope coefficients, reporting also their mean, median, and the fraction of estimates that are significantly different from zero at the 10% level (based on heteroskedasticity-consistent standard errors). Panel a reports coefficients from regressions of Δp_t^j on marginal index funds' final inflows, $\Delta\tilde{d}_t^{f,j,\text{Index}}$. Panels b–e report coefficients from regressions of Δp_t^j on the past-performance ($\Delta\tilde{d}_t^{f,\text{perf},j,\text{Index}}$), macro-news ($\Delta\tilde{d}_t^{f,\text{macro news},j,\text{Index}}$), risk-aversion ($\Delta\tilde{d}_t^{f,\text{risk},j,\text{Index}}$), and residual sentiment ($\Delta\tilde{d}_t^{f,\text{sentiment},j,\text{Index}}$) components of funds' final inflows, respectively. The sample consists of U.S. stocks with an average market capitalization above 10 billion USD and available IBES data (286 firms).

Internet Appendix

A Details on the Morningstar Data

For the set of of funds we have, we pull the market value of all holdings, shares held and portfolio weights, as well as the ISIN and CUSIP for each instrument held. While we also pull information related to the currency of the instrument and the type of instrument, we use these variables only to cross check the equivalent instrument characteristics we pull from Refinitiv Eikon and Datastream.

Then we compile a list of all ISINs, and if the ISIN is not available, the CUSIPs, held by our sample of funds. We end up with close to 2 million ISINs or CUSIP. These are classified into types of assets such as Equities, Government Debt, Corporate Debt etc., where each subgroup has further narrow classifications. For example, ordinary shares and depository receipts are the largest categories in the Equity group. We discard the depository receipts in the analysis in this paper.

From Refinitiv Eikon, we also pull the mappings between the ISIN of an asset and its CUSIP. When analyzing the holdings, we make sure to keep only holdings that have consistent ISIN/CUSIP classifications with Refinitiv. What we mean by this is that if the Morningstar holdings data reports both the ISIN and the CUSIP and they are different from the ISIN - CUSIP pair we pull from Refinitiv we consider this a mistake in the Morningstar data and drop that holding, given that we do not know which asset we can attribute the entry to.

When constructing the change in weights for a given asset and fund, we make sure that we do not discard information. More precisely, if for example for fund i and asset j we observe entries in the holdings data from March 2008 to April 2014 then we assume that the fund purchased stock i for the first time in March 2008 so the holdings of this instrument at the end of Feb 2008 are zero and similarly we assume the holdings at the end of May 2014 are zero as by then the asset is sold. This way we ensure we don't throw away relevant information when constructing the changes in weights.

Regarding the growth rate of assets under management we use the sum of the total market value of all ISINs. We cross check this number with the reported AUM in Morningstar Direct collected via a survey and if we find significant discrepancies in the two variables we discard these funds.

We construct the net-of-fee returns from the reported share class net-of-fee returns which are aggregated to the fund level while the flows are backed out from the growth rate of the assets under management and the net-of-fee returns and are further cross-checked with reported surveyed data on flows in Morningstar Direct.

The fund's ROS currency is constructed from the "base currency", which is the currency in which the share class of the fund is sold, combined with the share class AUM. First, we construct the total AUM by base currency for a given fund. By date, for a given fund, we select the currency with the largest AUM and then take the mode of that currency over time for a given fund. The mode currency represents the ROS currency of the fund.

For the index fund/active fund classification we use the Morningstar Direct variable called "Index Fund". A fund is classified as an index fund if "Index Fund=Yes" and as an active fund if "Index Fund=No". To construct the tracking error, used to further split the active funds, we use the reported "Primary Prospectus Benchmark", provided in Morningstar Direct. The "Broad Investment Strategy" and the "Narrow Investment Strategies" are provided by the variables "Global Broad Category Group" and "Global Category" in Morningstar Direct, respectively.

Finally, we also discard outliers at different stages of the analysis as, with any big data source, there seems to be apparent mistakes in the Morningstar Direct data set as well.

B Refinitiv Eikon/Datastream

At an ISIN level, we construct the following time series variables and characteristics:

- "Type of Asset" – we classify an ISIN as equity vs fixed income etc, where the available level of classification is very granular. The variable in Eikon that we use is: "Asset Category Description"
- "Currency" of the ISIN or CUSIP– this is the currency of issuance of the ISIN. We cross check the currency reported in Eikon for a given ISIN and the currency reported for that same ISIN or CUSIP by the funds reporting in Morningstar. In the vast majority of the cases they are the same. We end up using the Morningstar reported currency if unique currency is reported by all investors for the given security. If multiple currencies are reported in Morningstar by different players we use the Eikon classification.
- "Market capitalization" at the ISIN or CUSIP level is obtained from Datastream, and, if missing, for all dates we supplement the series using Eikon. Notice that we drop all depository receipts and drop all equities for which a depository receipt conversion ratio is reported in Eikon.
- "Price" measured in "Currency" – the price we download is the "Closing Price" which corrects for shares' splits, which is consistent with our model. If we cannot find the price in Eikon or Datastream, we back it out from Morningstar, calculated using the market value and shares reported as holdings of a given ISIN for each fund. All prices are translated into the currency of issuance of the ISIN. We further remove observations where the monthly or quarterly price growth rate exceeds 100 percent in absolute value. The correlation between the price growth rates from the Morningstar and Eikon/Datastream data sources, after this cleaning, is 96

percent. Notice that we supplement the Eikon series with Datastream or Morningstar prices only if the Eikon price is not available for any one date and take care to exclude stale price series.

- "Sector" – We classify firms as belonging in one of the following sectors: Banks, Consumer Goods, Energy, Manufacturing, Other Financials, Services based on the Eikon variables: "Parent Industry Sector", "TRBC Economic Sector Name" and "TRBC Business Sector Name".
- "Country of Exposure" – the country where the main operational risk of the firm is and if missing we use proxies. Then based on this variables and the variable which is the currency of issuance of the ISIN we keep only ISINs where the country of exposure is the same as the currency of issuance. We do that as we want to focus on US firms that issue in US dollars to capture the US stock market rather than Brazilian firms issuing in USD, for example. We construct the "Country of Exposure" variable based on the Eikon variable "Country of Risk" and if missing, we proxy the country of exposure using one of the following variables "Issuer Country", "Ultimate Parent" and "Country of Headquarters" in that order.

C Stock Market Daily Indices

The data source is Global Financial Data and the list of stock market indices in local currency is:

- AUD – AORDD ; Australia ASX All-Ordinaries
- BRL – BR20; DJ Brazil Titans 20
- CAD – SPTSECP; S&P/TSX 60 Large Cap Capped Index
- CHF – SSMID; Swiss Market Index
- CLP – IGPAD; Santiago SE S&P CLX Indice General de Precios de Acciones
- CNH – CSI300D; Shanghai-Shenzhen CSI-300 Return Index Stock Indices
- COP – IGBCD; Colombia IGBC General Index (with GFD extension)
- CZK – PXD; Prague SE PX Index
- DKK – OMXCPID; OMX Copenhagen All-Share Price Index
- EGP – EGX30D; Egypt EGX-30 Index Large Cap
- EUR – STOXXE; EuroStoxx Price Index
- GBP – FTASD; UK FTSE All-Share Index
- HKD – HSID; Hong Kong Hang Seng Composite Index
- HUF – HTLD; Vienna OETEB Hungary Traded Index (Forint)
- IDR – ID1; Dow Jones Indonesia Stock Index

- ILS – TAALLSD; Tel Aviv All-Share Price Index
- INR – BSE500D; Mumbai BSE-500 Index
- JPY – N500D; Japan Nikkei 500 Index
- KRW – KS11D; Korea SE Stock Price Index (KOSPI)
- MXN – BMXD; Mexico Banamex-30 Index
- MYR – KLSED; Malaysia KLSE Composite
- NOK – OSEAXD; Oslo SE All-Share Index Total Return Indices
- NZD – NZCID; New Zealand SE S&P/NZX All-Share Capital Index
- PHP – PSID; Manila SE Composite Index
- PLN – PTLD; Vienna OETEB Poland Traded Index
- RUB – MCXD; Russia Moscow Index (MOEX) Composite
- SEK – OMXSPID; OMX Stockholm All-Share Price Index
- SGD – FTSTID; Singapore FTSE Straits-Times Index
- THB – SET100D; Thailand SET-100 Index
- TRY – XU100D; Istanbul SE IMKB-100 Price Index
- TWD – TSE50D; Taiwan FTSE/TSE-50 Price Index
- USD – SPXD ; S&P 500/Cowles Composite Price Index
- ZAR – JALSHD; FTSE/JSE All-Share Index

D Firm-level Analyst Forecasts

We obtain firm-level consensus analyst forecasts from the I/B/E/S US Summary Statistics file. For each firm and quarter we collect forecasts for a set of firm-level accounting fundamentals, which we index by $x \in \mathcal{X}$. The variables in $\mathcal{X}$ and their I/B/E/S codes are:

Fundamental	I/B/E/S code
Earnings per share	EPS
Book value per share	BPS
Cash flow per share	CPS
Capital expenditure (level)	CPX
Cash earnings per share	CSH
Dividend per share	DPS
Earnings per share before goodwill	EBG
EBIT (level)	EBI
EBITDA per share	EBS
EBITDA (level)	EBT
Enterprise value (level)	ENT
Earnings per share (alternate definition)	EPX
Funds from operations per share	FFO
GAAP earnings per share (fully reported)	GPS
Gross margin (percent)	GRM
Net asset value (level)	NAV
Net debt (level)	NDT
Net income (level)	NET
Operating profit (level)	OPR
Pre-tax profit (level)	PRE
Return on assets (percent)	ROA
Return on equity (percent)	ROE
Revenue (level)	SAL

For ISIN j, fundamental $x \in \mathcal{X}$, and announcement date t, we define the standardized forecast surprise as

$$s^j_{t,x} = \frac{y^j_{t,x} - \mathbb{E}\big[\, y^j_{t,x} \mid \mathcal{I}_{t-\Delta-}\big]}{\widehat{\sigma}^j_{t,x}}, \tag{21}$$

where $y^j_{t,x}$ denotes the realized value of fundamental x for firm j at date t, and $\mathbb{E}[\, y^j_{t,x} \mid \mathcal{I}_{t-\Delta-}]$ is the expectation conditional on the information set just prior to the announcement. The denominator $\widehat{\sigma}^j_{t,x}$ is the cross-sectional standard deviation of individual analyst forecasts for firm j, fundamental x, and announcement date t, as reported by I/B/E/S.

For each ISIN j, we then apply principal component analysis (PCA) to the panel of standardized surprises $\{s^j_{t,x}\}$, using all fundamentals $x \in \mathcal{X}$ for which we observe at least 50 non-missing quarterly observations.

E Marginal Trader Decomposition

Let $X_t^{i,j}$ define the shares held by fund i of ISIN j. Fund $i's$ equity holdings of ISIN j can be expressed as:

$$P_t^j X_t^{i,j} = \omega_t^{i,j} W_t^i S_t^{l/c^i},$$

which, when linearized, implies:

$$P_t^j X_t^{i,j} \approx \widehat{X^{i,j}}\widehat{P^j} + \left(p_t^j - \widehat{P^j}\right)\widehat{X^{i,j}}\widehat{P^j} + \widehat{P^j}\left(X_t^{i,j} - \widehat{X^{i,j}}\right),$$

where we log linearize $P_t^j, W_t^i, S_t^{l/c^i}$ and linearize $X_t^{i,j}, \omega_t^{i,j}$ around sample averages. Since $\widehat{X^{i,j}}\widehat{P^j} \approx \left(\widehat{W^i}\widehat{S}^{l/c^i}\widehat{\omega}^{i,j}\right)$, then

$$\Delta P_t^j X_t^{i,j} \approx \Delta p_t^j \left(\widehat{W^i}\widehat{S}^{l/c^i}\widehat{\omega}^{i,j}\right) + \widehat{P^j}\Delta X_t^{i,j}.$$

Re-writing equation (4), after splitting the equity holdings into marginal and non-marginal investors' equity holdings implies:

$$\left(\sum_{\left\{i\in I:\Delta X_t^{i,j}=0\right\}} \frac{\left(\widehat{W^i}\widehat{S}^{l/c^i}\widehat{\omega}^{i,j}\right)}{\widehat{P^jQ^j}}\right)\Delta p_t^j + \sum_{\left\{i\in I:\Delta X_t^{i,j}\neq 0\right\}} \frac{\widehat{W^i}\widehat{S}^{l/c^i}\widehat{\omega}^{i,j}}{\widehat{P^jQ^j}}\left(\frac{\Delta\omega_t^{i,j}}{\widehat{\omega}^{i,j}} + \Delta w_t^i + \Delta s_t^{l/c^i}\right) = \Delta p_t^j + \Delta q_t^j.$$

Next we use the same steps as in the main text. After scaling up the equation above using the inverse of the coverage ratio and expressing the equity holdings subcomponents as arithmetic averages and residuals, we obtain the following expression for equity price growth rates:

$$\begin{aligned}\Delta p_t^j \;=\; & \left(\begin{array}{c} \sum_m \sum_{\left\{i:\ i\in\tilde{I}\cap c^i\in m\cap\Delta X_t^{i,j}\neq 0\right\}} \frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\left(\Delta s_t^{l/m}\right) \\ \sum_{\tau\in\Upsilon}\sum_{\left\{i:\ i\in\tilde{I}\cap i\in\tau\cap\Delta X_t^{i,j}\neq 0\right\}} \frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\left(\alpha_t^{f,\tau} + \alpha_t^{\omega,\tau,j} + \bar{r}_t^{NF,\tau}\right) \\ +\sum_{\tau\in\Upsilon}\sum_{\left\{i:\ i\in\tilde{I}\cap i\in\tau\cap\Delta X_t^{i,j}=0\right\}} \frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\Delta p_t^j \end{array}\right) \\ & + \sum_{\left\{i\in I:\Delta X_t^{i,j}\neq 0\right\}} \frac{\mu^{i,j}}{\widehat{P^jQ^j}}\left(\varepsilon_t^{r,i} + \varepsilon_t^{f,i} + \varepsilon_t^{\omega,i,j}\right) - \Delta q_t^j.\end{aligned}$$

Simplifying the equation above further we can express the growth rate of the price of ISIN j only as a function of the holdings by marginal investors and new issuance:

$$\begin{aligned}
\Delta p_t^j &= \frac{1}{\Theta^j}\sum_{\tau\in\Upsilon}\sum_{\left\{i:\ i\in\tilde{I}\cap c^i\in m\cap\Delta X_t^{i,j}\neq 0\right\}}\frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\left(\Delta s_t^{l/m}\right)\\
&+\frac{1}{\Theta^j}\sum_{\tau\in\Upsilon}\sum_{\left\{i:\ i\in\tilde{I}\cap i\in\tau\cap\Delta X_t^{i,j}\neq 0\right\}}\frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\left(\alpha_t^{f,\tau}+\alpha_t^{\omega,\tau,j}+\bar{r}_t^{NF,\tau}\right)\\
&+\frac{1}{\Theta^j}\sum_{\left\{i\in I:\Delta X_t^{i,j}\neq 0\right\}}\frac{\mu^{i,j}}{\widehat{P^jQ^j}}\left(\varepsilon_t^{r,i}+\varepsilon_t^{f,i}+\varepsilon_t^{\omega,i,j}\right)-\frac{1}{\Theta^j}\Delta q_t^j.\\
\Theta^j &= \left(1-\left(\sum_{\tau\in\Upsilon}\sum_{\left\{i:\ i\in\tilde{I}\cap i\in\tau\cap\Delta X_t^{i,j}=0\right\}}\frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\right)\right).
\end{aligned}$$

We arrive at the following decomposition:

$$\Delta p_t^j = \underbrace{\Delta\tilde{d}_t^{s,j}+\underbrace{\Delta\tilde{d}_t^{f,j}+\Delta\tilde{d}_t^{\omega,j}+\Delta\tilde{d}_t^{r^{NF},j}}_{\Delta\tilde{d}_t^{ROS,j}}}_{\Delta\tilde{d}_t^{j}}+\tilde{d}_t^{Resid,j}-\frac{1}{\Theta^j}\Delta q_t^j \tag{22}$$

where

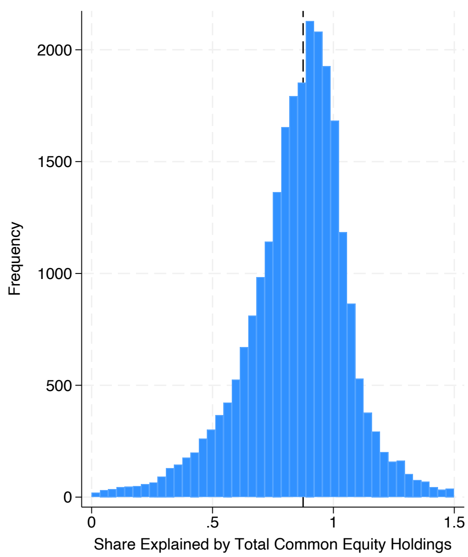
$$\begin{aligned}
\Delta\tilde{d}_t^{s,j} &= \frac{1}{\Theta^j}\sum_{\tau\in\Upsilon}\sum_{\left\{i:\ i\in\tilde{I}\cap c^i\in m\cap\Delta X_t^{i,j}\neq 0\right\}}\frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\left(\Delta s_t^{l/m}\right),\\
\Delta\tilde{d}_t^{f,j} &= \frac{1}{\Theta^j}\sum_{\tau\in\Upsilon}\sum_{\left\{i:\ i\in\tilde{I}\cap i\in\tau\cap\Delta X_t^{i,j}\neq 0\right\}}\frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\left(\alpha_t^{f,\tau}\right),\\
\Delta\tilde{d}_t^{\omega,j} &= \frac{1}{\Theta^j}\sum_{\tau\in\Upsilon}\sum_{\left\{i:\ i\in\tilde{I}\cap i\in\tau\cap\Delta X_t^{i,j}\neq 0\right\}}\frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\left(\alpha_t^{\omega,\tau,j}\right),\\
\Delta\tilde{d}_t^{r^{NF},j} &= \frac{1}{\Theta^j}\sum_{\tau\in\Upsilon}\sum_{\left\{i:\ i\in\tilde{I}\cap i\in\tau\cap\Delta X_t^{i,j}\neq 0\right\}}\frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\left(\bar{r}_t^{NF,\tau}\right),\\
\tilde{d}_t^{Resid,j} &= \frac{1}{\Theta^j}\sum_{\left\{i\in I:\Delta X_t^{i,j}\neq 0\right\}}\frac{\mu^{i,j}}{\widehat{P^jQ^j}}\left(\varepsilon_t^{r,i}+\varepsilon_t^{f,i}+\varepsilon_t^{\omega,i,j}\right).
\end{aligned}$$

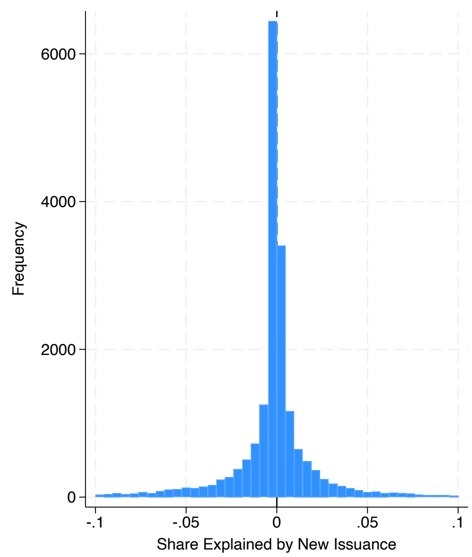
The main difference with equation (11) from the main text is that in the "marginal trader decomposition" the equity holdings' subcomponents are scaled up by the factor $\frac{1}{\Theta^j}$ and we consider only the holdings of the marginal traders when constructing the common subcomponents of equity holdings.

At monthly frequency, in our sample, equity mutual funds change their shares held across two consecutive months, on average, about 59% of the time, for a given ISIN.[36] That number is around 78% at quarterly frequency. The equivalent numbers for allocation funds are 51% at monthly and 70% at quarterly frequency.[37]

Below, we present the monthly results of our marginal traders' decomposition and point out that the results are very similar to our benchmark specification which does not exclude the non-marginal traders. As we argue in the text, the lack of change of the shares held likely reveals meaningful information related to the lack of significant news for the ISIN over the period, which is also reflected in smaller price movements for that ISIN over that same period. This is why, we do not observe a significant difference between the results from our benchmark decomposition vs the results from the decomposition based on only marginal traders' holdings.

Figure E.26: ISIN-Level Equity Price Growth Rate Decomposition: Histograms (Marginal Traders)





[36]This number is based on the average frequency of rebalancing variable across funds defined in the main text.

[37]In contrast, for fixed income funds, the equivalent numbers are 34% and 50% for monthly and quarterly frequency, respectively, implying that fixed income funds are much more likely than equity funds to buy and hold a security without adjusting the shares held.

Figure E.27: ISIN-Level Equity Price Growth Rate Decomposition: Histograms subcomponents (Marginal Traders)

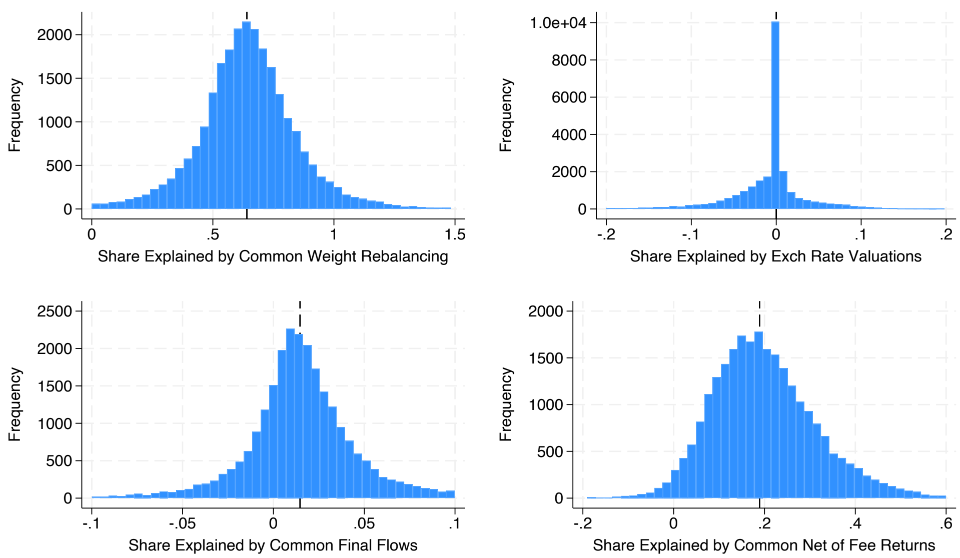
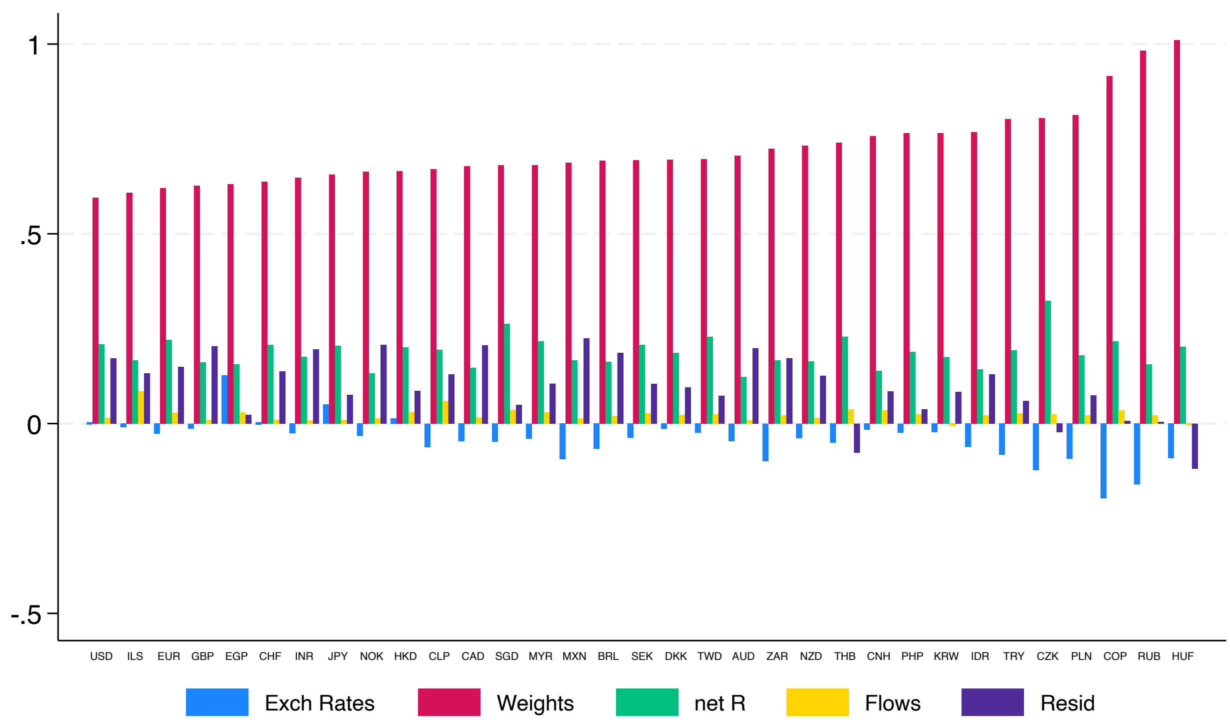
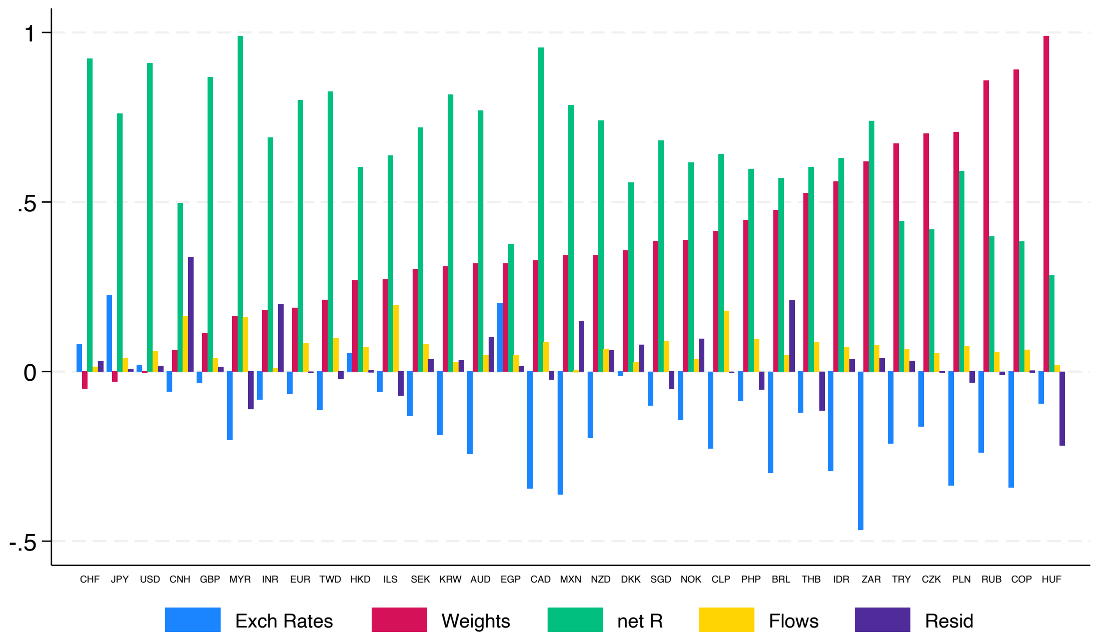


Figure E.28: ISIN-Level Equity Price Growth Rate Decomposition:: Panel Regressions (Marginal Traders)



Notes: This figure presents the coefficients from panel regressions of the equity holdings subcomponents of marginal investors on Δp_t^j by stock market (as denoted by the currency associated with that stock market). "Exch Rates" is the exchange rate "common" subcomponent, $\Delta\tilde{d}_t^{s,j}$; "Weights" is the portfolio weight changes "common" subcomponent, $\Delta\tilde{d}_t^{\omega,j}$; "net R" is the net-of-fee returns "common" subcomponent, $\Delta\tilde{d}_t^{r^{NF},j}$; "Flows" is the final flows "common" subcomponent, $\Delta\tilde{d}_t^{f,j}$; and "Resid" is the residual (unobservable) subcomponent, $\Delta\tilde{d}_t^{Resid,j}$. We allow for ISIN-level fixed effects.

Figure E.29: Aggregate Stock Market Price Growth Rate Decomposition



Notes: This figure presents OLS coefficients from regressions of the equity holdings subcomponents of marginal investors on the aggregate stock market price growth rate, $\Delta p_t^{SM,l}$ (where the stock market is denoted by the currency associated with that market). "Exch Rates" is the exchange rate "common" subcomponent, $\Delta \tilde{D}_t^{s,l}$; "Weights" is the portfolio weight changes "common" subcomponent, $\Delta \tilde{D}_t^{\omega,l}$; "net R" is the net-of-fee returns "common" subcomponent, $\Delta \tilde{D}_t^{r^{NF},l}$; "Flows" is the final flows "common" subcomponent, $\Delta \tilde{D}_t^{f,l}$; and "Resid" is the residual (unobservable) subcomponent, $\Delta \tilde{D}_t^{Resid,l}$.

Table E.6: ISIN-Level Equity Price Growth Rate Decomposition: Panel Regressions (Marginal Traders)

Currency	$\Delta\tilde{d}_t^j$	$\Delta\tilde{d}_t^{\omega,j}$	$\Delta\tilde{d}_t^{s,j}$	$\Delta\tilde{d}_t^{f,j}$	$\Delta\tilde{d}_t^{r^{NF},j}$	$\Delta\tilde{d}_t^{Resid,j}$	Δq_t^j
AUD	0.792***	0.706***	-0.046***	0.009***	0.123***	0.199***	-0.006***
BRL	0.809***	0.693***	-0.067***	0.021***	0.162***	0.187***	-0.004
CAD	0.794***	0.678***	-0.047***	0.016***	0.147***	0.206***	0.001
CHF	0.856***	0.638***	0.001	0.010***	0.208***	0.137***	-0.006**
CLP	0.864***	0.670***	-0.062***	0.060***	0.195***	0.130***	0.000
CNH	0.915***	0.758***	-0.016***	0.035***	0.139***	0.085***	0.000
COP	0.970***	0.916***	-0.197***	0.035***	0.216***	0.007	-0.005
CZK	1.031***	0.805***	-0.123***	0.025	0.323***	-0.023	0.006
DKK	0.891***	0.695***	-0.014***	0.023***	0.187***	0.095***	-0.012**
EGP	0.945***	0.631***	0.128***	0.030***	0.157***	0.023	-0.029***
EUR	0.843***	0.621***	-0.027***	0.029***	0.220***	0.149***	-0.006***
GBP	0.785***	0.627***	-0.013***	0.010***	0.162***	0.204***	-0.007**
HKD	0.910***	0.665***	0.014***	0.030***	0.201***	0.086***	-0.002
HUF	1.118***	1.010***	-0.091**	-0.004	0.203***	-0.119	-0.000
IDR	0.871***	0.768***	-0.062***	0.022***	0.143***	0.129***	0.001
ILS	0.850***	0.608***	-0.010***	0.086***	0.167***	0.132***	-0.016***
INR	0.806***	0.647***	-0.026***	0.008***	0.176***	0.196***	0.002
JPY	0.923***	0.657***	0.050***	0.010***	0.205***	0.076***	-0.002***
KRW	0.913***	0.766***	-0.023***	-0.005***	0.175***	0.083***	-0.003**
MXN	0.773***	0.688***	-0.094***	0.013***	0.166***	0.225***	-0.001
MYR	0.888***	0.681***	-0.040***	0.029***	0.217***	0.105***	-0.004
NOK	0.778***	0.664***	-0.033***	0.014***	0.133***	0.207***	-0.013
NZD	0.873***	0.733***	-0.038***	0.015***	0.164***	0.126***	-0.001
PHP	0.956***	0.766***	-0.024***	0.025***	0.189***	0.038**	-0.004
PLN	0.922***	0.813***	-0.093***	0.022***	0.180***	0.074***	-0.004
RUB	1.000***	0.983***	-0.161***	0.021***	0.156***	0.005	0.004
SEK	0.891***	0.694***	-0.038***	0.027***	0.207***	0.105***	-0.002
SGD	0.931***	0.680***	-0.048***	0.036***	0.262***	0.050***	-0.014*
THB	0.956***	0.740***	-0.051***	0.038***	0.229***	-0.076*	-0.107***
TRY	0.940***	0.803***	-0.082***	0.027***	0.193***	0.060***	0.000
TWD	0.925***	0.696***	-0.024***	0.024***	0.229***	0.074***	-0.000
USD	0.820***	0.595***	0.001***	0.015***	0.209***	0.172***	-0.003***
ZAR	0.813***	0.724***	-0.099***	0.021***	0.166***	0.173***	-0.012*

Note: This table reports the coefficients from panel regressions of the total common component of equity holdings of marginal traders, Δd_t^j, and its subcomponents on Δp_t^j by stock market (as denoted by the currency associated with that stock market). The subcomponents are the portfolio weight changes "common" subcomponent, $\Delta d_t^{\omega,j}$; the exchange rate "common" subcomponent, $\Delta d_t^{s,j}$; the final flows "common" subcomponent, $\Delta d_t^{f,j}$; and the net-of-fee returns "common" subcomponent, $\Delta d_t^{r^{NF},j}$. We also report regressions for the residual (unobservable) subcomponent, $\Delta d_t^{Resid,j}$, and for the change in shares outstanding, Δq_t^j. We allow for ISIN-level fixed effects and cluster the standard errors by ISIN. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%.

Table E.7: Aggregate Stock Market Price Growth Rate Decomposition

Currency	$\Delta\tilde{D}^{l}$	R^2	$\Delta\tilde{D}^{s,l}$	R^2	$\Delta\tilde{D}^{\omega,l}$	R^2	$\Delta\tilde{D}^{r^{NF},l}$	R^2	$\Delta\tilde{D}^{f,l}$	R^2	$\Delta\tilde{D}^{Resid,l}$	R^2
AUD	0.89***	0.90	-0.24***	0.22	0.32***	0.41	0.77***	0.72	0.05***	0.05	0.10***	0.09
BRL	0.80***	0.83	-0.30***	0.40	0.48***	0.54	0.57***	0.70	0.05***	0.05	0.21***	0.27
CAD	1.02***	0.87	-0.34***	0.33	0.33***	0.26	0.96***	0.73	0.09***	0.13	-0.02	-0.00
CHF	0.97***	0.93	0.08**	0.04	-0.05	0.01	0.92***	0.79	0.01	-0.00	0.03	0.01
CLP	1.01***	0.69	-0.23***	0.15	0.41***	0.20	0.64***	0.42	0.18***	0.22	-0.00	-0.01
CNH	0.67***	0.40	-0.06***	0.12	0.06	-0.00	0.50***	0.47	0.16***	0.23	0.34***	0.14
COP	1.00***	0.76	-0.34***	0.32	0.89***	0.67	0.38***	0.36	0.06***	0.05	-0.00	-0.01
CZK	1.01***	0.70	-0.16***	0.12	0.70***	0.38	0.42***	0.33	0.05***	0.04	-0.00	-0.01
DKK	0.93***	0.83	-0.01	-0.00	0.36***	0.34	0.56***	0.65	0.03	0.03	0.08*	0.03
EGP	0.95***	0.72	0.20	0.09	0.32**	0.12	0.38***	0.41	0.05***	0.06	0.02	-0.01
EUR	1.01***	0.94	-0.07***	0.07	0.19***	0.37	0.80***	0.93	0.08***	0.13	-0.00	-0.01
GBP	0.99***	0.94	-0.03*	0.02	0.11***	0.13	0.87***	0.89	0.04***	0.06	0.01	-0.00
HKD	1.00***	0.95	0.05***	0.40	0.27***	0.33	0.60***	0.75	0.07***	0.25	0.00	-0.01
HUF	1.20***	0.59	-0.09	0.02	0.99***	0.42	0.28***	0.14	0.02	-0.00	-0.22**	0.04
IDR	0.97***	0.85	-0.29***	0.44	0.56***	0.43	0.63***	0.56	0.07***	0.12	0.04	0.00
ILS	1.04***	0.71	-0.06**	0.05	0.27***	0.17	0.64***	0.57	0.20***	0.19	-0.07	0.00
INR	0.80***	0.91	-0.08***	0.30	0.18***	0.29	0.69***	0.89	0.01	-0.00	0.20***	0.37
JPY	1.00***	0.88	0.22***	0.41	-0.03	0.00	0.76***	0.81	0.04	0.01	0.01	-0.01
KRW	0.97***	0.89	-0.19***	0.19	0.31***	0.37	0.82***	0.78	0.03	0.00	0.03	0.00
MXN	0.77***	0.68	-0.36***	0.38	0.34***	0.28	0.79***	0.69	0.00	-0.01	0.15***	0.06
MYR	1.11***	0.73	-0.20***	0.13	0.16*	0.02	0.99***	0.50	0.16***	0.13	-0.11**	0.02
NOK	0.90***	0.86	-0.14***	0.35	0.39***	0.45	0.62***	0.78	0.04**	0.03	0.10***	0.06
NZD	0.95***	0.64	-0.20***	0.07	0.34***	0.14	0.74***	0.48	0.07***	0.04	0.06	0.00
PHP	1.05***	0.83	-0.09***	0.11	0.45***	0.31	0.60***	0.45	0.09***	0.12	-0.05	0.01
PLN	1.04***	0.77	-0.34***	0.37	0.71***	0.49	0.59***	0.57	0.07***	0.11	-0.03	-0.00
RUB	1.08***	0.68	-0.24**	0.14	0.86***	0.43	0.40***	0.42	0.06**	0.06	-0.01	-0.01
SEK	0.97***	0.89	-0.13***	0.16	0.30***	0.38	0.72***	0.84	0.08***	0.13	0.04	0.00
SGD	1.06***	0.92	-0.10***	0.17	0.39***	0.40	0.68***	0.73	0.09***	0.20	-0.05*	0.02
THB	1.10***	0.65	-0.12***	0.21	0.53***	0.23	0.60***	0.52	0.09***	0.07	-0.11*	0.01
TRY	0.97***	0.88	-0.21***	0.11	0.67***	0.54	0.44***	0.46	0.07***	0.13	0.03	0.00
TWD	1.02***	0.86	-0.11***	0.20	0.21***	0.12	0.83***	0.67	0.10***	0.12	-0.02	-0.00
USD	0.99***	0.98	0.02***	0.24	-0.00	-0.01	0.91***	0.98	0.06***	0.22	0.02	0.00
ZAR	0.97***	0.80	-0.47***	0.28	0.62***	0.43	0.74***	0.50	0.08***	0.05	0.04	0.00

Note: This table reports OLS coefficients from regressions of the total "common" component of equity holdings of marginal traders, ΔD^{l}, and its subcomponents on the aggregate stock market price growth rate (where the stock market is denoted by the currency associated with that market). The subcomponents are the exchange rate "common" subcomponent, $\Delta D^{s,l}$; the portfolio weight changes "common" subcomponent, $\Delta D^{\omega,l}$; the net-of-fee returns "common" subcomponent, $\Delta D^{r^{NF},l}$; and the final flows "common" subcomponent, $\Delta D^{f,l}$. We also report results for the residual (unobservable) subcomponent, $\Delta D^{Resid,l}$. The table also presents the corresponding R^2 values next to each component. Robust standard errors. * significant at 10%; ** at 5%; *** at 1%.

F Additional Figures Using Monthly Sample

Figure F.30: Total AUM USD Trillions; Monthly

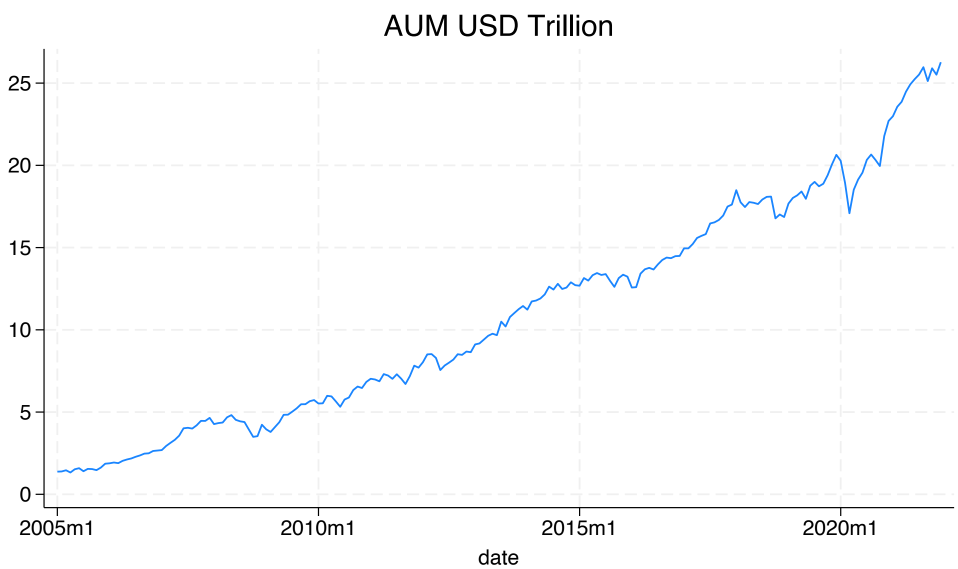


Figure F.31: Sample Aggregate vs Market Index Stock Return Correlations

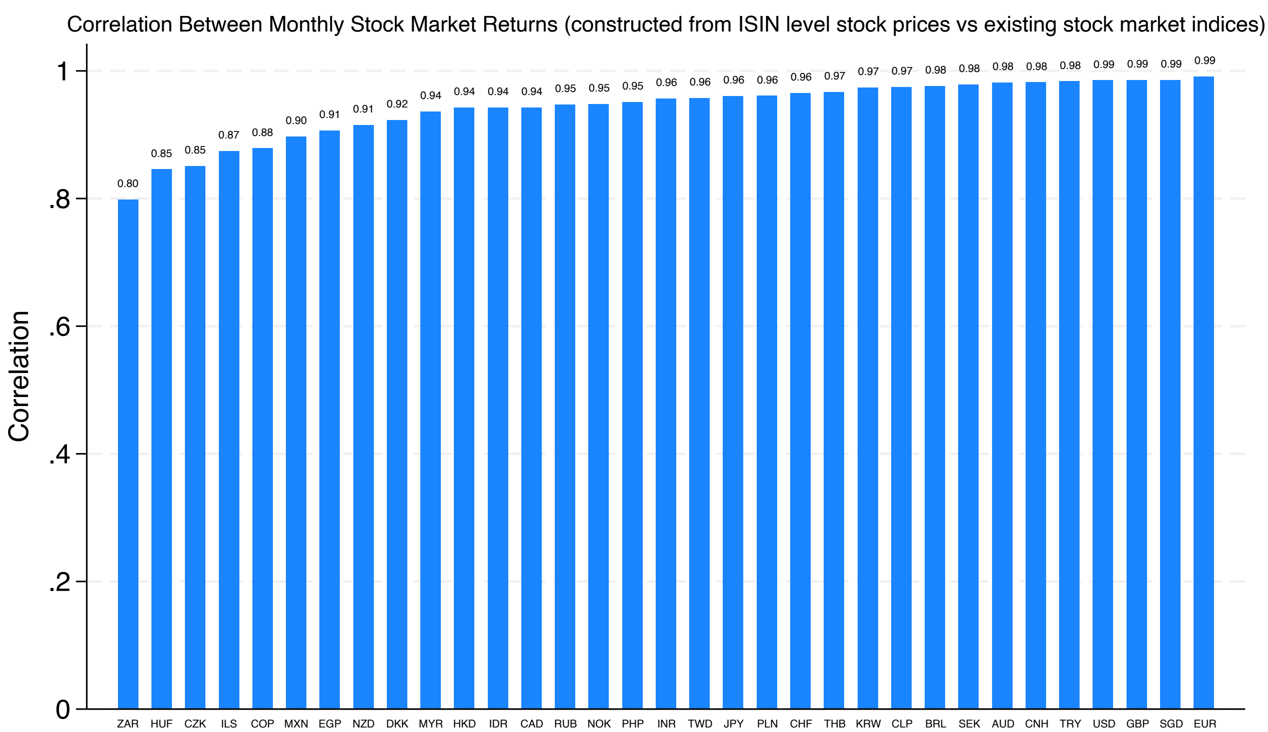


Figure F.32: Number of Funds Within Each Type (for Net-of-Fee Returns and Flows Components)

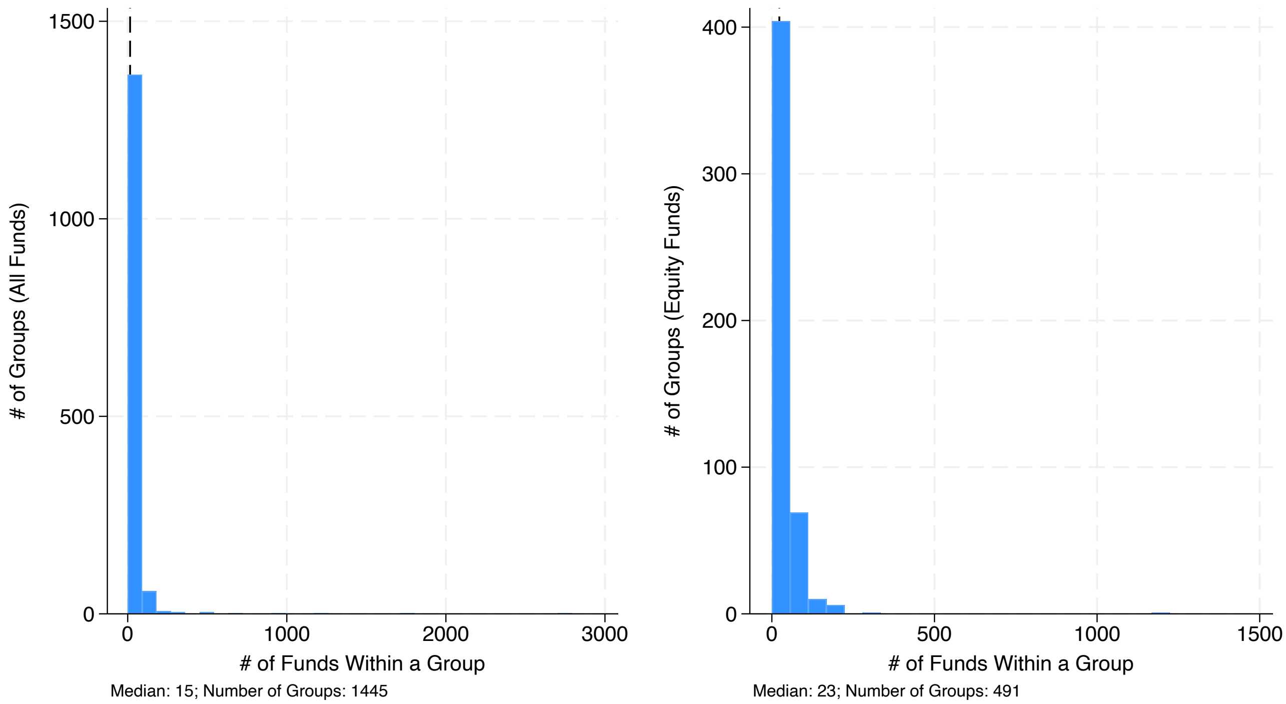


Figure F.33: Examples of Fund-level and Average Scaled Flows For Select Categories

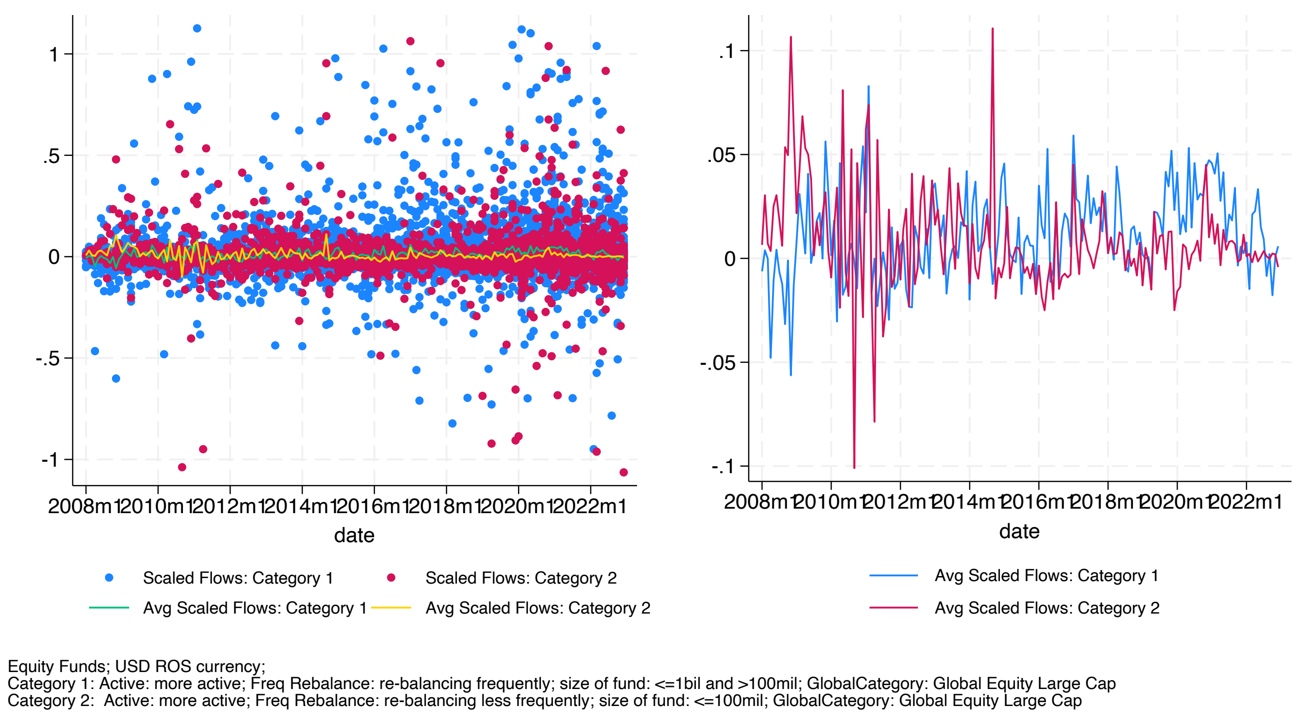
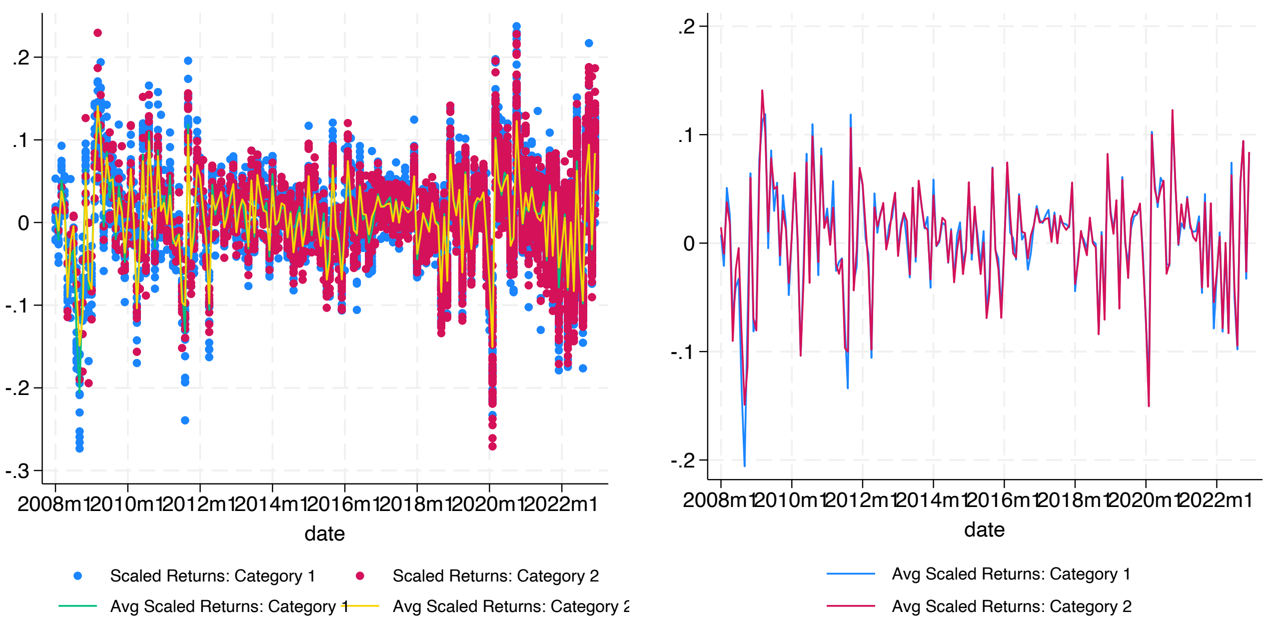
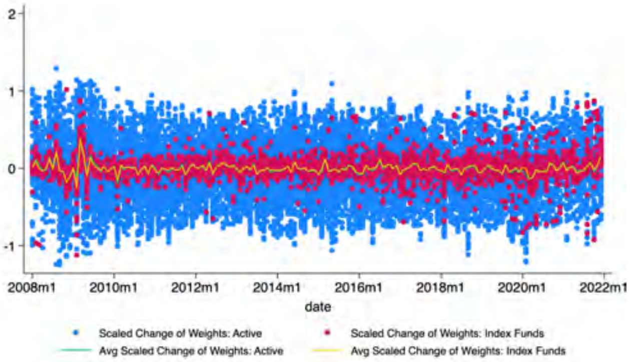


Figure F.34: Examples of Fund-level and Average Scaled Net-of-Fee Returns For Select Categories

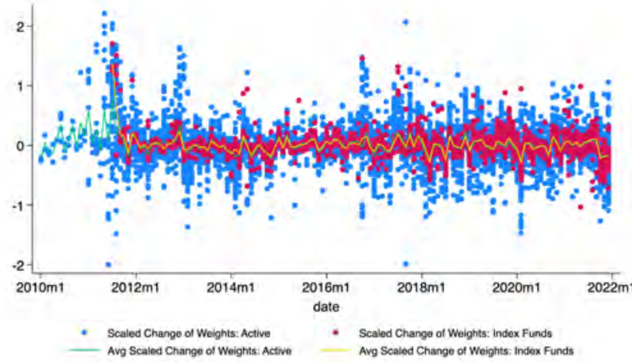


Equity Funds; USD ROS currency;
Category 1: Active: more active; Freq Rebalance: re-balancing frequently; size of fund: <=1bil and >100mil; GlobalCategory: Global Equity Large Cap
Category 2: Active: more active; Freq Rebalance: re-balancing less frequently; size of fund: <=100mil; GlobalCategory: Global Equity Large Cap

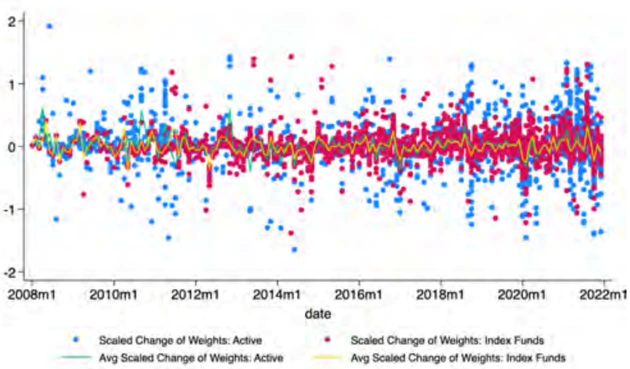
Figure F.35: Portfolio Weight Changes for Select Stocks



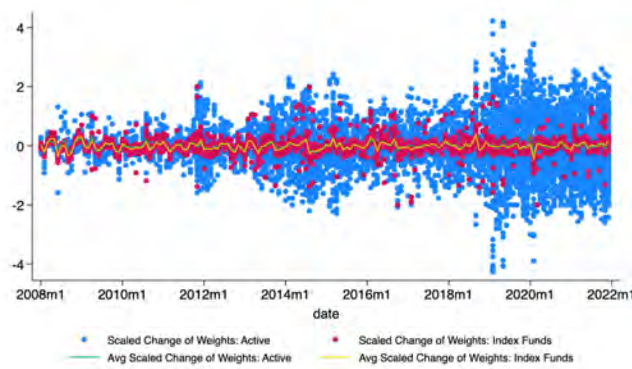
(a) HSBC



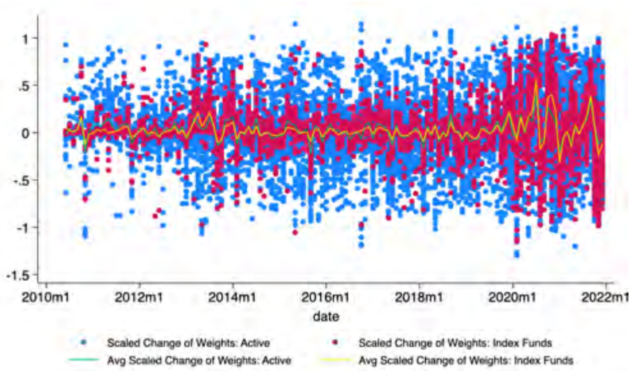
(b) Sberbank Rossii



(c) Rosneft

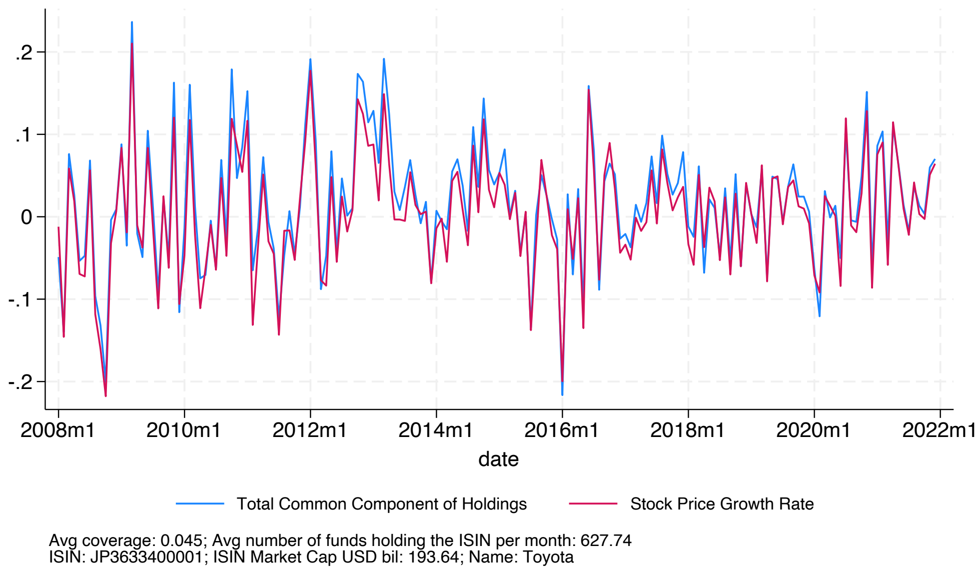


(d) Petrobras

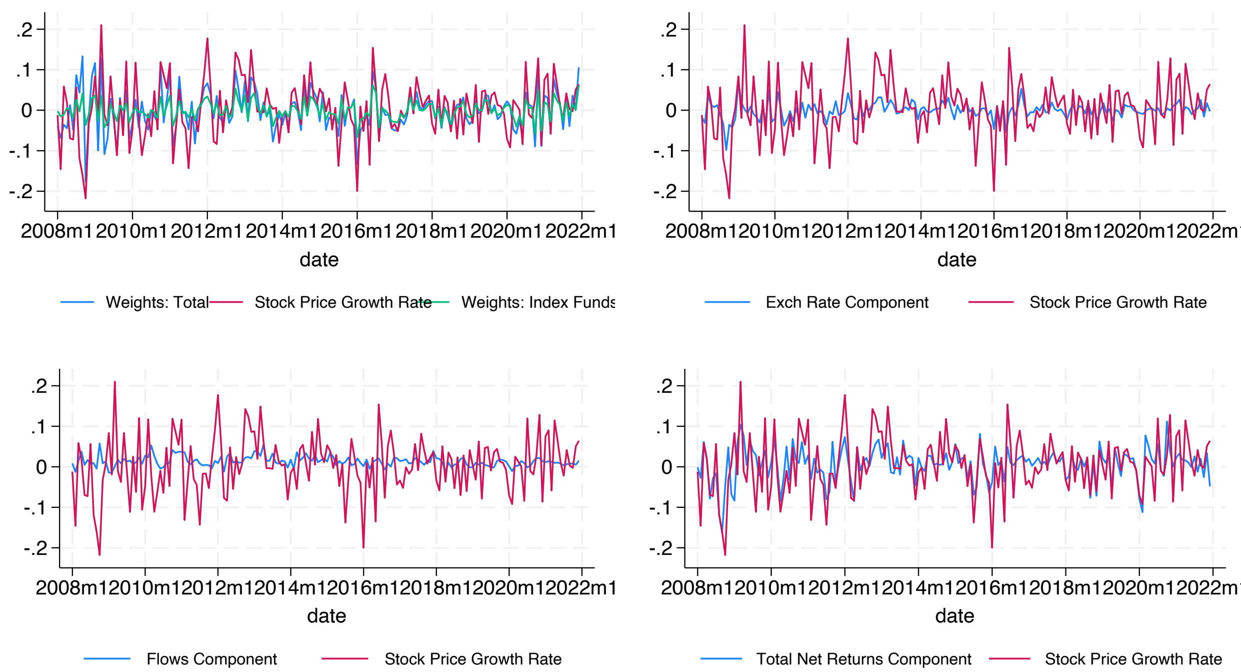


(e) Tesla

Figure F.36: Common Equity Holdings Components: Toyota

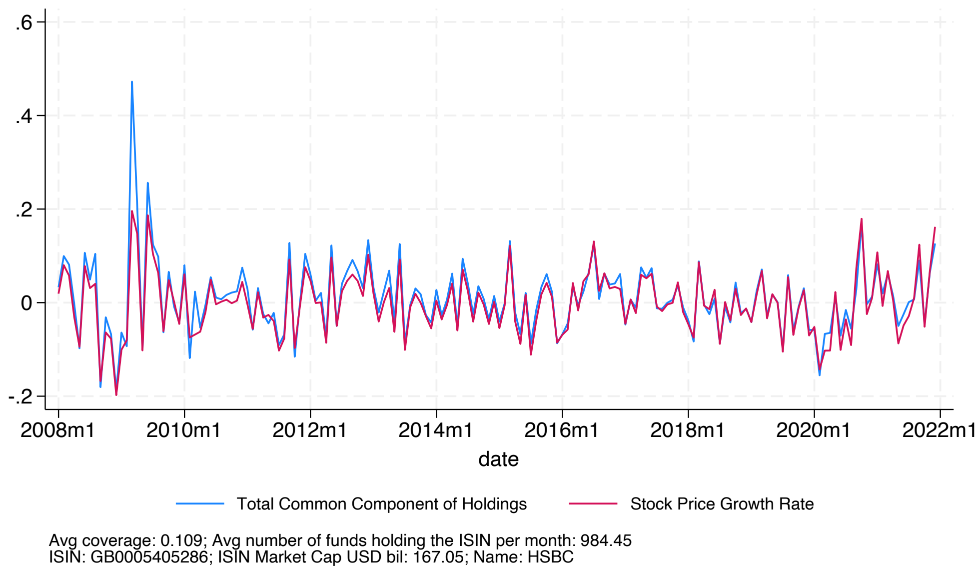


(a) Total

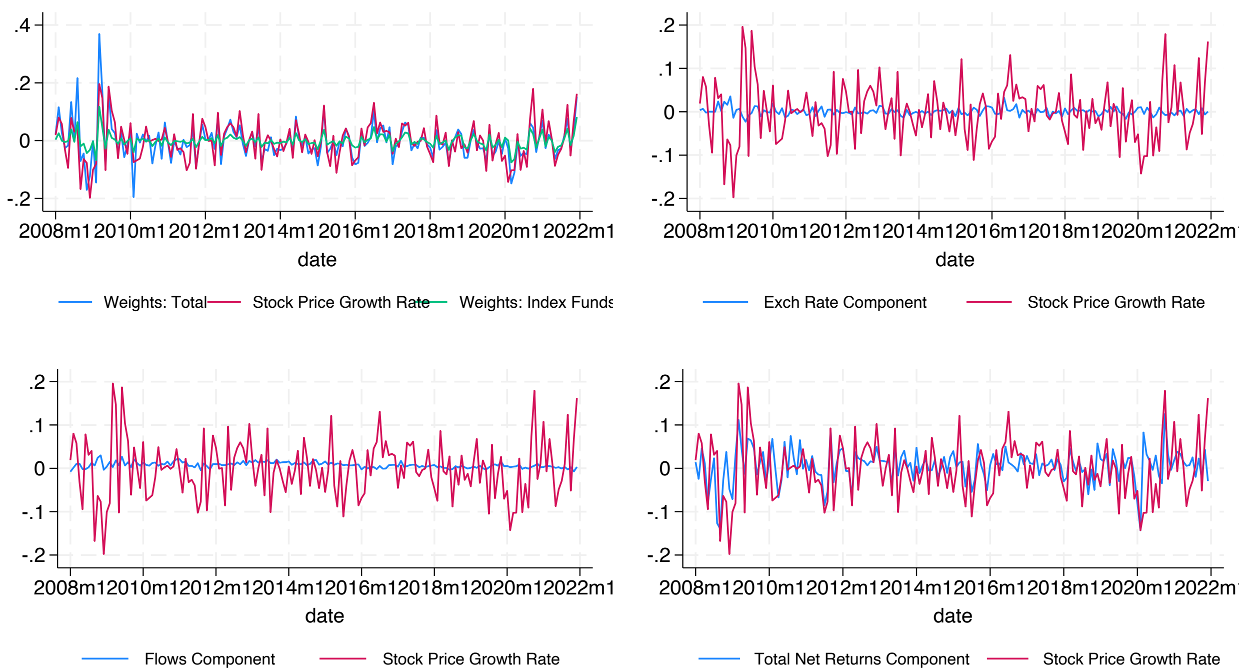


(b) subcomponents

Figure F.37: Common Equity Holdings Components: HSBC

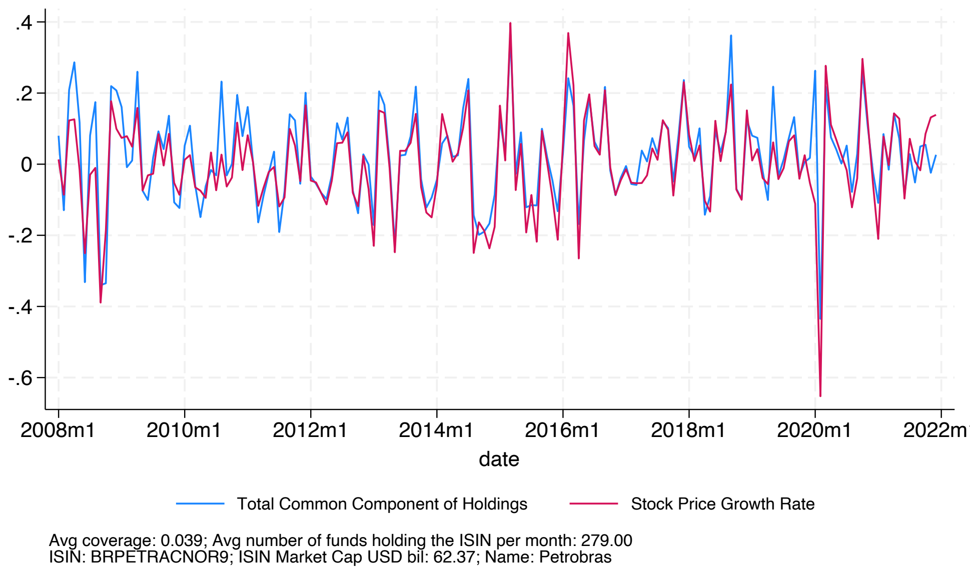


(a) Total

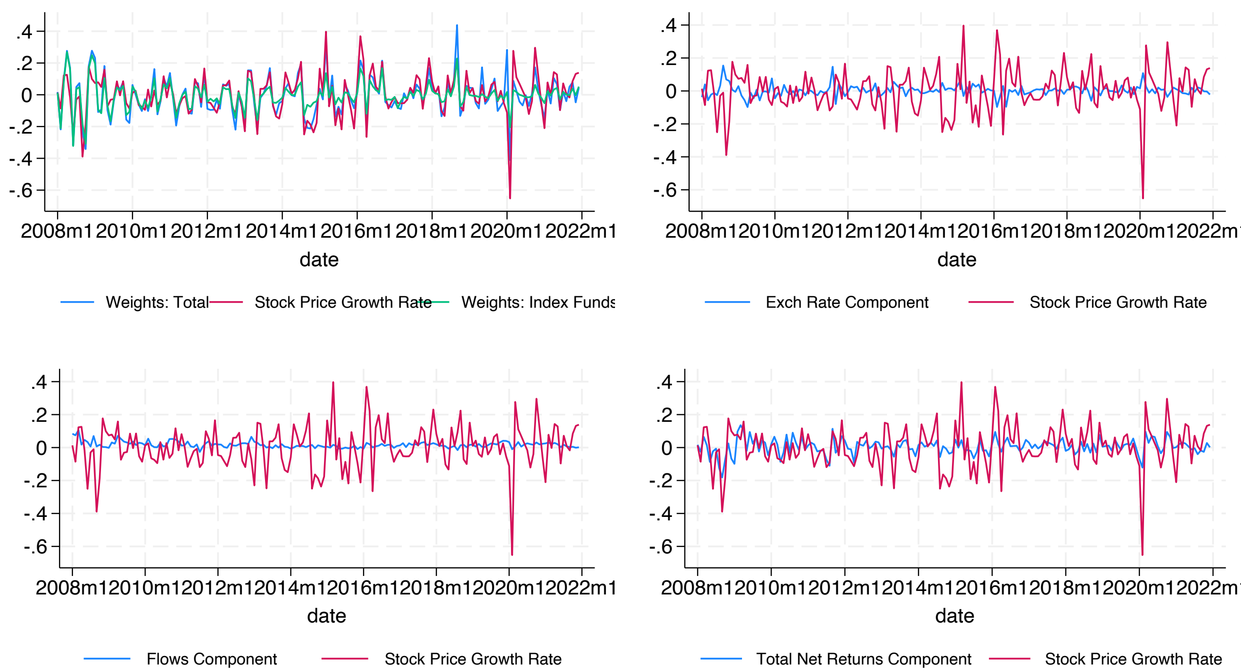


(b) subcomponents

Figure F.38: Common Equity Holdings Components: Petrobras

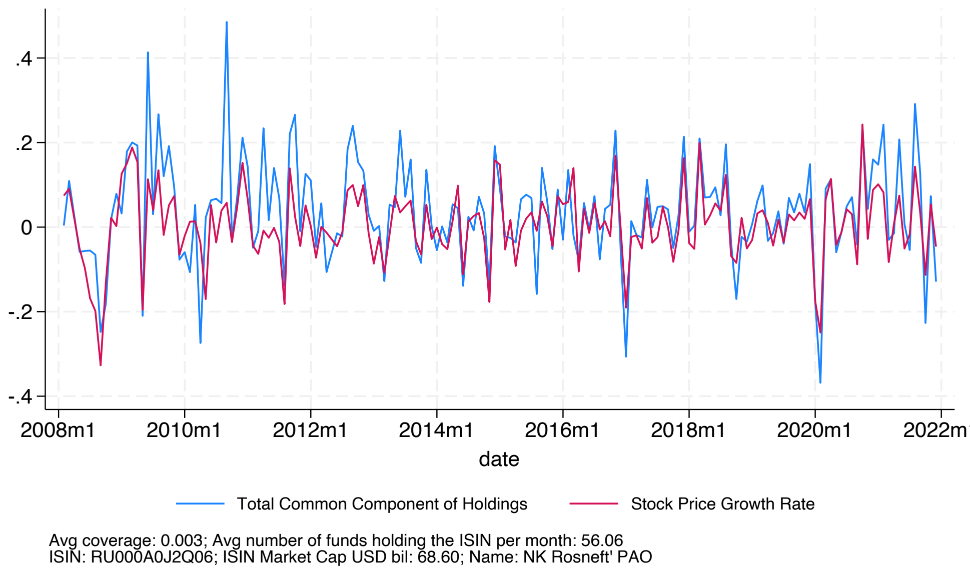


(a) Total

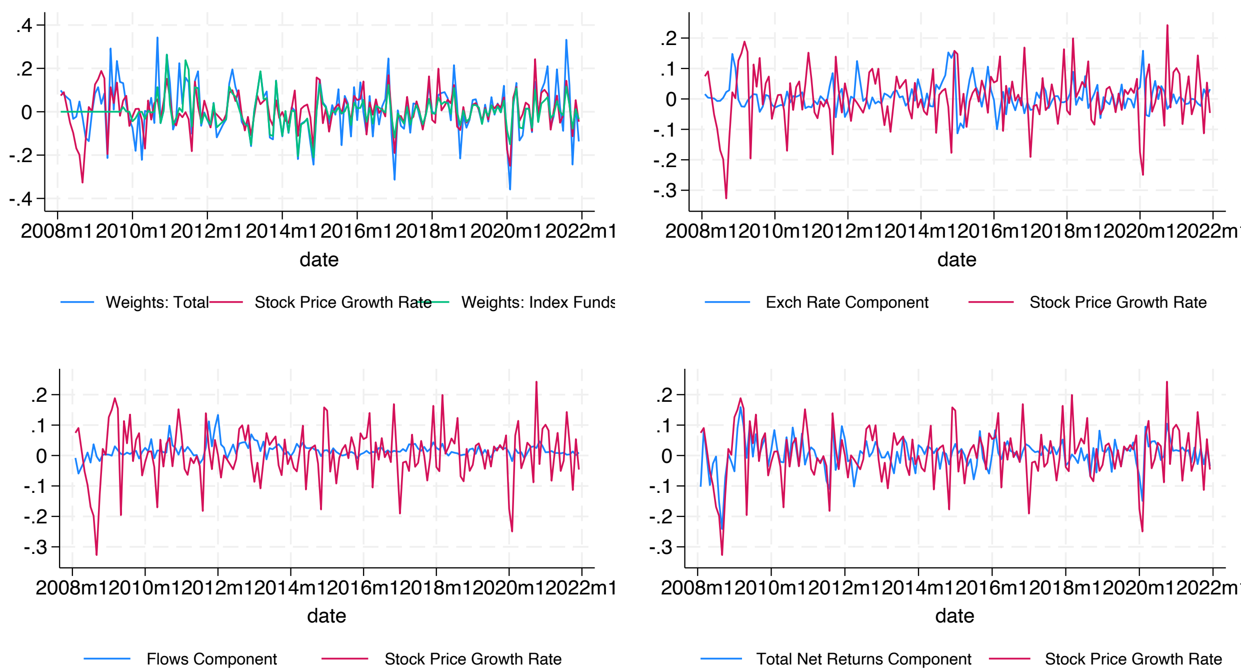


(b) subcomponents

Figure F.39: Common Equity Holdings Components: NK Rosneft' PAO

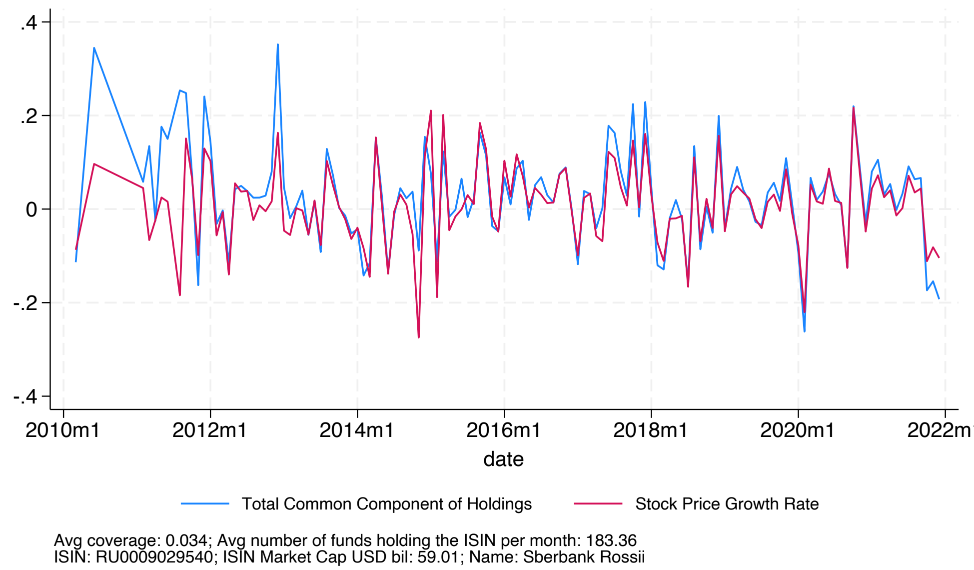


(a) Total

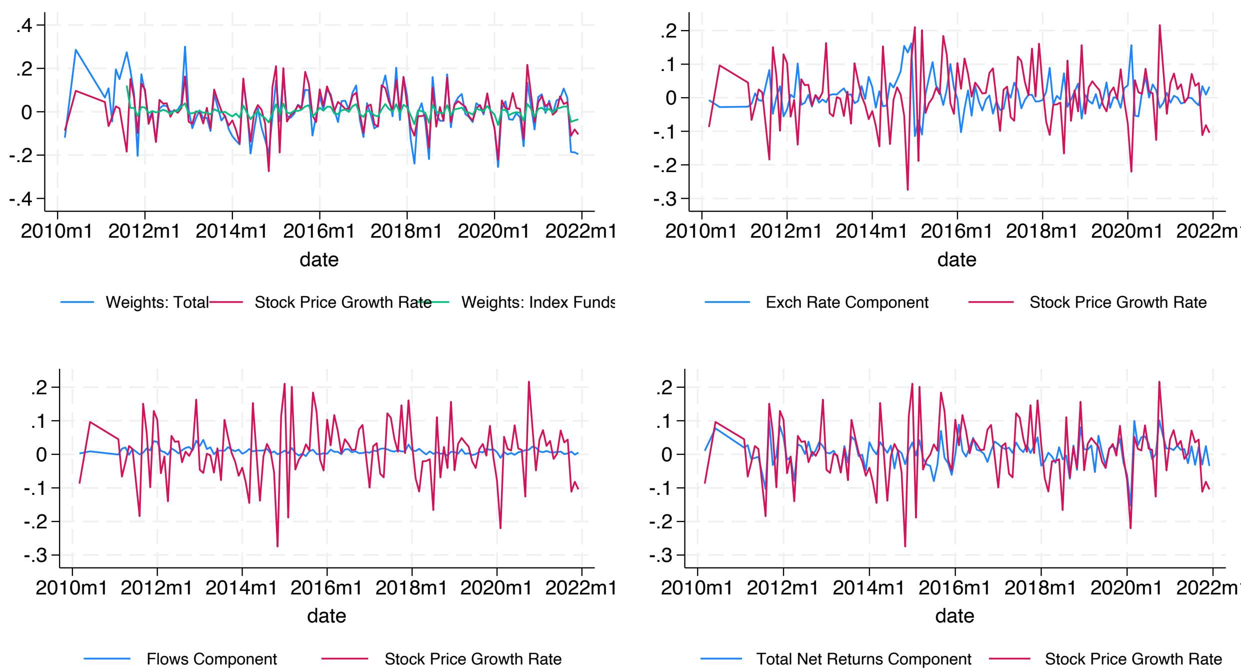


(b) subcomponents

Figure F.40: Common Equity Holdings Components: Sberbank Rossii

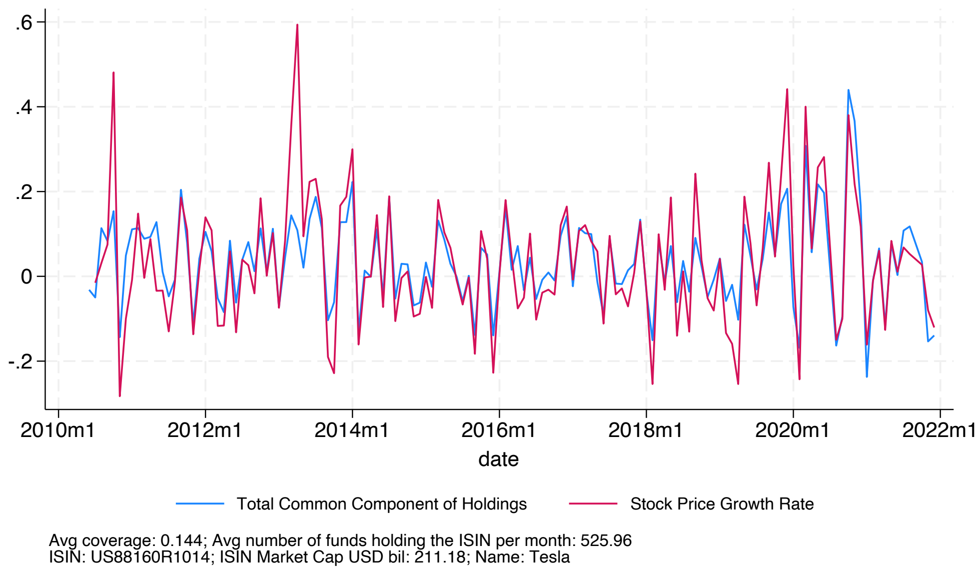


(a) Total

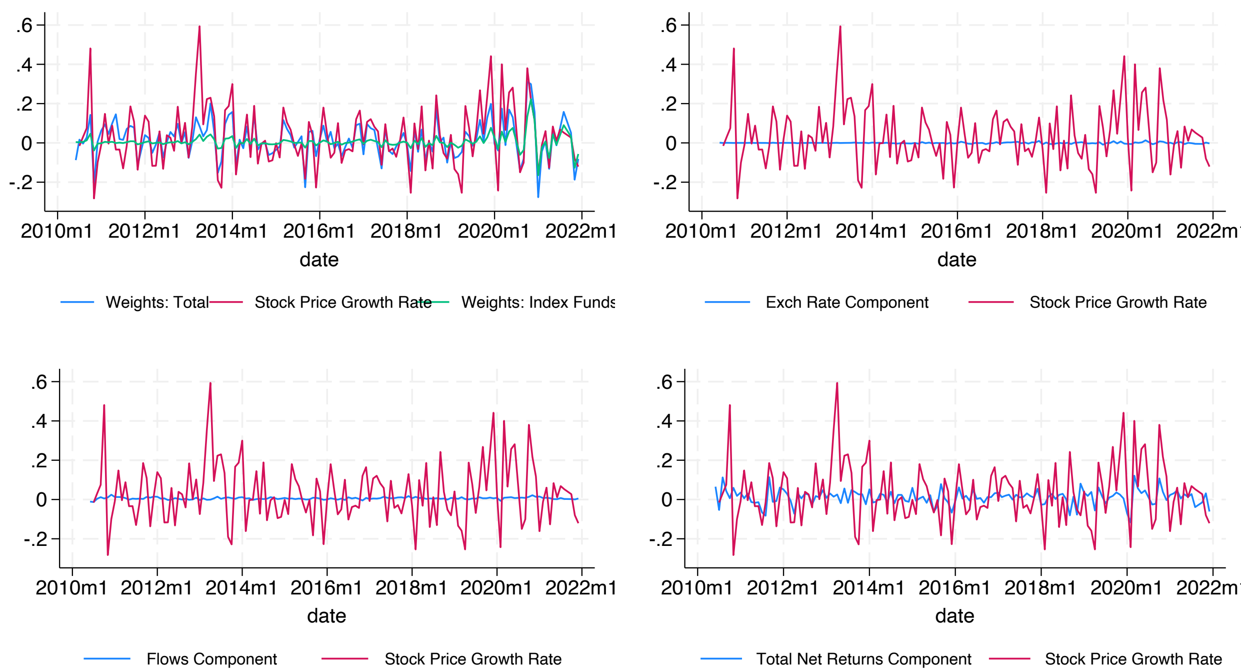


(b) subcomponents

Figure F.41: Common Equity Holdings Components: Tesla

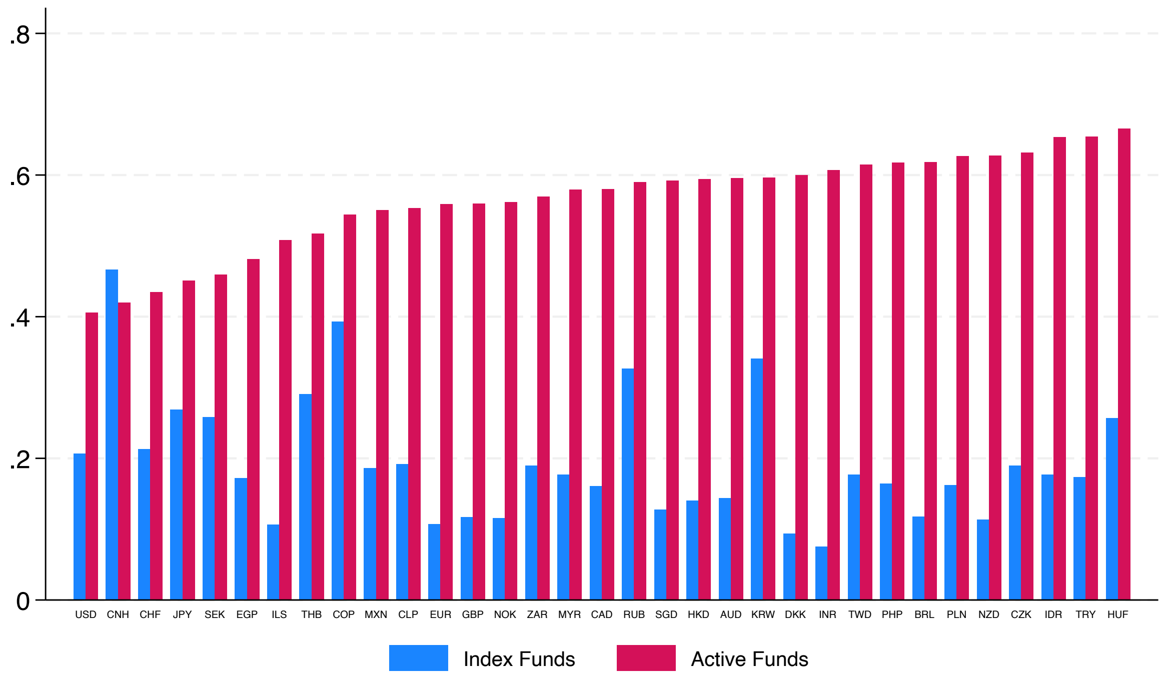


(a) Total



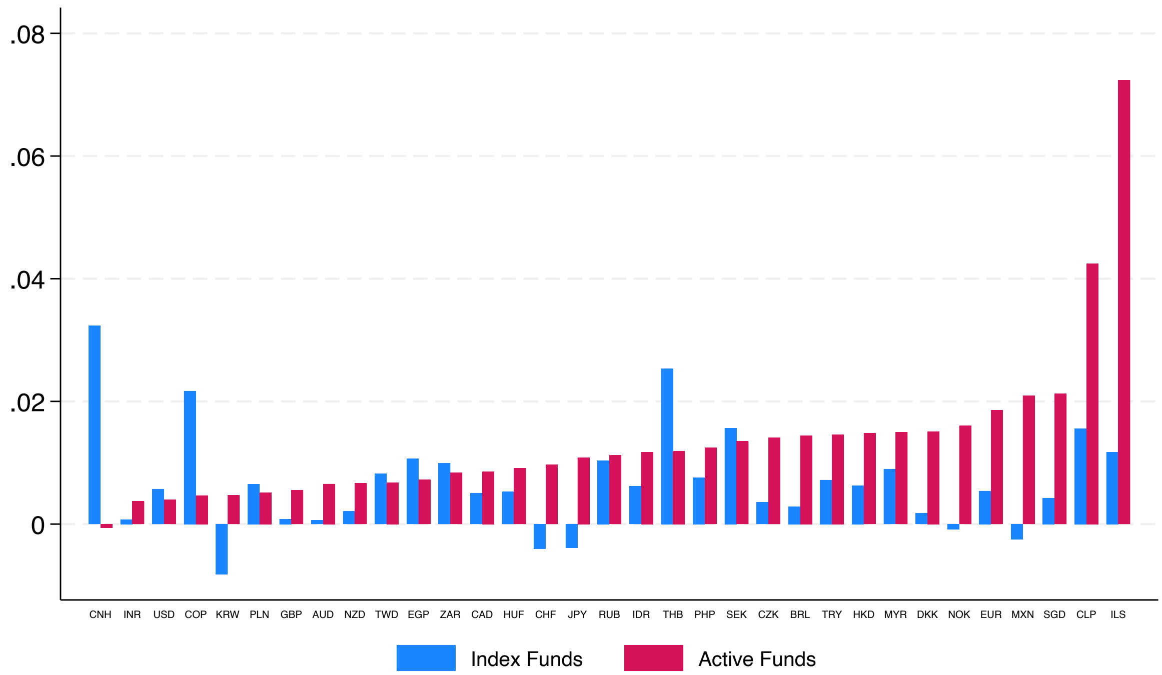
(b) subcomponents

Figure F.42: ISIN-Level Equity Price Growth Rate Decomposition: Index Funds vs Active Funds Portfolio Weight Changes: Panel Regressions



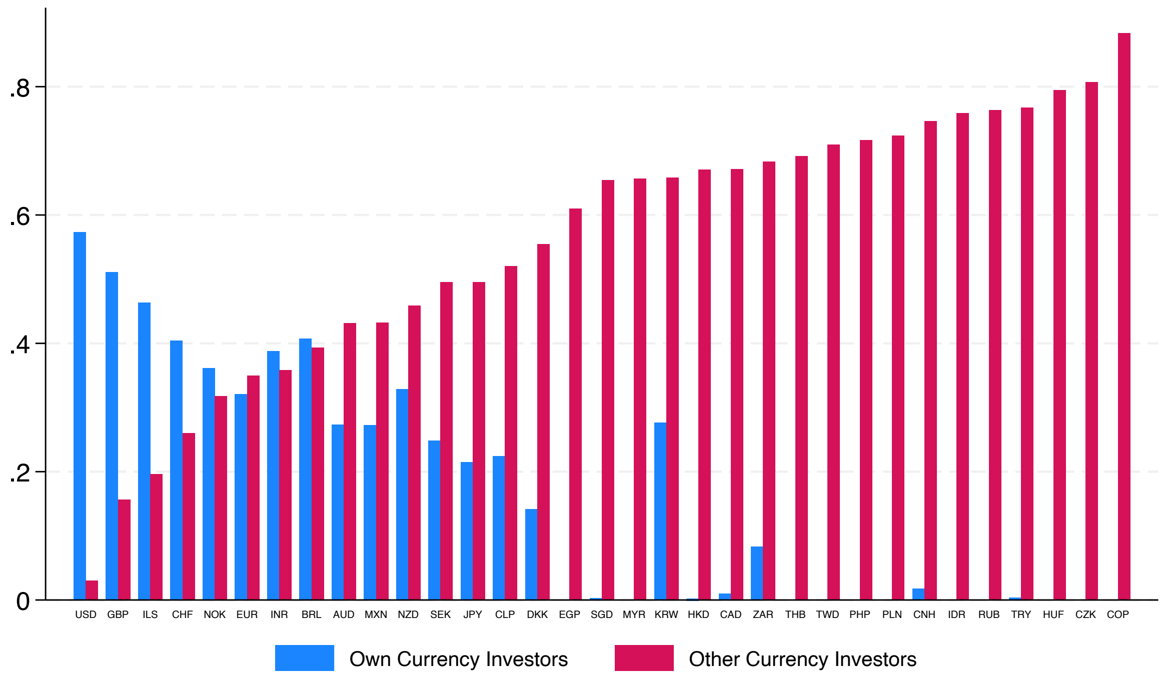
This figure presents coefficients from panel regressions of the portfolio weight changes "common" subcomponents, broken down by index and active funds, on Δp_t^j by stock market (as denoted by the currency associated with that market).

Figure F.43: ISIN-Level Equity Price Growth Rate Decomposition: Index Funds vs Active Funds Flows: Panel Regressions



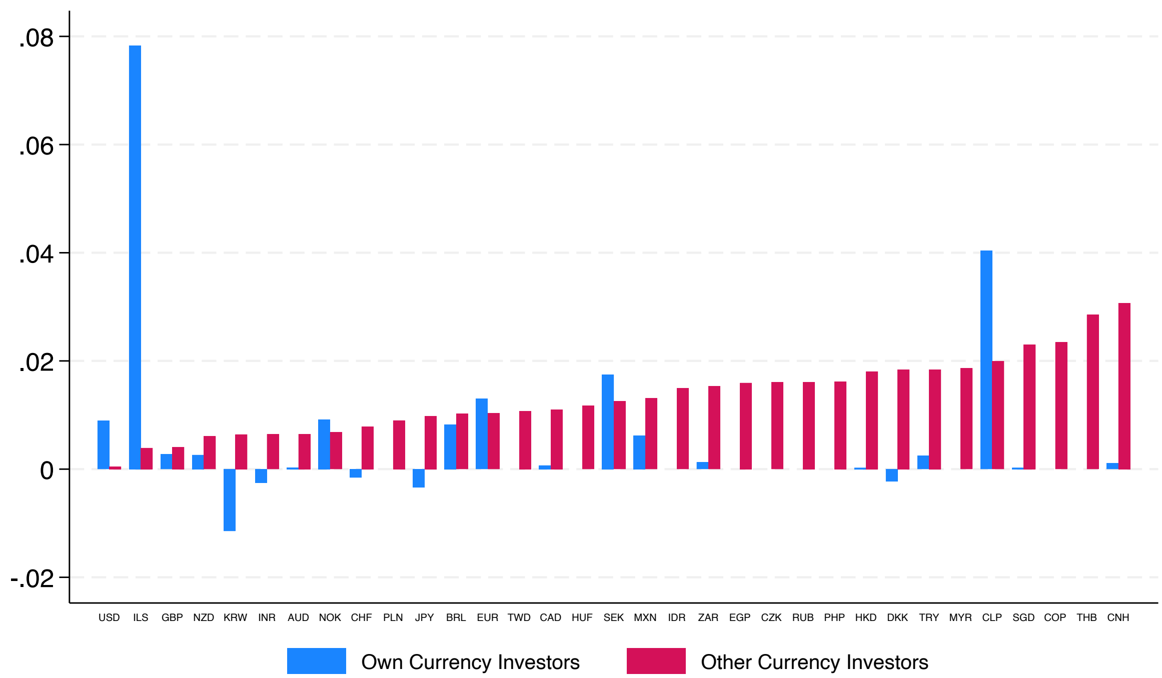
This figure presents coefficients from panel regressions of the final flows "common" subcomponents, broken down by index and active funds, on Δp_t^j by stock market (as denoted by the currency associated with that market).

Figure F.44: ISIN-Level Equity Price Growth Rate Decomposition: Local vs Other Currency Investors Portfolio Weight Changes: Panel Regressions



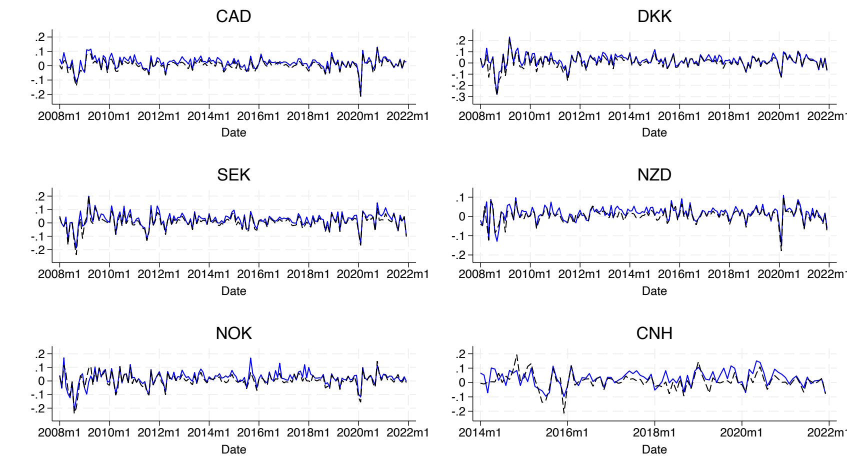
This figure presents coefficients from panel regressions of the portfolio weight changes "common" subcomponents, broken down by local-currency and foreign-currency investors, on Δp_t^j by stock market (as denoted by the currency associated with that market).

Figure F.45: ISIN Level Equity Price Growth Rate Decomposition: Local vs Other Currency Investors Flows: Panel Regressions



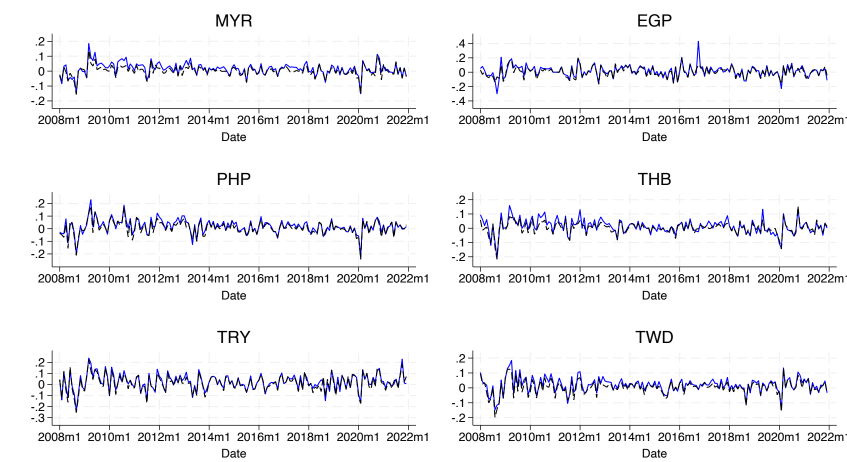
This figure presents coefficients from panel regressions of the final flows "common" subcomponents, broken down by local-currency and foreign-currency investors, on Δp_t^j by stock market (as denoted by the currency associated with that market).

Figure F.46: Stock Market Price Growth Rate vs Total Common Component of Equilibrium Holdings



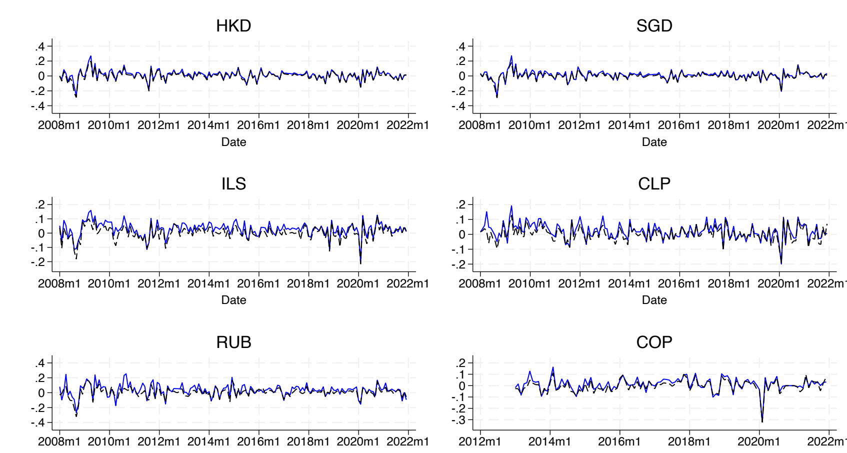
The black dashed line represents the stock price growth rate and the solid blue line is the change in total common equity holdings.

(a) Select Advanced Economies



The black dashed line represents the stock price growth rate and the solid blue line is the change in total common equity holdings.

(b) Select Emerging Markets



The black dashed line represents the stock price growth rate and the solid blue line is the change in total common equity holdings.

(c) Select Emerging Markets (cont.)

G Quarterly Sample Results

Figure G.47: Total AUM USD Trillions; Quarterly

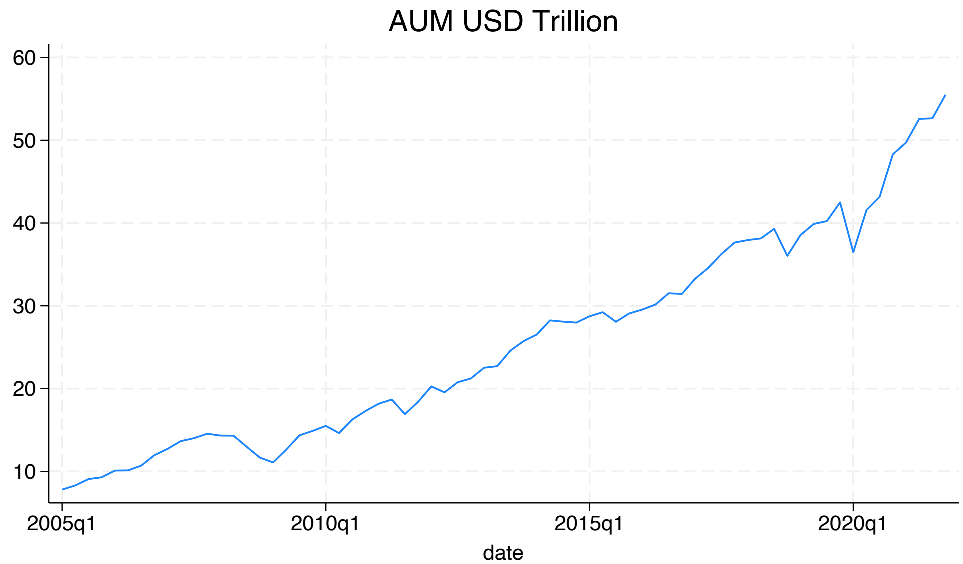


Figure G.48: AUM by Investment Type and ROS Currency (Quarterly Sample, USD Trillions)

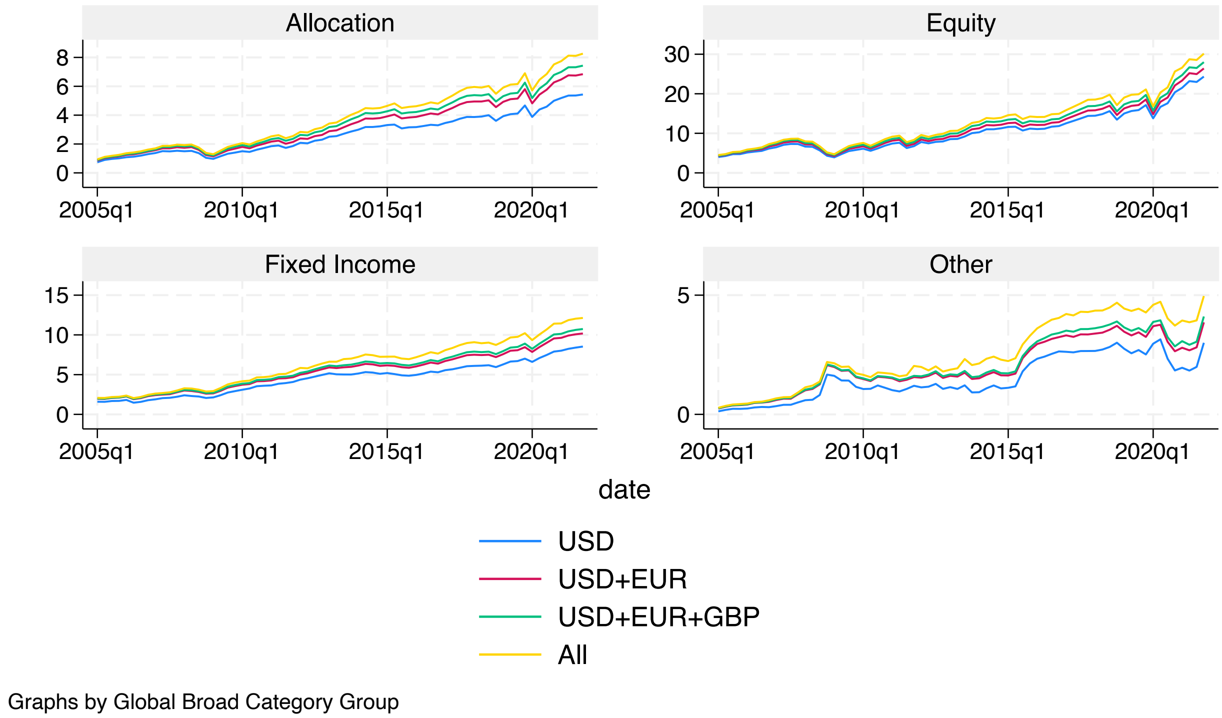


Figure G.49: AUM by Investment Type and Index Funds/Active Funds (Quarterly Sample, USD Trillions)

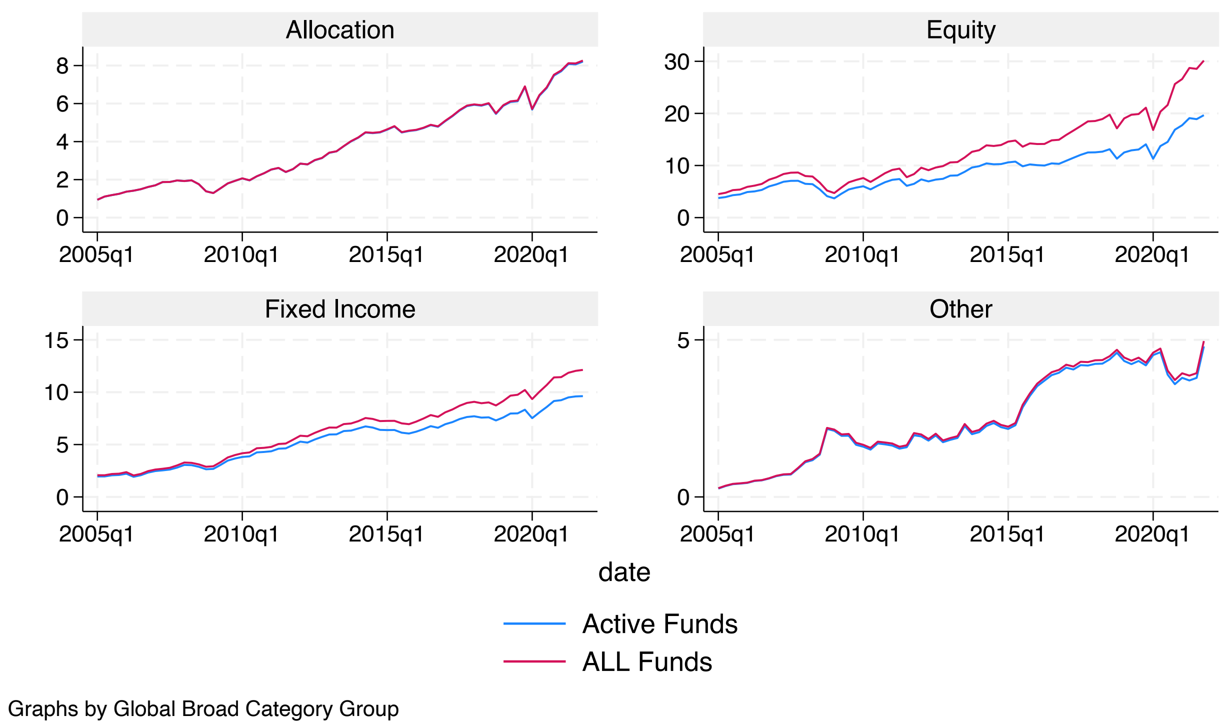
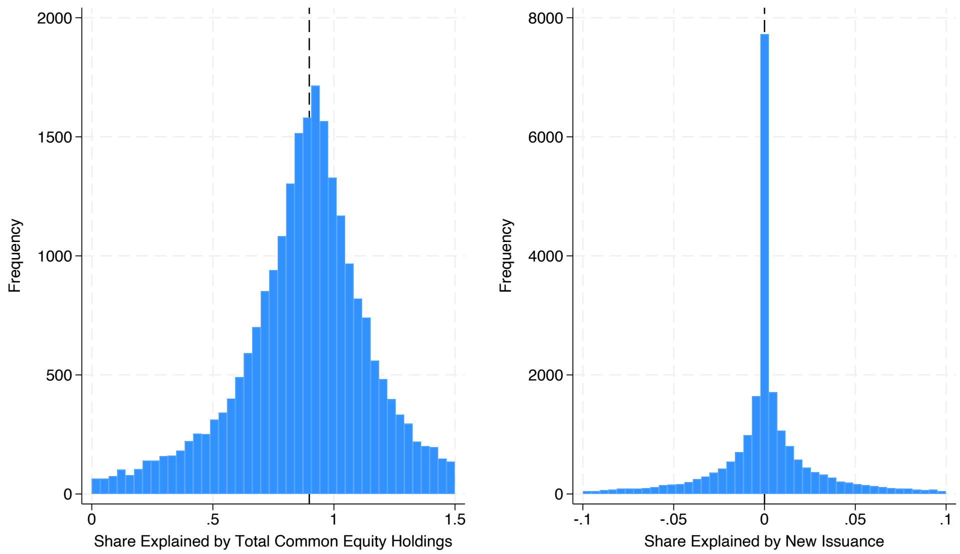


Table G.8: Coverage and Market Capitalization (Quarterly Sample)

Currency	*AvgCoverage*	*CoverageStart*	*CoverageEnd*	*AvgMarketCapUSDbil*	*MarketCapStartUSDbil*	*MarketCapEndUSDbil*	*ISINs*
AUD	0.13	0.10	0.17	965.58	824.02	1391.19	665.00
BRL	0.11	0.04	0.20	745.65	768.39	652.62	269.00
CAD	0.11	0.08	0.16	1367.25	1017.48	2098.44	679.00
CHF	0.19	0.09	0.27	1201.98	979.68	1910.70	216.00
CLP	0.03	0.01	0.05	176.79	161.77	118.47	71.00
CNH	0.03	0.00	0.10	3284.02	669.38	8445.96	1150.00
COP	0.02	0.00	0.04	110.89	79.68	73.89	20.00
CZK	0.08	0.06	0.06	28.24	58.20	32.42	6.00
DKK	0.15	0.05	0.24	206.52	150.99	416.52	93.00
EGP	0.05	0.04	0.05	33.74	66.95	28.37	51.00
EUR	0.16	0.09	0.24	5983.49	6566.57	9242.04	1779.00
GBP	0.22	0.09	0.34	2547.03	2556.40	3029.97	1220.00
HKD	0.12	0.08	0.16	907.22	648.64	1051.90	482.00
HUF	0.22	0.14	0.30	9.27	14.23	15.17	11.00
IDR	0.08	0.04	0.09	325.79	135.30	413.33	212.00
ILS	0.04	0.04	0.07	148.12	122.18	267.71	252.00
INR	0.12	0.05	0.18	1434.99	906.18	3157.44	943.00
JPY	0.10	0.06	0.16	4581.66	3620.58	6619.88	2763.00
KRW	0.15	0.14	0.16	1144.16	802.22	1896.85	1416.00
MXN	0.09	0.05	0.13	315.77	287.70	365.28	112.00
MYR	0.05	0.06	0.04	309.53	214.21	321.80	344.00
NOK	0.10	0.07	0.20	227.10	255.97	354.74	182.00
NZD	0.11	0.05	0.17	51.22	19.94	104.19	78.00
PHP	0.07	0.06	0.05	172.41	62.13	234.21	102.00
PLN	0.05	0.03	0.07	125.73	114.19	159.07	118.00
RUB	0.03	0.01	0.04	323.45	353.51	391.72	66.00
SEK	0.20	0.14	0.28	424.34	327.64	865.42	377.00
SGD	0.10	0.09	0.13	320.90	299.06	325.55	212.00
THB	0.05	0.04	0.04	450.00	216.89	622.26	281.00
TRY	0.08	0.07	0.04	187.22	159.91	129.72	176.00
TWD	0.12	0.09	0.18	910.49	665.58	2069.62	982.00
USD	0.31	0.23	0.35	22409.96	14088.58	47634.64	5726.00
ZAR	0.12	0.08	0.14	335.60	292.10	334.20	230.00

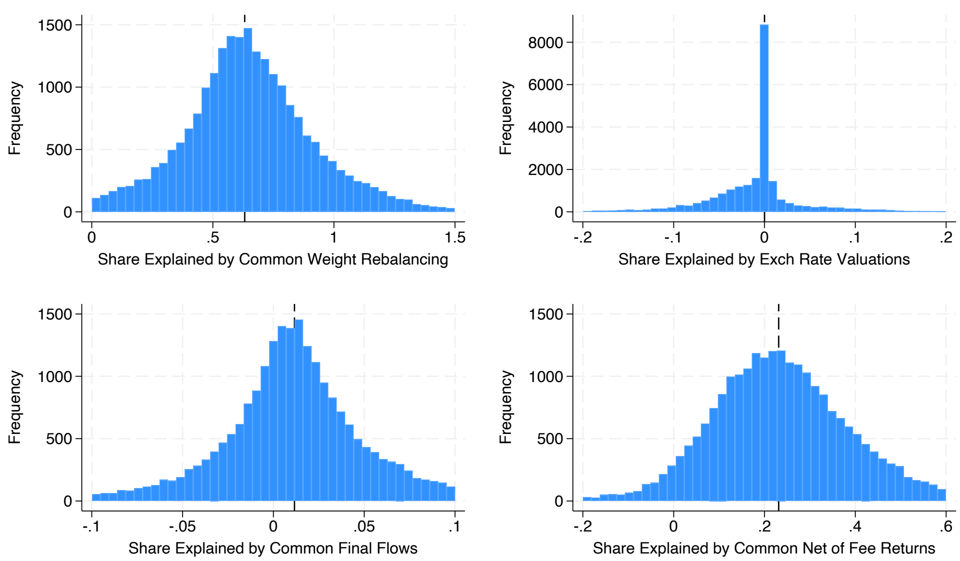
This table presents the sample average, starting date and ending date coverage ratios, weighted by the market capitalization of the ISIN. The coverage ratio for an ISIN is defined as total observed holdings of this ISIN in our data set over the market capitalization of the ISIN, translated in the same currency. It also reports the sample average, starting and ending date market capitalization for all ISINs issued in a given currency and the number of ISINs in our sample. We have kept only firms for which the currency of issuance is the same as the main region of operation.

Figure G.50: ISIN-Level Equity Price Growth Rate Decomposition: Histograms (Quarterly Sample)



We plot only the set of ISINs for which $\frac{Cov\left(\Delta d^j, \Delta p_t^j\right)}{Var\left(\Delta p_t^j\right)}$ is between 0 and 1.5.

Figure G.51: ISIN-Level Equity Price Growth Rate Decomposition: Historgams subcomponents (Quarterly Sample)



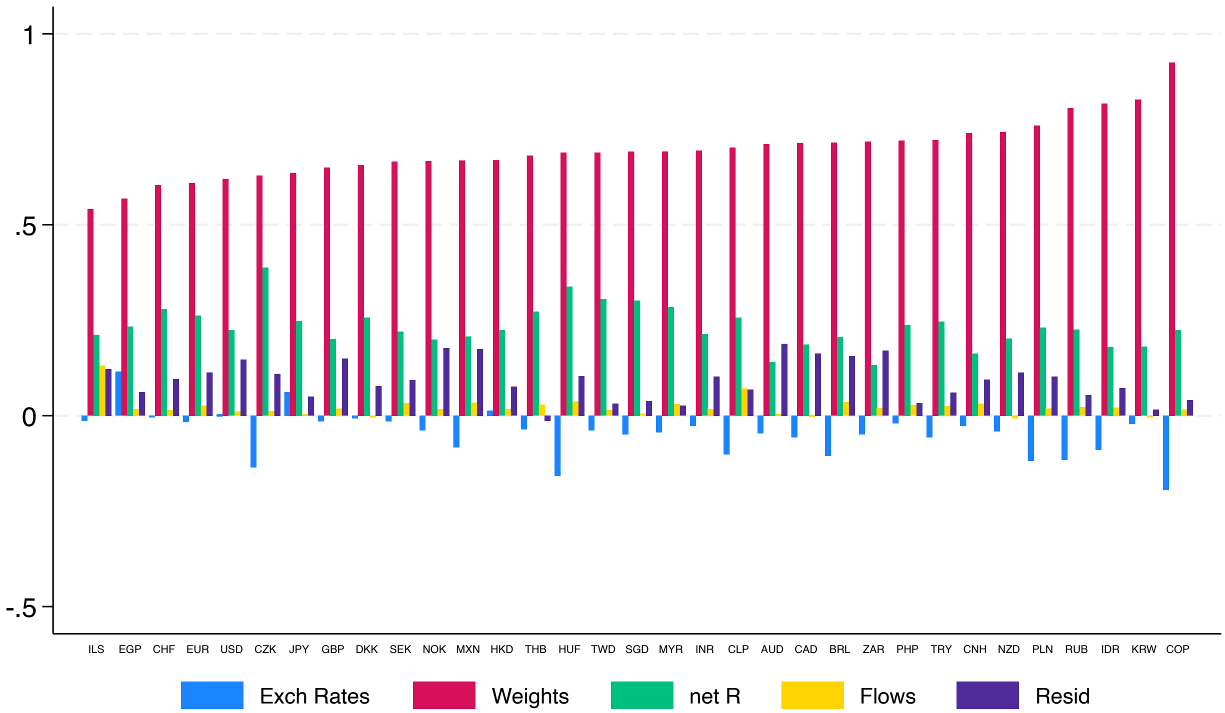
We plot only the set of ISINs for which $\frac{Cov\left(\Delta d^j, \Delta p_t^j\right)}{Var\left(\Delta p_t^j\right)}$ is between 0 and 1.5.

Table G.9: ISIN-Level Equity Price Growth Rate Decomposition: Panel Regressions (Quarterly Sample)

Currency	Δd_t^j	$\Delta d_t^{\omega,j}$	$\Delta d_t^{s,j}$	$\Delta d_t^{f,j}$	$\Delta d_t^{r^{NF},j}$	$\Delta d_t^{Resid,j}$	Δq_t^j
AUD	0.809***	0.712***	-0.047***	0.004**	0.140***	0.188***	-0.003
BRL	0.851***	0.715***	-0.105***	0.035***	0.206***	0.156***	0.007
CAD	0.842***	0.714***	-0.057***	-0.002	0.186***	0.163***	0.005**
CHF	0.893***	0.604***	-0.004**	0.014***	0.279***	0.096***	-0.011**
CLP	0.928***	0.702***	-0.102***	0.071***	0.257***	0.068***	-0.003
CNH	0.908***	0.740***	-0.027***	0.032***	0.163***	0.094***	0.002
COP	0.971***	0.925***	-0.194***	0.016***	0.223***	0.040	0.011
CZK	0.892***	0.629***	-0.136**	0.012	0.387***	0.109	0.002
DKK	0.901***	0.656***	-0.007**	-0.005	0.257***	0.077***	-0.022**
EGP	0.934***	0.568***	0.115***	0.018***	0.233***	0.061**	-0.005
EUR	0.882***	0.609***	-0.016***	0.026***	0.262***	0.113***	-0.005***
GBP	0.854***	0.649***	-0.015***	0.018***	0.201***	0.149***	0.003
HKD	0.924***	0.670***	0.013***	0.017***	0.224***	0.076***	-0.001
HUF	0.904***	0.689***	-0.158***	0.036**	0.337***	0.104	0.008
IDR	0.929***	0.817***	-0.089***	0.022***	0.180***	0.072***	0.001
ILS	0.869***	0.541***	-0.014***	0.131***	0.212***	0.122***	-0.008
INR	0.899***	0.694***	-0.026***	0.018***	0.213***	0.102***	0.001
JPY	0.948***	0.635***	0.062***	0.003***	0.248***	0.050***	-0.002***
KRW	0.982***	0.828***	-0.022***	-0.004***	0.180***	0.016**	-0.002
MXN	0.827***	0.669***	-0.083***	0.034***	0.208***	0.175***	0.002
MYR	0.963***	0.692***	-0.044***	0.031***	0.284***	0.026**	-0.011**
NOK	0.844***	0.666***	-0.038***	0.017***	0.199***	0.177***	0.021
NZD	0.896***	0.743***	-0.042***	-0.007	0.202***	0.113***	0.010
PHP	0.965***	0.720***	-0.020***	0.027***	0.238***	0.033*	-0.002
PLN	0.889***	0.759***	-0.119***	0.019***	0.230***	0.102***	-0.008
RUB	0.936***	0.805***	-0.116***	0.022***	0.225***	0.054*	-0.009**
SEK	0.903***	0.665***	-0.015***	0.032***	0.220***	0.093***	-0.004
SGD	0.948***	0.691***	-0.050***	0.005	0.301***	0.038**	-0.013
THB	0.947***	0.681***	-0.036***	0.029***	0.272***	-0.014	-0.067***
TRY	0.936***	0.722***	-0.057***	0.025***	0.246***	0.060***	-0.004
TWD	0.969***	0.689***	-0.038***	0.014***	0.305***	0.031***	0.000
USD	0.855***	0.620***	0.001***	0.010***	0.223***	0.147***	0.002*
ZAR	0.820***	0.718***	-0.049***	0.019***	0.132***	0.170***	-0.010*

Note: This table reports the coefficients from panel regressions of the total common component of equity holdings, Δd_t^j, and its subcomponents on Δp_t^j by stock market (as denoted by the currency associated with that stock market). The subcomponents are the portfolio weight changes "common" subcomponent, $\Delta d_t^{\omega,j}$; the exchange rate "common" subcomponent, $\Delta d_t^{s,j}$; the final flows "common" subcomponent, $\Delta d_t^{f,j}$; and the net-of-fee returns "common" subcomponent, $\Delta d_t^{r^{NF},j}$. We also report regressions for the residual (unobservable) subcomponent, $\Delta d_t^{Resid,j}$, and for the change in shares outstanding, Δq_t^j. We allow for ISIN-level fixed effects and cluster the standard errors by ISIN. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%.

Figure G.52: ISIN-Level Equity Price Growth Rate Decomposition: Panel Regressions (Quarterly Sample)



Notes: This figure presents the coefficients from panel regressions of the equity holdings subcomponents on Δp_t^j by stock market (as denoted by the currency associated with that stock market). "Exch Rates" is the exchange rate "common" subcomponent, $\Delta d_t^{s,j}$; "Weights" is the portfolio weight changes "common" subcomponent, $\Delta d_t^{\omega,j}$; "net R" is the net-of-fee returns "common" subcomponent, $\Delta d_t^{r^{NF},j}$; "Flows" is the final flows "common" subcomponent, $\Delta d_t^{f,j}$; and "Resid" is the residual (unobservable) subcomponent, $\Delta d_t^{Resid,j}$. We allow for ISIN-level fixed effects.

Table G.10: ISIN-Level Equity Price Growth Rate Decomposition: Index Funds vs Active Funds Portfolio Weight Changes and Flows: Panel Regressions (Quarterly Sample)

Currency	$\Delta d^{\omega,j}_{Index}$	$\Delta d^{\omega,j}_{Active}$	$\Delta d^{f,j}_{Index}$	$\Delta d^{f,j}_{Active}$
AUD	0.175***	0.608***	-0.002	0.007***
BRL	0.101***	0.642***	0.003**	0.033***
CAD	0.129***	0.639***	0.005***	-0.003*
CHF	0.144***	0.471***	0.000	0.014***
CLP	0.230***	0.564***	0.018***	0.062***
CNH	0.394***	0.473***	0.034***	0.004***
COP	0.418***	0.520***	0.018***	-0.002
CZK	0.096	0.541***	0.003	0.019*
DKK	0.068***	0.612***	0.001	-0.005
EGP	0.156***	0.464***	0.014**	0.008*
EUR	0.073***	0.565***	0.006***	0.023***
GBP	0.089***	0.599***	0.001***	0.018***
HKD	0.142***	0.589***	0.007***	0.014***
HUF	0.227	0.598***	0.010	0.036**
IDR	0.172***	0.714***	0.009***	0.017***
ILS	0.106***	0.463***	0.018***	0.118***
INR	0.070***	0.657***	0.002***	0.020***
JPY	0.240***	0.444***	0.011***	-0.006***
KRW	0.245***	0.694***	-0.004***	-0.000
MXN	0.167***	0.539***	0.002	0.034***
MYR	0.161***	0.618***	0.005***	0.030***
NOK	0.094***	0.605***	0.003*	0.015***
NZD	0.135***	0.663***	0.005	-0.011
PHP	0.129***	0.645***	0.009***	0.024***
PLN	0.192***	0.636***	0.013***	0.013***
RUB	0.316***	0.672***	0.005	0.026***
SEK	0.203***	0.504***	0.020***	0.016***
SGD	0.121***	0.630***	0.005*	0.004
THB	0.169***	0.562***	0.016***	0.018***
TRY	0.166***	0.610***	0.011***	0.020***
TWD	0.177***	0.579***	0.008***	0.010***
USD	0.214***	0.419***	0.006***	0.005***
ZAR	0.093***	0.651***	0.003**	0.018***

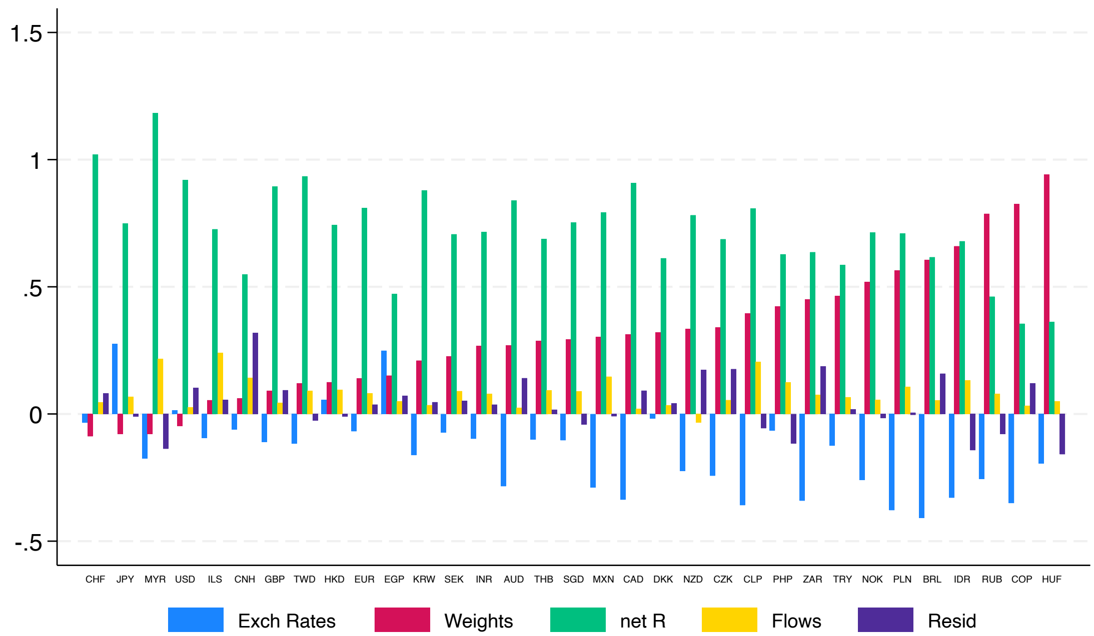
Note: This table reports coefficients from panel regressions of the portfolio weight changes and final flows "common" subcomponents, broken down by index and active funds, on Δp^j_t by stock market (as denoted by the currency associated with that market). Specifically, $\Delta d^{\omega,j}_{Index}$ and $\Delta d^{\omega,j}_{Active}$ denote the portfolio weight changes "common" subcomponents of index and active funds, respectively, while $\Delta d^{f,j}_{Index}$ and $\Delta d^{f,j}_{Active}$ denote the final flows "common" subcomponents of index and active funds, respectively. We allow for ISIN-level fixed effects and cluster the standard errors by ISIN. * significant at 10%; ** at 5%; *** at 1%.

Table G.11: ISIN-Level Equity Price Growth Rate Decomposition: Local vs Other Currency Investors Portfolio Weight Changes and Flows: Panel Regressions (Quarterly Sample)

Currency	$\Delta d^{\omega,j}_{LocalCurr}$	$\Delta d^{\omega,j}_{OtherCurr}$	$\Delta d^{f,j}_{LocalCurr}$	$\Delta d^{f,j}_{OtherCurr}$
AUD	0.299***	0.448***	0.007***	-0.002
BRL	0.358***	0.455***	0.018***	0.021***
CAD	0.005***	0.713***	0.000***	-0.001
CHF	0.308***	0.317***	0.006***	0.010***
CLP	0.186***	0.592***	0.057***	0.030***
CNH	0.012***	0.750***	0.000	0.031***
COP	.	0.921***	.	0.016***
CZK	.	0.629***	.	0.012
DKK	0.101***	0.579***	0.000	-0.005
EGP	.	0.571***	.	0.018***
EUR	0.332***	0.321***	0.029***	-0.002**
GBP	0.469***	0.235***	0.016***	0.003***
HKD	0.003***	0.671***	0.001***	0.017***
HUF	.	0.692***	.	0.036**
IDR	.	0.818***	.	0.022***
ILS	0.397***	0.225***	0.129***	0.004**
INR	0.376***	0.415***	0.013***	0.010***
JPY	0.188***	0.484***	0.007***	-0.003***
KRW	0.498***	0.462***	-0.009***	0.004***
MXN	0.221***	0.462***	0.010**	0.025***
MYR	0.045***	0.685***	-0.002	0.032***
NOK	0.286***	0.423***	0.015***	0.003*
NZD	0.376***	0.437***	0.003	-0.012*
PHP	.	0.720***	.	0.027***
PLN	.	0.758***	.	0.019***
RUB	.	0.835***	.	0.022***
SEK	0.436***	0.274***	0.032***	0.002
SGD	0.021***	0.689***	-0.000	0.005
THB	0.616***	0.288***	0.017***	0.021***
TRY	0.003	0.721***	0.006*	0.024***
TWD	0.069***	0.664***	-0.006***	0.016***
USD	0.604***	0.019***	0.010***	0.001***
ZAR	0.429***	0.356***	0.015***	0.007***

Note: This table reports coefficients from panel regressions of the portfolio weight changes and final flows "common" subcomponents, broken down by local-currency and foreign-currency investors, on Δp^j_t by stock market (as denoted by the currency associated with that market). Specifically, $\Delta d^{\omega,j}_{LocalCurr}$ and $\Delta d^{\omega,j}_{OtherCurr}$ denote the portfolio weight changes "common" subcomponents of local-currency and foreign-currency investors, respectively, while $\Delta d^{f,j}_{LocalCurr}$ and $\Delta d^{f,j}_{OtherCurr}$ denote the final flows "common" subcomponents of local-currency and foreign-currency investors, respectively. We allow for ISIN-level fixed effects and cluster the standard errors by ISIN. * significant at 10%; ** at 5%; *** at 1%.

Figure G.53: Aggregate Stock Market Price Growth Rate Decomposition (Quarterly Sample)



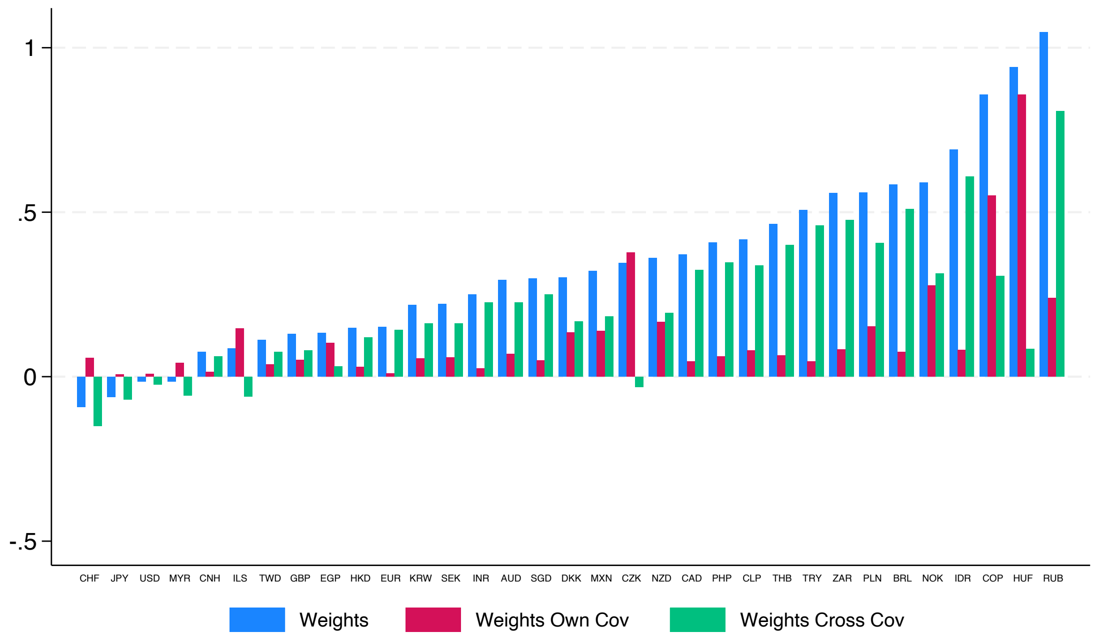
Notes: This figure presents OLS coefficients from regressions of the equity holdings subcomponents on the aggregate stock market price growth rate, $\Delta p_t^{SM,l}$ (where the stock market is denoted by the currency associated with that market). "Exch Rates" is the exchange rate "common" subcomponent, $\Delta D_t^{s,l}$; "Weights" is the portfolio weight changes "common" subcomponent, $\Delta D_t^{\omega,l}$; "net R" is the net-of-fee returns "common" subcomponent, $\Delta D_t^{r^{NF},l}$; "Flows" is the final flows "common" subcomponent, $\Delta D_t^{f,l}$; and "Resid" is the residual (unobservable) subcomponent, $\Delta D_t^{Resid,l}$.

Table G.12: Aggregate Stock Market Price Growth Rate Decomposition (Quarterly Sample)

Currency	ΔD^{l}	R^2	$\Delta D^{s,l}$	R^2	$\Delta D^{\omega,l}$	R^2	$\Delta D^{r^{NF},l}$	R^2	$\Delta D^{f,l}$	R^2	$\Delta D^{Resid,l}$	R^2
AUD	0.85***	0.89	-0.28***	0.40	0.27***	0.30	0.84***	0.83	0.02	-0.00	0.14***	0.15
BRL	0.87***	0.74	-0.41***	0.59	0.61***	0.55	0.62***	0.75	0.05**	0.06	0.16**	0.08
CAD	0.90***	0.84	-0.34***	0.57	0.31***	0.27	0.91***	0.78	0.02	-0.01	0.09	0.04
CHF	0.94***	0.67	-0.03	-0.01	-0.09	-0.00	1.02***	0.85	0.05*	0.02	0.08	-0.00
CLP	1.05***	0.75	-0.36***	0.37	0.40***	0.16	0.81***	0.54	0.21***	0.25	-0.06	-0.01
CNH	0.69***	0.38	-0.06***	0.12	0.06	-0.02	0.55***	0.54	0.14**	0.13	0.32	0.09
COP	0.86***	0.75	-0.35***	0.43	0.83***	0.71	0.36***	0.33	0.03	0.00	0.12	0.03
CZK	0.84***	0.81	-0.24***	0.21	0.34***	0.15	0.69***	0.53	0.05*	0.03	0.18***	0.14
DKK	0.95***	0.85	-0.02	-0.01	0.32***	0.42	0.61***	0.76	0.03	0.04	0.04	-0.01
EGP	0.92***	0.84	0.25	0.12	0.15	0.03	0.47***	0.47	0.05	0.04	0.07	0.01
EUR	0.96***	0.91	-0.07*	0.05	0.14***	0.23	0.81***	0.92	0.08***	0.12	0.04	-0.00
GBP	0.92***	0.86	-0.11*	0.10	0.09	0.05	0.89***	0.88	0.04*	0.02	0.09	0.05
HKD	1.02***	0.89	0.06***	0.50	0.13	0.05	0.74***	0.83	0.10***	0.25	-0.01	-0.02
HUF	1.16***	0.92	-0.20***	0.39	0.94***	0.80	0.36***	0.58	0.05***	0.12	-0.16***	0.17
IDR	1.14***	0.77	-0.33***	0.52	0.66***	0.32	0.68***	0.55	0.13***	0.25	-0.14	0.03
ILS	0.93***	0.70	-0.10**	0.12	0.05	-0.01	0.73***	0.67	0.24***	0.27	0.06	-0.01
INR	0.97***	0.88	-0.10***	0.27	0.27***	0.33	0.72***	0.86	0.08*	0.16	0.04	-0.01
JPY	1.01***	0.90	0.28***	0.37	-0.08	0.01	0.75***	0.71	0.07*	0.05	-0.01	-0.02
KRW	0.96***	0.89	-0.16***	0.26	0.21***	0.28	0.88***	0.85	0.04	0.01	0.05	0.00
MXN	0.95***	0.77	-0.29***	0.36	0.30***	0.26	0.79***	0.74	0.15***	0.08	-0.01	-0.02
MYR	1.15***	0.79	-0.18***	0.11	-0.08	-0.01	1.18***	0.73	0.22***	0.19	-0.14	0.03
NOK	1.03***	0.66	-0.26***	0.45	0.52***	0.28	0.71***	0.75	0.06**	0.05	-0.02	-0.02
NZD	0.86***	0.71	-0.22***	0.16	0.33***	0.13	0.78***	0.48	-0.03	-0.01	0.17***	0.08
PHP	1.11***	0.90	-0.07*	0.09	0.42***	0.27	0.63***	0.50	0.12***	0.21	-0.12**	0.08
PLN	1.00***	0.86	-0.38***	0.47	0.56***	0.48	0.71***	0.68	0.11***	0.15	0.00	-0.02
RUB	1.07***	0.35	-0.26***	0.20	0.79*	0.19	0.46***	0.49	0.08***	0.11	-0.08	-0.02
SEK	0.95***	0.91	-0.07***	0.20	0.23***	0.36	0.71***	0.89	0.09***	0.26	0.05	0.01
SGD	1.03***	0.89	-0.10***	0.21	0.29***	0.24	0.75***	0.75	0.09***	0.16	-0.04	-0.00
THB	0.97***	0.70	-0.10***	0.35	0.29***	0.14	0.69***	0.77	0.09**	0.09	0.02	-0.02
TRY	0.99***	0.86	-0.13	0.02	0.46***	0.27	0.59***	0.57	0.07**	0.08	0.02	-0.02
TWD	1.03***	0.88	-0.12***	0.23	0.12**	0.09	0.93***	0.81	0.09***	0.09	-0.03	-0.01
USD	0.91***	0.94	0.01***	0.24	-0.05	0.09	0.92***	0.98	0.03	0.01	0.10**	0.17
ZAR	0.82***	0.79	-0.34***	0.44	0.45***	0.36	0.64***	0.50	0.08***	0.06	0.19***	0.15

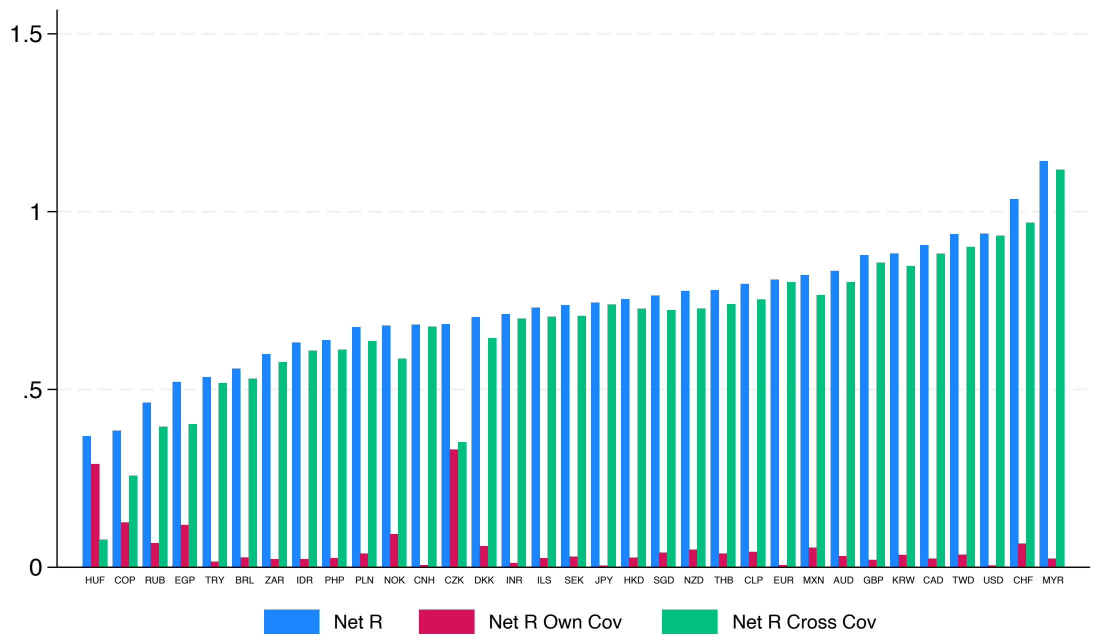
Note: This table reports OLS coefficients from regressions of the total "common" component of equity holdings, ΔD^{l}, and its subcomponents on the aggregate stock market price growth rate (where the stock market is denoted by the currency associated with that market). The subcomponents are the exchange rate "common" subcomponent, $\Delta D^{s,l}$; the portfolio weight changes "common" subcomponent, $\Delta D^{\omega,l}$; the net-of-fee returns "common" subcomponent, $\Delta D^{r^{NF},l}$; and the final flows "common" subcomponent, $\Delta D^{f,l}$. We also report results for the residual (unobservable) subcomponent, $\Delta D^{Resid,l}$. The table also presents the corresponding R^2 values next to each component. Robust standard errors. * significant at 10%; ** at 5%; *** at 1%.

Figure G.54: The Importance of Own vs Cross-Covariance Subcomponents: Portfolio Weight Changes (Quarterly Sample)



Notes: This figure presents coefficients from panel regressions of the portfolio weight changes "common" subcomponent, $\Delta D_t^{\omega,l}$, on Δp_t^j by stock market (as denoted by the currency associated with that market). The estimates are further decomposed into parts associated with *own* and *cross* comovements between portfolio weight changes and equity price growth rates. "Weight" refers to the total portfolio weight changes "common" subcomponent, $\Delta D_t^{\omega,l}$. "Weights Own Cov" corresponds to β^{ω}_{OwnCov}, defined in (13), and captures how much of the overall stock price movement is explained by the ISIN-level comovement of portfolio weight changes with their own-ISIN prices, scaled appropriately. "Weights Cross Cov" corresponds to $\beta^{\omega}_{CrossCov}$, also defined in (13), and measures the contribution of ISIN-level comovement between portfolio weight changes and cross-ISIN prices, scaled appropriately.

Figure G.55: The Importance of Own vs Cross-Covariance subcomponents: Net-of-Fee Returns (Quarterly Sample)



Notes: This figure presents coefficients from panel regressions of the net-of-fee returns "common" subcomponent, $\Delta D_t^{r^{NF},l}$ on $\Delta p_t^{SM,l}$ by stock market (as denoted by the currency associated with that market). The estimates are further decomposed into parts associated with *own* and *cross* comovements between net-of-fee returns and equity price growth rates. "Net R" refers to the total net-of-fee returns "common" subcomponent, $\Delta D_t^{r^{NF},l}$. "Net R Own Cov" corresponds to $\beta^{r^{NF}}_{OwnCov} = \sum_j \left(\nu^{j,l}\right)^2 \frac{\text{Var}\left(\Delta p_t^j\right)}{\text{Var}\left(\sum_j \nu^{j,l} \Delta p_t^j\right)} \frac{\text{Cov}\left(\Delta p_t^j, \Delta d_t^{j,r^{NF}}\right)}{\text{Var}(\Delta p_t^j)}$, and captures how much of the overall stock price movement is explained by the ISIN-level comovement of net-of-fee returns with their own-ISIN prices, scaled appropriately. "Net R Cross Cov" corresponds to $\beta^{r^{NF}}_{CrossCov} = \sum_j \sum_{k \neq j} \nu^{j,l} \nu^{k,l} \frac{\text{Cov}\left(\Delta d_t^{j,r^{NF}}, \Delta p_t^k\right)}{\text{Var}(\Delta p_t^k)} \frac{\text{Var}(\Delta p_t^k)}{\text{Var}\left(\sum_j \nu^{j,l} \Delta p_t^j\right)}$, and measures the contribution of ISIN-level comovement between net-of-fee returns and cross-ISIN prices, scaled appropriately.

H Structural model

H.1 Optimal active fund portfolio shares

Recall that the an active fund i's optimization problem is to solve:

$$\max_{\{\omega_t^{i,j,A}\}} c^p \left(\sum_{c=1}^{C} \sum_{j \in J^c} \omega_t^{i,j,A} E_t^i \frac{P_{t+1}^{j,USD}}{P_t^{j,USD}} \right) - \sum_{c=1}^{C} \sum_{j \in J^c} \frac{\varphi}{2} \left(\omega_t^{i,j,A} \right)^2 - \sum_{z=1}^{Z} \frac{\mu^z}{2} \left(\sum_{j \in J^z} \omega_t^{i,j,A} \right)^2 - \sum_{c=1}^{C} \frac{\mu^c}{2} \left(\sum_{j \in J^c} \omega_t^{i,j,A} \right)^2,$$

subject to the constraint that the weights need to sum-up to one:

$$\sum_{c=1}^{C} \sum_{j \in J^c} \omega_t^{i,j,A} \leq 1, \tag{23}$$

with Lagrange multiplier λ_t^A.

Then, the first-order conditions (FOC) imply that we can express a single asset manager's optimal portfolio weight in terms of its expected return and the total weights placed on the stocks in its industry and its country:

$$\omega_t^{i,j,A} : \varphi \omega_t^{i,j,A} = c^p \left(E_t^i \frac{P_{t+1}^{j,USD}}{P_t^{j,USD}} \right) - \mu^z \left(\sum_{j \in J^z} \omega_t^{i,j,A} \right) - \mu^c \left(\sum_{j \in J^c} \omega_t^{i,j,A} \right) - \lambda_t^A. \tag{24}$$

We then sum this expression across different groups of stocks to solve out for these total industry and total country weights as well as for the λ_t^A Lagrange multiplier (using equation 23).

$$\begin{aligned} \sum_{j \in J^c} \omega_t^{i,j,A} &= \frac{c^p \sum_{j \in J^c} \left(E_t^i \frac{P_{t+1}^{j,USD}}{P_t^{j,USD}} \right) - \frac{N^c}{Z} \mu^z \sum_{z=1}^{Z} \left(\sum_{j \in J^z} \omega_t^{i,j,A} \right) - N^c \lambda_t^A}{N^c \mu^c + \varphi}, \\ &= \frac{c^p \sum_{j \in J^c} \left(E_t^i \frac{P_{t+1}^{j,USD}}{P_t^{j,USD}} \right) - \frac{N^c}{Z} \mu^z - N^c \lambda_t^A}{N^c \mu^c + \varphi}. \end{aligned} \tag{25}$$

To obtain the first line of this equation, note that this sum is over all firms in country c, each of which belongs to a particular industry z (e.g., the technology industry for Apple). For each of these firms, the industry diversification motive means that the portfolio weight allocated to that entire industry *globally* enters into the FOC in equation (24). That is, for fund i's optimal weight on Apple, the fund takes into account its total allocation to all global technology firms including ones in other countries, like Samsung. But importantly, this same industry-level weight also matters for fund i's weight on other same-country technology firms, like Microsoft. Thus, when we sum over all country c firms, we obtain a sum over the industry-level portfolio weights of all industries, *each* *multiplied by the number of country c firms in that industry.* With our assumption of a uniform firm distribution across countries and industries, this simplifies to a constant $\frac{N^c}{Z}$ times the sum of fund i's weights allocated to all industries.

Because this sum $\sum_{z=1}^{Z}\left(\sum_{j\in J^z}\omega_t^{i,j,A}\right)$ is just the sum of fund i's weights on all stocks, it will be equal to 1, thus delivering the second line of this equation.[38]

We analogously sum equation (24) over industries to solve for the total portfolio weight on industry z which when combined with the equation above implies:

$$\begin{aligned}\sum_{j\in J^z}\omega_t^{i,j,A} &= \frac{c^p\sum_{j\in J^z}\left(E_t^i\frac{P_{t+1}^{j,USD}}{P_t^{j,USD}}\right)-\frac{N^z}{C}\mu^c\sum_{c=1}^{C}\left(\sum_{j\in J^c}\omega_t^{i,j,A}\right)-N^z\lambda_t^A}{N^z\mu^z+\varphi},\\ &= \frac{c^p\sum_{j\in J^z}\left(E_t^i\frac{P_{t+1}^{j,USD}}{P_t^{j,USD}}\right)-\frac{N^z}{C}\mu^c-N^z\lambda_t^A}{N^z\mu^z+\varphi}.\end{aligned} \tag{26}$$

Then, summing equation (25) over all countries and again using the summing-up condition allows us to express the Lagrange multiplier as the expected fee earned from the unweighted average return over all stocks globally less each of the diversification preference parameters scaled by the size of the relevant group (number of industries, countries, or all stocks).

$$\lambda_t^A=\frac{c^p}{CN^c}\sum_{c=1}^{C}\sum_{j\in J^c}\left(E_t^i\frac{P_{t+1}^{j,USD}}{P_t^{j,USD}}\right)-\frac{\mu^z}{Z}-\frac{\mu^c}{C}-\frac{\varphi}{CN^c}.$$

Then, we can substitute this expression back into equations (25) and (26) to obtain the optimal country and industry weights:

$$\begin{aligned}\sum_{j\in J^c}\omega_t^{i,j,A} &= \frac{c^pE_t^i\left[\frac{1}{N^c}\sum_{j\in J^c}E_t^i\left(\frac{P_{t+1}^{j,USD}}{P_t^{j,USD}}\right)-\frac{1}{CN^c}\sum_{c=1}^{C}\sum_{j\in J^c}\left(E_t^i\frac{P_{t+1}^{j,USD}}{P_t^{j,USD}}\right)\right]}{\mu^c+\frac{\varphi}{N^c}}+\frac{1}{C}\\ \text{and}\quad \sum_{j\in J^z}\omega_t^{i,j,A} &= \frac{c^pE_t^i\left[\frac{1}{N^z}\sum_{j\in J^z}E_t^i\left(\frac{P_{t+1}^{j,USD}}{P_t^{j,USD}}\right)-\frac{1}{CN^c}\sum_{c=1}^{C}\sum_{j\in J^c}\left(E_t^i\frac{P_{t+1}^{j,USD}}{P_t^{j,USD}}\right)\right]}{\mu^z+\frac{\varphi}{N^z}}+\frac{1}{Z},\end{aligned}$$

[38]This sums first within each industry and then across all industries while equation (23) sums first within each country and then across all countries, but both methods arrive at the sum over all firms in the global investment universe.

We then substitute these expressions into equation (24) to obtain the optimal asset j weight:

$$\begin{aligned}
\omega_t^{i,j,A} &= \frac{c^p E_t^i\left[\frac{P_{t+1}^{j,USD}}{P_t^{j,USD}} - \tilde{R}_{t+1}^{c,z}\right]}{\varphi} + \frac{1}{CN^c}, \\
\text{where } \tilde{R}_{t+1}^{c,z} &\equiv \frac{1-\tilde{\mu}^z-\tilde{\mu}^c}{CN^c}\sum_{c=1}^{C}\sum_{j\in J^c}\frac{P_{t+1}^{j,USD}}{P_t^{j,USD}} + \frac{\tilde{\mu}^z}{N^z}\sum_{j\in J^z}\frac{P_{t+1}^{j,USD}}{P_t^{j,USD}} + \frac{\tilde{\mu}^c}{N^c}\sum_{j\in J^c}\frac{P_{t+1}^{j,USD}}{P_t^{j,USD}}, \\
\tilde{\mu}^c &\equiv \frac{\mu^c}{\mu^c + \frac{\varphi}{N^c}} \text{ and } \tilde{\mu}^z \equiv \frac{\mu^z}{\mu^z + \frac{\varphi}{N^z}}.
\end{aligned}$$

where we use the fact that the total number of assets is $CN^c = ZN^z$. The country (industry) weight can be intuitively interpreted as the uniform weight, but tilted toward the expected unweighted average country (industry) return relative to the unweighted average global return. This relative return's role in determining these weights rises with the fund fee rate and falls with the strength of the country (industry) diversification preference.

H.2 Solving for asset prices

Market clearing with all index and active funds is:

$$\sum_{i\in I^A}\omega_t^{i,j,A}W_t^{i,A} + \omega_t^{j,I^c}W_t^{I^c} = P_t^{j,USD}Q^j$$

where the portfolio weights and wealth AUMs derived above are:

$$\omega_t^{j,I^c} = \frac{P_t^{j,USD}Q^j}{\sum_{k=1}^{J^c}P_t^{k,USD}Q^k}$$

$$\omega_t^{i,j,A} = \frac{c^p E_t^i\left[\frac{P_{t+1}^{j,USD}}{P_t^{j,USD}} - \tilde{R}_{t+1}^{c,z}\right]}{\varphi} + \frac{1}{CN^c}$$

$$W_t^{i,A} = (1-c^p)\,W_{t-1}^{i,A}\sum_{c=1}^{C}\sum_{j\in J^c}\omega_{t-1}^{i,j,A}\frac{P_t^{j,USD}}{P_{t-1}^{j,USD}} + Flow_t^{i,A}$$

$$W_t^{I^c} = (1-c^p)\,W_{t-1}^{I^c}\sum_{j\in J^c}\frac{P_t^{j,USD}}{P_{t-1}^{j,USD}}\omega_{t-1}^{j,I^c} + Flow_t^{I^c}$$

Recalling that fund returns are just average (gross) price growth rates (as we abstract from dividends), we can then linearize the model and solve for price changes as a function of returns beliefs (through weights) and flows.

Log-linearized weight changes: For index funds, we have:

$$\Delta \ln \omega_t^{j,I^c} = \Delta p_t^{j,USD} - \sum_{k\in J^c} \bar{\omega}^{k,I^c} \Delta p_t^{k,USD} = \left(1-\bar{\omega}^{j,I^c}\right) \Delta p_t^{j,USD} - \sum_{k\in J^c\setminus j} \bar{\omega}^{k,I^c} \Delta p_t^{k,USD}$$

For active funds, ignoring Jensen inequality terms and writing the returns in terms of log price changes we have:

$$\begin{aligned}\ln \omega_t^{i,j,A} = & \frac{1}{\bar{\omega}^{i,j,A} C N^c} + \frac{c^p}{\bar{\omega}^{i,j,A}\varphi} E_t^i \Delta p_{t+1}^{j,USD} - \frac{c^p \tilde{\mu}^c}{\bar{\omega}^{i,j,A}\varphi N^c} \sum_{j\in J^c} E_t^i \Delta p_{t+1}^{j,USD} \\ & - \frac{c^p \tilde{\mu}^z}{\bar{\omega}^{i,j,A}\varphi N^z} \sum_{j\in J^z} E_t^i \Delta p_{t+1}^{j,USD} - \frac{c^p\left(1-\tilde{\mu}^z-\tilde{\mu}^c\right)}{\bar{\omega}^{i,j,A}\varphi C N^c} \sum_{c=1}^{C} \sum_{j\in J^c} E_t^i \Delta p_{t+1}^{j,USD}.\end{aligned}$$

Then, in changes, we have

$$\begin{aligned}\Delta \ln \omega_t^{i,j,A} = & \frac{c^p}{\bar{\omega}^{i,j,A}\varphi}(E_t^i \Delta p_{t+1}^{j,USD} - E_{t-1}^i \Delta p_t^{j,USD}) - \frac{c^p \tilde{\mu}^c}{\bar{\omega}^{i,j,A}\varphi N^c} \sum_{j\in J^c}(E_t^i \Delta p_{t+1}^{j,USD} - E_{t-1}^i \Delta p_t^{j,USD}) \\ & - \frac{c^p \tilde{\mu}^z}{\bar{\omega}^{i,j,A}\varphi N^z} \sum_{j\in J^z}(E_t^i \Delta p_{t+1}^{j,USD} - E_{t-1}^i \Delta p_t^{j,USD}) \\ & - \frac{c^p\left(1-\tilde{\mu}^z-\tilde{\mu}^c\right)}{\bar{\omega}^{i,j,A}\varphi C N^c} \sum_{c=1}^{C} \sum_{j\in J^c}(E_t^i \Delta p_{t+1}^{j,USD} - E_{t-1}^i \Delta p_t^{j,USD}). \qquad (27)\end{aligned}$$

Linearized market clearing conditions: As we do in Section 3, we linearize the market clearing conditions in logs of weights and levels of flows (as flows can take on negative values). Unlike in Section 3, we do not have an exchange rate term since we've written asset prices in USD terms:

$$\sum_{i\in I^A} \mu^{i,j,A} \ln \omega_t^{i,j,A} + \sum_{i\in I^A} \mu^{i,j,A} w_t^{i,A} + \mu^{j,I^c}\left(\ln \omega_t^{j,I^c} + w_t^{I^c}\right) = p_t^{j,USD},$$

where, given our linearization, we have sums of individual funds' portfolio weights and flows weighted by steady state holdings of a particular stock j as shares of the stock's steady-state market cap.

$$\mu^{i,j,A} = \frac{\bar{\omega}^{i,j,A} \bar{W}^{i,A}}{\bar{P}^{j,USD} Q_j^c}; \mu^{j,I^c} = \frac{\bar{\omega}^{j,I^c} \bar{W}^{I^c}}{\bar{P}^{j,USD} Q_j^c}.$$

In changes, this is:

$$\sum_{i\in I^A} \mu^{i,j,A} \Delta \ln \omega_t^{i,j,A} + \sum_{i\in I^A} \mu^{i,j,A} \Delta w_t^{i,A} + \mu^{j,I^c}\left(\Delta \ln \omega_t^{j,I^c} + \Delta w_t^{I^c}\right) = \Delta p_t^{j,USD},$$

where the linearized evolution of AUMs for our two fund times are:

$$\begin{aligned}
\exp\Delta w_t^{I^c} &= \left(1-c^{p,I}\right)\sum_{j\in J^c}\exp\Delta p_t^{j,USD}\omega_{t-1}^{j,I^c} + flow_t^{I^c} \\
\text{and}\quad \exp\Delta w_t^{i,A} &= \left(1-c^{p}\right)\sum_{c=1}^{C}\sum_{j\in J^c}\exp\Delta p_t^{j,USD}\omega_{t-1}^{i,j,A} + flow_t^{i,A}, \\
\text{where}\quad flow_t^{I^c} &= \frac{Flow_t^{I^c}}{W_{t-1}^{I^c}} \text{ and } flow_t^{i,A} = \frac{Flow_t^{i,A}}{W_{t-1}^{i,A}}.
\end{aligned}$$

Then, in changes, and approximating around $\overline{\Delta p^{j,USD}} = 0$,

$$\Delta w_t^{I^c} = \left(1-c^{p,I}\right)\sum_{j\in J^c}\Delta p_t^{j,USD}\bar{\omega}^{j,I^c} + flow_t^{I^c}$$

$$\text{and}\quad \Delta w_t^{i,A} = \left(1-c^{p}\right)\sum_{c=1}^{C}\sum_{j\in J^c}\Delta p_t^{j,USD}\bar{\omega}^{i,j,A} + flow_t^{i,A}.$$

Combining all linearized equations:

$$\begin{aligned}
&\sum_{i\in I^A}\mu^{i,j,A}\Delta\ln\omega_t^{i,j,A} + \sum_{i\in I^A}\mu^{i,j,A}flow_t^{i,A} + \mu^{j,I^c}flow_t^{I^c} \\
= &\left(1-\mu^{j,I^c}\right)\Delta p_t^{j,USD} - \left(1-c^{p}\right)\sum_{c=1}^{C}\sum_{k\in J^c}\left(\sum_{i\in I^A}\mu^{i,j,A}\bar{\omega}^{i,k,A}\Delta p_t^{k,USD}\right) + \mu^{j,I^c}c^{p,I}\sum_{k\in J^c}\bar{\omega}^{k,I^c}\Delta p_t^{k,USD}
\end{aligned}$$

The equation above exists for all stocks where $j = 1, ..., CN^c$. For simplicity, assume that the index fund fees are close to zero, i.e. $c^{p,I} \to 0$. The set of all equations forms a linear matrix equation in the vector of all price changes and we can use it to solve for the vector of all prices as a function of weights, and flows.

$$\begin{aligned}
\mathbf{\Delta P}_t^{USD} &= \mathbf{\Phi}^{-1}\left[\mathbf{\Delta}\ln\boldsymbol{\omega}_t^{j,A} + \mathbf{flow}_t^{A} + \mathbf{flow}_t^{I^c}\right], \\
\text{where}\quad \mathbf{\Delta P}_t^{USD} &= \left[\Delta p_t^{1,USD}\ \ ...\ \ \Delta p_t^{CN^c,USD}\right]', \\
\mathbf{\Delta}\ln\boldsymbol{\omega}_t^{A} &= \left[\sum_{i\in I^A}\mu^{i,1,A}\Delta\ln\omega_t^{i,1,A}\ \ ...\ \ \sum_{i\in I^A}\mu^{i,CN^c,A}\Delta\ln\omega_t^{i,CN^c,A}\right]', \\
\mathbf{flow}_t^{A} &= \left[\sum_{i\in I^A}\mu^{i,1,A}flow_t^{i,A}\ \ ...\ \ \sum_{i\in I^A}\mu^{i,CN^c,A}flow_t^{i,A}\right]', \\
\text{and}\quad \mathbf{flow}_t^{I^c} &= \left[\mu^{1,I^c}flow_t^{I^c}\ \ ...\ \ \mu^{CN^c,I^c}flow_t^{I^c}\right]'.
\end{aligned}$$

The matrix $\mathbf{\Phi}$ is:

$$\mathbf{\Phi} = \begin{bmatrix} 1-\mu^{1,I^c}-(1-c^p)\sum_{i\in I^A}\mu^{i,1,A}\bar{\omega}^{i,1,A} & -(1-c^p)\sum_{i\in I^A}\mu^{i,1,A}\bar{\omega}^{i,2,A} & \cdots & -(1-c^p)\sum_{i\in I^A}\mu^{i,1,A}\bar{\omega}^{i,CN^c,A} \\ -(1-c^p)\sum_{i\in I^A}\mu^{i,2,A}\bar{\omega}^{i,1,A} & 1-\mu^{2,I^c}-(1-c^p)\sum_{i\in I^A}\mu^{i,2,A}\bar{\omega}^{i,2,A} & \cdots & -(1-c^p)\sum_{i\in I^A}\mu^{i,2,A}\bar{\omega}^{i,CN^c,A} \\ \vdots & \vdots & \ddots & \vdots \\ -(1-c^p)\sum_{i\in I^A}\mu^{i,CN^c,A}\bar{\omega}^{i,1,A} & -(1-c^p)\sum_{i\in I^A}\mu^{i,CN^c,A}\bar{\omega}^{i,2,A} & \cdots & 1-\mu^{CN^c,I^c}-(1-c^p)\sum_{i\in I^A}\mu^{i,CN^c,A}\bar{\omega}^{i,CN^c,A} \end{bmatrix}$$

H.3 Empirical Implementation

Flows

To further assess the drivers of $\Delta\ln\omega_t^{i,j,A}$, $flow_t^{i,A}$ and $flow_t^{I^{US}}$ based on the model described in the previous section, we amend the representativeness model of Section 3. Moreover, we utilize the marginal trader decomposition in Internet Appendix Section E which uses information only from the portfolio weight changes if the fund is also changing the number of shares held.

More specifically, we replace $\alpha_t^{f,\tau}$ and $\alpha_t^{\omega,\tau,j}$ with the following term constructed from a number of panel regressions using the functional forms in the previous section. Starting with the common component of final fund flows, we express $\alpha_t^{f,\tau}$ as

$$\alpha_t^{f,\tau} = \alpha_t^{f,macro,\tau} + \alpha_t^{f,risk,\tau} + \alpha_t^{f,perform,\tau} + \alpha_t^{f,sentiment,\tau}. \tag{28}$$

Each of these terms on the right are parts of the fitted value from the following panel regression across funds:

$$\begin{aligned} flow_t^{i,\tau} \;&=\; \mu^{i,f,\tau} + \mu^{f,\tau,macro}\Delta S\&P_t^{macro,US} + \mu^{f,\tau,risk}RA_t^{news} \\ &+ \sum_{l=1}^{6}\mu_l^{f,\tau,NF}r_{t-l}^{i,NF} + \sum_{l=1}^{6}\mu_l^{f,\tau,US}\Delta p_{t-l}^{SM,US} + \sum_{l=1}^{6}\mu_l^{f,\tau,c}\Delta p_{t-l}^{SM,c} + \varepsilon_t^{i,flow}. \end{aligned} \tag{29}$$

where $\Delta S\&P_t^{macro,US}$ and RA_t^{news} are an S&P macro news index and risk aversion news, each constructed as in Rey and Stavrakeva (2024). $\Delta S\&P_t^{macro,US}$ is constructed by regressing the daily S&P growth rate on a set of contemporaneous and lagged macroeconomic news and summing the daily fitted values of this regression to monthly frequency. RA_t^{news} is the residuals of a daily regression of the risk aversion measure developed by Bekaert et al. (2017) on contemporaneous and lagged macro news, also summed to the monthly frequency. That is, risk aversion news are movements in the risk aversion measure that are orthogonal to contemporaneous and lagged US macroeconomic news at daily frequency. The other regressors include past fund performance in the form of lagged fund i net-of-fee returns, lagged S&P performance, and ROS stock market performance for non-US funds. To increase the number of observations in these regressions, we now define types by $\{Index \times Broad\ Strategy \times ROS\ Currency\}$ with $Index$ being an indicator of index funds.

The subcomponents in equation (28) are then within-fund-type averages of the fund-level fitted values from regression (29) as follows:[39]

$$\begin{aligned}
\alpha_t^{f,macro,\tau} &= \mu^{f,\tau,macro}\Delta S\&P_t^{macro,US} \\
\alpha_t^{f,risk,\tau} &= \mu^{f,\tau,risk}RA_t^{news} \\
\alpha_t^{f,perform,\tau} &= \sum_{l=1}^{6}\mu_l^{f,\tau,NF}\sum_{k\in\tau}\frac{r_{t-l}^{k,NF}}{|\tau|} + \sum_{l=1}^{6}\mu_l^{f,\tau,US}\Delta p_{t-l}^{SM,US} + \sum_{l=1}^{6}\mu_l^{f,\tau,c}\Delta p_{t-l}^{SM,c} \\
\alpha_t^{f,sentiment,\tau} &= \sum_{k\in\tau}\frac{\mu^{k,f,\tau}+\varepsilon_t^{k,flow}}{|\tau|}
\end{aligned}$$

The definition of the $\alpha_t^{f,sentiment,\tau}$ term would essentially capture a time fixed effect not explained by the other regressors in regression (29). As such, it is similar to the cross-fund average of the fund flow shocks in Dou et al. (Forthcoming).

If we do not have enough observations within any type of funds to estimate the panel regression (at least 50 funds and 500 fund-time observations), we revert to our simple unweighted within-type average based on the finer type definitions as in the baseline case of Section 3. In our results below, this average variation gets attributed to $\alpha_t^{f,sentiment,\tau}$ with the other subcomponents being set to zero.

Portfolio Weights

Next, we similarly decompose $\alpha_t^{\omega,\tau',j}$ as follows:

$$\alpha_t^{\omega,\tau',j} = \alpha_t^{\omega,\tau',prices,j} + \alpha_t^{\omega,\tau',firm\ news,j} + \alpha_t^{\omega,\tau',sentiment,j}, \quad (30)$$

with investor type τ' now defined by the set $\{Index \times Broad\ Strategy \times ROS\ Local\ Currency\}$ and $Index$ being an indicator of index funds.

We construct the subcomponents based on the fitted values in two stages, again restricting attention to the "marginal" trader version of the decomposition. First, we regress the portfolio weight changes on lagged price drivers of expectations. In a second stage, we regress the residual from this regression on own and industry-specific firm news. This will give a conservative estimate of the importance of firm news as any correlation of this news with lagged prices drivers will be

[39]Because regression (29) contains fund-level past returns, $\alpha_t^{f,\tau}$ does not exactly equal the simple within-type, within-month averages $\alpha_t^{f,\tau}$ in the corresponding baseline marginal investors decomposition (estimated in Section E in the Internet Appendix), but they correspond very closely in the data.

attributed to those terms.[40]

The estimation procedure also accounts for the mixed frequency between quarterly earnings report surprise measures of firm news and monthly holdings in a way that retains information about the dynamics of responses to firm news. This is done by estimating separate regressions for months that are concurrent with the earnings report and that are one, two, and three months out from the report where this latter case only occurs for December end-of-quarter reports that are released in January. This approach is quite flexible as it also allows for other terms, like those associated with momentum and reversal, to become relatively less important during months of report releases.

Specifically, we first estimate the following for each p, an index of the timing of months relative to the release months of quarterly reports:

$$\begin{aligned}\frac{\Delta\omega^{i,j,A}_{t(p)}}{\widehat{\omega}^{i,j,A}} &= \mu_1^{i,j,\omega,\tau'} + \sum_{k\in\{Ind,US\}}\sum_{l=1}^{2}\mu^{j,\tau',k,l}\left(\Delta p^{j,USD}_{t(p)-l} - \Delta p^{k,avg}_{t(p)-l}\right) \\ &\quad + \sum_{k\in\{Ind,US\}}\mu^{j,\tau',k,mom}\frac{\sum_{l=3}^{12}\left(\Delta p^{j,USD}_{t(p)-l} - \Delta p^{k,avg}_{t(p)-l}\right)}{10} + \varepsilon^{i,j,\omega}_{1,t(p)},\end{aligned}$$

The first two lags are meant to capture reversal-type strategies while the average price growth rate between months 3 and 12 captures momentum-type strategies. We focus on relative price reversal and momentum (relative to the industry and country-level stock market prices) as the theoretical model we build suggests, which is also consistent with these type of strategies being executed in a long/short manner. We obtain the fitted lagged price terms:

$$\begin{aligned}\alpha^{\omega,\tau',prices,j}_{t(p)} &= \sum_{k\in\{Ind,US\}}\sum_{l=1}^{2}\mu^{j,\tau',k,l}\left(\Delta p^{j,USD}_{t(p)-l} - \Delta p^{k,avg}_{t(p)-l}\right) \\ &\quad + \sum_{k\in\{Ind,US\}}\mu^{j,\tau',k,mom}\frac{\sum_{l=3}^{12}\left(\Delta p^{j,USD}_{t(p)-l} - \Delta p^{k,avg}_{t(p)-l}\right)}{10}.\end{aligned}$$

The second regression is the portfolio weight change less the lagged price terms regressed on principal components of the IBES surprises for firm j (defined as the surprise divided by the dispersion in forecasts which is referred to as SUE score in the IBES data) and the 5 largest other firms in firm

[40] While rational earnings report surprises should be unforecastable by lagged price movements, this is not the case in reality for IBES surprises (see Chan et al. 1996).

j's industry, denoted by the set $J^{j,other}$:

$$\frac{\Delta\omega^{i,j,A}_{t(p)}}{\widehat{\omega}^{i,j,A}} - \alpha^{\omega,\tau',prices,j}_{t(p)} = \mu^{i,j,\omega,\tau'}_2 + \sum_{m=1}^{P^j} \mu^{j,\omega,m,\tau'}_{own} PC^{firm,m,j}_{t(p)} + \sum_{j'\in J^{j,other}} \sum_{m=1}^{P^{j'}} \mu^{j,\omega,m,\tau'}_{j'} PC^{firm,m,j'}_{t(p)} + \varepsilon^{i,j,\omega}_{2,t(p)}, \tag{31}$$

from which we obtain the fitted values:[41]

$$\alpha^{\omega,\tau',firm\ news,j}_{t(p)} = \sum_{m=1}^{P^j} \mu^{j,\omega,m,\tau'}_{own} PC^{firm,m,j}_{t(p)} + \sum_{j'\in J^{j,other}} \sum_{m=1}^{P^{j'}} \mu^{j,\omega,m,\tau'}_{j'} PC^{firm,m,j'}_{t(p)} \tag{32}$$

$$\alpha^{\omega,\tau',sentiment,j}_{t(p)} = \sum_{k\in\tau'} \frac{1}{|\tau'|}\left(\mu^{i,j,\omega,\tau'}_2 + \varepsilon^{i,j,\omega}_{2,t(p)}\right). \tag{33}$$

$\left\{PC^{firm,m,j}_{t(p)}\right\}_{m=1}^{P^j}$ are the first P^j principal components of the scaled IBES surprises where P^j is the firm-specific number of components that explain at least 80 percent of the variation of these surprises.[42] Sentiment is captured by the average residual. Once again, if there are not enough observations for a given type of investor-ISIN group (defined as at least 50 funds and at least 500 observations), we use the previous simple average within type defined by $\{Index \times Broad\ Strategy \times ROS\ Local\ Currency\}$ and this variation gets attributed to $\alpha^{\omega,\tau',sentiment,j}_{t(p)}$ with the other subcomponents set to 0 for that type.

Our alternative structural decomposition then consists of substituting the estimates of $\alpha^{\omega,\tau',j}_t$ and $\alpha^{f,\tau}_t$ into equation (22) in the Internet Appendix to construct:

$$\Delta\tilde{d}^{f,z,j,NonIndex}_t = \frac{1}{\Theta^j}\sum_{\tau\in\Upsilon}\left(\sum_{\left\{i\in\tilde{I}\cap NonIndex\cap\tau|\Delta X^{i,j}_t\neq 0\right\}} \frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\right)\alpha^{f,\tau,z}_t,$$

$$\Delta\tilde{d}^{f,z,j,Index}_t = \frac{1}{\Theta^j}\sum_{\tau\in\Upsilon}\left(\sum_{\left\{i\in\tilde{I}\cap Index\cap\tau|\Delta X^{i,j}_t\neq 0\right\}} \frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\right)\alpha^{f,\tau,z}_t,$$

for $z = \{macro, risk, perform, sentiment\}$.

$$\Delta\tilde{d}^{\omega,m,j,NonIndex}_t = \frac{1}{\Theta^j}\sum_{\tau\in\Upsilon}\left(\sum_{\left\{i\in\tilde{I}\cap NonIndex\cap\tau|\Delta X^{i,j}_t\neq 0\right\}} \frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\right)\alpha^{\omega,\tau',m,j}_t,$$

[41] Since the regressors in equations (31) and (33) contain no fund-level information, equation (30) further decomposes the same common component of active funds portfolio weight change as in the corresponding marginal trader decomposition in Internet Appendix Section E.

[42] The news terms in these monthly regressions are observations from the most recent quarterly release.

for $m = \{prices, firm\ news, sentiment\}$.