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ABSTRACT

We introduce a novel empirical decomposition of equity price growth rates in terms of equity holdings, based on market-clearing conditions. Although our sample holdings cover only an average of 5% of market capitalization, our reconstructed equity holdings account for, on average, 89% of the time variation in over 20,000 individual stock prices and 96% of the fluctuations in 33 aggregate stock markets. Using this decomposition, we introduce new stylized facts to inform asset pricing models. We find that changes in portfolio weights explain most of the variation of individual stock prices, while aggregate wealth effects are more important for the overall stock market fluctuations. Equity markets are global and exchange rates play a key equilibrating role. They dampen local stock market volatility for all stock markets, except those associated with the three safe-haven currencies---USD, JPY, and CHF---and currencies pegged to the USD.

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1 Introduction

One of the fundamental questions in asset pricing and macroeconomics is identifying the determinants of equilibrium asset prices. In this paper, we introduce a novel decomposition of equity price growth rates as a function of equilibrium equity holdings, based on market-clearing conditions—nominal equity supply must equal nominal equity holdings.

Our methodology utilizes information from a sub-sample of equity holdings, specifically from asset managers, covering the period from 2008 to 2021. It is founded on a minimal set of assumptions: market-clearing conditions, linearization, and the premise that the equity holdings of our sub-sample of asset managers accurately reflect the behavior of all equity investors. Despite our sample's mean coverage ratio (observed asset managers' holdings relative to equity market capitalization) being only 5%, our reconstructed equilibrium holdings account for 89% of the variation of the equity price growth rates for over 20,000 stocks, on average, and 96% of the average fluctuations of 33 aggregate stock market log price changes, at monthly frequency.[1]

The proof being in the pudding, the tight fit validates our framework and the informativeness of asset managers' holdings 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 behaviour of some of them is enough to reconstruct the entire market. As we rely on a minimal set of assumptions, any model of equity prices can be nested in and informed by our approach.

We can further break down equilibrium holdings into sub-components with intuitive economic interpretation in order to disentangle the key determinants of stock price growth rates. More specifically, we express equilibrium holdings as a function of: (i) changes in portfolio weights, (ii) final investors' inflows into and outflows from funds, (iii) reinvestment of the

[1] The main text presents the results at a monthly frequency but the same conclusions can be drawn from performing our decomposition at a quarterly frequency, which also includes a larger set of funds that report quarterly holdings (see the Online Appendix).

net-of-fee fund returns, and (iv) exchange rate valuation effects, due to foreign investors being an important source of demand for many global equities. Components (i) and (ii) are the main variables of interest in the vast majority of asset pricing models, as they are direct measures of the choice variables of investors and are key for understanding the drivers of investors' behavior. The net-of-fee return component of equilibrium holdings (iii) captures the importance of wealth effects for equity determination. Finally, one cannot study *global* equity prices without emphasizing the importance of exchange rates, which is formally measured by component (iv). Exchange rates are a second price that helps clear equity markets. For example, when an investor located in the US purchases a Brazilian stock denominated in BRL, she is simultaneously increasing the demand for BRL and for this stock, thereby, putting upward pressure on both prices to clear the market.[2]

The decomposition leads to new general facts which can inform asset pricing models. In particular, we find that:

(i) *"Stock picking" is alive and well*: Changes in portfolio weights explain the largest share of price changes at the individual stock level for all countries, with non-index funds, which we refer to as active funds, being the main driver. Moreover, we further document that it is truly "stock picking", rather than "industry picking", that explains the bulk of individual equity price growth. *Final flows into funds are positively and statistically significantly correlated with log equity price changes*, but explain a small fraction of stock price movements.

(ii) *Exchange rates play a crucial equilibrating role in nearly all stock markets*, with greater importance in more "open" stock markets, such as emerging markets. Currency movements, unconditionally, are associated with a reduction in local stock market volatility, except in markets associated with "safe haven" currencies such as the USD, CHF, and

[2]We further break down our sub-components of equity holdings by investor type such as index funds vs non-index funds, local vs foreign investors, and we also provide an alternative decomposition which focuses only on the holdings of the "marginal" traders, i.e., the traders changing their shares held over two consecutive periods, for a given stock.

JPY, as well as those currencies pegged to the USD. For currencies outside this "safe haven" group, the exchange rate appreciates when equity holdings increase, implying that local-currency equity prices need to increase by less in order to clear the equity market.[3] Conversely, fluctuations of the USD, JPY, and CHF provide an unconditional hedge for foreign equity investors with respect to local stock market fluctuations. They tend to depreciate when the stock market goes up and to appreciate in bad times.[4]

(iii) *Micro is not like macro*: The main drivers of individual stock price growth rates can differ significantly from those driving aggregate stock market price growth rates *due to heterogeneous portfolio weight changes within and across "currency borders".* Notably, the US, Japanese, and Swiss markets are unique. Stocks in these "safe haven" currency markets lack close substitutes, leading to funds rebalancing within the same "currency border". This explains why, for these countries, portfolio weight changes are the most important driver of individual equity price growth, but portfolio weight changes tend to cancel out in the aggregate. Hence, wealth effects explain most of the aggregate stock market price fluctuations. In contrast, in other stock markets, particularly emerging markets, funds tend to change their portfolio weights more across "currency borders". For instance, funds might move out of the Brazilian stock market to buy stocks in the Turkish stock market (they do not rebalance as much within the Brazilian stock market). This implies that, in emerging markets, portfolio weight changes are a crucial driver for both individual and aggregate stock prices.

We demonstrate that our method of reconstructing market-clearing conditions from the bottom up works remarkably well for equities. This raises the question: could the same methodology be used for other markets? The international goods market with its billions of

[3]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.

[4]The CHF exhibits properties of a "safe haven" currency at the monthly, but not quarterly, frequency unlike the USD and JPY, where the results are robust across frequencies.

differentiated products traded in many countries at different prices seems impractical. An application to the fixed income market would also be very difficult, as the set of securities is less stable, with many issuances and expiring securities, and the market features investors with many different objectives. Attempting to reconstruct total fixed income holdings from only observable holdings would be close to impossible.[5] It may well be that global equity markets give us a unique opportunity to reconstruct the entire holdings and supply network from the most granular level to the aggregate. This unique opportunity allows us to directly measure all of the equity holdings' sub-components for over 20,000 individual stocks in 33 countries, opening avenues for testing various existing asset pricing theories and motivating new theoretical research.

The paper is organized as follows. Section 2 reviews the literature. Section 3 presents our decomposition for the individual equity and aggregate stock market price growth rates, based on market-clearing identities. Section 4 describes the data used, while Section 5 contains the results. Section 6 answers the question of whether the importance of the portfolio weight change sub-component, as a driver of individual equity price growth rates, is due to "stock picking" versus "industry picking." Section 7 discusses some implications of our results for theories. Section 8 concludes.

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.[6] Koijen and

[5]In particular, for fixed income markets, market makers, banks, and even central banks hold large fractions of outstanding fixed income assets, and their objectives differ significantly from mutual funds' objectives. ISIN-level data on holdings for these investors is usually not available to researchers and even if it is available to policy makers, it is impossible to combine across regulatory jurisdictions due to confidentiality issues. In contrast, equities are exchange-traded, implying no role for market makers, and banks and central banks hold very little equity. The main investors are mutual funds which, since 2008, also intermediate much of the holdings of retail investors and pension funds.

[6]Since the key result in our paper relies on equity investors, on average, being similar within a particular style of investing/type of fund, 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

Yogo (2019a) introduce a novel framework, based on models of demand from the industrial organization literature, to estimate asset demand elasticities from data on mutual fund holdings. Koijen et al. (forthcoming) apply this framework to study the impact of 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.[7] 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.

Compared to these papers, we exploit granular data to directly construct, rather than estimate, all of the sub-components of equity holdings and are able to account for almost all of the equity price growth fluctuations using just *observed* equilibrium equity holdings. In contrast to the literature, we perform an ex-post (i.e., contemporaneous), rather than ex-ante, decomposition.

Our paper is also related to Gabaix and Koijen (2021), who develop a model to analyze stock market fluctuations, emphasizing the importance of the rigidity of fund mandates and final fund flows for explaining aggregate US stock price fluctuations. They find that the impact of final fund flows on equity prices is vastly amplified due to wealth effects. This paper strengthens this conclusion by finding that wealth effects, captured by our net-of-fee returns component, explain a very large fraction of the *aggregate* stock market price growth rate for equity markets in a large number of countries, not only in the US.

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 the existing papers focus on matching empirical facts based on prices, our

related to our work, which focuses on the performance of investment funds. For a survey, see Wermers (2011).

[7] 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.

decomposition presents a whole new set of moments related to *quantities* that need to be matched by theoretical models. Some of the more prominent papers include Basak and Pavlova (2013), who provide a model of asset prices with institutional investors following benchmarks, Buffa et al. (2022) who generate novel asset pricing implications from a model allowing for a continuum of active versus passive behavior by funds. An alternative class of models of institutional investors focuses on the frequency of portfolio rebalancing and shows that infrequent portfolio rebalancing can generate data-consistent patterns including hump-shaped dynamics in asset prices and post-earnings-announcement drift (see, for example, Duffie 2010, Hong and Stein 1999, Hanson and Stein 2015, Bacchetta et al. 2023 and Fink 2021).[8] Our empirical results based on splitting funds into various categories such as index funds vs active funds and funds that rebalance more or less frequently can directly speak to some of the testable implications of these papers.

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 novel fact related to the special-ness of currencies in equity markets: i.e., an interesting pattern of rebalancing of mutual funds within and across "currency borders", with the US, Japanese, and Swiss stock markets playing a special role. Our paper is also related to Hau and Rey (2006), who explore the comovements of equity prices, international portfolio equity flows, and exchange rates theoretically and empirically while Camanho et al. (2022) estimate the elasticity of foreign exchange using disaggregated data on equity flows by mutual funds and granular instruments.[9] Similarly to this paper, they find that higher equity demand is linked to exchange rate appreciation. The characteristics of USD and JPY as "safe haven" currencies are consistent with Stavrakeva and Tang (Forthcoming, 2024) who show that a strong information channel of US forward guidance during the global financial crisis led to higher risk aversion.

[8]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.

[9]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.

This ended up appreciating the USD against a number of currencies (except for the JPY) by triggering a "flight to safety". Some of our empirical findings regarding the co-movement between exchange rates and stock market indices are shared by Bruno et al. (2022), who find that higher local-currency stock returns are associated with a weaker dollar. In contrast to their paper, we provide a microfoundation and explain why this co-movement exists.

Finally, the approach of decomposing equity price movements into sub-components 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 sub-components.[10]

3 Market-Clearing Decomposition

In this section, we present the theoretical underpinnings of our equity price decomposition in terms of equilibrium supply and holdings.

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

[10]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.

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 importance of investor i for ISIN j.

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 sub-components of the change in holdings and the change in ISIN-level supply due to certain corporate actions such as stock issuances or buy-backs.[11]

To summarize, the change in the total equity holdings of stock j is decomposed into four sub-components, 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), measured in the investors' currency.

[11] 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.

3.1.1 Empirical Methodology

Constructing the sub-components 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 sub-components into averages and residuals, within narrow types of investors. In step two, we impose two assumptions related to the "representativeness" of our sample of equity holdings. The first representativeness assumption is 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. Second, we assume 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.

Steps one and two imply that we can scale up the *averages* of our observed equilibrium holdings sub-components, appropriately scaled by the importance of each fund type for ISIN j, by the inverse of the coverage ratio, to obtain what we call the *"common" sub-components of equity holdings* of our market-clearing decomposition. As we will show in the results section, the "common" sub-components of equity holdings will account for almost all of the equity price growth variation, thus validating this approach, and will allow us to reconstruct market-clearing conditions using only *observed* equity holdings data, despite the low sample coverage.

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 $\Upsilon' = \textit{Active} \times \textit{Broad Strategy} \times \textit{Freq Rebalance} \times \textit{ROS Local Currency}$ 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.[12] For mutual funds, the investor's

[12] 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.

currency is the predominant currency in which the fund sells shares to its final investors (i.e., the ROS currency).

Similarly to the portfolio weight change sub-component, 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 $\Upsilon = \textit{Active} \times \textit{Size} \times \textit{Broad Strategy} \times \textit{Narrow Strategy} \times \textit{Freq Rebalance} \times \textit{ROS Currency}$ 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 sub-categories are "ROS Currency", "Size" and "Narrow Strategy".[13] "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 $\widehat{H}_{\tilde{I}}^{j,\tau} \equiv \sum_{\{i| \; i \in \tilde{I} \cap i \in \tau\}} \frac{\mu^{i,j}}{\widehat{P^j Q^j}}$ and $\widehat{H}_{\tilde{I}^{miss}}^{j,\tau} \equiv \sum_{\{i| \; i \in \tilde{I}^{miss} \cap i \in \tau\}} \frac{\mu^{i,j}}{\widehat{P^j Q^j}}$, where $\tilde{I}$ is the set of funds we observe in our sample that hold ISIN j and $\tilde{I}^{miss} \equiv I \setminus \tilde{I}$

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

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 in our sample with a ROS currency m, as a fraction of the sample average market capitalization of stock j. $\widehat{H}_{\tilde{I}^{miss}}^{j,m}$ 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:

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

where

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

We further assume that:

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

where the scaling parameter κ^j is specific to the ISIN but not to the investor type. Given that the set τ conditions on the ROS currency of the fund, equation (9) also implies $\widehat{H}_{\tilde{I}^{miss}}^{j,m} = \kappa^j \widehat{H}_{\tilde{I}}^{j,m}$.

Our "*representative holdings ratios*" assumption is equivalent to equation (9). A slight re-writing of equation (9) allows us to define precisely "*representative holdings ratios*" for ISIN j as:

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

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

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

which implies

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

Therefore, assumption (9), combined with equation (10), implies that we can re-write equation (8) as:

$$\Delta p_t^j \quad = \quad \underbrace{\Delta d_t^{s,j} + \underbrace{\Delta d_t^{f,j} + \Delta d_t^{\omega,j} + \Delta d_t^{r^{NF},j}}_{\Delta d_t^{ROS,j}}}_{\Delta d_t^j} + d_t^{Resid,j} - \Delta q_t^j \tag{11}$$

where

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

We proxy the population average net-of-fee returns, flows, and portfolio weight change terms, for each fund type, using sample averages, which is the second *"representativeness"* assumption we make. Thus, to compute the "common" sub-components of ISIN j holdings, further broken down by fund type, τ, we scale up the sample averages of portfolio weight changes, net-of-fee returns and final flows, for a given fund type, τ, by a scaling factor that is the inverse of the total coverage ratio, $\frac{\widehat{P^jQ^j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}$, times the sample average holdings by funds of type τ, relative to the sample average market capitalization of the ISIN, $\frac{\sum_{\{i|\ i\in\tilde{I}\cap i\in\tau\}}\mu^{i,j}}{\widehat{P^jQ^j}}$. The scaling factor is given by $\frac{\sum_{\{i:\ i\in\tilde{I}\cap i\in\tau\}}\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}$ and it has an intuitive interpretation. It captures the average sample holdings of stock j by funds of type τ relative to the total average sample holdings of stock j.

We then further sum up these fund-type-specific "common" sub-components of ISIN j holdings, across fund types, in order to obtain what we refer to as the *"common" sub-components 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" sub-component, $\Delta d_t^{s,j}$, is analogously defined. The only difference is that as we directly observe the exchange rate change relevant for all investors. Moreover, for the exchange rate "common" sub-component, the only relevant fund type is the currency of ROS of the fund. Δd_t^{j} is the sum of all "common" sub-components and we will refer to it as the *total "common" component of equity holdings*. $\Delta d_t^{ROS,j}$, on the other hand, captures the total "common" component of equity holdings, denominated in the currencies of ROS of the final investors. Finally, $d_t^{Resid,j}$ is unobservable and will be backed out as a residual. It captures the joint importance of 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" sub-components 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 sub-components of "common" equity holdings 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 sub-component 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), a local currency depreciation, positive $\Delta d_t^{s,j}$, will increase the value of the local-currency stock market, holding the other sub-components of "common" equity holdings fixed. Intuitively, conditional on given equity holdings, denominated in the currencies of the investors, $\Delta d_t^{ROS,j}$, local currency depreciation implies higher *local currency* equity holdings, resulting in a higher equilibrium local-currency stock market price.

Notice that this is the relationship between the exchange rate valuation "common" sub-component and local-currency stock prices, *conditional* on the other sub-components of "common" holdings, captured by $\Delta d_t^{ROS,j}$, not adjusting. In contrast, 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. In other words, we would expect $Cov(\Delta d_t^{s,j}, \Delta d_t^{ROS,j}) < 0$. Moreover, if the exchange rate, corresponding to the ISIN currency against 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 for equity markets, and higher equity holdings by USD investors have to be entirely absorbed by an increase of the local-currency stock market price.

The last two sub-components 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

In order to also study the key drivers of the aggregate stock market price growth rate, we aggregate equation (11) across ISINs, by constructing a weighted average of the equity price growth rates and its sub-components. The weights used 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 and are given by $\nu^{j,l} = \frac{\widehat{P^jQ^j}}{\sum_{\{j:c^j=l\}} \widehat{P^jQ^j}}$. 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 $D_t^{x,l} = \sum_{\{j:c^j=l\}} \nu^{j,l} \Delta d_t^{x,j}$. $D_t^{Resid,l}$ is once again backed out as a residual.

We will construct the sub-components of decompositions (11) and (12) at monthly frequency. We report two robustness checks in an Online Appendix. The first is results for quarterly frequency since many of the funds in our data set report their positions only at a quarterly frequency. The second is a similar decomposition but focusing only on the holdings of "marginal" funds, i.e., the funds that change the shares held of a particular stock over the given month. This is not our preferred specification as a lack of "share rebalancing" could still result from an active decision not to change shares held in response to a lack of news relevant to an ISIN over the month or too little news to justify paying transaction costs. This hypothesis is corroborated by the fact that most funds tend to change at least some of the shares in their portfolios every single month, eliminating the possibility that there are institutional constraints that only allow funds to rebalance at quarter ends, for example.

4 Data Description and Summary Statistics

We use equity mutual fund data from Morningstar. We have data on over 36,000 mutual funds that self-report in the Morningstar Direct database. 16,810 of these are Equity funds, 7,838 are Allocation funds, and the rest are categorized as Fixed Income or Other, where Money Market Funds comprise the bulk of the Other category. 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.[14] Total assets under management peaks at about 22 trillion USD (a little over 11 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 22367 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

[14]Figure A.23 in the Online Appendix present the total AUM across all funds. Equivalent graphs for the quarterly data are presented in the Online Appendix in Figures A.41–A.42.

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.[15] 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.[16]

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.[17] The average correlation across all stock markets is 94 percent, with the respective numbers for the US, Eurozone and UK stock markets being 98, 99 and 99 percent (see Figure A.24 in the Online 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 21% at the end of our monthly sample with the coverage being the highest for the US, Eurozone, UK, and other advanced economies.[18]

Table 1 also reports the number of ISINs per stock market that we use to construct our stock market price indices, which ranges from as few as 5 ISINs for the CZK to 5,794 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

[15]The samples for MXN, CNH and COP start in Jan 2009, Jan 2014 and Jan 2012, respectively.
[16]We do not include depository receipts in our sample.
[17]The list of stockmarket indices is reported in the Data Appendix.
[18]The respective range for the quarterly data is 2–40% (see Table A.10 in the Online Appendix).

returns sub-components of equity holdings is 959. Of this number, 340 fund types are those with a "Broad Strategy" classification of "Equity", a category that comprises the bulk of equity holdings (see Figure A.25 in the Online 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" sub-component of equity holdings at an ISIN level is 80.

5 Results

In this section we use our empirical methodology to construct the market-clearing conditions for stocks. We document many novel facts related to the importance of the various equity holding sub-components as (non-causal) drivers of equity price growth movements at the individual and aggregate stock market level and interesting heterogeneity across ISINs and aggregate stock markets.

Before we discuss the fit of our decomposition, 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.[19] It is clear that there is significant heterogeneity of both 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, given the high correlation across stock prices, and hence, 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 Industrial, Commercial Bank of China. Figure A.28 in the Online 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

[19] Figures A.26–A.27 in an Online Appendix present another example for two more fund types.

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, the explanatory power of $d^{Resid,j}$ is small.

5.1 Individual Equity Price Growth Rates

In this sub-section, we quantitatively assess the fit of the total "common" equity holdings component of equity price growth rates and it's sub-components, as well as the rest of the terms in equation (4). We perform the following variance covariance decomposition.

$$1 = \sum_{y=\left\{\Delta d^{s,j},\Delta d^{f,j},\Delta d^{\omega,j},\Delta d^{r^{NF},j},d^{Resid,j}\right\}} \beta^{p,y} - \beta^{p,\Delta q^j}, \text{ where}$$

$$\beta^{p,x} = \frac{Cov\left(x_t, \Delta p_t^j\right)}{Var\left(\Delta p_t^j\right)} \text{ and } x = \left\{\Delta d^j, \Delta d^{s,j}, \Delta d^{f,j}, \Delta d^{\omega,j}, \Delta d^{r^{NF},j}, d^{Resid,j}, \Delta q^j\right\}.$$

We estimate $\beta^{p,x}$ by regressing x_t on Δp_t^j at the ISIN level. Notice that we compute $d^{Resid,j}$ as a residual. This variance covariance decomposition should make it clear that, throughout the paper, we are using the term "importance" in a purely statistical, and not 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 explains a surprisingly large share of the variation in the change of log equity prices, with a large part of the distribution of $\beta^{p,\Delta d}$ being close to 1. As a matter of fact, out of the 22367 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 20726 ISINs. From now on we focus only on the sub-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 0.5 and 1.5, which captures almost all ISINs we started with. Within that sub-set of ISINs, the average scaled covariance is very high at 89 %. In summary, the total "common" component of equity holdings, constructed from *observed* data on holdings, net-of-fee returns, flows of equity mutual funds, and exchange rate data, tracks remarkably closely the change in the 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 allow for ISIN-level fixed effects and for heteroskedasticity-consistent standard errors, clustered by ISIN. The estimated panel regression coefficients range from 0.77 to 1.02 , with a mean of 0.86 , 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, which are appropriately weighted by the importance of the final investor for a given stock. 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. We emphasize there is nothing mechanical in the fit of our decomposition.

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 very 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). Surprisingly, the total "common" component of equity holdings still explains stock price growth rates almost perfectly for some ISINs that are held by only a few funds or for which we do not have a great coverage. What appears to be a sufficient condition is that our two representativeness assumptions, discussed in section 3.1.1, are satisfied.

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 A.29 and A.30 in the Online 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 A.31–A.33 in the Online 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 A.28b in the Online 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 A.28e and A.34), albeit still very good.

New Issuance/Buybacks

The second panel of Figure 6 shows the importance of new issuance/buybacks as an explanatory variable 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 drivers 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. 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 lows, the fact that it is the total "common" component of equity holdings, which is calculated from the far-less-volatile averages of these same variables, that explains most of the variation 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 $d^{Resid,j}$ is not a very important driver of equity price growth rates is not obvious.

5.1.1 Sub-components of "Common" Equity Holdings

Next, we discuss the relative importance of the sub-components of the "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 sub-components on Δp_t^j by stock market. We also examine the importance of different types of funds for the explanatory power of the portfolio weight change and final fund flow sub-components of equity holdings. In particular, we separate these "common" equity holdings sub-components by index funds vs active funds and own currency vs other currency investors. The panel regression results are presented in Tables 3 and 4.[20] The sum of the index funds' and active funds' sub-components 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.[21]

Weights

From the panel regressions, it is clear that the portfolio weight change "common" sub-component explains the lion's share of stock price growth (on average, 71%, and between 60% for the USD and 85% for the COP), where all the estimated covariances are also highly statistically significant. Changes in portfolio weights account for 65% of the variation of the stock market associated with the Euro, 66% for the JPY, 64% for the GBP and 77% for the CNH. The variance explained by portfolio weight changes tends to be even higher for emerging markets (it is 72% 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. Hence, "active" investing and "stock-picking" seems alive and well. In section 6, we argue it's "stock-picking" rather than "industry-picking" that drivers the large explanatory power of the "common" sub-component associated with portfolio weight changes.

Another important finding is that, for a number of stock markets, we see home bias in the portfolio weight change "common" sub-component 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" sub-component reflects the behaviour of investors whose ROS currency is the USD. Currency home bias is also important, but to a lesser degree, for the GBP, the

[20] The same results are presented visually in Figures A.35–A.38 in the Online Appendix.

[21] Finally, we also break down the importance of the equity holdings sub-components for select individual ISINs in Figures 8–10 and Figures A.29–A.34 presented in the Online Appendix.

CHF, and the JPY stock markets. One can conjecture that just like in macroeconomics, where Keynesian multipliers are higher for closed economies, for countries with equity markets that approach "autarky", "wealth multipliers" (i.e., feedback effects between wealth and asset prices) may be more important as well.

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 1%. It's both flows into index funds and active funds that are significant and contribute positively in the variance covariance decomposition for almost all currencies. Similarly, for most currencies, both own and foreign currency investors' flows are positively correlated with the equity price growth rates and are statistically significant.

Net-of-Fee Returns

The portfolio weight changes and flows into mutual funds components are usually determined by the behaviour of portfolio managers and final investors in our models. The net-of-fee returns sub-component of equity holdings, in contrast, can be understood as a wealth effect. It enters positively and significantly and explains a non-trivial share of the variance (on average, 18%, and between 13% for the CNH and 25% for the SGD). **Exchange rates**

The exchange rate sub-component, $\Delta d^{s,j}$, enters significantly and negatively for most currencies, indicating exchange rates appreciate when stock prices go up, unconditionally. The estimated average coefficient in the panel regressions is -0.05 . 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 *causally* that international net equity flows of mutual funds into a stock market appreciates the currency of that stock market.[22]

Very interestingly, however, there are five currencies that exhibit an opposite co-movement 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" currencies and the last two are pegged to the USD. 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.

For these currencies, it is likely that these unconditional co-movements are dominated by "flight-to-safety" episodes where stock prices decrease and investors seek refuge in USD and JPY fixed income markets, for example. We touch here 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 belong to this select set of "safe haven" currencies according to our data.[23] We formally disentangle the *unconditional* relationship between equity holdings and exchange rates in the next section, where we focus on aggregate stock markets.

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 at the micro level, for each individual ISIN, and analyzed

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

[23]This is consistent with the paper by Stavrakeva and Tang (Forthcoming, 2024) 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 elasticities and cross-elasticities of substitution across bonds using granular data on bond funds based in the US and the euro area, Nenova (2023) show that US Treasuries are global safe assets while German Bunds are regional safe assets.

the relative importance of each sub-component of our equity stock price decomposition, we proceed to aggregate our data to the stock market level. Again, we define the stock market to be all ISINs for which the currency of issuance is the same as the currency of 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 the key drivers of the overall stock market price growth is key to motivate existing theories. Furthermore, it is key for policy makers alike to study the drivers of the aggregate stock market, in order to understand the impact of policies on aggregate stock market fluctuations, which can further transmit to real economic variables as consumer wealth effects.

We are going to once again perform a variance covariance decomposition but, this time, focusing on the aggregate stock market and using the variables defined in equation (12):

$$\begin{aligned}
1 \approx & \quad \sum_x \beta^{p,x}, \\
\text{where } \beta^{p,x} = & \quad \frac{Cov\left(x_t, p_t^{SM,l}\right)}{Var\left(\Delta p_t^{SM,l}\right)} \\
\text{and } x = & \quad \left\{\Delta D^{s,l}, \Delta D^{f,l}, \Delta D^{\omega,l}, \Delta D^{r^{NF},l}, D^{Resid,l}\right\} \\
\text{and } \Delta p_t^{SM,l} = & \quad \sum_{\{j:c^j=l\}} \nu^{j,l} \Delta p_t^j.
\end{aligned}$$

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 explanatory power of the total "common" equity holdings component, defined as: $\beta^{p,D^l} = \frac{Cov\left(D_t^l, p_t^{SM,l}\right)}{Var\left(\Delta p_t^{SM,l}\right)}$.

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 0.96 with the smallest and largest scaled covariances being 0.70 for CNH and 1.05 for the THB. The numbers for the USD, EUR, GBP and JPY are 0.96, 0.96, 0.94 and 0.96 respectively.

To visually explore the fit, Figure 15 and Figure A.39 in the Online 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 construct 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 importance of the equity holdings "common" sub-components as drivers of overall stock price growth rates. The scaled covariances for the sub-components are presented in Figure 14 and Table 5 where we also present the adjusted R^2 from regressing the respective sub-component on the aggregate stock price growth rate. The key result is that we observe a dramatic change between the micro level and the macro level, which we carefully dissect in the next sub-sections. Aggregation matters!

Portfolio weight changes: "Micro is not like Macro"

The main finding is that the importance of the portfolio weight change "common" sub-component falls dramatically at the aggregate level. Portfolio weight changes still remain a very important driver of stock prices for emerging markets—BRL (68%), CLP (54%), IDR (62%), 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" sub-component is always statistically significantly correlated with the stock price growth rate, with the exception of CNH, USD, JPY and CHF.

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

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

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 is explained by the ISIN-level co-movement 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 co-movement of the portfolio weight change with respect to the cross-ISIN price, scaled appropriately.

Notice that in addition to the actual own and cross portfolio weight change covariances with the stock market price growth rate, the terms β^{ω}_{OwnCov} and $\beta^{\omega}_{CrossCov}$ are determined also by the size of the market. The more ISINs in a market there are, the lower $(\nu^{j,l})^2$ is for each ISIN and the more cross covariance terms there are, implying that the cross covariance terms will play an even more important role.

Figure 16 presents the results for β^{ω}_{OwnCov} and $\beta^{\omega}_{CrossCov}$. For exactly the three countries for which the co-movement of the "common" portfolio weight change sub-component of equity holdings with the aggregate stock market price is negative (i.e., USD, JPY, and CHF), $\beta^{\omega}_{CrossCov}$ is negative. This means that increasing the portfolio weight exposure with respect to one US stock is often associated with decreasing the weight exposure with respect to another US stock. In other words, investors rebalance within the US stock market border or "currency border", 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 implies that the importance of the own ISIN level covariances will be dampened for the aggregate stock market movement relative to the cross ISIN level 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, this does not occur anywhere else. In particular, for emerging markets, increasing or decreasing the weight fund managers place on a stock is very strongly correlated with going in and out of the "currency 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 remain the main driver of aggregate stock market fluctuations at the aggregate stock market level for their stock markets.

Final Flows Sub-Component

The final fund flows "common" sub-component of equity holdings has gained some importance in the aggregate variance covariance decomposition. This sub-component always comoves positively with the stock market price in a statistically significant way for 25 out of 33 stock markets. The average fraction of aggregate stock price movements explained by the final flows "common" sub-component is 6% and the maximum is 14% for MYR, followed by 13% for both CNH and MXN. The numbers for the USD, EUR and GBP are 6%, 6% and 3% and all are statistically significant at one percent.

Net-of-Fee Returns Sub-Component

The complement to the "micro-to-macro puzzle" we documented for the portfolio weight change "common" sub-component 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", an increase in stock prices leads to the net-of-fee returns being reinvested by asset managers, which further props up asset 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 net-of-fee return component explains most of the return variation in the USD, CHF, GBP and JPY 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 which would reflect the high correlation across stock market prices globally.

We perform a micro to macro decomposition of $\frac{Cov\left(D_t^{r^{NF},l},\Delta p_t^{SM,l}\right)}{Var\left(\Delta p_t^{SM,l}\right)}$, 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 effect 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.

The Importance of Exchange Rates For Aggregate Stock Market Fluctuations Last, but not least, we examine the explanatory power of our exchange rate valuation sub-component. As in our ISIN level equity price growth rate decompositions, we again observe that the exchange rate sub-component 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.[24] The contribution of the exchange rate

[24] 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 stabilised within some bands vis-à-vis a currency basket.

sub-component tends to be the most negative for emerging market economies and can be as negative as -48% for ZAR, -42% for MXN and -40% for BRL. The respective numbers for the USD, JPY and CHF are 2%, 23% and 8%.[25] The average scaled covariance is -17%. The exchange rate sub-component of equity holdings is statistically significant in all cases but DKK.

Next, we shed light on what is the main driver of the relationship between local stock markets and "equity"-weighted exchange rate indices, i.e., $\Delta D^{s,l}$, where the weights used to construct the exchange rate sub-component reflect the importance of the currency of the final investors for the local stock market. Since USD investors dominate global equity markets, $\Delta D^{s,l}$ will be almost entirely driven by variation in the local currency exchange rate against the USD.

More specifically, to examine further what drives the relationship between the exchange rate change component of equity holdings and stock price growth rates, we perform the following decomposition of $\beta^{p,\Delta D^{s,l}}$ as:

$$\beta^{p,\Delta D^{s,l}} \approx \frac{Var\left(\Delta D_t^{s,l}\right)}{Var\left(\Delta p_t^{SM,l}\right)} + \sum_x \frac{Cov\left(\Delta D_t^{s,l}, x_t\right)}{Var\left(\Delta p_t^{SM,l}\right)},$$
$$\text{where } x = \left\{\Delta D^{f,l}, \Delta D^{\omega,l}, \Delta D^{r^{NF},l}, D^{Resid,l}\right\}$$
$$\text{or } x = \left\{\Delta D^{ROS,l}, D^{Resid,l}\right\},$$

where, once again, we abstract from the change in issuance at the ISIN level.

Figure 18 reports the results from this decomposition. It is clear that the *unconditional* negative correlation between the exchange rate change valuation component of equity holdings and stock market price growth rates is due to the fact that higher equity holdings, as measured in the currency of the ROS of the funds, is associated with an appreciation not only of the equity price in local currency, but also of the local exchange rate. This can be

[25] The smaller explanatory power of the exchange rate sub-component for the USD stock market, in absolute value, simply reflects the very large home bias for USD stocks where exchange rates are a less important equilibrating mechanism for US stocks.

seen from the fact that $Cov\left(\Delta D_t^{s,l}, \Delta D_t^{ROS,l}\right) < 0$ for all currencies but JPY, USD, and HKD.[26]

Exploring further which ones of the sub-components of $\Delta D_t^{ROS,l}$ drive the negative unconditional covariance, for every market, but HKD and CNH, higher holdings for the currency due to equity portfolio weight changes into the local stock market is associated with an appreciation of the currency. This is the case also for the final flows component of equity holdings with the exception of the USD, JPY and HKD where the estimated co-variances are slightly positive rather than negative. Finally, the covariance between the exchange rate component and the net-of-fee returns equity holdings component is also negative in all cases but for the USD, HKD, JPY and EGP.

Table 6 also reports the regression results from regressing $D_t^{s,l}$ on $D_t^{\omega,l}$ or $D_t^{f,l}$, which allows us to examine the statistical significance and the adjusted R^2 from regressing the exchange rate indices on the portfolio weight change or final fund flows "common" sub-components. Considering $D_t^{\omega,l}$, the relationship is statistically significant for all currencies but five (CNH, DKK, EGP, ILS, MYR). The adjusted R^2, which captures what fraction of the exchange rate growth rate is explained by portfolio weight changes, in a non-causal sense, ranges from 0 to 59 percent with a mean of 15 percent. Regarding $D_t^{f,l}$, the estimated coefficients are statistically significant in 23 cases and the adjusted R^2 ranges from 0 to 14 percent, with a mean of 5 percent.

To summarize, with respect to the JPY and USD, we do not observe a negative unconditional correlation between equity holdings, as measured in the currency of the ROS of the fund, and the exchange rate component of equity holdings. This is most likely because the "flight-to-safety" demand in fixed income markets for USD and JPY is a relatively more important driver of this unconditional relationship. That is, when there are global negative shocks, we observe USD and JPY appreciation that is likely associated with inflows into

[26] The fact that the CHF and EGP appreciate when the local stock market does poorly can be explained by the high variance of the EGP and CHF exchange rate sub-component which swamps the negative co-variance between $\Delta D_t^{s,l}$ and $\Delta D_t^{ROS,l}$.

fixed income funds that invest in these currencies while equity funds that invest in these currencies, if anything, experience outflows.[27] Notice that positive portfolio weight changes into USD and JPY equities is still associated with an appreciation of these currencies. However, for all other currencies (besides also the HKD, which is pegged to the USD), we find that increased equity holdings, as measured in the investors' currencies, are associated with an appreciation of the local currency.

Finally, when considering patterns regarding the importance of the various "common" sub-components of equity holdings, we observe a very strong negative correlation between $\beta^{p,\Delta D^{s,l}}$ and $\beta^{p,\Delta D^{\omega,l}}$. For countries for which the exchange rate valuation channel dampens the overall stock market price growth rate volatility by more, the portfolio weight change "common" sub-component of equity holdings explains a larger fraction of the overall stock market price fluctuation.

6 "Stock Picking" vs "Industry Picking"?

In this section, we address the question whether individual ISIN-level stock prices are driven by "stock picking" or "industry picking". To answer this question, we further decompose the portfolio weight change "common" sub-component of equity holdings as a function of a portfolio weight change "common" sub-component specific to a given industry and country, and an idiosyncratic portfolio weight change "common" sub-component, specific to the individual stock, and backed out as a residual.

We re-write equation (5) as follows:

$$\frac{\Delta\omega_t^{i,j}}{\widehat{\omega}^{i,j}} = \left(\sum_{k\in\tau_i'}\frac{1}{|\tau_i'|}\frac{\Delta\omega_t^{k,j}}{\widehat{\omega}^{k,j}} - \sum_{l\in\gamma_j'}\sum_{k\in\tau_i'}\frac{1}{|\gamma_j'\times\tau_i'|}\frac{\Delta\omega_t^{k,l}}{\widehat{\omega}^{k,l}}\right) + \sum_{l\in\gamma_j'}\sum_{k\in\tau_i'}\frac{1}{|\gamma_j'\times\tau_i'|}\frac{\Delta\omega_t^{k,l}}{\widehat{\omega}^{k,l}} + \varepsilon_t^{\omega,i,j}, \quad (13)$$

where $\gamma' \in \Gamma'$ captures the ISIN type and $\Gamma' = Industry \times Currency\ of\ ISIN$ and $\gamma_j' = \{l \in \gamma' | j \in \gamma'\}$ is the set of all ISINs that are of the same type γ' as ISIN j. Finally, $|\gamma_j' \times \tau_i'|$

[27] The result regarding the final flows is only highly significant for the USD.

is the number of elements in the set $\gamma'_j \times \tau'_i$. Based on equation (13), we further decompose the portfolio weight change "common" sub-component of equity holdings as:

$$\begin{aligned}
\Delta d_t^{\omega,j} &= \Delta d_t^{\omega,j,iid} + \Delta d_t^{\omega,j,Ind}, &(14)\\
\text{where} \quad \Delta d_t^{\omega,j,Ind} &= \sum_{\tau\in\Upsilon} \frac{\sum_{\{i:\, i\in\tilde{I}\cap i\in\tau\}} \mu^{i,j}}{\sum_{i\in\tilde{I}} \mu^{i,j}} \alpha_t^{\omega,\tau,Ind,j}, &(15)\\
\text{and} \quad \alpha_t^{\omega,\tau,Ind,j} &= \sum_{l\in\gamma'_j} \sum_{k\in\tau'} \frac{1}{|\gamma'_j \times \tau'|} \frac{\Delta\omega_t^{k,l}}{\widehat{\omega}^{k,l}} \; \textit{for all } \tau \subseteq \tau'.
\end{aligned}$$

$\Delta d^{\omega,j,iid}$ is backed out as a residual from equation (14). Symmetrically, we perform the same decomposition at the aggregate stock market level:

$$\Delta D^{\omega,l} = \Delta D^{\omega,l,iid} + \Delta D^{\omega,l,Ind}, \tag{16}$$

where $\Delta D^{\omega,l,Ind} = \sum_{\{j:c^j=l\}} \nu^{j,l} \Delta d_t^{\omega,j,Ind}$ and $\Delta D^{\omega,l,iid} = \sum_{\{j:c^j=l\}} \nu^{j,l} \Delta d_t^{\omega,j,iid}$.

Table 7 reports the results from the variance co-variance decomposition where we break down the portfolio weight change sub-component according to equations (14) and (16). It is clear that idiosyncratic stock picking is key in explaining individual equity price growth rates, meaning it appears that ISIN-specific portfolio weight changes (potentially due to ISIN-specific news), rather than industry level portfolio weight changes (potentially due to industry-level news), is the main driver of individual stock prices. The average contributions towards equity price growth fluctuations of $\Delta d_t^{\omega,j,iid}$ and $\Delta d_t^{\omega,j,Ind}$, in the panel regressions across stock markets, are 50% and 21% respectively.

However, the effect of the idiosyncratic "stock picking" component completely dissipates at the aggregate stock market level and it is only the portfolio weight changes at the industry level that explain the importance of portfolio weight changes for aggregate stock market fluctuations.

7 Implications for Asset Pricing Theories

In this section, we synthesize the stylized facts that we document using our novel decomposition of individual equity price changes and aggregate stock market price growth rates. In addition to providing unconditional *quantitative* moments, in the form of our variance covariance decomposition, that need to be matched by quantitative models, we also document a number of important *qualitative* results. We discuss some of them below.

Starting with the portfolio weight changes, our results show large heterogeneity in weight changes across funds for a given stock, though much of that heterogeneity appears to cancel out, implying that the main driver of equity prices is the average behavior of investors. This is consistent with asset pricing models emphasizing public versus private information or heterogeneous beliefs and also models where only information that is available to *the whole market* is priced in. The results on "stock picking" versus "industry picking" can potentially be rationalized with models where many investors rely on firm-specific balance sheet news or information conveyed by firm managers in order to form their investment strategy with respect to a given firm. However, only the industry-specific component of these firm-specific news plays a role in terms of explaining aggregate stock prices.

Furthermore, our results reveal significant heterogeneity in the degree of home bias across countries. For some large equity markets, such as the US, JP, UK, we observe high home bias where most of the stock price fluctuations is explained by the behavior of local currency funds. However, we do not observe the same home bias for the Eurozone.

Moreover, to truly explain international stock markets, equity models need to incorporate exchange rate determination and to microfound heterogeneous portfolio weight changes across "currency borders" as well as "flight to safety". Models with endogenous market segmentation would be best suited to do that. A microfoundation of why investors rebalance within "currency borders" in the US, JP, and CH—also countries with "safe haven" currencies—is crucial in order to understand the "specialness" of these markets and currencies. Models with such a microfoundation will be able to explain why, at micro level, portfolio weight changes explain most of equity price movements, whereas it is wealth effects that account for the movement of aggregate stock prices for these three markets. In contrast, models for emerging market economies and other advanced economies should account for the fact that investors appear to take the currency and equity risk as a bundle and that they rebalance across "currency borders". In these countries, portfolio weight changes explain a large fraction of the fluctuation of both individual equity and aggregate stock market price growth rates, albeit wealth effects still increase in importance when studying aggregate stock price movements, relative to individual equity price fluctuations.

Finally, since our decomposition relies only on linearized market clearing conditions, any structural model of equities and exchange rates can be nested in our methodology. For example, by specifying an optimization problem for asset demand and nesting it within our framework, one could make progress regarding the estimation of structural parameters such as demand elasticities and distinguish them from investor-specific demand shocks (see Koijen and Yogo 2019b).

8 Conclusion

Data on mutual funds' holdings, which cover, on average, as little as 5% of ISIN-level equity market capitalization allow us to reconstruct total "common" equilibrium equity holdings that account for most of 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 should motivate all asset pricing theories, given the minimal set of assumptions we impose to derive these empirical results.

In particular, 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 et al.

(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. We show that the observed scaled net-supply subcomponents can jointly explain a large fraction of exchange rate movements. This exchange rate decomposition allows us to explore the international propagation of macroeconomic news and risk aversion shocks across equity and exchange rate markets.

References

Bacchetta, P., E. van Wincoop, and E. R. Young (2023): "Infrequent Random Portfolio Decisions in an Open Economy Model," *Review of Economic Studies*, 90, 1125–1154.

Barberis, N. and A. Shleifer (2003): "Style Investing," *Journal of Financial Economics*, 68, 161–199.

Basak, S. and A. Pavlova (2013): "Asset Prices and Institutional Investors," *American Economic Review*, 103, 1728–58.

Bertaut, C., S. Curcuru, E. Faia, and P.-O. Gourinchas (2023): "The Global (Mis)Allocation of Capital," Tech. rep., mimeo.

Bruno, V., I. Shim, and H. S. Shin (2022): "Dollar beta and stock returns," *Oxford Open Economics*, 1, odac003.

Buffa, A., D. Vayanos, and P. Woolley (2022): "Asset Management Contracts and Equilibrium Prices," *Journal of Political Economy*, 130, 3146–3201.

Camanho, N., H. Hau, and H. Rey (2022): "Global Portfolio Rebalancing and Exchange Rates," *The Review of Financial Studies*, 35, 5228–5274.

Campbell, J. Y. and R. J. Shiller (1988): "Stock Prices, Earnings, and Expected Dividends," *Journal of Finance*, 43, 661–676.

Duffie, D. (2010): "Presidential Address: Asset Price Dynamics with Slow-Moving Capital," *Journal of Finance*, 55, 1237–1267.

Fink, J. (2021): "A review of the Post-Earnings-Announcement Drift," *Journal of Behavioral and Experimental Finance*, 29.

Froot, K. A. and T. Ramadorai (2005): "Currency returns, intrinsic value, and institutional-investor flows," *The Journal of Finance*, 60, 1535–1566.

Gabaix, X. and R. Koijen (2021): "In Search of the Origins of Financial Fluctuations: The Inelastic Markets Hypothesis," Swiss finance institute research paper no. 20-91.

Hacioglu-Hoke, S., D. Ostry, A. Rousset-Planat, H. Rey, V. Stavrakeva, and J. Tang (2023): "The Importance of Asset Managers in Currency Markets," Mimeo, London Business School.

Hanson, S. and J. Stein (2015): "Monetary policy and long-term real rates," *Journal of Financial Economics*, 115, 429 – 448.

Hau, H. and H. Rey (2006): "Exchange Rates, Equity Prices and Capital Flows," *Review of Financial Studies*, 19, 273–317.

Hong, H. and J. Stein (1999): "A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets," *The Journal of Finance*, 54, 2143–2184.

Jiang, Z., R. Richmond, and T. Zhang (2024): "Understanding the Strength of the Dollar," *Mimeo*.

Kashyap, A., N. Kovrijnykh, J. Li, and A. Pavlova (2023): "Is there Too Much Benchmarking in Asset Management?" *American Economic Review*, 113, 1112–1141.

Koijen, R., R. Richmond, and M. Yogo (forthcoming): "Which Investors Matter for Equity Valuations and Expected Returns?" *Review of Economic Studies*.

Koijen, R. and M. Yogo (2019a): "A Demand System Approach to Asset Pricing," *Journal of Political Economy*, 127, 1475–1515.

——— (2019b): "A Demand System Approach to Asset Pricing," *Journal of Political Economy*, 127, 1475–1515.

Kouri, P. J. K. (1976): "The Exchange Rate and the Balance of Payments in the Short Run and in the Long Run: A Monetary Approach," *The Scandinavian Journal of Economics*, 78, 280–304.

Maggiori, M., B. Neiman, and J. Schreger (2020): "International Currencies and Capital Allocation," *Journal of Political Economy*, 128, 2019–2066.

Nenova, T. (2023): "Global or Regional Safe Assets: Evidence from Bond Substitution Patterns," Mimeo, London Business School.

Ozdenoren, E. and K. Yuan (2017): "Contractual Externalities and Systemic Risk," *Review of Economic Studies*, 84, 1789–1817.

Rey, H., V. Stavrakeva, and J. Tang (2024): "Exchange Rates and Currency Centrality in Equity Markets," Mimeo, London Business School.

Stavrakeva, V. and J. Tang (Forthcoming, 2024): "The Dollar during the Great Recession: The Information Channel of US Monetary Policy and the Flight to Safety," *Journal of Finance*.

Tesar, L. L. and I. M. Werner (1995): "Home bias and high turnover," *Journal of international Money and Finance*, 14, 467–492.

Wermers, R. (2011): "Performance measurement of mutual funds, hedge funds, and institutional accounts," *Annu. Rev. Financ. Econ.*, 3, 537–574.

A Appendix

A.1 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 reciepts in the analysis in this paper.

From Refinitiv Eikon, we also pull the mappings between the ISIN of an asset and its CUSIP. When analysing 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.

A.2 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.

A.3 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; SP/TSX 60 Large Cap Capped Index
- CHF – SSMID; Swiss Market Index
- CLP – IGPAD; Santiago SE SP 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 SP/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 ; SP 500/Cowles Composite Price Index
- ZAR – JALSHD; FTSE/JSE All-Share Index

B Tables and Figures

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

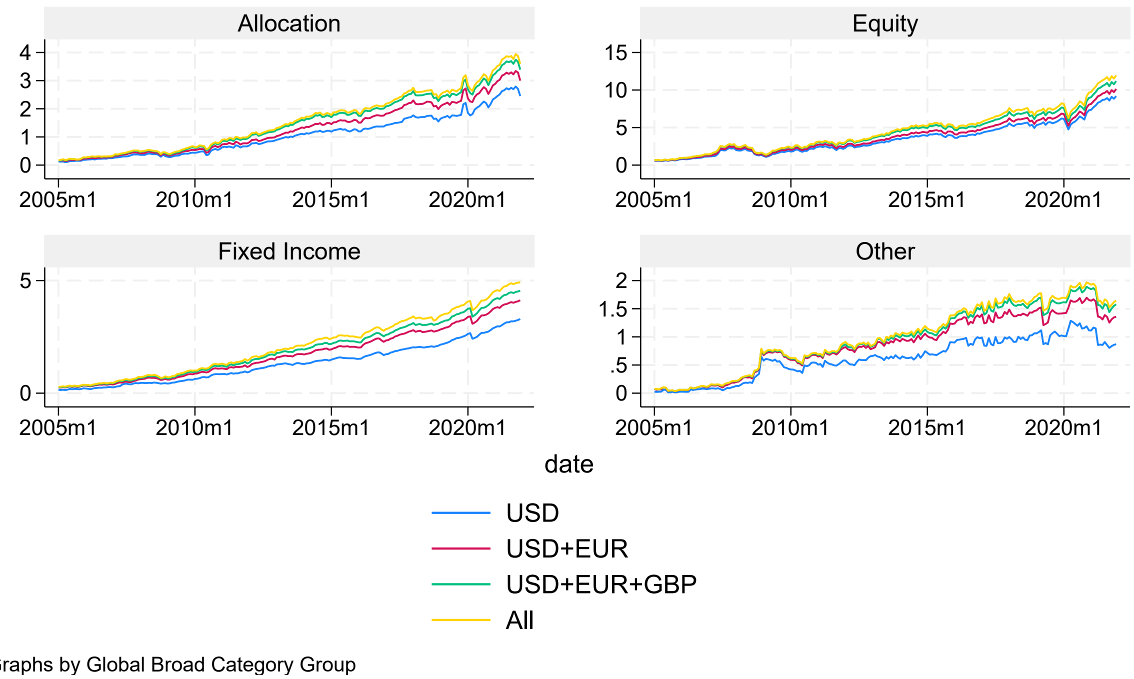


Figure 2: AUM by Investment Type and Index Funds/Active Funds (Monthly, USD Trillions)

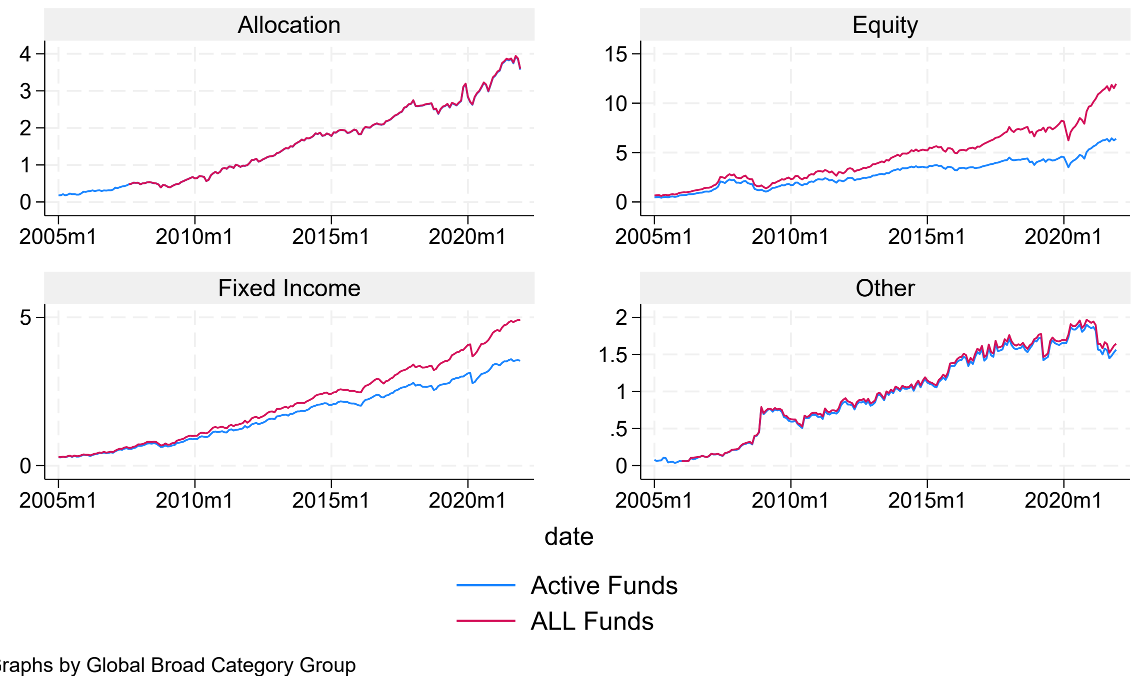
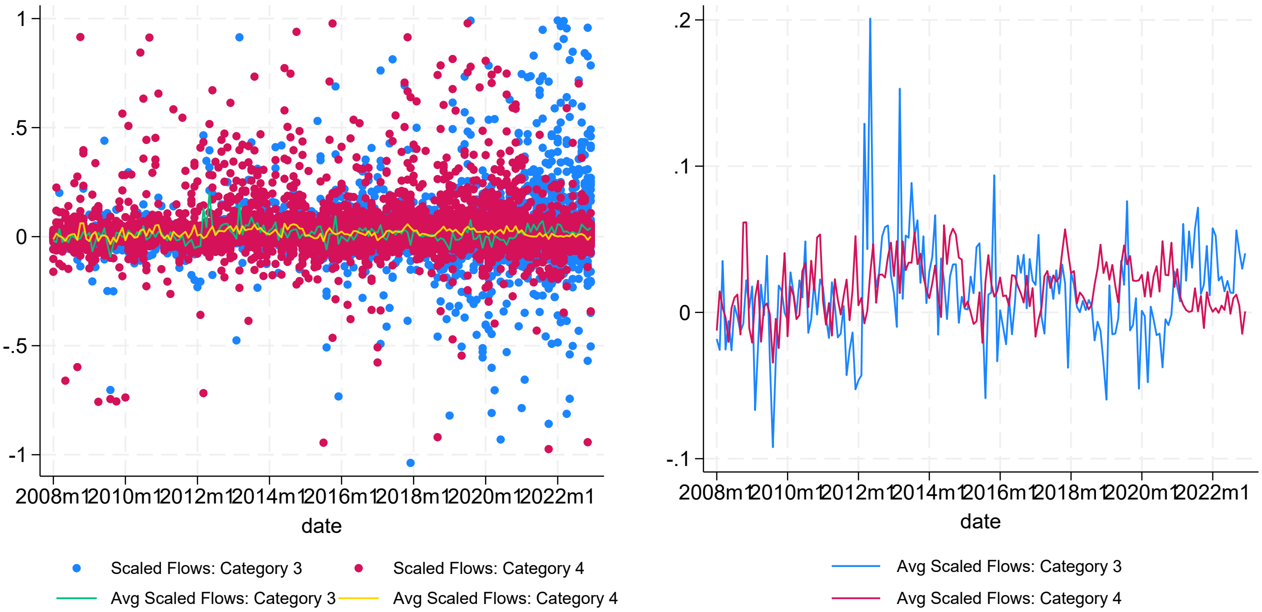


Table 1: Coverage and Market Capitalization (Monthly Sample)

Currency	*AvgCoverage*	*CoverageStart*	*CoverageEnd*	*AvgMarketCapUSDbil*	*MarketCapStartUSDbil*	*MarketCapEndUSDbil*	*ISINs*
AUD	0.06	0.04	0.09	998.86	754.13	1435.70	571.00
BRL	0.05	0.02	0.08	726.13	596.83	617.48	252.00
CAD	0.05	0.04	0.08	1370.47	1057.08	2147.87	615.00
CHF	0.09	0.03	0.14	1205.77	881.33	1930.86	225.00
CLP	0.02	0.00	0.03	171.05	139.78	108.42	70.00
CNH	0.00	0.00	0.01	3451.68	10.98	9479.44	1238.00
COP	0.02	0.00	0.03	112.47	82.48	77.38	27.00
CZK	0.04	0.04	0.03	28.19	51.94	32.10	5.00
DKK	0.06	0.02	0.11	218.07	115.68	493.93	94.00
EGP	0.02	0.01	0.02	31.83	65.15	26.62	42.00
EUR	0.07	0.03	0.11	6069.20	5667.63	9319.04	1485.00
GBP	0.13	0.05	0.21	2542.41	2349.27	3099.47	1109.00
HKD	0.05	0.03	0.07	897.13	616.23	1045.85	480.00
HUF	0.09	0.03	0.12	16.55	19.79	27.47	12.00
IDR	0.03	0.02	0.05	305.27	120.45	400.96	206.00
ILS	0.02	0.02	0.03	136.68	108.31	252.85	169.00
INR	0.05	0.02	0.09	1356.98	796.67	3153.75	874.00
JPY	0.06	0.02	0.13	4512.08	3407.55	6553.49	2862.00
KRW	0.06	0.03	0.08	1142.13	756.02	1960.71	1442.00
MXN	0.05	0.03	0.07	294.48	207.85	371.86	115.00
MYR	0.03	0.03	0.02	361.16	266.65	370.08	383.00
NOK	0.05	0.02	0.09	223.20	219.27	358.58	134.00
NZD	0.04	0.02	0.06	51.88	21.22	111.42	68.00
PHP	0.03	0.03	0.02	171.68	55.09	234.22	102.00
PLN	0.03	0.01	0.04	124.35	97.54	159.07	118.00
RUB	0.01	0.00	0.02	407.29	245.80	603.73	64.00
SEK	0.05	0.02	0.10	430.28	312.92	932.63	328.00
SGD	0.05	0.03	0.06	310.99	284.07	327.16	198.00
THB	0.01	0.01	0.01	441.91	190.55	672.90	292.00
TRY	0.04	0.03	0.03	185.15	189.99	119.22	179.00
TWD	0.05	0.02	0.08	905.81	518.94	2102.39	1040.00
USD	0.13	0.08	0.16	22126.05	13951.53	47409.69	5756.00
ZAR	0.05	0.04	0.06	327.43	281.09	335.31	171.00

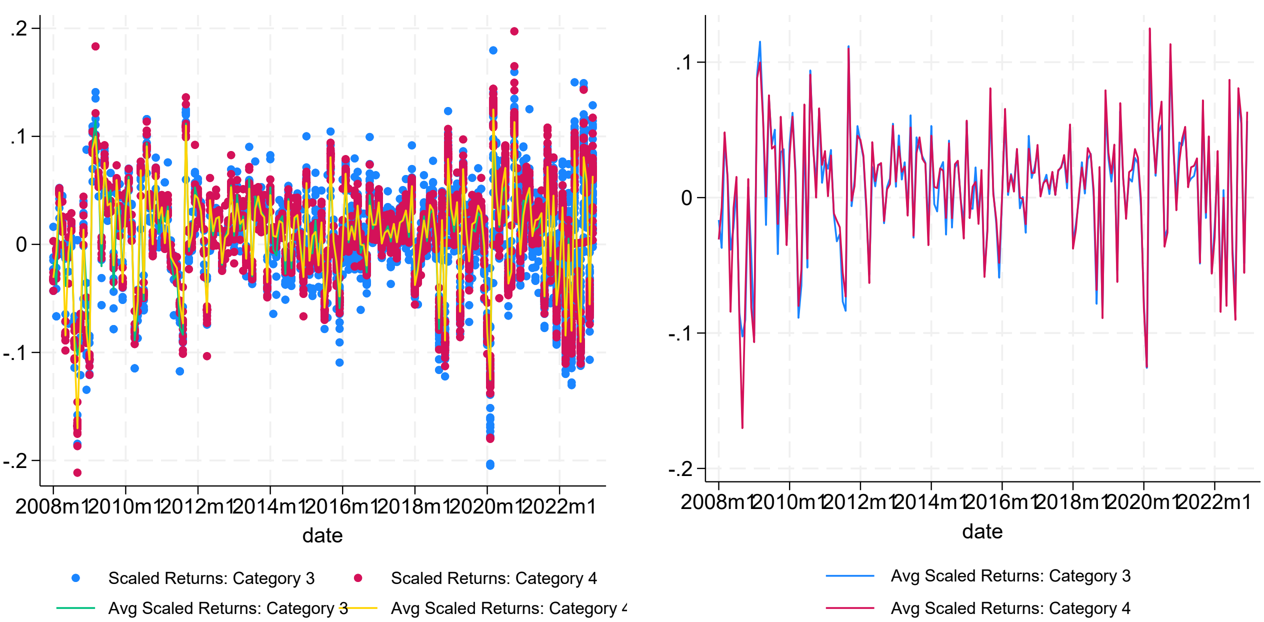
This table presents the sample average, starting date and ending date coverage ratios, weighted by the market capitalization of the ISIN. The coverage ratio for an ISIN is defined as total observed holdings of this ISIN in our data set over the market capitalization of the ISIN, translated in the same 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

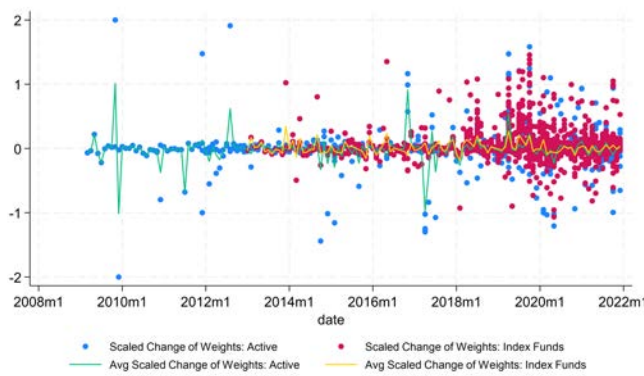


Equity Funds; USD ROS currency;
Category 3 : Active: more active; Freq Rebalance: re-balancing frequently; size of fund: <=100mil; GlobalCategory: US Equity Large Cap Blend
Category 4: Active: Index Funds; Freq Rebalance: re-balancing frequently; size of fund: >1bil; GlobalCategory: US Equity Large Cap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

Figure 5: Portfolio Weight Change for Select Stocks

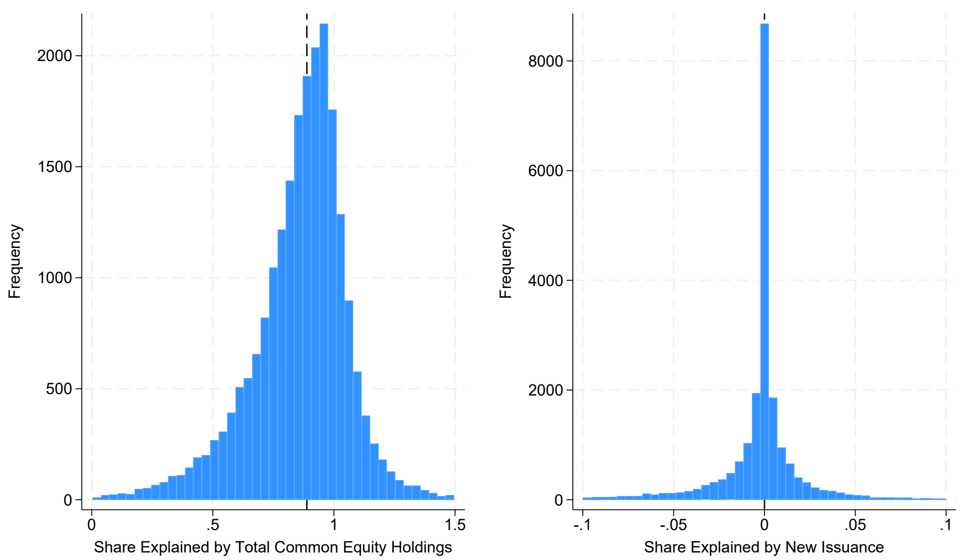
(a) Apple

(b) LVMH



(c) Industrial and Commercial Bank of China Ltd

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



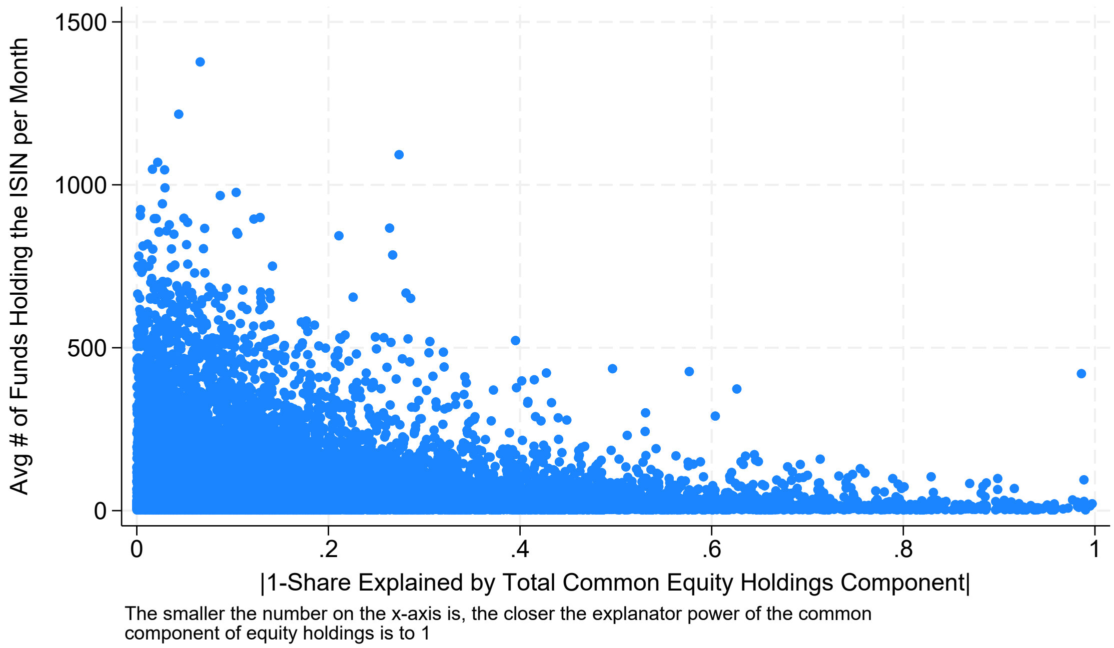
We plot only the set of ISINs for which $\frac{Cov\left(\Delta d^j, \Delta p_t^j\right)}{Var\left(\Delta p_t^j\right)}$ is between 0 and 1.5.

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

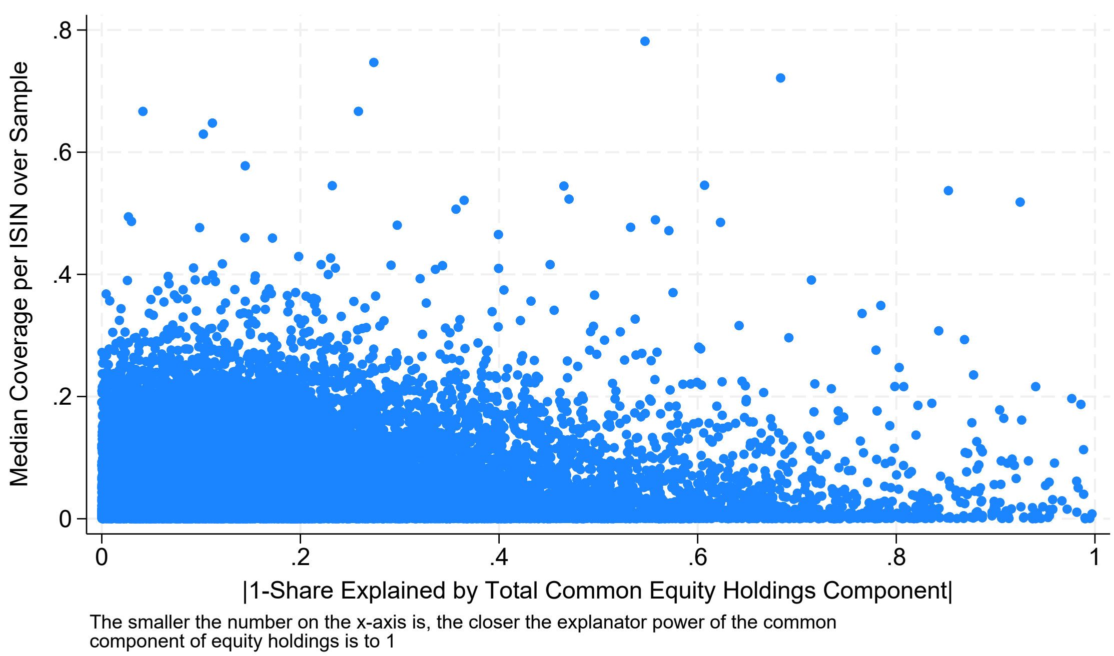
Currency	Δd_t^j	$\Delta d_t^{\omega,j}$	$\Delta d_t^{s,j}$	$\Delta d_t^{f,j}$	$\Delta d_t^{r^{NF},j}$	$\Delta d_t^{Resid,j}$	Δq_t^j
AUD	0.780***	0.704***	-0.064***	0.008***	0.133***	0.206***	-0.010***
BRL	0.795***	0.745***	-0.118***	0.013***	0.155***	0.199***	-0.007**
CAD	0.773***	0.678***	-0.049***	0.009***	0.134***	0.221***	-0.002
CHF	0.870***	0.646***	0.003**	0.003**	0.217***	0.122***	-0.008**
CLP	0.870***	0.737***	-0.105***	0.024***	0.216***	0.119***	-0.005
CNH	0.907***	0.768***	-0.014***	0.026***	0.128***	0.091***	-0.001
COP	0.880***	0.852***	-0.191***	0.020***	0.199***	0.097**	-0.006
CZK	1.020***	0.799***	-0.104**	0.027*	0.298***	-0.016	0.003
DKK	0.845***	0.661***	-0.013***	0.012***	0.185***	0.142***	-0.013**
EGP	0.892***	0.659***	0.072***	0.010***	0.152***	0.087***	-0.020***
EUR	0.845***	0.647***	-0.029***	0.017***	0.209***	0.144***	-0.009***
GBP	0.786***	0.638***	-0.008***	0.005***	0.151***	0.204***	-0.006*
HKD	0.890***	0.681***	0.012***	0.016***	0.181***	0.104***	-0.005*
HUF	0.905***	0.754***	-0.113***	0.010	0.254***	0.096**	0.001
IDR	0.856***	0.769***	-0.066***	0.012***	0.141***	0.144***	0.002
ILS	0.824***	0.669***	-0.040***	0.017***	0.178***	0.155***	-0.020**
INR	0.786***	0.663***	-0.043***	0.007***	0.160***	0.216***	0.002
JPY	0.924***	0.664***	0.049***	0.006***	0.204***	0.074***	-0.002**
KRW	0.927***	0.809***	-0.042***	0.003***	0.157***	0.067***	-0.004***
MXN	0.825***	0.745***	-0.110***	0.021***	0.170***	0.170***	-0.003
MYR	0.846***	0.655***	-0.045***	0.017***	0.219***	0.145***	-0.008**
NOK	0.789***	0.685***	-0.054***	0.011***	0.146***	0.209***	-0.004
NZD	0.834***	0.706***	-0.062***	0.012***	0.179***	0.161***	-0.004
PHP	0.905***	0.727***	-0.027***	0.015***	0.190***	0.090***	-0.003
PLN	0.834***	0.740***	-0.098***	0.015***	0.177***	0.164***	-0.002
RUB	0.894***	0.797***	-0.096***	0.019***	0.174***	0.105***	-0.001
SEK	0.880***	0.696***	-0.029***	0.023***	0.190***	0.121***	0.002
SGD	0.888***	0.662***	-0.047***	0.019***	0.253***	0.107***	-0.005
THB	0.877***	0.683***	-0.052***	0.020***	0.226***	-0.084**	-0.205***
TRY	0.896***	0.770***	-0.089***	0.020***	0.195***	0.104***	0.000
TWD	0.926***	0.716***	-0.030***	0.014***	0.227***	0.072***	-0.000
USD	0.802***	0.601***	0.001***	0.010***	0.190***	0.188***	-0.006***
ZAR	0.805***	0.725***	-0.101***	0.017***	0.163***	0.182***	-0.012*

Note: In this table we report the coefficients from panel regressions of the total "common" component of equity holdings (and its sub-components) on Δp_t^j by stock market (as denoted by the currency associated with that stock market). We also report the coefficients from panel regressions of the change in ISIN-level shares issued and the residual holdings sub-component on Δp_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

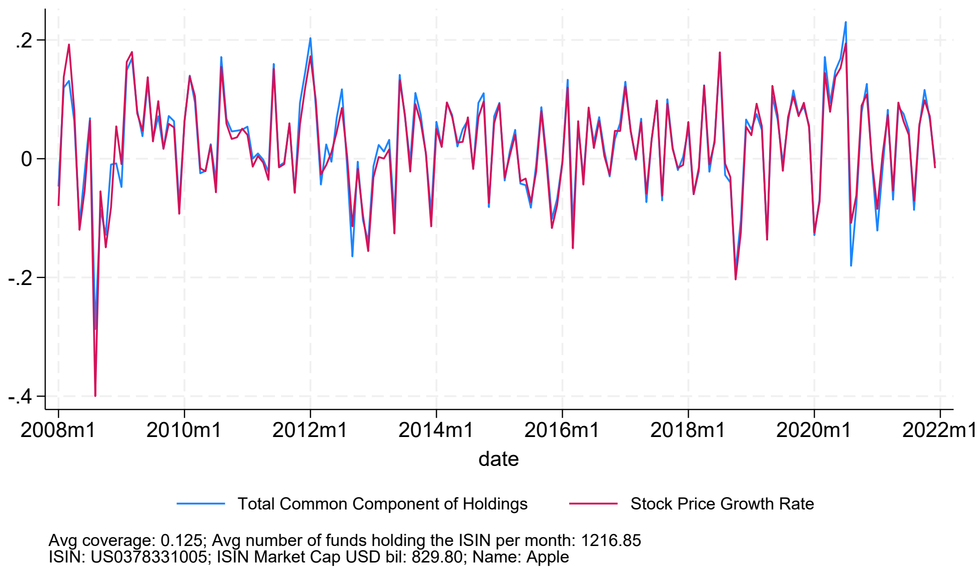


(a) Against Average Number of Funds

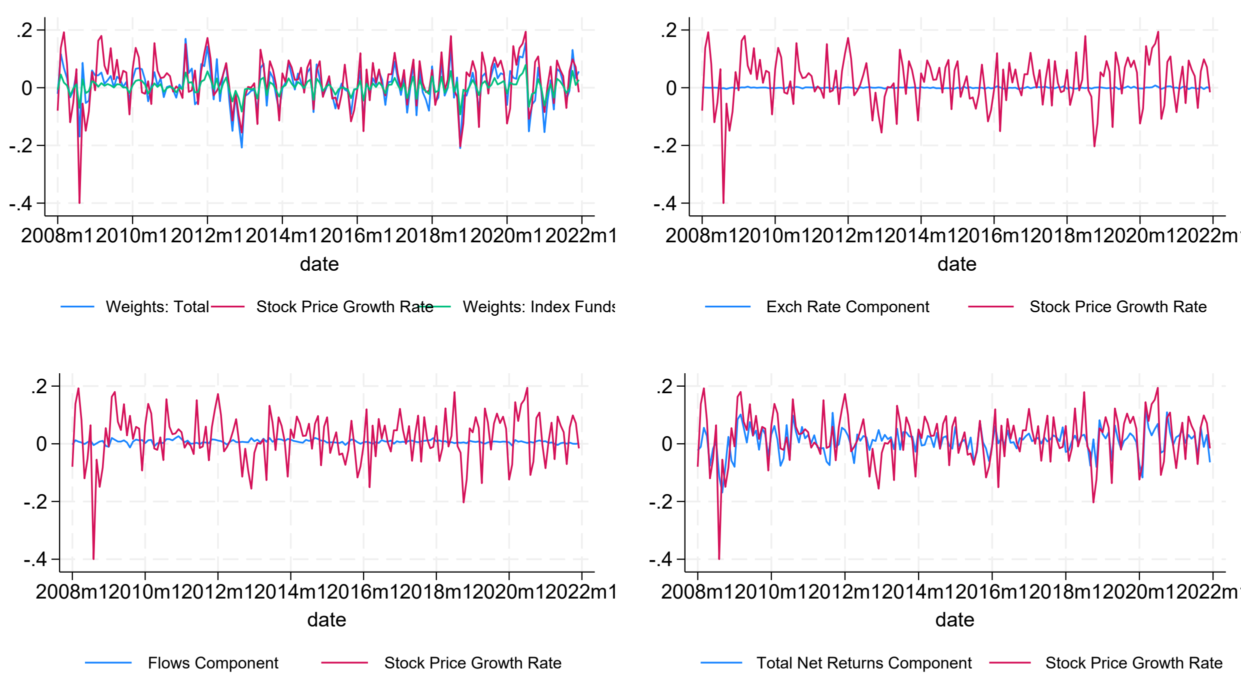


(b) Against Coverage

Figure 8: “Common” Equity Holdings Components: Apple

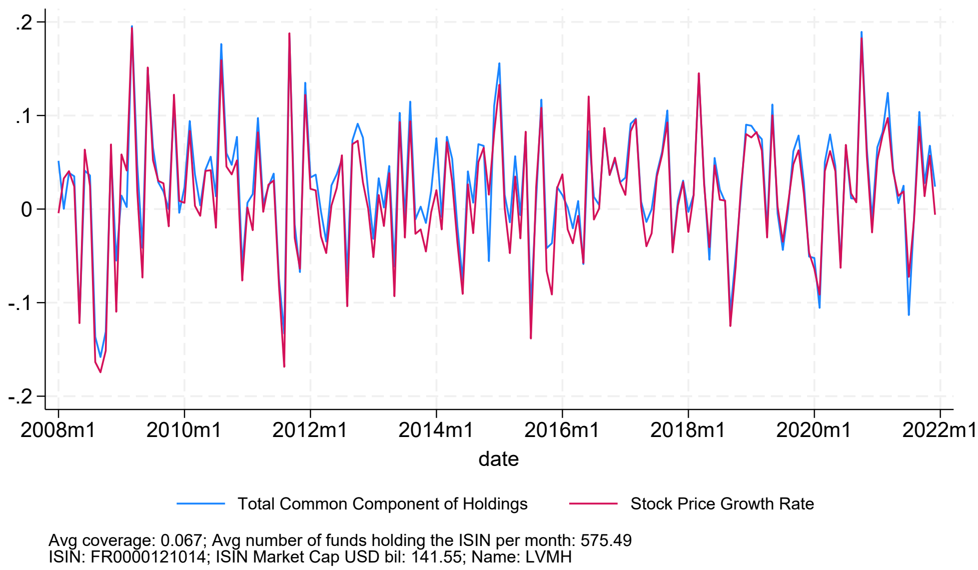


(a) Total

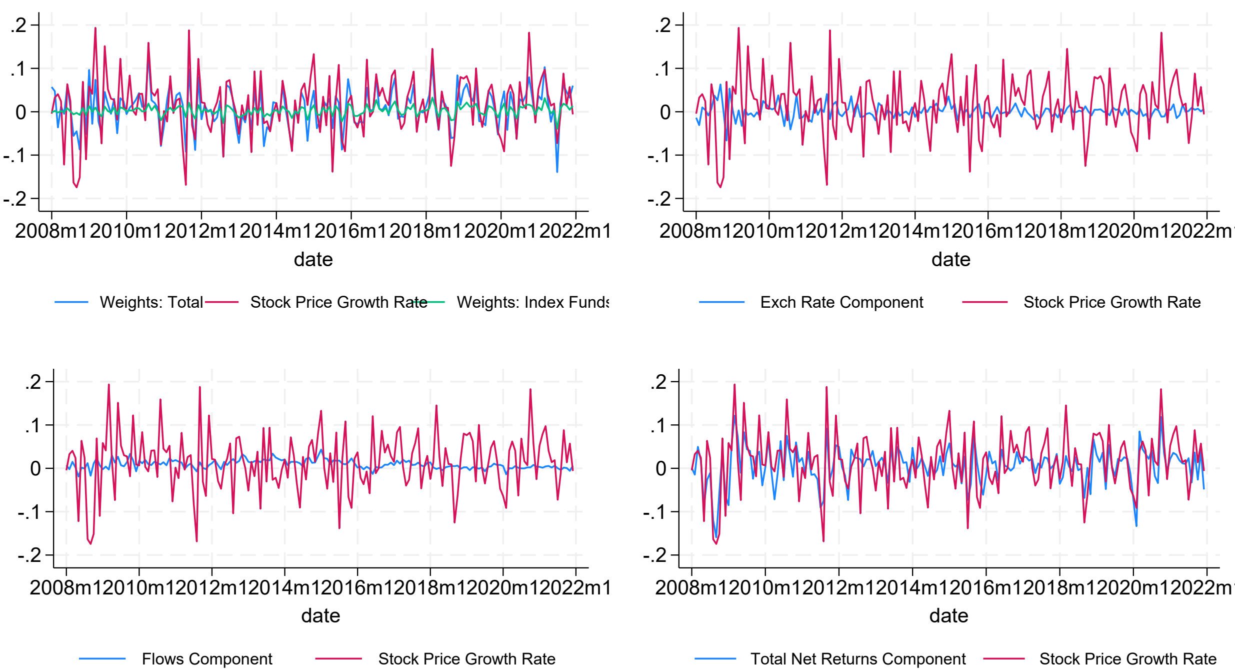


(b) Sub-components

Figure 9: “Common” Equity Holdings Components: LVMH

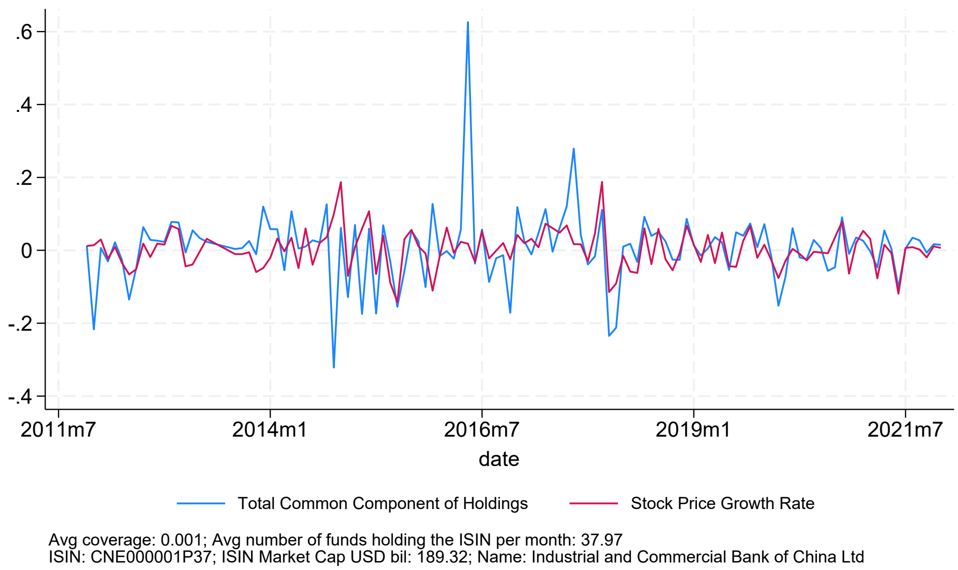


(a) Total

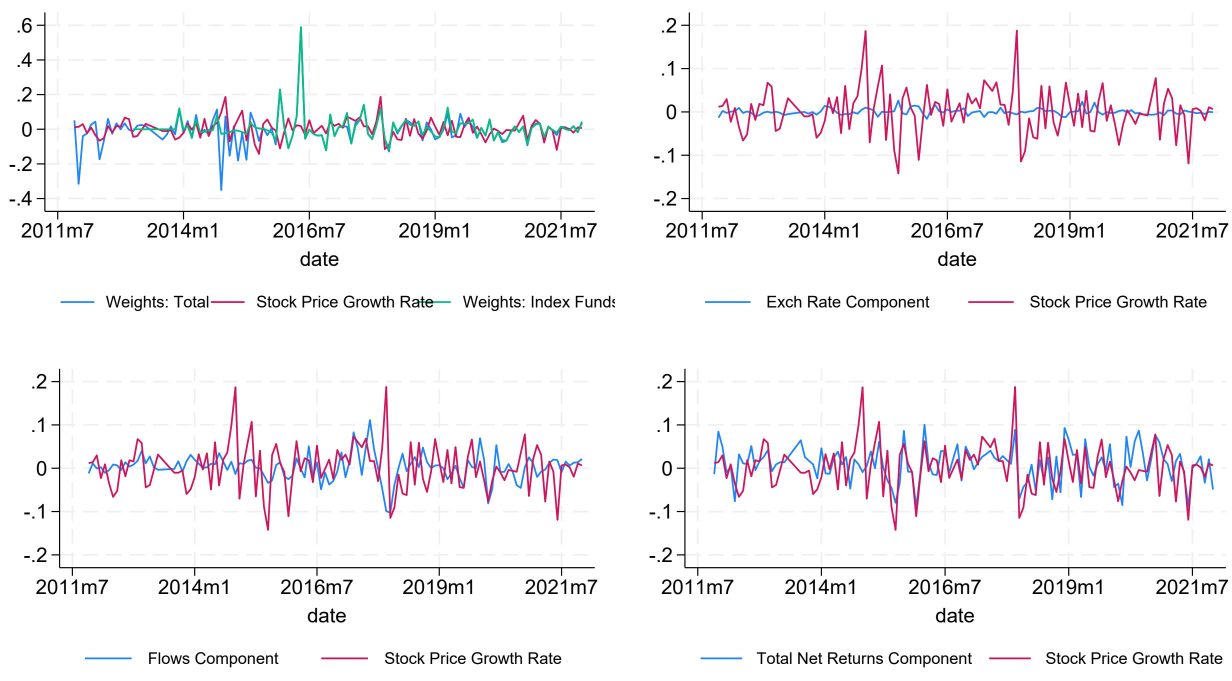


(b) Sub-Components

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

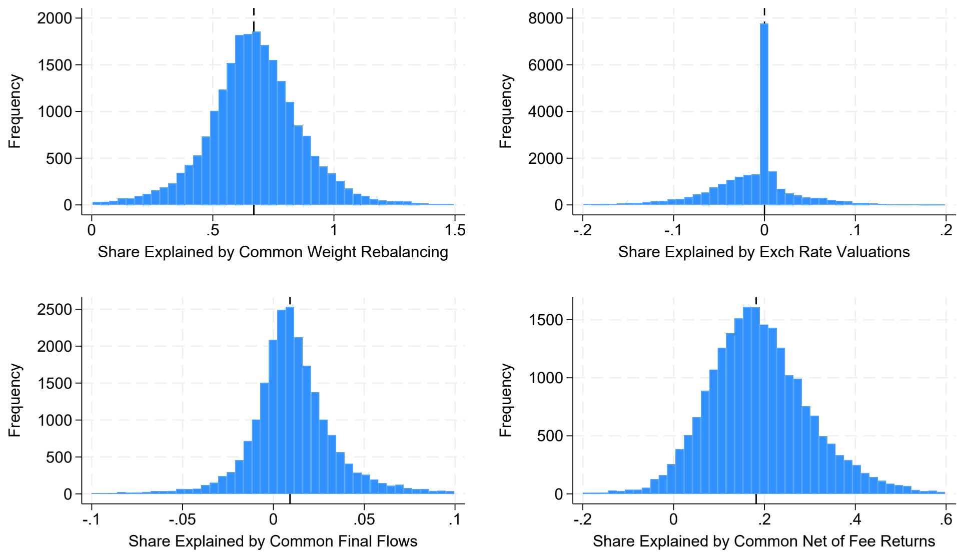


(a) Total



(b) Sub-Components

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



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

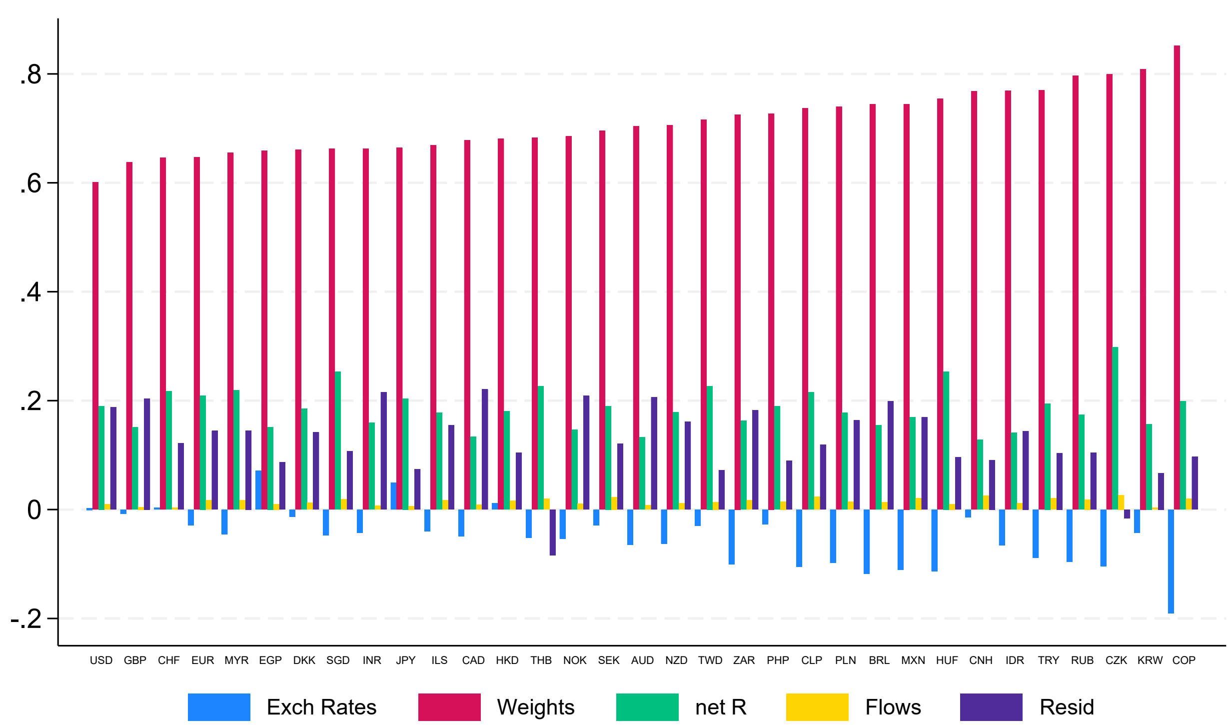


Table 3: ISIN-Level Equity Price Growth Rate Decomposition: Index Funds vs Active Funds Portfolio Weight Changes and Flows: Panel Regressions

Currency	$\Delta d^{\omega,j}_{Index}$	$\Delta d^{\omega,j}_{Active}$	$\Delta d^{f,j}_{Index}$	$\Delta d^{f,j}_{Active}$
AUD	0.183***	0.596***	0.003***	0.006***
BRL	0.203***	0.596***	0.007***	0.008***
CAD	0.173***	0.578***	0.004***	0.008***
CHF	0.265***	0.392***	-0.008***	0.012***
CLP	0.288***	0.542***	0.022***	0.009***
CNH	0.463***	0.450***	0.026***	0.001***
COP	0.414***	0.505***	0.024***	0.001
CZK	0.184***	0.662***	0.021**	0.012
DKK	0.121***	0.584***	0.001	0.012***
EGP	0.169***	0.478***	0.008***	0.002
EUR	0.140***	0.547***	0.006***	0.013***
GBP	0.149***	0.532***	0.001***	0.004***
HKD	0.151***	0.595***	0.007***	0.013***
HUF	0.189***	0.647***	0.014**	0.007
IDR	0.211***	0.648***	0.009***	0.007***
ILS	0.282***	0.468***	0.014***	0.007***
INR	0.123***	0.596***	0.003***	0.007***
JPY	0.347***	0.384***	-0.002***	0.008***
KRW	0.304***	0.674***	-0.002*	0.005***
MXN	0.208***	0.584***	0.009***	0.014***
MYR	0.191***	0.573***	0.013***	0.012***
NOK	0.193***	0.544***	0.004***	0.008***
NZD	0.219***	0.578***	0.011***	0.006***
PHP	0.187***	0.614***	0.009***	0.010***
PLN	0.176***	0.641***	0.009***	0.010***
RUB	0.387***	0.571***	0.011**	0.014***
SEK	0.341***	0.410***	0.016***	0.009***
SGD	0.147***	0.582***	0.008***	0.016***
THB	0.218***	0.582***	0.028***	0.006***
TRY	0.189***	0.653***	0.012***	0.014***
TWD	0.185***	0.617***	0.013***	0.008***
USD	0.211***	0.403***	0.006***	0.004***
ZAR	0.228***	0.550***	0.013***	0.008***

Note: In this table we report the coefficients of panel regressions of the portfolio weight change and flow sub-components, broken down by index funds and active funds, on Δp^j_t by stock market (as denoted by the currency associated with that stock market). We allow for ISIN level fixed effects and cluster the standard errors by ISIN. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%

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

Currency	$\Delta d^{\omega,j}_{OwnCurr}$	$\Delta d^{\omega,j}_{OtherCurr}$	$\Delta d^{f,j}_{OwnCurr}$	$\Delta d^{f,j}_{OtherCurr}$
AUD	0.067***	0.646***	0.001***	0.007***
BRL	0.121***	0.682***	0.002*	0.013***
CAD	.	0.679***	.	0.010***
CHF	0.348***	0.333***	-0.006***	0.010***
CLP	.	0.736***	.	0.024***
CNH	0.117***	0.764***	0.004	0.025***
COP	.	0.868***	.	0.022***
CZK	.	0.832***	.	0.029**
DKK	0.028**	0.651***	0.000	0.012***
EGP	.	0.613***	.	0.008***
EUR	0.194***	0.501***	0.008***	0.011***
GBP	0.487***	0.190***	0.001***	0.004***
HKD	.	0.680***	.	0.017***
HUF	.	0.748***	.	0.014**
IDR	.	0.772***	.	0.012***
ILS	.	0.670***	.	0.017***
INR	0.182***	0.574***	0.000	0.008***
JPY	0.310***	0.440***	-0.003***	0.008***
KRW	0.204***	0.770***	-0.022***	0.008***
MXN	0.159***	0.654***	0.007***	0.016***
MYR	.	0.656***	.	0.017***
NOK	0.187***	0.537***	0.003**	0.008***
NZD	0.174***	0.654***	0.003*	0.011***
PHP	.	0.728***	.	0.015***
PLN	.	0.749***	.	0.015***
RUB	.	0.787***	.	0.019***
SEK	0.275***	0.523***	0.016***	0.010***
SGD	.	0.661***	.	0.019***
THB	.	0.685***	.	0.021***
TRY	.	0.770***	.	0.021***
TWD	.	0.715***	.	0.014***
USD	0.585***	0.021***	0.009***	0.000***
ZAR	.	0.728***	.	0.018***

Note: In this table we report the coefficients of panel regressions of the portfolio weight change and flow sub-components, broken down by own currency and foreign currency investors, on Δp^j_t by stock market (as denoted by the currency associated with that stock market). We allow for ISIN level fixed effects and cluster the standard errors by ISIN. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%

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

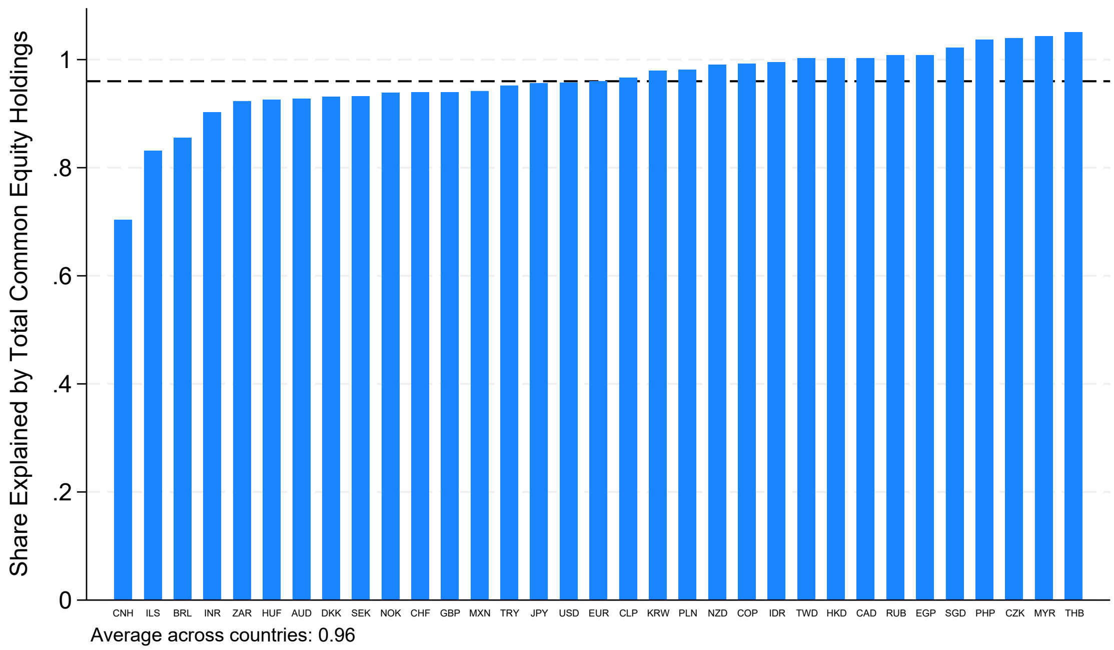


Figure 14: Aggregate Stock Market Price Growth Rate Decomposition

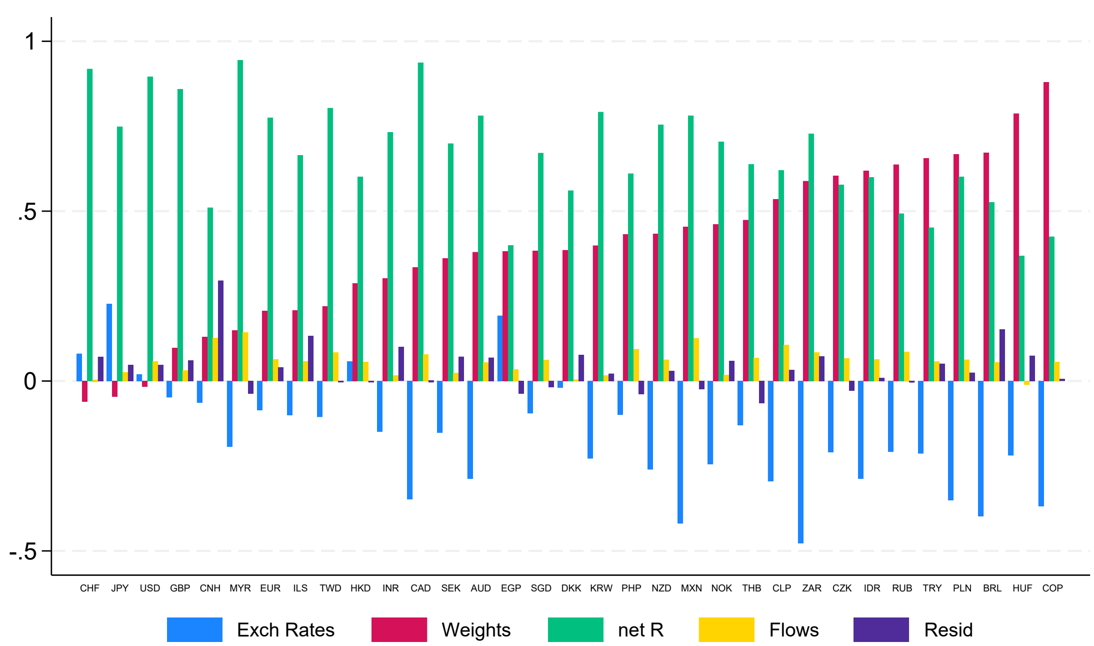
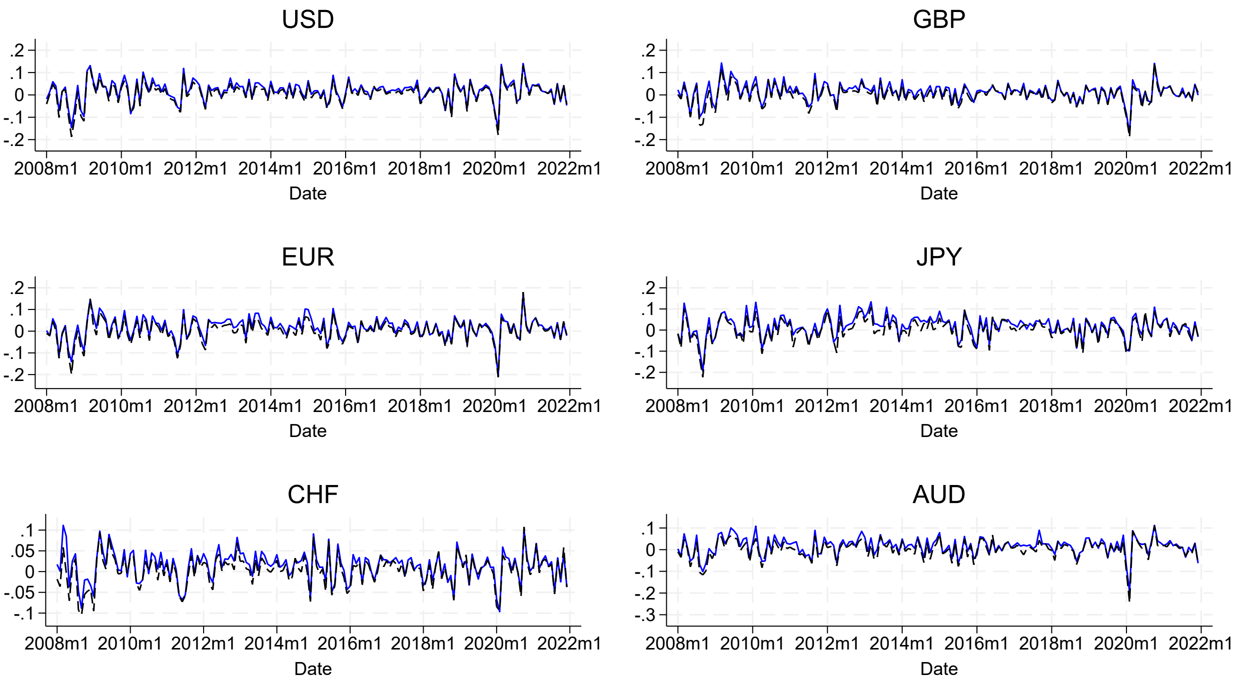


Table 5: Aggregate Stock Market Price Growth Rate Decomposition

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	0.93^{***}	0.91	-0.29^{***}	0.22	0.38^{***}	0.46	0.78^{***}	0.70	0.05^{***}	0.06	0.07^{**}	0.05
BRL	0.86^{***}	0.84	-0.40^{***}	0.42	0.67^{***}	0.62	0.53^{***}	0.60	0.06^{***}	0.09	0.15^{***}	0.15
CAD	1.00^{***}	0.91	-0.35^{***}	0.32	0.33^{***}	0.24	0.94^{***}	0.71	0.08^{***}	0.15	-0.00	-0.01
CHF	0.94^{***}	0.90	0.08^{*}	0.02	-0.06	0.01	0.92^{***}	0.76	0.00	-0.01	0.07^{**}	0.05
CLP	0.97^{***}	0.83	-0.30^{***}	0.16	0.54^{***}	0.26	0.62^{***}	0.35	0.11^{***}	0.17	0.03	-0.00
CNH	0.70^{***}	0.41	-0.06^{***}	0.12	0.13	0.02	0.51^{***}	0.48	0.13^{***}	0.14	0.30^{***}	0.10
COP	0.99^{***}	0.85	-0.37^{***}	0.32	0.88^{***}	0.74	0.43^{***}	0.41	0.06^{***}	0.07	0.01	-0.01
CZK	1.04^{***}	0.82	-0.21^{***}	0.13	0.60^{***}	0.33	0.58^{***}	0.43	0.07^{***}	0.09	-0.03	-0.00
DKK	0.93^{***}	0.87	-0.02	-0.00	0.39^{***}	0.35	0.56^{***}	0.62	0.00	-0.00	0.08	0.04
EGP	1.01^{***}	0.77	0.19^{*}	0.05	0.38^{***}	0.20	0.40^{***}	0.35	0.03^{***}	0.04	-0.04	-0.00
EUR	0.96^{***}	0.96	-0.09^{***}	0.07	0.21^{***}	0.41	0.77^{***}	0.91	0.06^{***}	0.12	0.04^{*}	0.04
GBP	0.94^{***}	0.95	-0.05^{**}	0.04	0.10^{***}	0.11	0.86^{***}	0.89	0.03^{***}	0.05	0.06^{**}	0.05
HKD	1.00^{***}	0.97	0.06^{***}	0.37	0.29^{***}	0.36	0.60^{***}	0.73	0.06^{***}	0.22	-0.00	-0.01
HUF	0.93^{***}	0.69	-0.22^{***}	0.28	0.79^{***}	0.54	0.37^{***}	0.46	-0.01	-0.00	0.07	0.01
IDR	1.00^{***}	0.88	-0.29^{***}	0.41	0.62^{***}	0.46	0.60^{***}	0.53	0.06^{***}	0.13	0.01	-0.01
ILS	0.83^{***}	0.54	-0.10^{***}	0.05	0.21^{**}	0.04	0.66^{***}	0.44	0.06^{**}	0.03	0.13	0.02
INR	0.90^{***}	0.85	-0.15^{***}	0.32	0.30^{***}	0.37	0.73^{***}	0.80	0.02	0.00	0.10^{*}	0.06
JPY	0.96^{***}	0.92	0.23^{***}	0.39	-0.05	0.01	0.75^{***}	0.76	0.03	0.01	0.05^{*}	0.02
KRW	0.98^{***}	0.84	-0.23^{***}	0.17	0.40^{***}	0.42	0.79^{***}	0.72	0.02	-0.00	0.02	-0.00
MXN	0.94^{***}	0.87	-0.42^{***}	0.33	0.45^{***}	0.30	0.78^{***}	0.61	0.13^{***}	0.18	-0.02	-0.00
MYR	1.04^{***}	0.84	-0.19^{***}	0.13	0.15^{**}	0.02	0.94^{***}	0.52	0.14^{***}	0.18	-0.04	0.00
NOK	0.94^{***}	0.76	-0.24^{***}	0.34	0.46^{***}	0.34	0.70^{***}	0.78	0.02	0.01	0.06	0.01
NZD	0.99^{***}	0.83	-0.26^{***}	0.08	0.43^{***}	0.24	0.75^{***}	0.40	0.06^{***}	0.06	0.03	-0.00
PHP	1.04^{***}	0.90	-0.10^{***}	0.14	0.43^{***}	0.30	0.61^{***}	0.46	0.09^{***}	0.19	-0.04	0.01
PLN	0.98^{***}	0.83	-0.35^{***}	0.36	0.67^{***}	0.46	0.60^{***}	0.55	0.06^{***}	0.13	0.02	-0.00
RUB	1.01^{***}	0.54	-0.21^{***}	0.09	0.64^{***}	0.31	0.49^{***}	0.44	0.09^{***}	0.12	-0.00	-0.01
SEK	0.93^{***}	0.92	-0.15^{***}	0.16	0.36^{***}	0.50	0.70^{***}	0.80	0.02	0.02	0.07	0.05
SGD	1.02^{***}	0.95	-0.10^{***}	0.15	0.38^{***}	0.42	0.67^{***}	0.71	0.06^{***}	0.17	-0.02	-0.00
THB	1.05^{***}	0.80	-0.13^{***}	0.21	0.47^{***}	0.30	0.64^{***}	0.55	0.07^{***}	0.05	-0.07	0.01
TRY	0.95^{***}	0.91	-0.21^{**}	0.10	0.66^{***}	0.52	0.45^{***}	0.47	0.06^{***}	0.16	0.05^{*}	0.02
TWD	1.00^{***}	0.90	-0.11^{***}	0.17	0.22^{***}	0.14	0.80^{***}	0.67	0.08^{***}	0.14	-0.00	-0.01
USD	0.96^{***}	0.98	0.02^{***}	0.23	-0.02	0.02	0.90^{***}	0.98	0.06^{***}	0.23	0.05^{**}	0.09
ZAR	0.92^{***}	0.87	-0.48^{***}	0.28	0.59^{***}	0.41	0.73^{***}	0.50	0.08^{***}	0.10	0.07^{**}	0.03

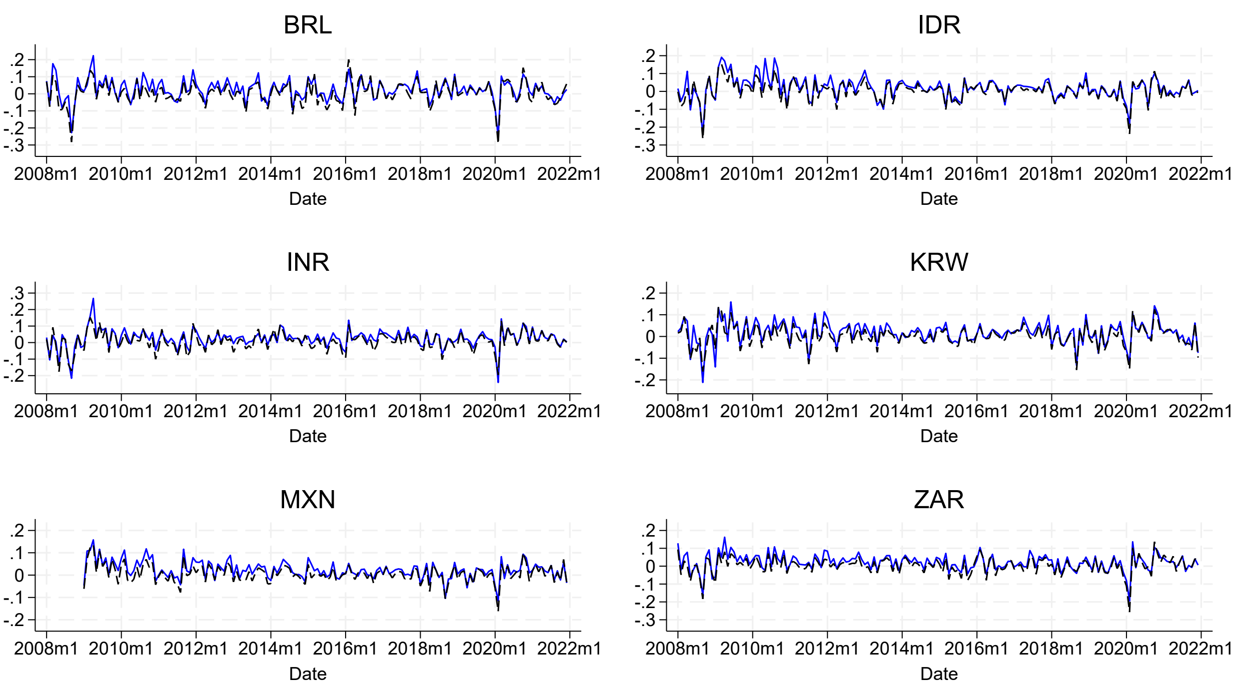
Note: In this table we report the OLS coefficients from regressing the total "common" component of equity holdings and its sub-components on the aggregate stock market price growth rate (where the stock market is denoted by the currency associated with that stock market). We also report the equivalent regression for the residual holdings component. Robust standard errors. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%

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 Sub-components: Portfolio Weight Changes

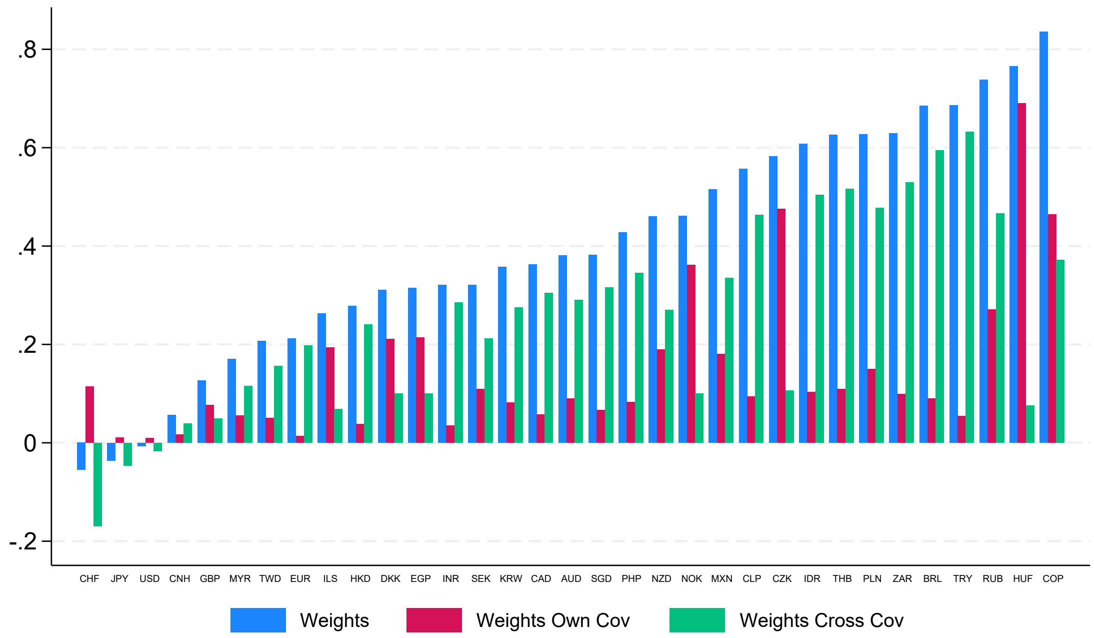


Figure 17: The Importance of Own vs Cross-Covariance Sub-components: Net-of-Fee Returns

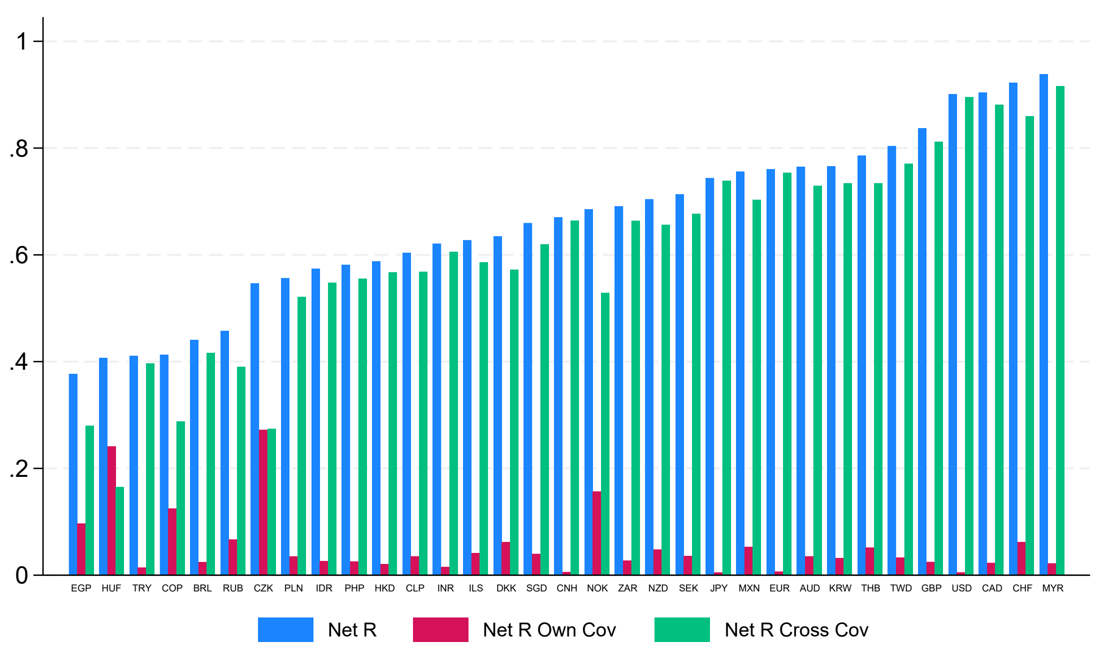
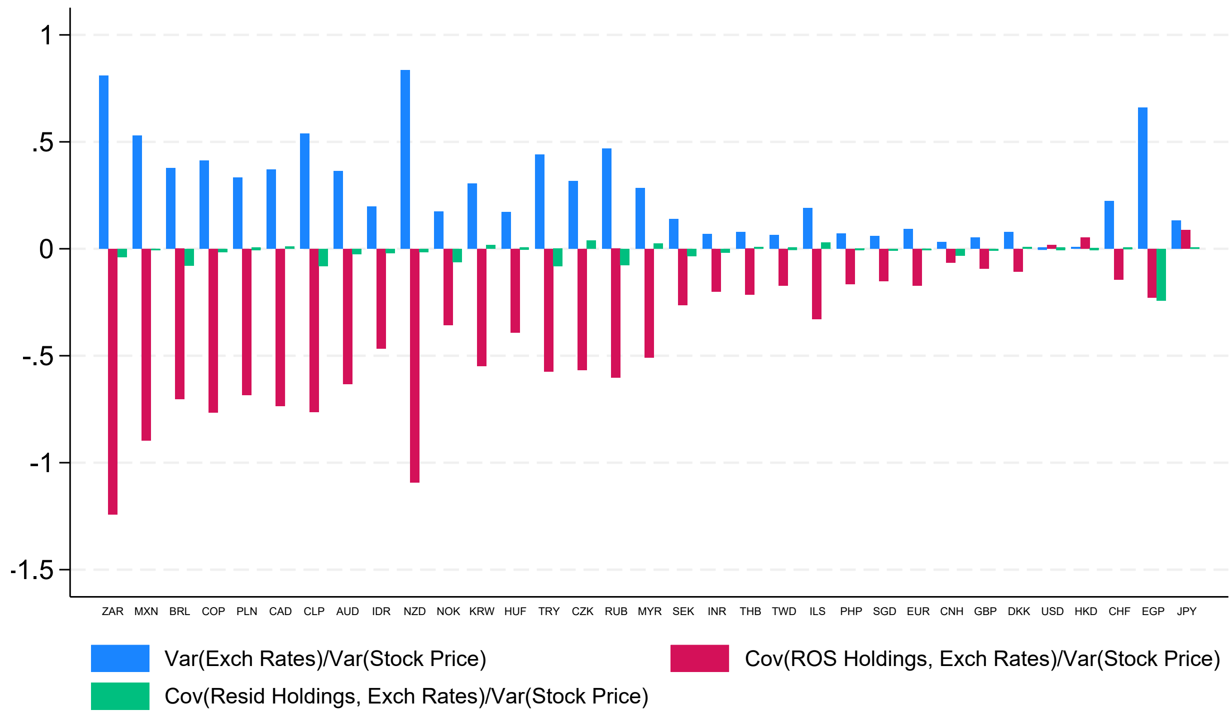


Figure 18: Further Decomposing $\beta^{p,D^{s,l}}$ Using Sub-components of Equity Holdings



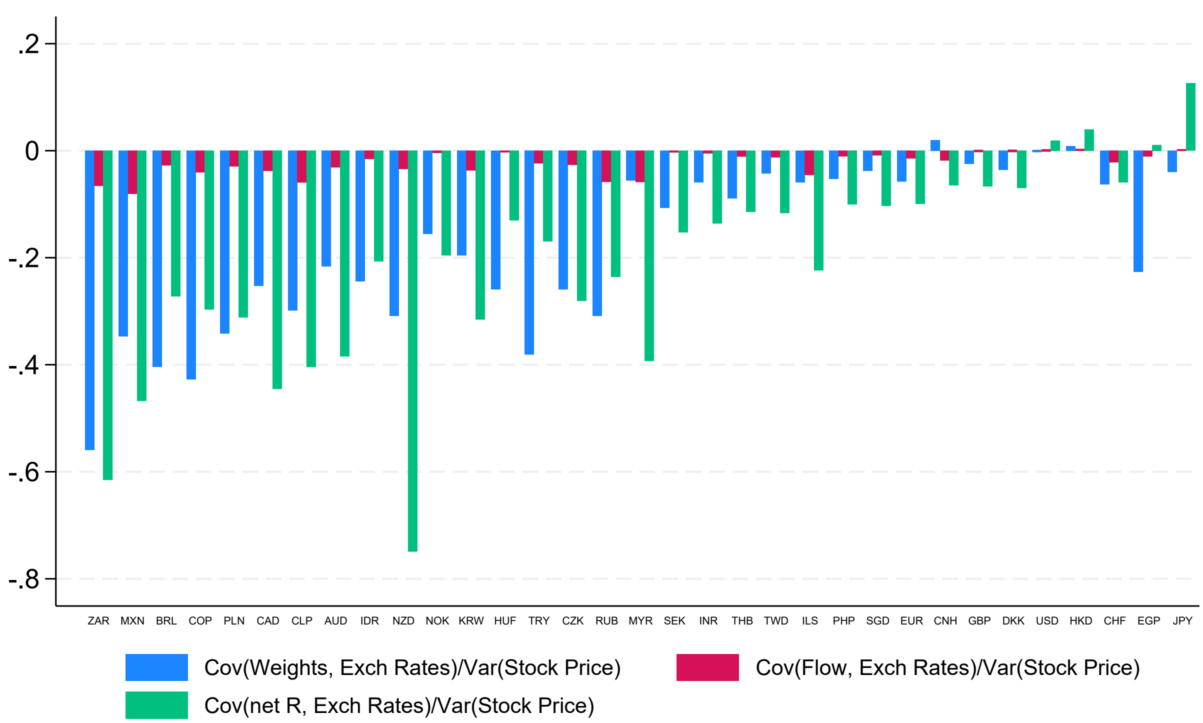


Table 6: Link Between Weighted-Average Exchange Rates and Portfolio Weight Changes or Flow Sub-Components

Currency	$\Delta D^{\omega,l}$	R^2	$\Delta D^{f,l}$	R^2
AUD	-0.69***	0.41	-0.68***	0.05
BRL	-0.55***	0.59	-0.83***	0.05
CAD	-0.56***	0.37	-0.94***	0.09
CHF	-0.29***	0.08	-0.61**	0.06
CLP	-0.27***	0.15	-0.95***	0.10
CNH	0.03	0.01	-0.17**	0.09
COP	-0.41***	0.42	-1.04***	0.09
CZK	-0.24***	0.19	-0.54***	0.04
DKK	-0.08	0.03	-0.04	-0.01
EGP	-0.33	0.11	-0.46	0.00
EUR	-0.56***	0.35	-0.44***	0.07
GBP	-0.29***	0.13	-0.06	-0.00
HKD	0.04*	0.03	0.25***	0.09
HUF	-0.23***	0.34	-0.10	-0.00
IDR	-0.30***	0.36	-0.51**	0.04
ILS	-0.07	0.01	-0.46***	0.10
INR	-0.24***	0.20	-0.16	0.01
JPY	-0.34***	0.10	0.04	-0.01
KRW	-0.52***	0.33	-0.25	0.02
MXN	-0.52***	0.33	-0.93***	0.14
MYR	-0.07	0.01	-0.52***	0.10
NOK	-0.25***	0.22	-0.17	-0.00
NZD	-0.40***	0.14	-0.59	0.02
PHP	-0.09***	0.06	-0.23***	0.03
PLN	-0.36***	0.36	-0.98***	0.08
RUB	-0.24***	0.15	-0.98***	0.12
SEK	-0.41***	0.32	-0.14	-0.00
SGD	-0.11***	0.06	-0.39***	0.05
THB	-0.12***	0.13	-0.14*	0.01
TRY	-0.46***	0.39	-1.15***	0.06
TWD	-0.13***	0.08	-0.25**	0.04
USD	-0.09***	0.07	0.07***	0.03
ZAR	-0.67***	0.46	-1.00***	0.08

Note: In this table we report the coefficients from regressing $D^{s,l}$ on $D^{\omega,l}$ or $D^{f,l}$. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%

Table 7: Stock Picking vs Industry Picking: Panel Regressions

Currency	$\Delta d_t^{\omega,j,Ind}$	$\Delta d^{\omega,j,iid}$	$\Delta d^{\omega,j}$	$\Delta D_t^{\omega,l,Ind}$	$\Delta D^{\omega,l,iid}$	$\Delta D^{\omega,l}$
AUD	0.125***	0.579***	0.704***	0.427***	-0.048*	0.380***
BRL	0.241***	0.504***	0.745***	0.593***	0.079**	0.672***
CAD	0.132***	0.547***	0.678***	0.347***	-0.012	0.335***
CHF	0.076***	0.570***	0.646***	-0.046	-0.015	-0.061
CLP	0.308***	0.429***	0.737***	0.532***	0.003	0.536***
CNH	0.116***	0.652***	0.768***	0.097	0.033	0.130
COP	0.552***	0.300***	0.852***	0.677***	0.203***	0.880***
CZK	0.615**	0.184	0.799***	0.561***	0.043*	0.604***
DKK	0.193***	0.468***	0.661***	0.343***	0.043	0.386***
EGP	0.308***	0.351***	0.659***	0.347***	0.034	0.382***
EUR	0.086***	0.561***	0.647***	0.207***	0.000	0.207***
GBP	0.055***	0.583***	0.638***	0.084*	0.014	0.098***
HKD	0.105***	0.577***	0.681***	0.283***	0.005	0.288***
HUF	0.552***	0.202***	0.754***	0.716***	0.072*	0.788***
IDR	0.216***	0.553***	0.769***	0.643***	-0.024	0.619***
ILS	0.171***	0.499***	0.669***	0.206***	0.002	0.208**
INR	0.172***	0.491***	0.663***	0.375***	-0.073***	0.302***
JPY	0.024***	0.641***	0.664***	-0.062	0.016	-0.046
KRW	0.134***	0.674***	0.809***	0.348***	0.051*	0.399***
MXN	0.197***	0.548***	0.745***	0.351***	0.102**	0.454***
MYR	0.093***	0.563***	0.655***	0.178**	-0.029	0.149**
NOK	0.189***	0.496***	0.685***	0.537***	-0.076	0.461***
NZD	0.215***	0.491***	0.706***	0.488***	-0.055**	0.433***
PHP	0.215***	0.513***	0.727***	0.441***	-0.010	0.431***
PLN	0.258***	0.482***	0.740***	0.688***	-0.020	0.668***
RUB	0.353***	0.444***	0.797***	0.522***	0.115	0.637***
SEK	0.132***	0.564***	0.696***	0.348***	0.013	0.361***
SGD	0.170***	0.492***	0.662***	0.369***	0.015	0.384***
THB	0.241***	0.441***	0.683***	0.445***	0.029	0.474***
TRY	0.293***	0.476***	0.770***	0.664***	-0.008	0.656***
TWD	0.145***	0.570***	0.716***	0.343***	-0.123***	0.220***
USD	0.044***	0.556***	0.601***	0.054***	-0.071***	-0.017
ZAR	0.174***	0.551***	0.725***	0.560***	0.028*	0.589***

Note: In this table we report the coefficients of panel regressions (for the ISIN level decomposition) and OLS regressions (for the stock market decomposition) of the "common" portfolio weight change sub-component, which is further broken down into industry and idiosyncratic components, on either the equity price growth rate or the stock market price growth rate, respectively. For the panel level regressions we allow for ISIN level fixed effects and cluster the standard errors by ISIN and for the OLS regressions we use robust standard errors. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%

A Online Appendix

A.1 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:

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

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 sub-components as arithmetic averages and residuals, we obtain the following expression for equity price growth rates:

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

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:

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

where

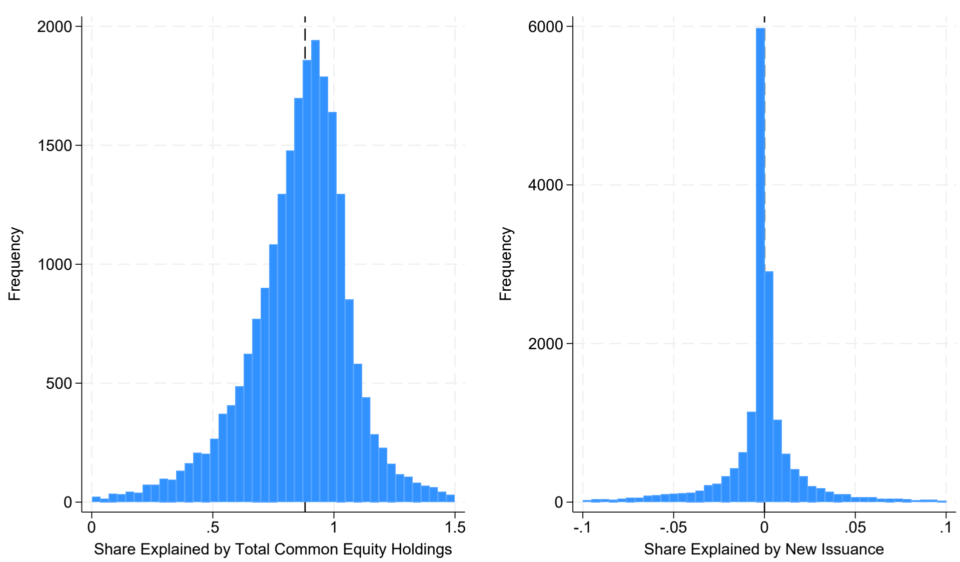
$$\begin{aligned}
\Delta\tilde{d}_t^{s,j} &= \frac{1}{\Theta^j}\sum_{\tau\in\Upsilon}\sum_{\left\{i:\ i\in\tilde{I}\cap c^i\in m\cap\Delta X_t^{i,j}\neq 0\right\}}\frac{\mu^{i,j}}{\sum_{i\in\tilde{I}}\mu^{i,j}}\left(\Delta s_t^{l/m}\right),\\
\Delta\tilde{d}_t^{f,j} &= \frac{1}{\Theta^j}\sum_{\tau\in\Upsilon}\sum_{\left\{i:\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

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

At monthly frequency, in our sample, equity mutual funds change their shares held across two consecutive months, on average, about 60% of the time, for a given ISIN.[28] That number is around 77% at quarterly frequency. The equivalent numbers for allocation funds are 63% at monthly and 79% at quarterly frequency.[29]

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 A.19: IISIN-Level Equity Price Growth Rate Decomposition: Histograms (Marginal Traders)



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

[29]In contrast, for fixed income funds, the equivalent numbers are 31% and 49% 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 A.20: ISIN-Level Equity Price Growth Rate Decomposition: Histograms Sub-Components (Marginal Traders)

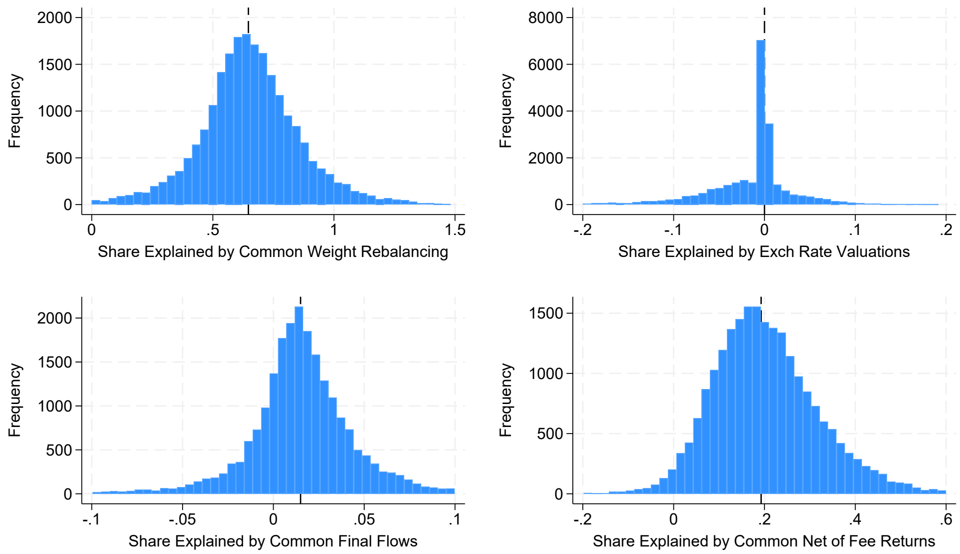


Figure A.21: ISIN-Level Equity Price Growth Rate Decomposition:: Panel Regressions (Marginal Traders)

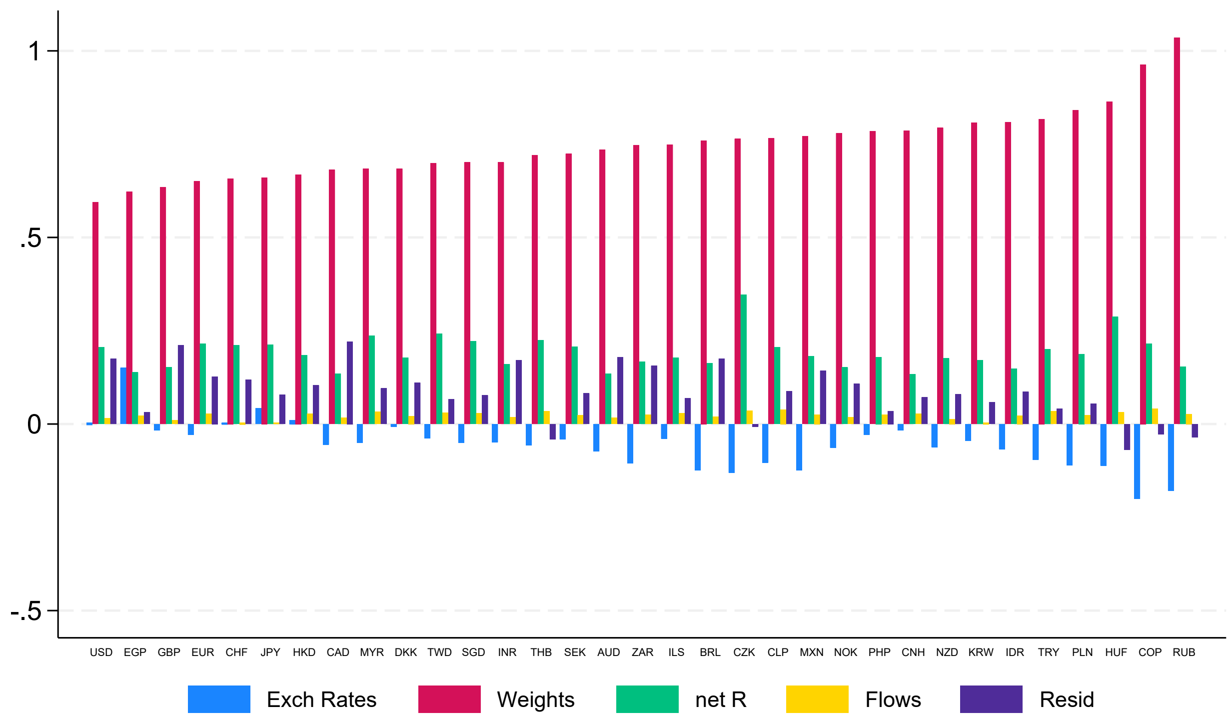


Table A.8: ISIN-Level Equity Price Growth Rate Decomposition: Panel Regressions (Marginal Traders)

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	0.815***	0.735***	-0.073***	0.017***	0.135***	0.178***	-0.006**
BRL	0.819***	0.760***	-0.124***	0.020***	0.163***	0.175***	-0.007**
CAD	0.778***	0.681***	-0.055***	0.017***	0.135***	0.221***	0.001
CHF	0.873***	0.658***	0.002	0.002	0.211***	0.118***	-0.009**
CLP	0.908***	0.766***	-0.104***	0.039***	0.206***	0.088***	0.004
CNH	0.929***	0.786***	-0.017***	0.027***	0.133***	0.071***	0.000
COP	1.019***	0.964***	-0.201***	0.041***	0.216***	-0.027	-0.007
CZK	1.015***	0.764***	-0.131***	0.035	0.346***	-0.007	0.005
DKK	0.877***	0.684***	-0.007**	0.021***	0.178***	0.110***	-0.013*
EGP	0.934***	0.623***	0.150***	0.022***	0.139***	0.032	-0.029***
EUR	0.865***	0.651***	-0.029***	0.028***	0.215***	0.127***	-0.007***
GBP	0.780***	0.634***	-0.017***	0.010***	0.152***	0.212***	-0.005
HKD	0.892***	0.669***	0.011***	0.028***	0.184***	0.104***	-0.003
HUF	1.072***	0.864***	-0.112**	0.032***	0.288***	-0.070	0.002
IDR	0.913***	0.809***	-0.067***	0.023***	0.148***	0.086***	0.001
ILS	0.916***	0.749***	-0.039***	0.029***	0.178***	0.069***	-0.013
INR	0.831***	0.701***	-0.049***	0.018***	0.161***	0.170***	0.001
JPY	0.919***	0.661***	0.042***	0.004***	0.213***	0.079***	-0.002**
KRW	0.936***	0.808***	-0.045***	0.002	0.171***	0.059***	-0.003**
MXN	0.854***	0.771***	-0.124***	0.025***	0.182***	0.143***	-0.003
MYR	0.903***	0.684***	-0.050***	0.032***	0.237***	0.095***	-0.001
NOK	0.886***	0.779***	-0.063***	0.018***	0.152***	0.108***	-0.006
NZD	0.921***	0.794***	-0.062***	0.013***	0.176***	0.079***	0.000
PHP	0.961***	0.785***	-0.028***	0.025***	0.180***	0.035*	-0.002
PLN	0.942***	0.841***	-0.110***	0.024***	0.188***	0.055***	-0.003
RUB	1.037***	1.035***	-0.178***	0.027***	0.153***	-0.036	0.001
SEK	0.914***	0.724***	-0.041***	0.024***	0.207***	0.082***	-0.003
SGD	0.902***	0.701***	-0.050***	0.029***	0.222***	0.077***	-0.014*
THB	0.922***	0.720***	-0.057***	0.034***	0.225***	-0.041	-0.094***
TRY	0.957***	0.817***	-0.095***	0.035***	0.200***	0.041***	-0.001
TWD	0.934***	0.699***	-0.039***	0.031***	0.242***	0.066***	0.001
USD	0.817***	0.594***	0.001***	0.016***	0.206***	0.175***	-0.003***
ZAR	0.834***	0.747***	-0.105***	0.025***	0.167***	0.156***	-0.009

Note: In this table we report the coefficients from panel regressions of the total "common" component of equity holdings (and its sub-components) on Δp_t^j by stock market (as denoted by the currency associated with that stock market). We also report the coefficients from panel regressions of the change in ISIN-level shares issued and the residual holdings sub-component on Δp_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 A.22: Aggregate Stock Market Price Growth Rate Decomposition

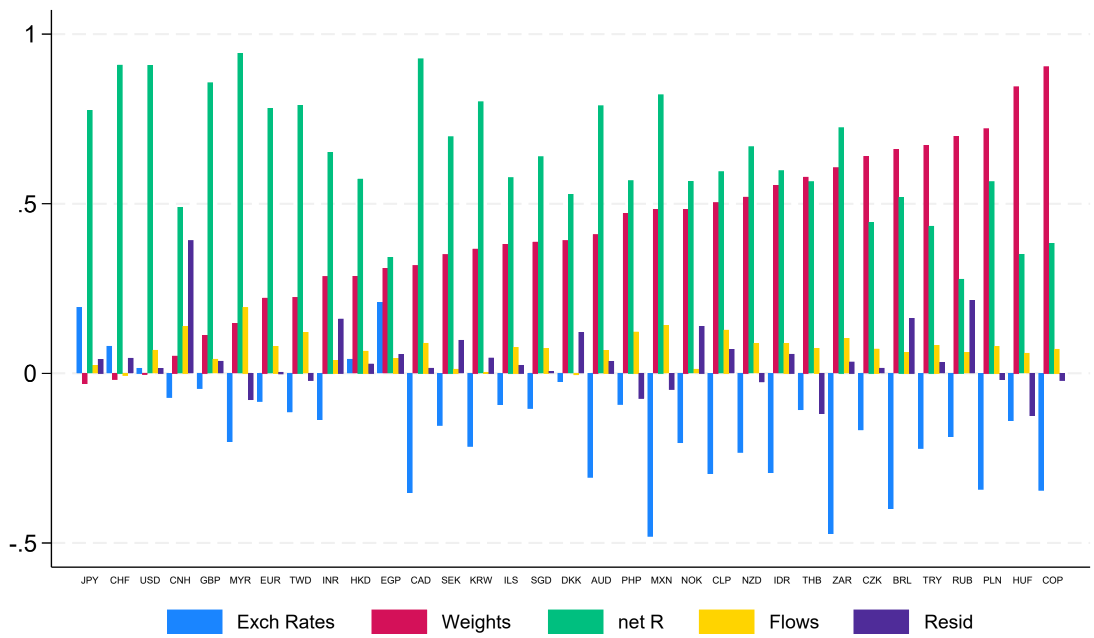


Table A.9: Aggregate Stock Market Price Growth Rate Decomposition

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	0.96***	0.89	-0.31***	0.23	0.41***	0.44	0.79***	0.69	0.07***	0.06	0.04	0.00
BRL	0.84***	0.80	-0.40***	0.43	0.66***	0.62	0.52***	0.61	0.06***	0.08	0.16***	0.13
CAD	0.98***	0.87	-0.35***	0.33	0.32***	0.24	0.93***	0.73	0.09***	0.13	0.02	-0.00
CHF	0.97***	0.92	0.08**	0.03	-0.02	-0.00	0.91***	0.77	-0.01	-0.01	0.05	0.02
CLP	0.93***	0.68	-0.30***	0.16	0.50***	0.22	0.59***	0.35	0.13***	0.15	0.07	0.01
CNH	0.61***	0.21	-0.07***	0.14	0.05	-0.01	0.49***	0.43	0.14***	0.15	0.39***	0.09
COP	1.02***	0.75	-0.34***	0.32	0.91***	0.66	0.38***	0.37	0.07***	0.07	-0.02	-0.01
CZK	0.99***	0.71	-0.17***	0.14	0.64***	0.33	0.45***	0.39	0.07***	0.08	0.02	-0.01
DKK	0.89***	0.83	-0.03	0.00	0.39***	0.33	0.53***	0.60	-0.01	-0.00	0.12**	0.07
EGP	0.91***	0.60	0.21	0.10	0.31**	0.08	0.34***	0.38	0.04***	0.05	0.06	-0.00
EUR	1.00***	0.94	-0.08***	0.08	0.22***	0.44	0.78***	0.91	0.08***	0.11	0.00	-0.01
GBP	0.97***	0.94	-0.05**	0.03	0.11***	0.12	0.86***	0.88	0.04***	0.06	0.04	0.01
HKD	0.97***	0.95	0.04***	0.38	0.29***	0.35	0.57***	0.71	0.07***	0.23	0.03	0.01
HUF	1.12***	0.44	-0.14**	0.07	0.85***	0.26	0.35***	0.31	0.06***	0.06	-0.13	0.00
IDR	0.95***	0.83	-0.29***	0.43	0.55***	0.40	0.60***	0.53	0.09***	0.13	0.06	0.01
ILS	0.94***	0.55	-0.09***	0.04	0.38***	0.12	0.58***	0.37	0.08***	0.04	0.02	-0.01
INR	0.84***	0.82	-0.14***	0.32	0.29***	0.34	0.65***	0.77	0.04	0.02	0.16***	0.14
JPY	0.96***	0.88	0.19***	0.35	-0.03	0.01	0.78***	0.80	0.02	0.00	0.04	0.01
KRW	0.95***	0.70	-0.22***	0.18	0.37***	0.39	0.80***	0.76	0.00	-0.01	0.05	-0.00
MXN	0.97***	0.83	-0.48***	0.36	0.48***	0.32	0.82***	0.59	0.14***	0.16	-0.05	0.01
MYR	1.08***	0.64	-0.20***	0.13	0.15*	0.02	0.94***	0.49	0.19***	0.16	-0.08	0.00
NOK	0.86***	0.74	-0.21***	0.32	0.48***	0.41	0.57***	0.72	0.01	-0.00	0.14**	0.06
NZD	1.04***	0.69	-0.23***	0.07	0.52***	0.26	0.67***	0.40	0.09***	0.06	-0.03	-0.00
PHP	1.07***	0.78	-0.09***	0.12	0.47***	0.27	0.57***	0.42	0.12***	0.15	-0.07	0.01
PLN	1.02***	0.70	-0.34***	0.36	0.72***	0.42	0.57***	0.54	0.08***	0.12	-0.02	-0.01
RUB	0.85***	0.42	-0.19**	0.12	0.70***	0.31	0.28***	0.32	0.06***	0.07	0.22	0.04
SEK	0.91***	0.86	-0.15***	0.17	0.35***	0.43	0.70***	0.80	0.01	-0.00	0.10	0.06
SGD	1.00***	0.91	-0.10***	0.16	0.39***	0.40	0.64***	0.68	0.07***	0.14	0.01	-0.01
THB	1.11***	0.64	-0.11***	0.16	0.58***	0.26	0.57***	0.49	0.07***	0.06	-0.12*	0.01
TRY	0.97***	0.85	-0.22***	0.11	0.67***	0.51	0.43***	0.45	0.08***	0.18	0.03	0.00
TWD	1.02***	0.82	-0.11***	0.19	0.22***	0.12	0.79***	0.66	0.12***	0.16	-0.02	-0.00
USD	0.99***	0.97	0.02***	0.23	-0.00	-0.01	0.91***	0.98	0.07***	0.23	0.01	0.00
ZAR	0.96***	0.81	-0.47***	0.28	0.61***	0.41	0.73***	0.49	0.10***	0.08	0.03	-0.00

Note: In this table we report the OLS coefficients from regressing the total "common" component of equity holdings and its sub-components on the aggregate stock market price growth rate (where the stock market is denoted by the currency associated with that stock market). We also report the equivalent regression for the residual holdings component. Robust standard errors. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%

A.2 Additional Figures Using Monthly Sample

Figure A.23: Total AUM USD Trillions; Monthly

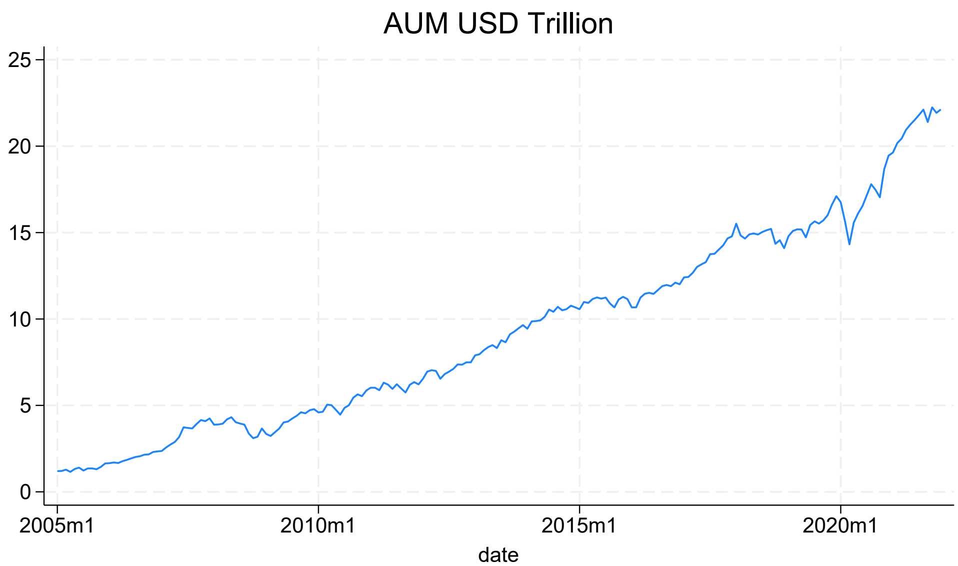


Figure A.24: Sample Aggregate vs Market Index Stock Return Correlations

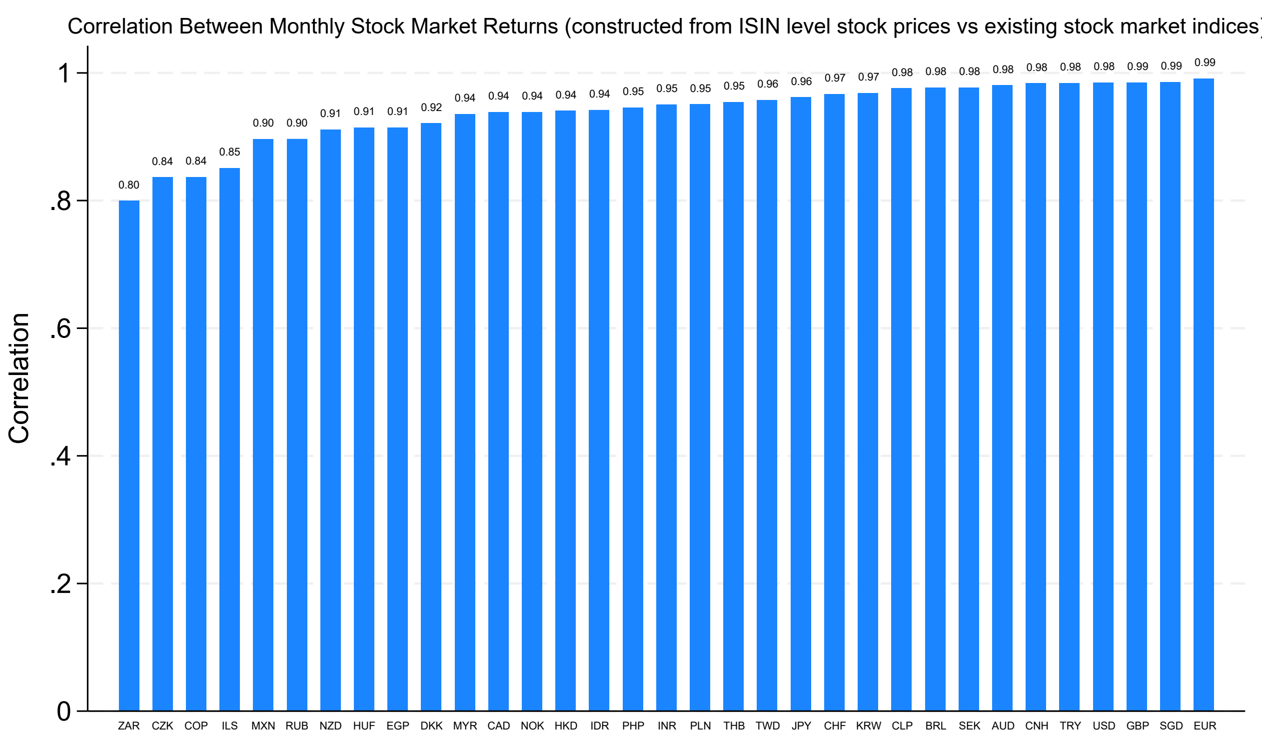


Figure A.25: Number of Funds Within Each Type (for Net-of-Fee Returns and Flows Components)

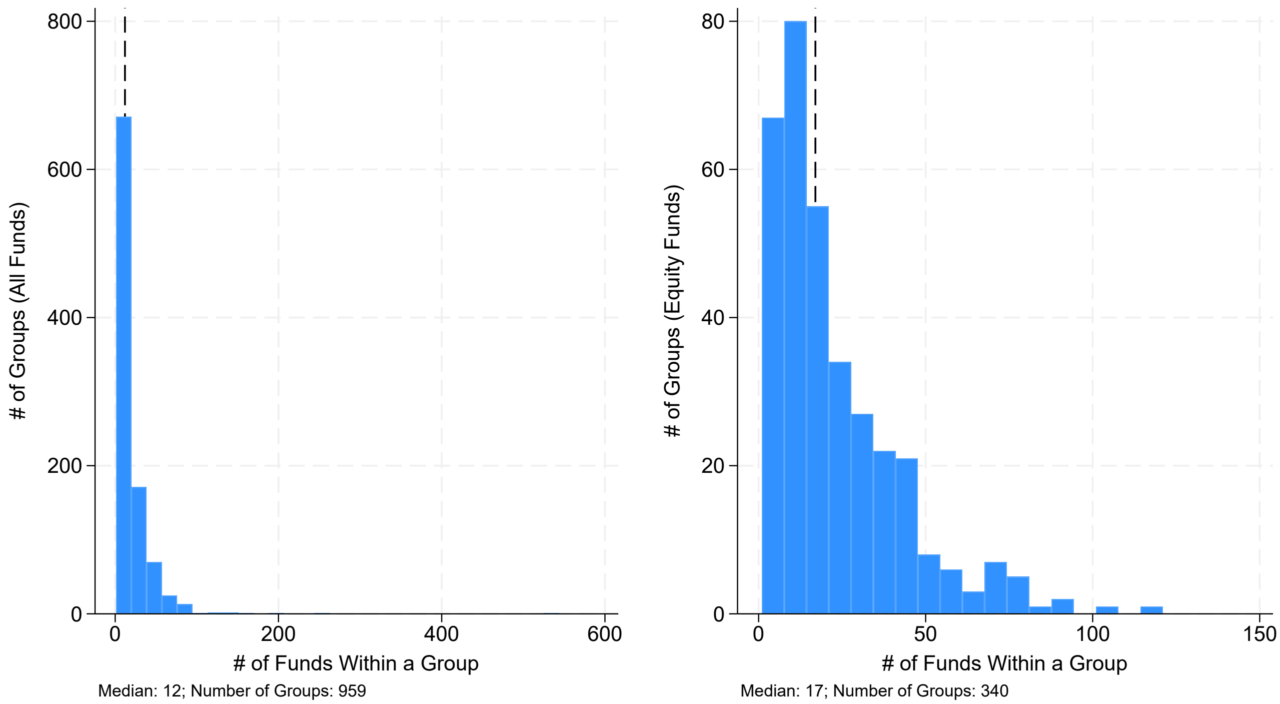
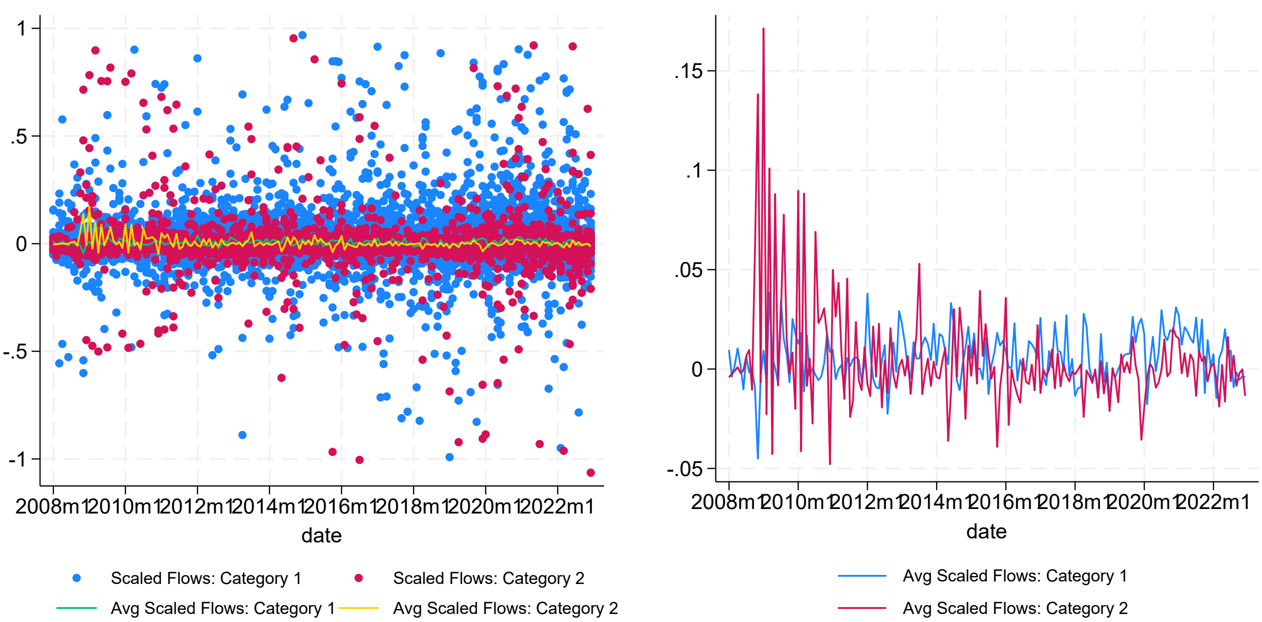
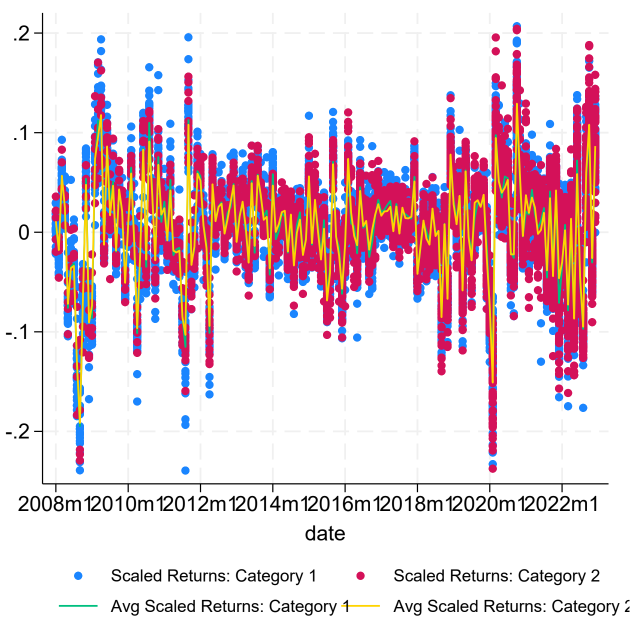


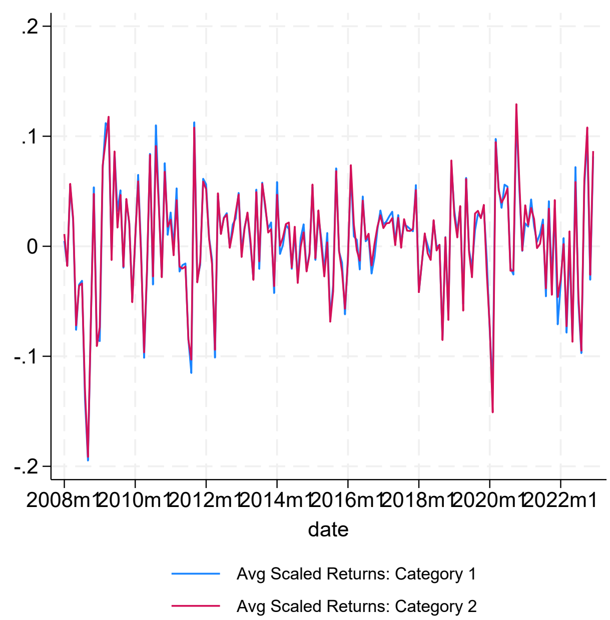
Figure A.26: Examples of Fund-level and Average Scaled Flows For Select Categories



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

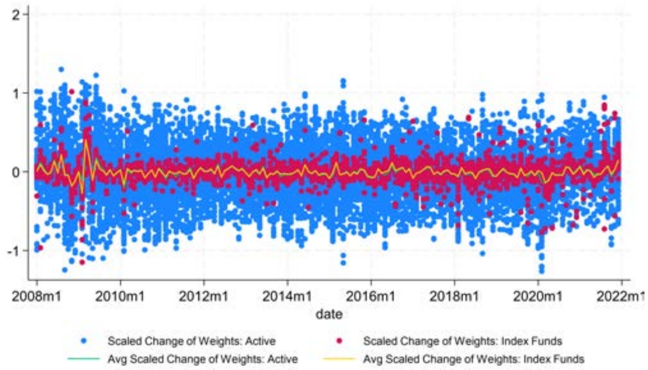
Figure A.27: Examples of Fund-level and Average Scaled Net-of-Fee Returns For Select Categories



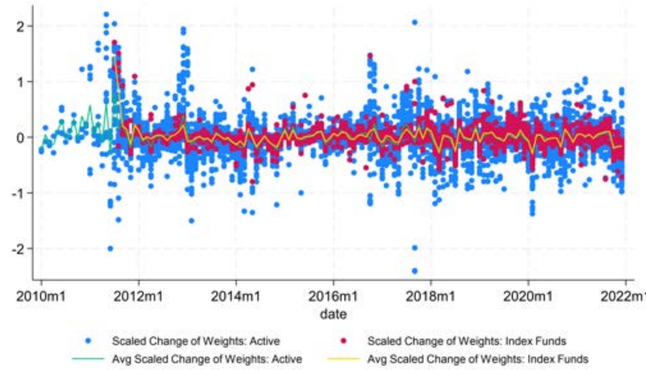


Equity Funds; USD ROS currency;
Category 1: Active: more active; Freq Rebalance: re-balancing frequently; size of fund: <=1bil and >100mil; GlobalCategory: Global Equity Large Cap
Category 2: Active: more active; Freq Rebalance: re-balancing less frequently; size of fund: <=100mil; GlobalCategory: Global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

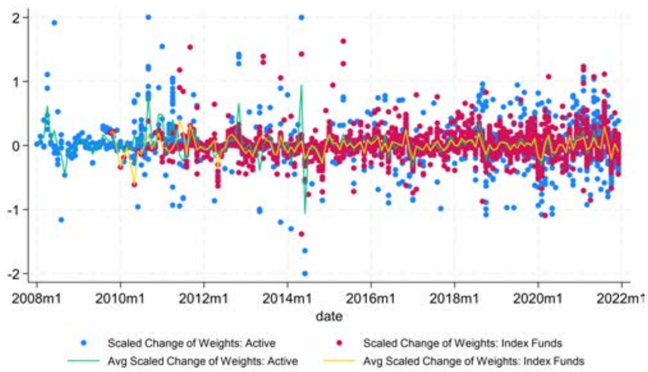
Figure A.28: Portfolio Weight Changes for Select Stocks



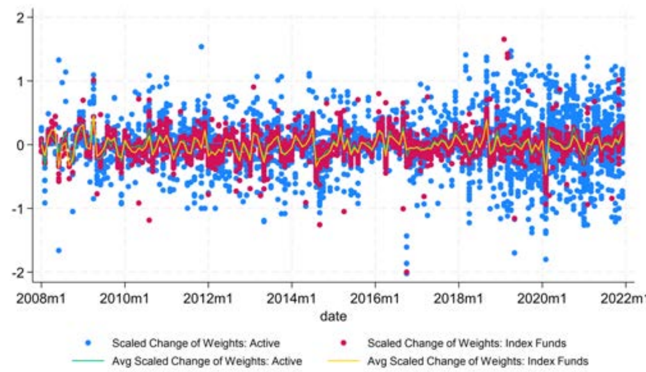
(a) HSBC



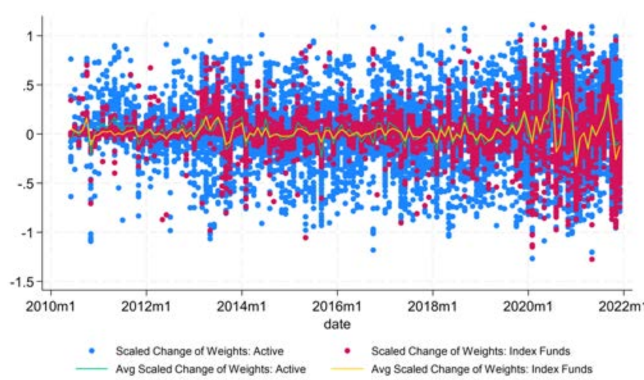
(b) Sberbank Rossii



(c) Rosneft

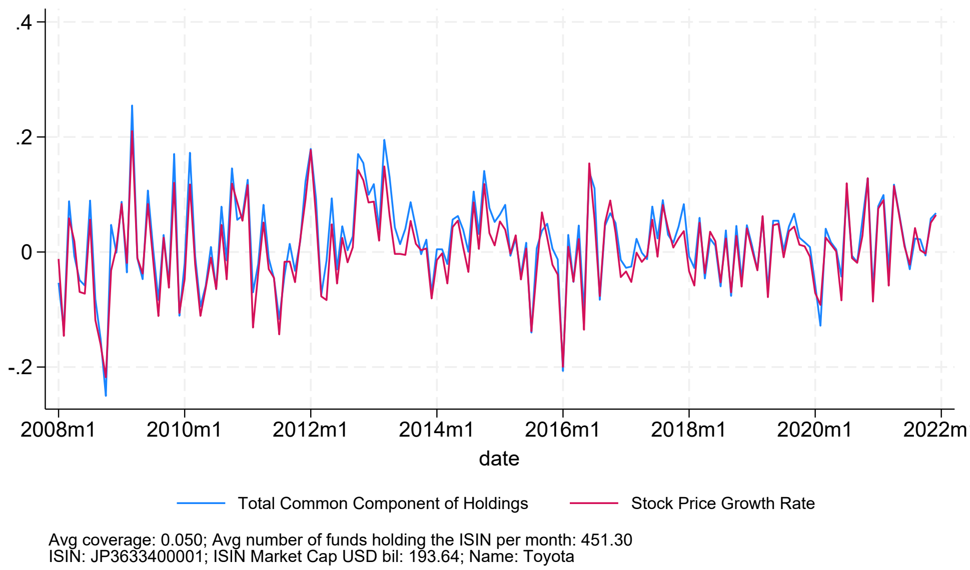


(d) Petrobras

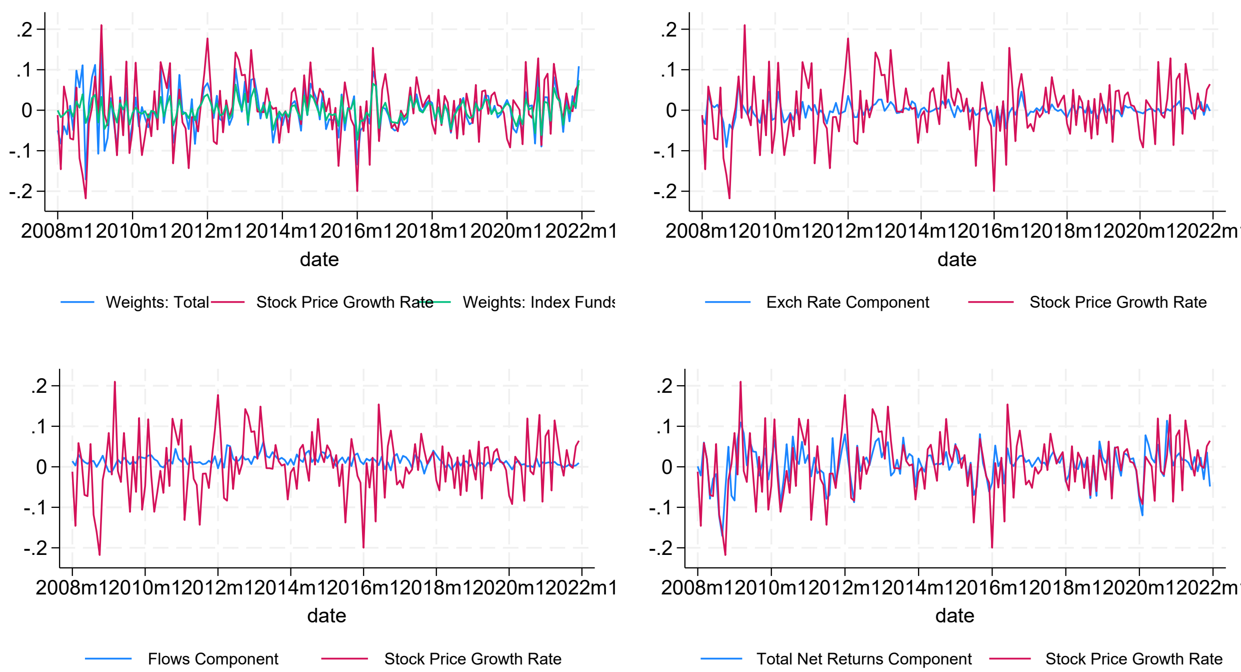


(e) Tesla

Figure A.29: "Common" Equity Holdings Components: Toyota

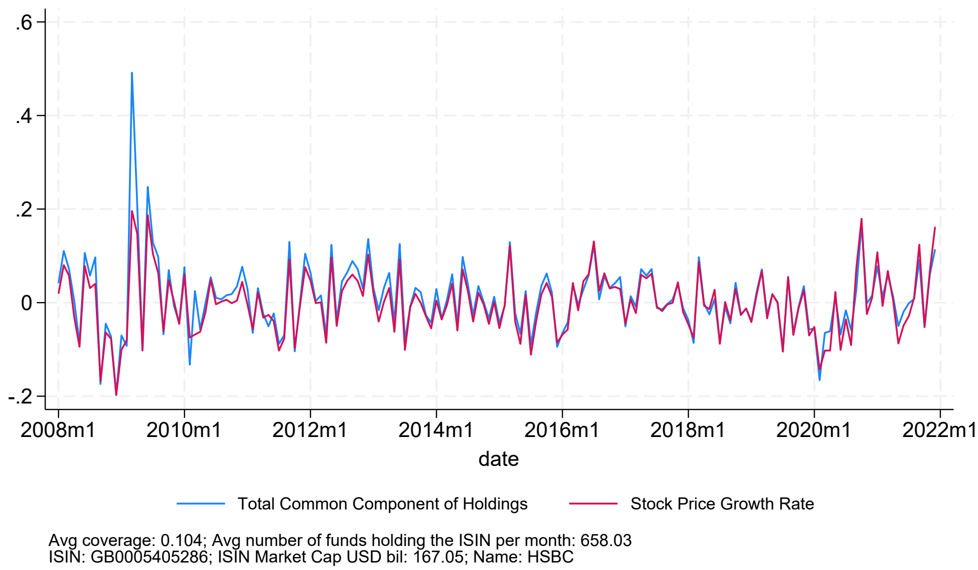


(a) Total

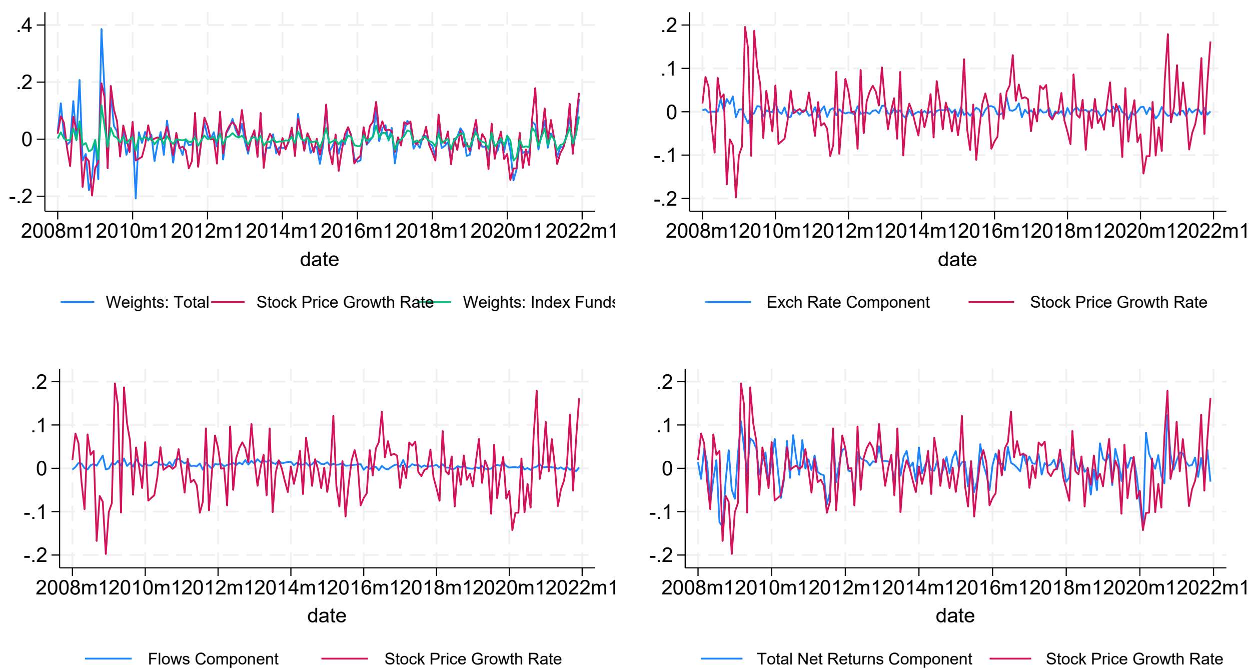


(b) Sub-Components

Figure A.30: "Common" Equity Holdings Components: HSBC

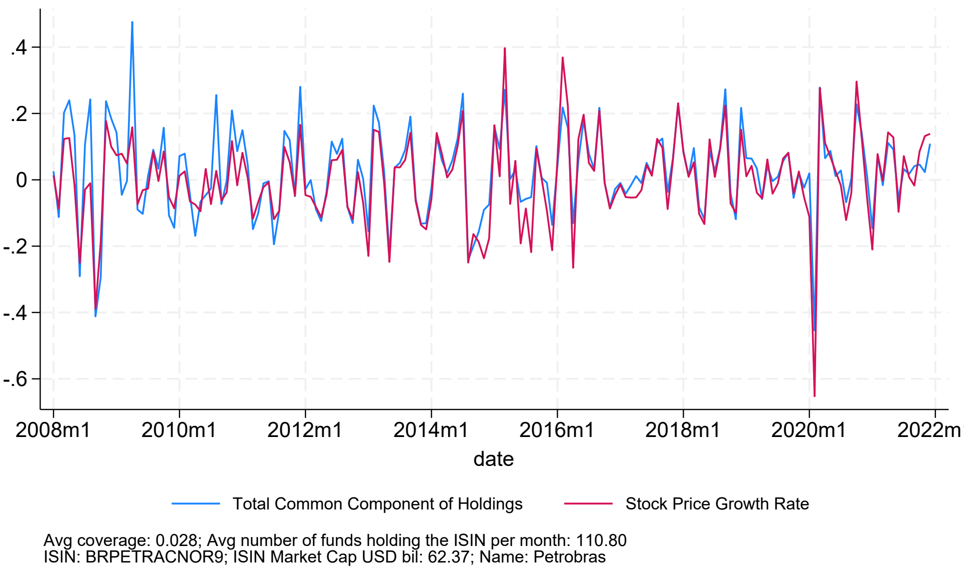


(a) Total

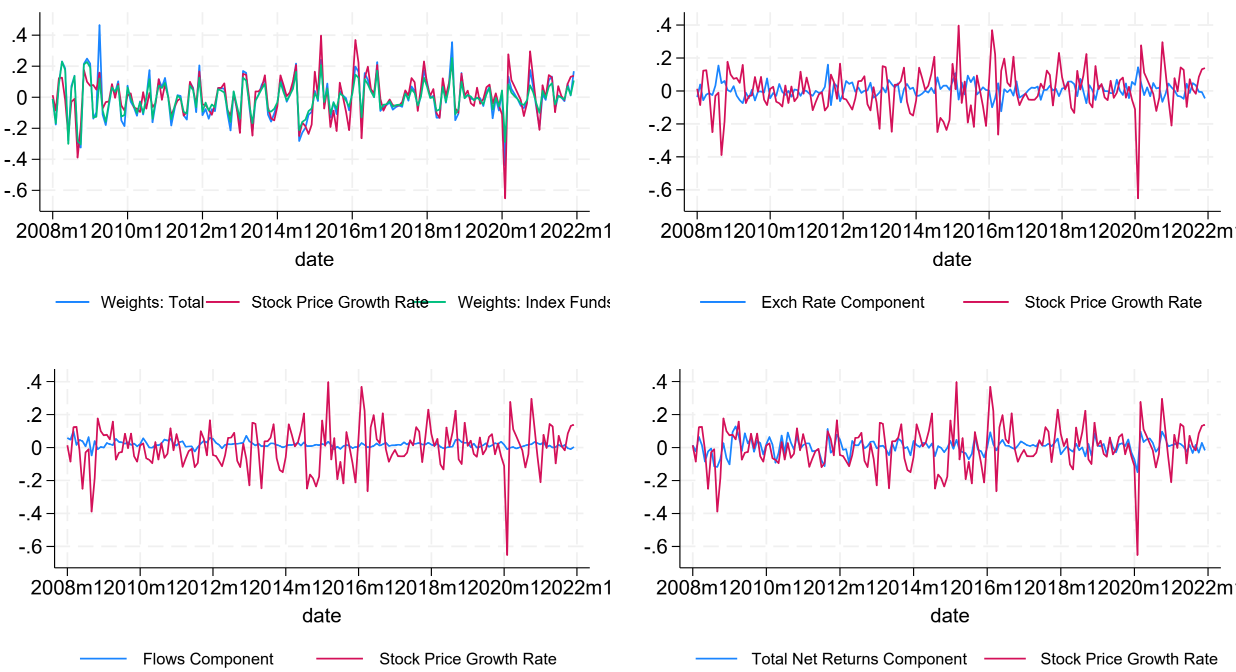


(b) Sub-Components

Figure A.31: "Common" Equity Holdings Components: Petrobras

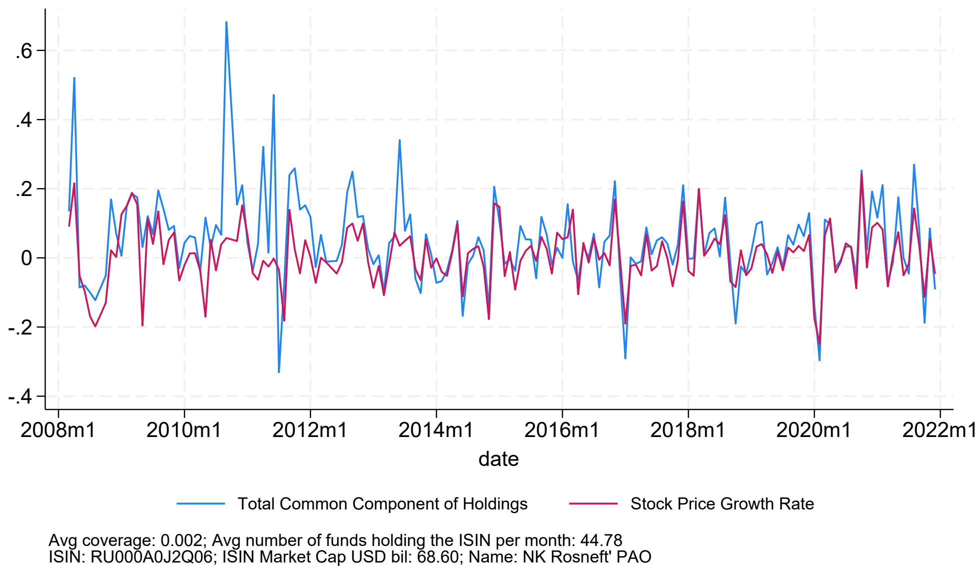


(a) Total

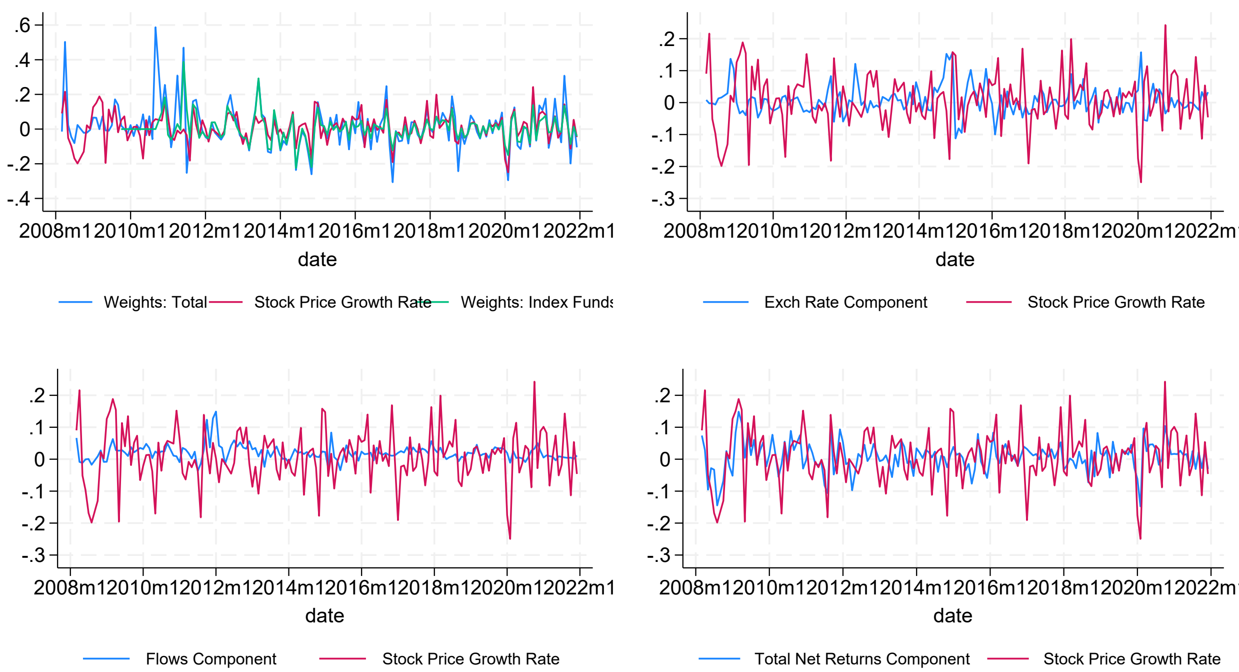


(b) Sub-Components

Figure A.32: "Common" Equity Holdings Components: NK Rosneft' PAO

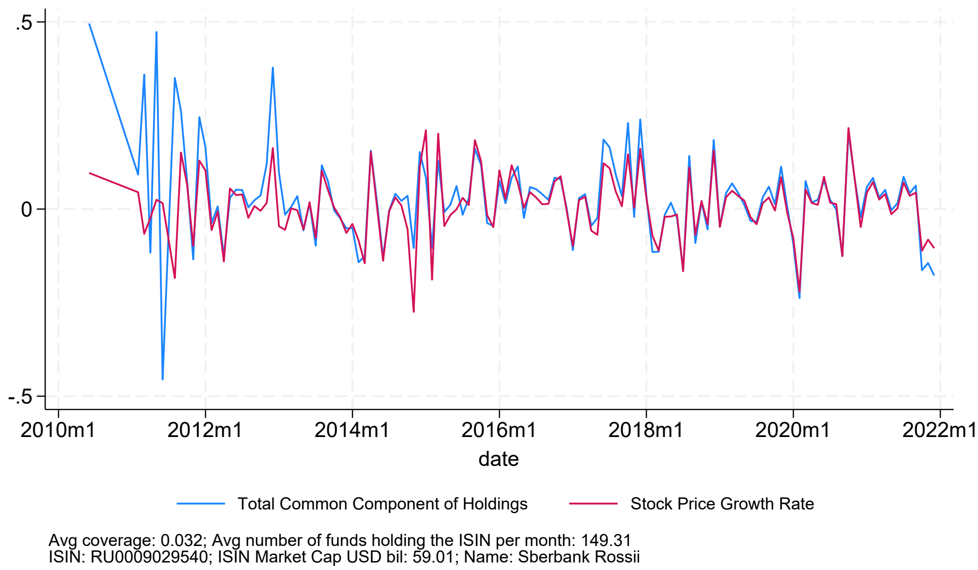


(a) Total

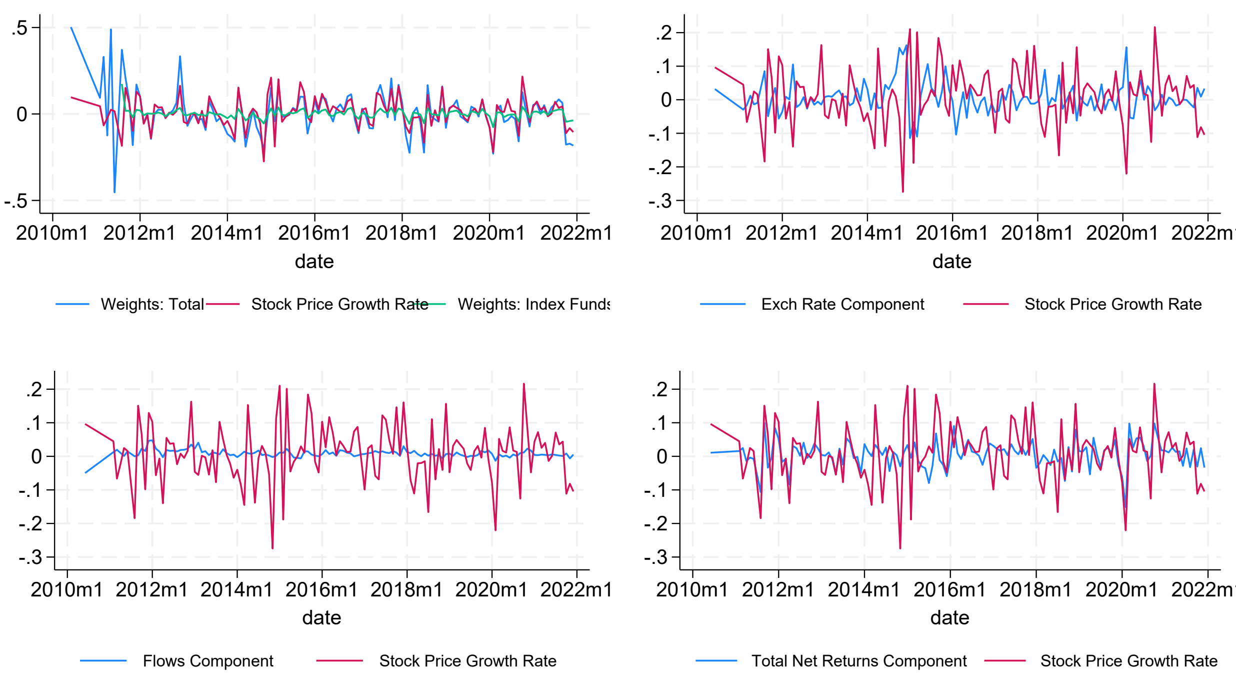


(b) Sub-Components

Figure A.33: “Common” Equity Holdings Components: Sberbank Rossii

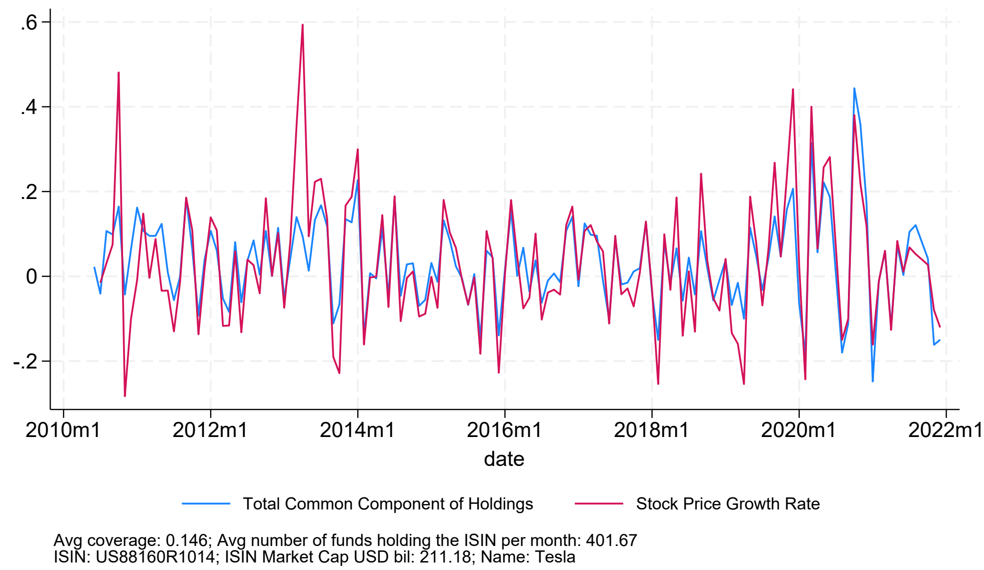


(a) Total

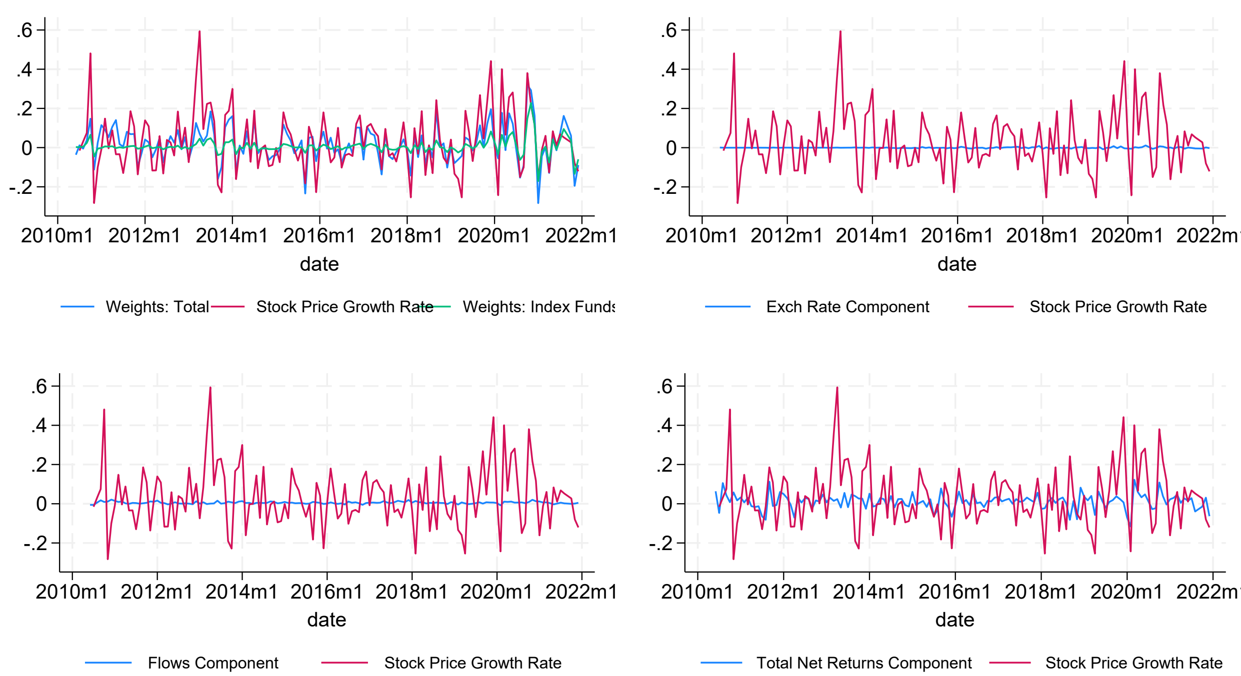


(b) Sub-Components

Figure A.34: "Common" Equity Holdings Components: Tesla



(a) Total



(b) Sub-Components

Figure A.35: ISIN-Level Equity Price Growth Rate Decomposition: Index Funds vs Active Funds Portfolio Weight Changes: Panel Regressions

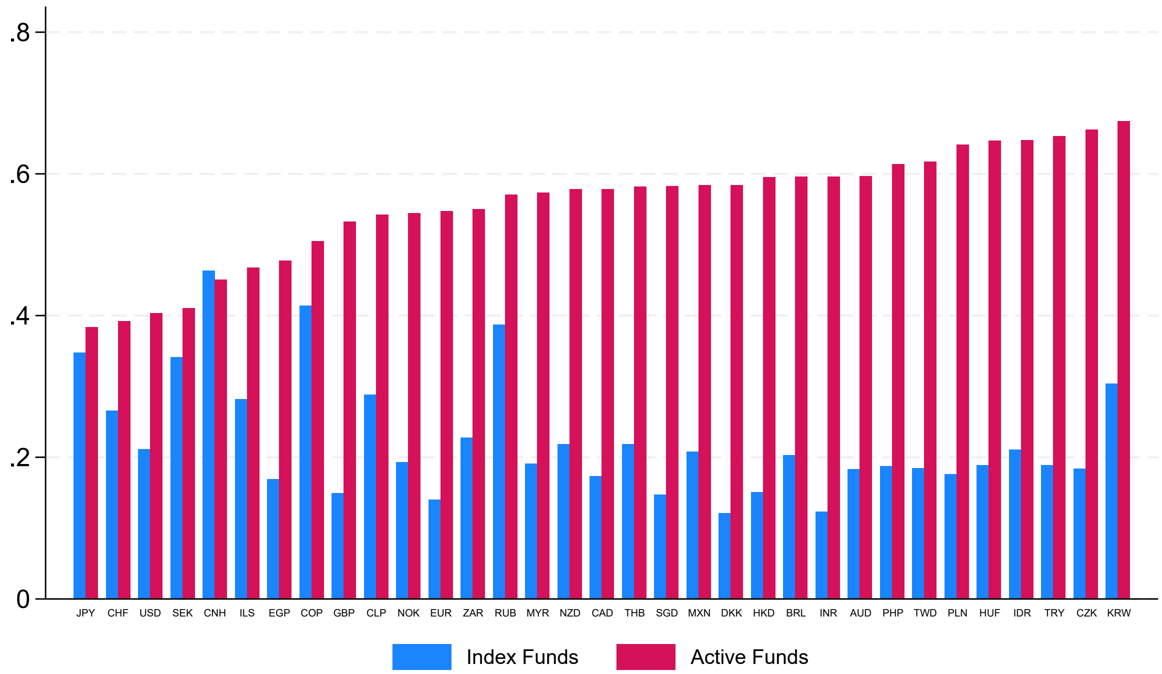


Figure A.36: ISIN-Level Equity Price Growth Rate Decomposition: Index Funds vs Active Funds Flows: Panel Regressions

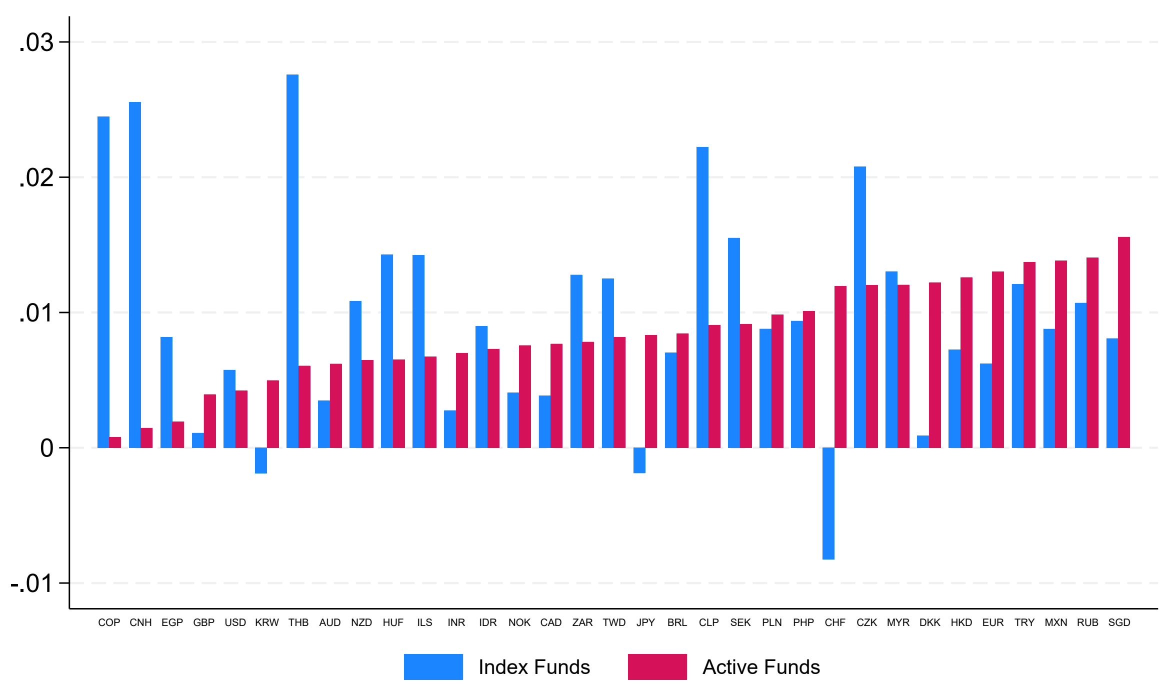


Figure A.37: ISIN-Level Equity Price Growth Rate Decomposition: Own vs Other Currency Investors Portfolio Weight Changes: Panel Regressions

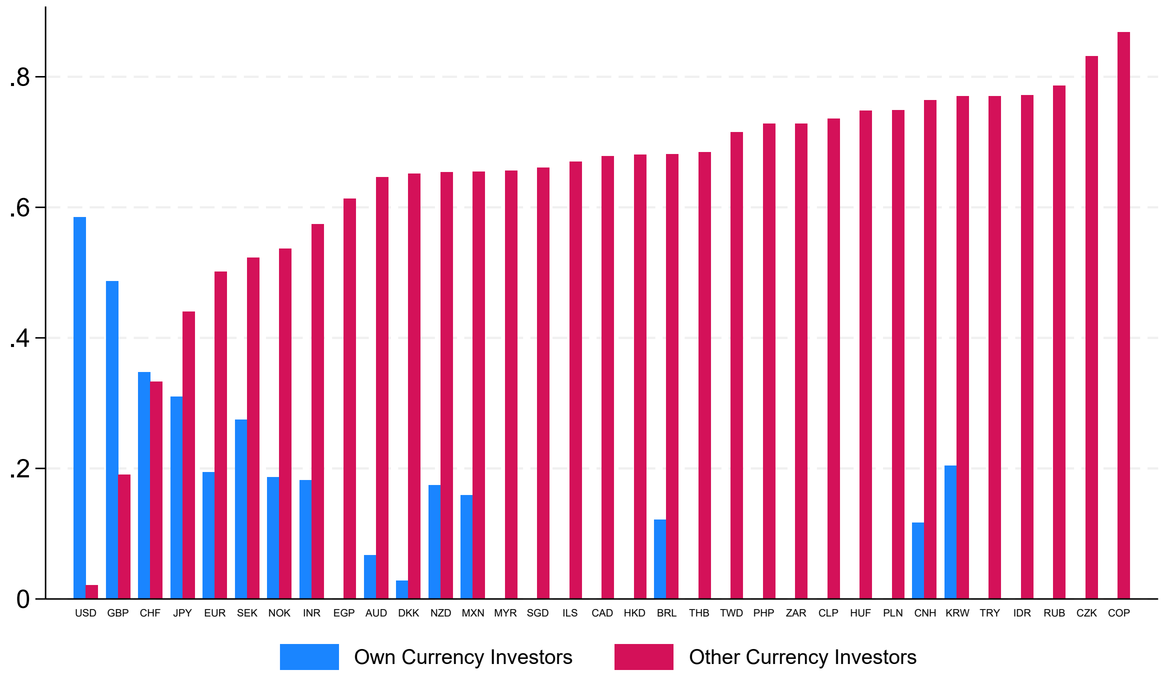


Figure A.38: ISIN Level Equity Price Growth Rate Decomposition: Own vs Other Currency Investors Flows: Panel Regressions

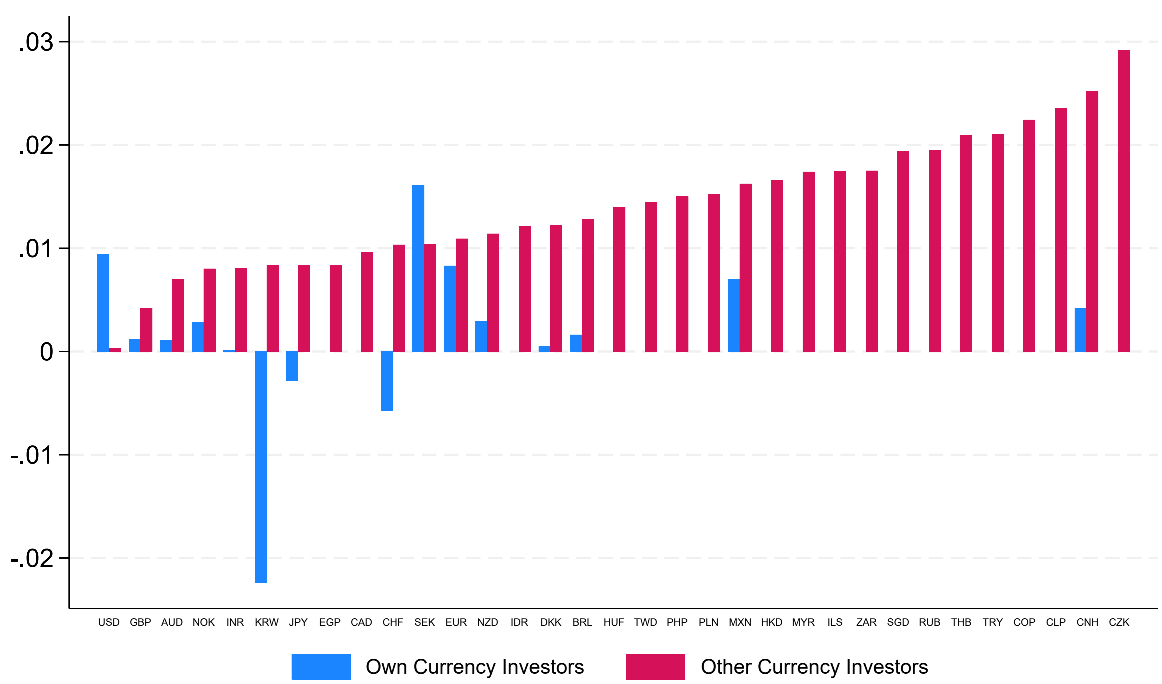
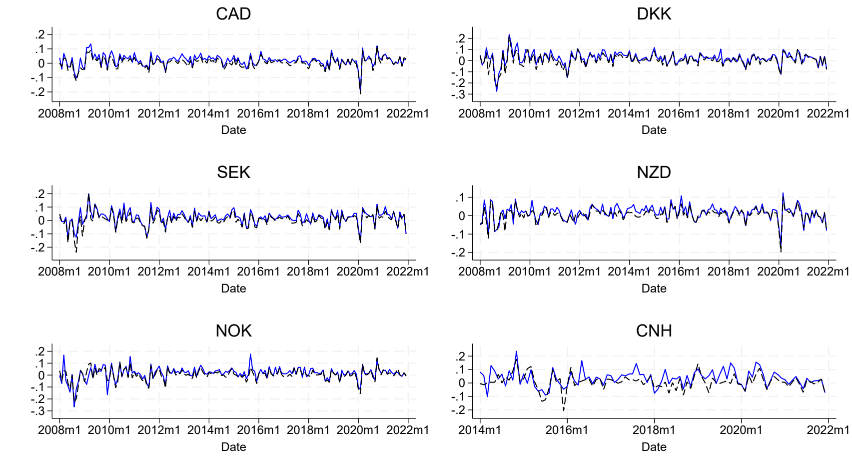
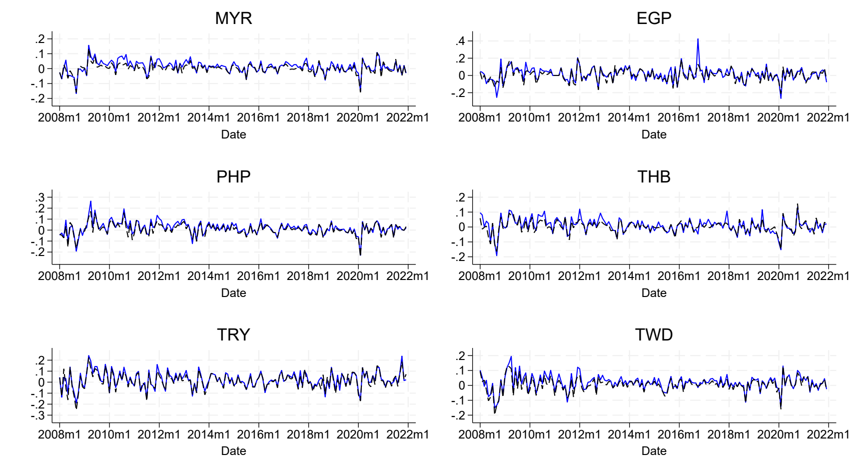


Figure A.39: Stock Market Price Growth Rate vs Total "Common" Component of Equilibrium Holdings



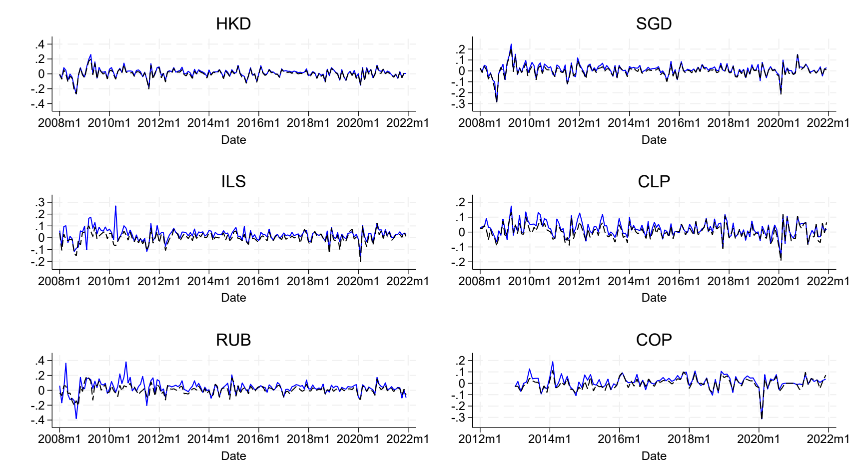
The black dashed line represents the stock price growth rate and the solid blue line is the change in total common equity holdings.

(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.)

A.3 Quarterly Sample Results

Figure A.40: Total AUM USD Trillions; Quarterly

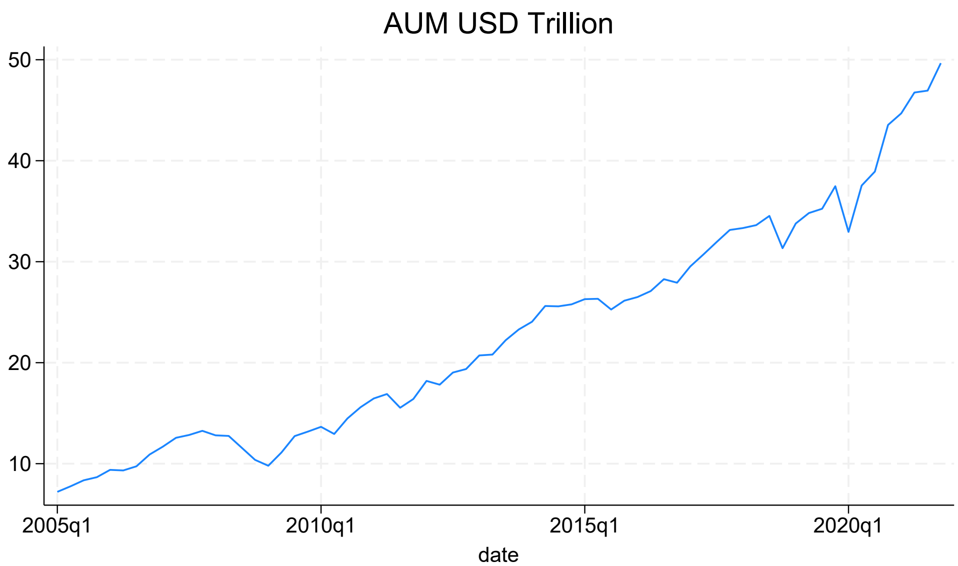


Figure A.41: AUM by Investment Type and ROS Currency (Quarterly Sample, USD Trillions)

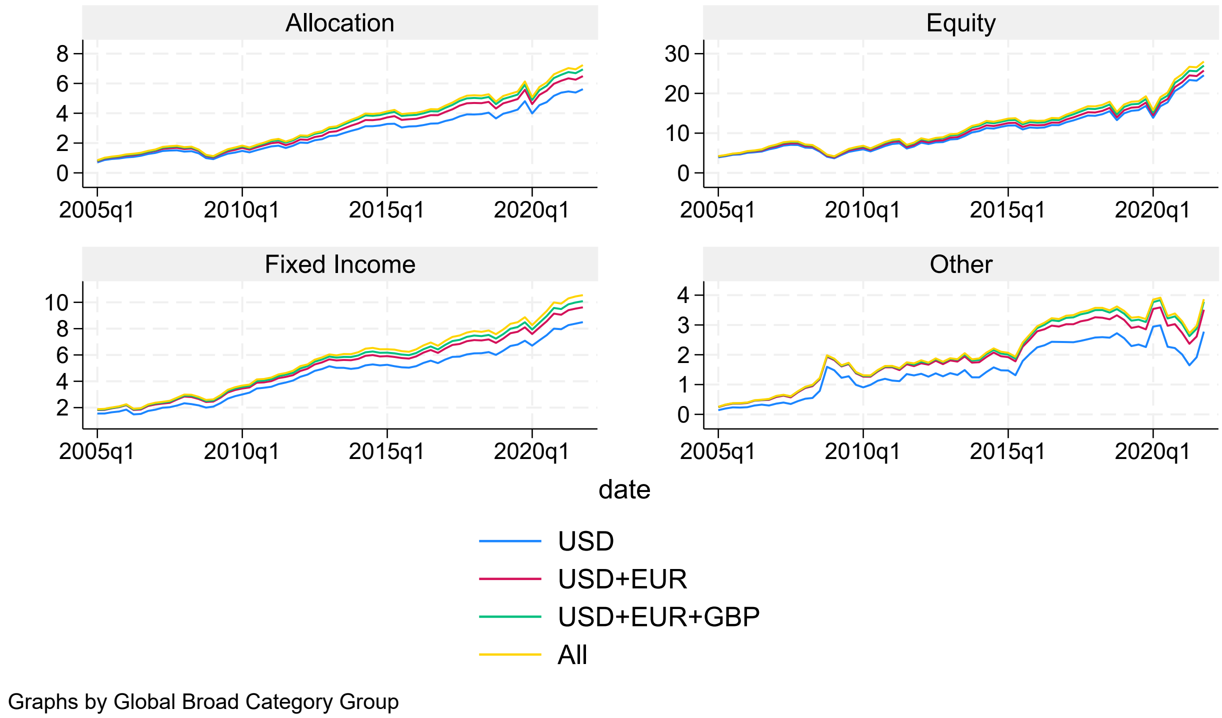


Figure A.42: AUM by Investment Type and Index Funds/Active Funds (Quarterly Sample, USD Trillions)

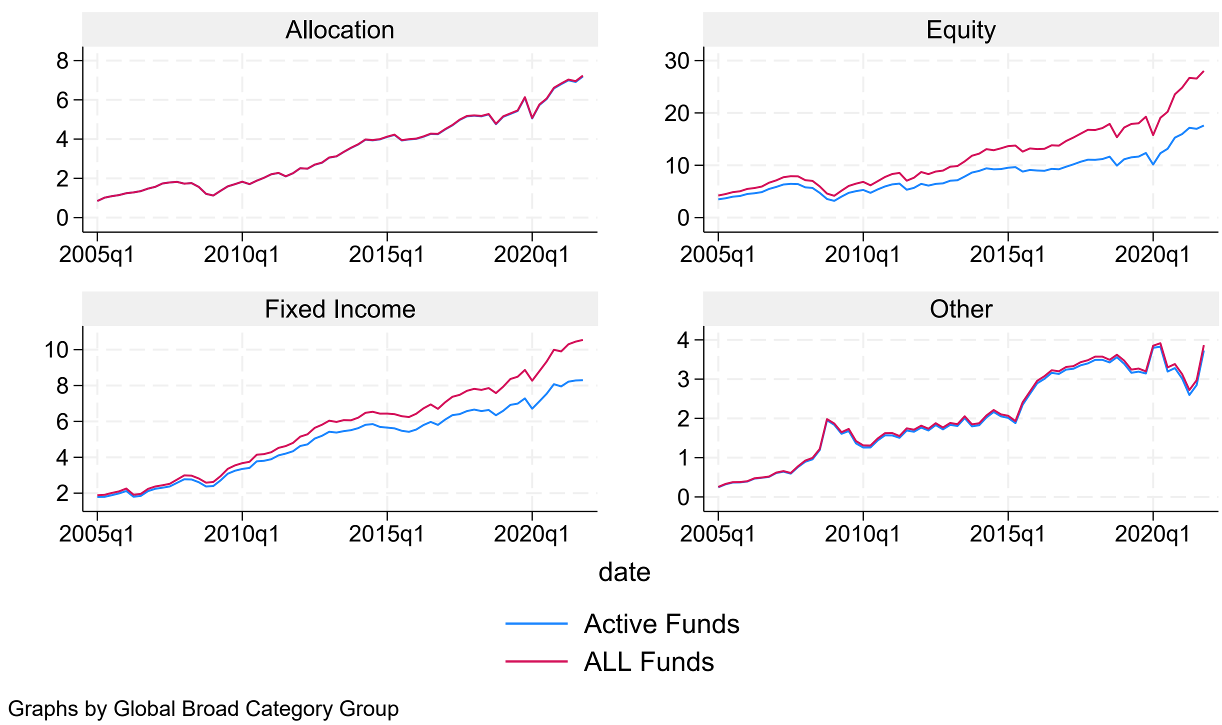
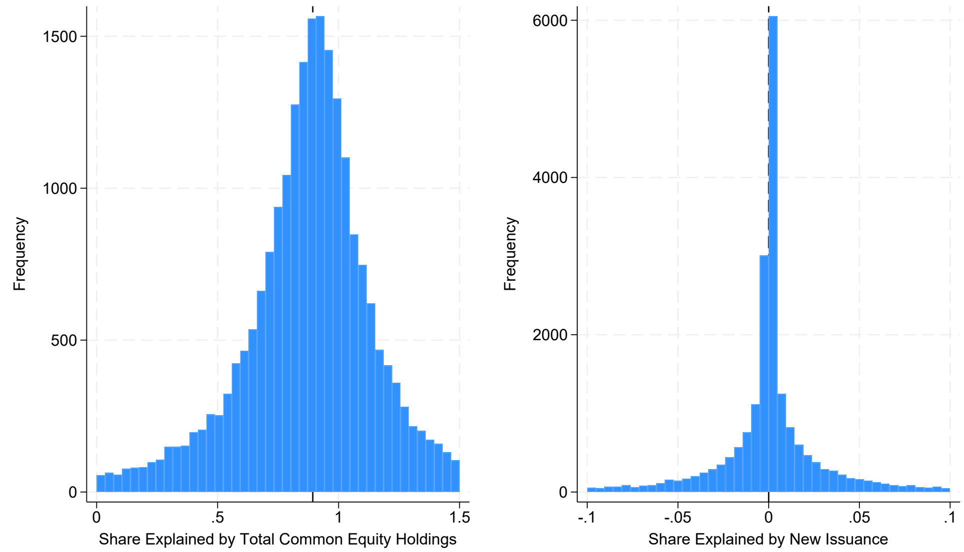


Table A.10: Coverage and Market Capitalization (Quarterly Sample)

Currency	*AvgCoverage*	*CoverageStart*	*CoverageEnd*	*AvgMarketCapUSDbil*	*MarketCapStartUSDbil*	*MarketCapEndUSDbil*	*ISINs*
AUD	0.11	0.08	0.15	945.14	779.68	1363.47	548.00
BRL	0.09	0.04	0.14	709.90	651.79	635.34	234.00
CAD	0.11	0.08	0.15	1332.56	1013.02	2057.77	633.00
CHF	0.18	0.08	0.25	1202.32	978.32	1917.21	209.00
CLP	0.03	0.01	0.04	175.24	162.65	116.48	65.00
CNH	0.02	0.00	0.06	2869.06	260.60	7957.53	939.00
COP	0.02	0.00	0.04	112.17	83.30	74.03	23.00
CZK	0.07	0.05	0.05	28.14	58.20	32.10	5.00
DKK	0.13	0.04	0.22	221.13	150.12	484.51	91.00
EGP	0.05	0.03	0.06	33.09	68.11	26.99	53.00
EUR	0.14	0.08	0.21	6046.18	6657.85	9327.93	1486.00
GBP	0.21	0.08	0.32	2553.99	2543.99	3037.25	1026.00
HKD	0.11	0.08	0.16	902.05	629.03	1050.08	472.00
HUF	0.15	0.09	0.21	14.54	19.34	22.46	11.00
IDR	0.07	0.03	0.09	317.89	131.76	399.72	196.00
ILS	0.03	0.04	0.05	128.62	106.99	227.00	152.00
INR	0.10	0.04	0.15	1387.07	871.67	3044.17	831.00
JPY	0.11	0.06	0.19	4560.20	3575.52	6624.64	2752.00
KRW	0.12	0.09	0.14	1148.53	784.68	1905.23	1253.00
MXN	0.09	0.05	0.12	306.08	246.67	350.97	103.00
MYR	0.05	0.05	0.03	321.53	218.22	331.71	334.00
NOK	0.09	0.07	0.14	199.19	227.40	311.35	134.00
NZD	0.07	0.05	0.09	49.42	18.90	101.96	59.00
PHP	0.07	0.06	0.06	170.45	59.69	223.63	99.00
PLN	0.05	0.02	0.06	124.21	110.71	157.60	112.00
RUB	0.03	0.00	0.04	324.02	369.57	405.48	55.00
SEK	0.17	0.13	0.24	419.88	325.61	844.98	334.00
SGD	0.09	0.09	0.11	292.65	278.21	292.14	199.00
THB	0.04	0.04	0.02	408.48	204.12	551.52	220.00
TRY	0.08	0.06	0.05	184.41	160.02	117.24	172.00
TWD	0.11	0.08	0.16	911.05	665.56	2076.39	957.00
USD	0.35	0.25	0.40	22380.45	14087.99	47499.11	5794.00
ZAR	0.13	0.09	0.14	328.69	286.62	328.74	181.00

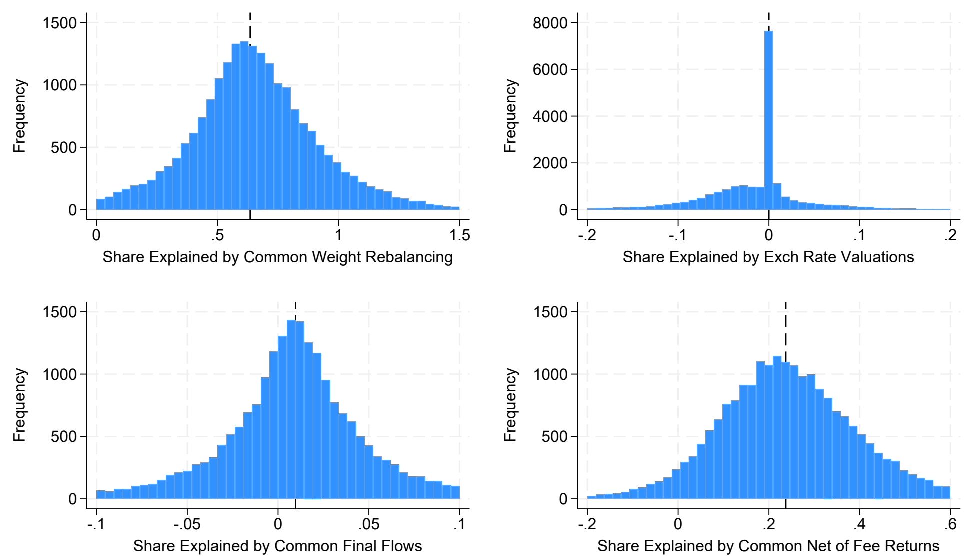
This table presents the sample average, starting date and ending date coverage ratios, weighted by the market capitalization of the ISIN. The coverage ratio for an ISIN is defined as total observed holdings of this ISIN in our data set over the market capitalization of the ISIN, translated in the same 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 A.43: 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 A.44: ISIN-Level Equity Price Growth Rate Decomposition: Historgams Sub-Components (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 A.11: 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	0.821^{***}	0.738^{***}	-0.076^{***}	-0.001	0.160^{***}	0.175^{***}	-0.004
BRL	0.875^{***}	0.816^{***}	-0.171^{***}	0.019^{***}	0.211^{***}	0.128^{***}	0.003
CAD	0.848^{***}	0.720^{***}	-0.060^{***}	0.005^{***}	0.183^{***}	0.156^{***}	0.004
CHF	0.893^{***}	0.604^{***}	-0.008^{***}	0.014^{***}	0.283^{***}	0.095^{***}	-0.012^{**}
CLP	0.933^{***}	0.750^{***}	-0.141^{***}	0.042^{***}	0.282^{***}	0.065^{**}	-0.002
CNH	0.973^{***}	0.794^{***}	-0.021^{***}	0.022^{***}	0.177^{***}	0.030^{***}	0.003
COP	0.938^{***}	0.907^{***}	-0.187^{***}	0.011^{*}	0.207^{***}	0.071	0.009
CZK	1.012^{***}	0.732^{***}	-0.142^{**}	0.034^{**}	0.388^{***}	-0.010	0.002
DKK	0.932^{***}	0.680^{***}	-0.013^{***}	0.008^{**}	0.256^{***}	0.054^{**}	-0.014
EGP	0.936^{***}	0.558^{***}	0.119^{***}	0.023^{***}	0.236^{***}	0.060^{**}	-0.004
EUR	0.896^{***}	0.638^{***}	-0.027^{***}	0.022^{***}	0.263^{***}	0.098^{***}	-0.006^{***}
GBP	0.833^{***}	0.654^{***}	-0.021^{***}	0.010^{***}	0.190^{***}	0.169^{***}	0.002
HKD	0.926^{***}	0.674^{***}	0.011^{***}	0.015^{***}	0.226^{***}	0.073^{***}	-0.001
HUF	0.870^{***}	0.688^{***}	-0.184^{***}	0.021	0.345^{***}	0.138	0.008
IDR	0.917^{***}	0.813^{***}	-0.090^{***}	0.016^{***}	0.178^{***}	0.084^{***}	0.002
ILS	0.863^{***}	0.663^{***}	-0.063^{***}	0.013^{***}	0.249^{***}	0.136^{***}	-0.001
INR	0.848^{***}	0.691^{***}	-0.042^{***}	0.003^{**}	0.196^{***}	0.151^{***}	-0.001
JPY	0.936^{***}	0.632^{***}	0.053^{***}	0.002^{**}	0.249^{***}	0.062^{***}	-0.002^{***}
KRW	0.916^{***}	0.765^{***}	-0.041^{***}	-0.006^{***}	0.197^{***}	0.080^{***}	-0.005^{**}
MXN	0.866^{***}	0.733^{***}	-0.123^{***}	0.027^{***}	0.228^{***}	0.134^{***}	-0.000
MYR	0.918^{***}	0.666^{***}	-0.047^{***}	0.019^{***}	0.280^{***}	0.071^{***}	-0.011^{**}
NOK	0.871^{***}	0.734^{***}	-0.072^{***}	0.010^{***}	0.199^{***}	0.135^{***}	0.005
NZD	0.935^{***}	0.789^{***}	-0.090^{***}	0.007^{*}	0.229^{***}	0.080^{***}	0.015
PHP	0.946^{***}	0.703^{***}	-0.025^{***}	0.027^{***}	0.242^{***}	0.050^{***}	-0.004
PLN	0.881^{***}	0.755^{***}	-0.129^{***}	0.014^{***}	0.241^{***}	0.116^{***}	-0.003
RUB	0.918^{***}	0.798^{***}	-0.127^{***}	0.028^{***}	0.220^{***}	0.067^{**}	-0.014^{*}
SEK	0.917^{***}	0.679^{***}	-0.020^{***}	0.032^{***}	0.227^{***}	0.077^{***}	-0.006
SGD	0.934^{***}	0.680^{***}	-0.053^{***}	0.006^{*}	0.301^{***}	0.051^{***}	-0.014
THB	0.896^{***}	0.664^{***}	-0.067^{***}	0.013^{***}	0.286^{***}	0.022	-0.082^{***}
TRY	0.949^{***}	0.745^{***}	-0.062^{***}	0.017^{***}	0.248^{***}	0.049^{***}	-0.002
TWD	0.954^{***}	0.687^{***}	-0.043^{***}	0.005^{***}	0.305^{***}	0.046^{***}	-0.000
USD	0.847^{***}	0.614^{***}	0.001^{***}	0.011^{***}	0.220^{***}	0.155^{***}	0.002
ZAR	0.826^{***}	0.740^{***}	-0.099^{***}	0.020^{***}	0.164^{***}	0.165^{***}	-0.009

Note: In this table we report the coefficients from panel regressions of the total "common" component of equity holdings (and its sub-components) on Δp_t^j by stock market (as denoted by the currency associated with that stock market). We also report the coefficients from panel regressions of the change in ISIN-level shares issued and the residual holdings sub-component on Δp_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 A.45: ISIN-Level Equity Price Growth Rate Decomposition: Panel Regressions (Quarterly Sample)

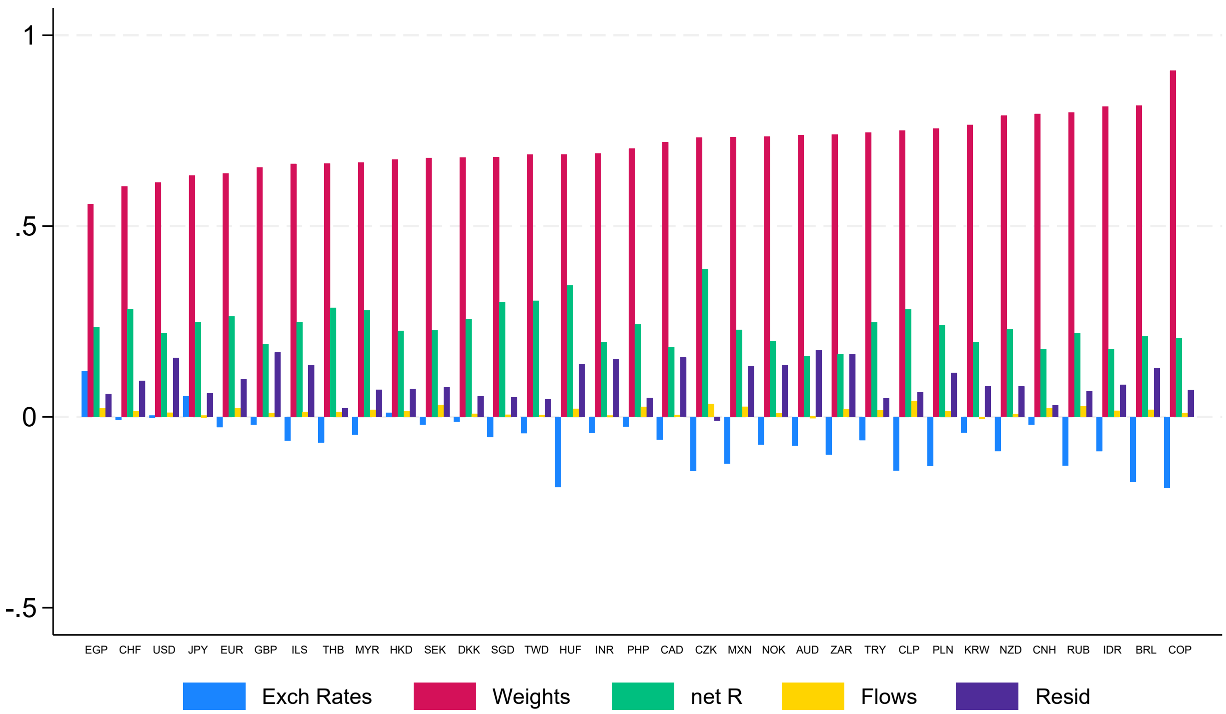


Table A.12: ISIN-Level Equity Price Growth Rate Decomposition: Index Funds vs Active Funds Portfolio Weight Changes and Flows: Panel Regressions (Quarterly Sample)

Currency	$\Delta d^{\omega,j}_{Index}$	$\Delta d^{\omega,j}_{Active}$	$\Delta d^{f,j}_{Index}$	$\Delta d^{f,j}_{Active}$
AUD	0.212***	0.596***	-0.003***	-0.005***
BRL	0.186***	0.682***	0.007***	0.016***
CAD	0.146***	0.638***	0.004**	-0.003***
CHF	0.197***	0.418***	-0.005***	0.010***
CLP	0.284***	0.554***	0.030***	0.021***
CNH	0.444***	0.468***	0.015***	0.004***
COP	0.438***	0.498***	0.011*	-0.003
CZK	0.111*	0.626**	0.024	0.005
DKK	0.079***	0.620***	0.002	-0.005
EGP	0.180***	0.416***	0.012	0.022***
EUR	0.102***	0.564***	0.006***	0.010***
GBP	0.114***	0.580***	0.001	0.007***
HKD	0.158***	0.583***	0.008***	0.001
HUF	0.267**	0.554***	0.014**	0.018**
IDR	0.214***	0.681***	0.010***	0.010***
ILS	0.263***	0.465***	0.010***	-0.002
INR	0.116***	0.620***	0.002***	0.001
JPY	0.305***	0.385***	0.007***	-0.002**
KRW	0.299***	0.605***	-0.005***	-0.002**
MXN	0.198***	0.576***	0.012***	0.017***
MYR	0.187***	0.576***	0.006***	0.011***
NOK	0.109***	0.655***	0.006***	-0.002
NZD	0.239***	0.642***	0.004	0.001
PHP	0.156***	0.599***	0.011***	0.019***
PLN	0.220***	0.605***	0.013***	-0.001
RUB	0.441***	0.618***	0.004	0.026***
SEK	0.252***	0.473***	0.023***	0.007***
SGD	0.133***	0.612***	0.003	-0.014***
THB	0.371***	0.391***	0.028***	-0.002
TRY	0.197***	0.617***	0.013***	0.007***
TWD	0.224***	0.549***	0.013***	-0.008***
USD	0.222***	0.403***	0.005***	0.005***
ZAR	0.175***	0.600***	0.006***	0.017***

Note: In this table we report the coefficients of panel regressions of the portfolio weight change and flow sub-components, broken down by index funds and active funds, on Δp^j_t by stock market (as denoted by the currency associated with that stock market). We allow for ISIN level fixed effects and cluster the standard errors by ISIN. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%

Table A.13: ISIN-Level Equity Price Growth Rate Decomposition: Own vs Other Currency Investors Portfolio Weight Changes and Flows: Panel Regressions (Quarterly Sample)

Currency	$\Delta d^{\omega,j}_{OwnCurr}$	$\Delta d^{\omega,j}_{OtherCurr}$	$\Delta d^{f,j}_{OwnCurr}$	$\Delta d^{f,j}_{OtherCurr}$
AUD	0.088***	0.657***	-0.002***	-0.007***
BRL	0.131***	0.748***	0.011***	0.013***
CAD	.	0.721***	.	-0.002
CHF	0.235***	0.403***	-0.008***	0.014***
CLP	.	0.750***	.	0.038***
CNH	.	0.790***	.	0.017***
COP	.	0.913***	.	0.008
CZK	.	0.732***	.	0.020
DKK	0.018*	0.667***	0.001	-0.005
EGP	.	0.543***	.	0.030***
EUR	0.194***	0.468***	0.017***	-0.002*
GBP	0.409***	0.299***	0.006***	0.002*
HKD	0.005**	0.674***	0.003***	0.004*
HUF	.	0.693***	.	0.020*
IDR	.	0.815***	.	0.014***
ILS	.	0.660***	.	0.004
INR	0.143***	0.612***	0.003	0.000
JPY	0.278***	0.448***	0.005***	-0.001**
KRW	0.112***	0.726***	-0.020***	0.000
MXN	0.106***	0.670***	0.005*	0.021***
MYR	.	0.666***	.	0.013***
NOK	0.065***	0.685***	-0.002	0.004
NZD	0.098***	0.732***	0.000	0.002
PHP	.	0.693***	.	0.023***
PLN	.	0.753***	.	0.007*
RUB	.	0.898***	.	0.027***
SEK	0.410***	0.323***	0.028***	0.001
SGD	.	0.677***	.	-0.013***
THB	0.515***	0.555***	-0.032***	0.029***
TRY	.	0.747***	.	0.013***
TWD	0.014***	0.686***	-0.003*	-0.001
USD	0.596***	0.022***	0.009***	0.001***
ZAR	0.187***	0.593***	0.012***	0.009***

Note: In this table we report the coefficients of panel regressions of the portfolio weight change and flow subcomponents, broken down by own currency and foreign currency investors, on Δp^j_t by stock market (as denoted by the currency associated with that stock market). We allow for ISIN level fixed effects and cluster the standard errors by ISIN. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%

Figure A.46: Aggregate Stock Market Price Growth Rate Decomposition (Quarterly Sample)

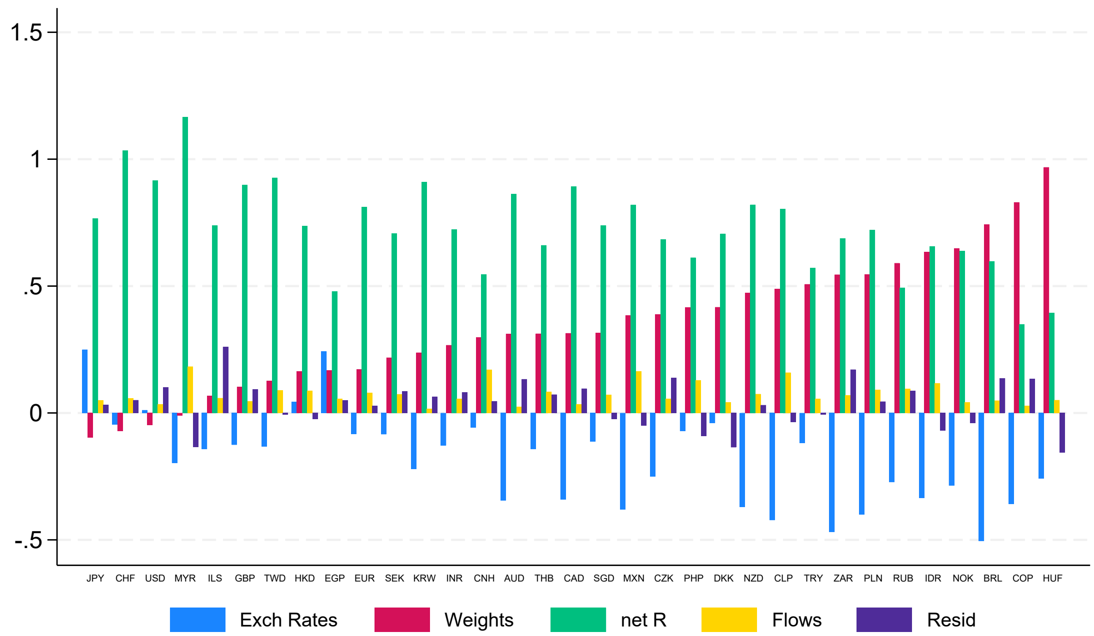


Table A.14: Aggregate Stock Market Price Growth Rate Decomposition (Quarterly Sample)

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^{***}	0.83	-0.35^{***}	0.41	0.31^{***}	0.32	0.86^{***}	0.82	0.02	-0.01	0.13^{**}	0.10
BRL	0.89^{***}	0.78	-0.50^{***}	0.57	0.74^{***}	0.59	0.60^{***}	0.67	0.05^{**}	0.04	0.14^{**}	0.07
CAD	0.90^{***}	0.83	-0.34^{***}	0.57	0.31^{***}	0.29	0.89^{***}	0.78	0.03	-0.00	0.10	0.04
CHF	0.97^{***}	0.66	-0.05	-0.00	-0.07	-0.01	1.03^{***}	0.85	0.06^{**}	0.02	0.05	-0.01
CLP	1.03^{***}	0.78	-0.42^{***}	0.39	0.49^{***}	0.20	0.80^{***}	0.51	0.16^{***}	0.22	-0.04	-0.01
CNH	0.96^{***}	0.56	-0.06^{**}	0.09	0.30^{*}	0.10	0.55^{***}	0.50	0.17^{***}	0.13	0.05	-0.03
COP	0.85^{***}	0.73	-0.36^{***}	0.43	0.83^{***}	0.69	0.35^{***}	0.31	0.03	-0.01	0.13^{*}	0.04
CZK	0.88^{***}	0.79	-0.25^{***}	0.20	0.39^{***}	0.18	0.68^{***}	0.52	0.06	0.03	0.14^{**}	0.07
DKK	1.13^{***}	0.81	-0.04	0.00	0.42^{***}	0.40	0.71^{***}	0.81	0.04	0.02	-0.14	0.05
EGP	0.94^{***}	0.84	0.24	0.11	0.17	0.04	0.48^{***}	0.46	0.06^{*}	0.05	0.05	-0.00
EUR	0.98^{***}	0.91	-0.08^{*}	0.06	0.17^{***}	0.28	0.81^{***}	0.91	0.08^{***}	0.09	0.03	-0.01
GBP	0.92^{***}	0.85	-0.13^{*}	0.11	0.10^{*}	0.07	0.90^{***}	0.87	0.05	0.02	0.09	0.04
HKD	1.03^{***}	0.88	0.04^{***}	0.47	0.16	0.09	0.74^{***}	0.82	0.09^{***}	0.20	-0.02	-0.01
HUF	1.16^{***}	0.60	-0.26^{***}	0.39	0.97^{***}	0.53	0.39^{***}	0.43	0.05^{*}	0.07	-0.16^{**}	0.01
IDR	1.07^{***}	0.73	-0.33^{***}	0.53	0.63^{***}	0.31	0.66^{***}	0.52	0.12^{***}	0.20	-0.07	-0.01
ILS	0.72^{***}	0.50	-0.14^{**}	0.11	0.07	-0.01	0.74^{***}	0.54	0.06	0.01	0.26	0.10
INR	0.92^{***}	0.87	-0.13^{***}	0.26	0.27^{***}	0.30	0.72^{***}	0.79	0.06	0.05	0.08	0.04
JPY	0.97^{***}	0.88	0.25^{***}	0.34	-0.10	0.02	0.77^{***}	0.72	0.05	0.01	0.03	-0.01
KRW	0.94^{***}	0.89	-0.22^{***}	0.28	0.24^{***}	0.29	0.91^{***}	0.82	0.02	-0.01	0.06	0.02
MXN	0.99^{***}	0.81	-0.38^{***}	0.35	0.38^{***}	0.29	0.82^{***}	0.67	0.16^{***}	0.20	-0.05	-0.00
MYR	1.14^{***}	0.81	-0.20^{***}	0.14	-0.01	-0.02	1.17^{***}	0.72	0.18^{***}	0.18	-0.13^{*}	0.04
NOK	1.04^{***}	0.65	-0.29^{***}	0.47	0.65^{***}	0.33	0.64^{***}	0.70	0.04	0.02	-0.04	-0.02
NZD	1.00^{***}	0.66	-0.37^{***}	0.21	0.47^{***}	0.17	0.82^{***}	0.42	0.07^{**}	0.03	0.03	-0.02
PHP	1.09^{***}	0.90	-0.07^{*}	0.11	0.42^{***}	0.28	0.61^{***}	0.49	0.13^{***}	0.23	-0.09^{*}	0.05
PLN	0.96^{***}	0.81	-0.40^{***}	0.45	0.55^{***}	0.43	0.72^{***}	0.67	0.09^{***}	0.10	0.05	-0.01
RUB	0.91^{***}	0.24	-0.27^{***}	0.18	0.59^{**}	0.11	0.49^{***}	0.47	0.10^{***}	0.14	0.09	-0.02
SEK	0.92^{***}	0.90	-0.08^{***}	0.19	0.22^{***}	0.32	0.71^{***}	0.89	0.07^{**}	0.10	0.09	0.05
SGD	1.01^{***}	0.91	-0.11^{***}	0.22	0.32^{***}	0.28	0.74^{***}	0.74	0.07^{***}	0.10	-0.02	-0.01
THB	0.91^{***}	0.70	-0.14^{***}	0.40	0.31^{***}	0.16	0.66^{***}	0.73	0.08^{**}	0.08	0.07	-0.00
TRY	1.02^{***}	0.88	-0.12	0.02	0.51^{***}	0.32	0.57^{***}	0.55	0.06^{*}	0.05	-0.01	-0.02
TWD	1.01^{***}	0.88	-0.13^{***}	0.26	0.13^{**}	0.09	0.93^{***}	0.80	0.09^{***}	0.09	-0.01	-0.02
USD	0.91^{***}	0.93	0.01^{***}	0.22	-0.05	0.09	0.92^{***}	0.98	0.03	0.02	0.10^{**}	0.15
ZAR	0.83^{***}	0.77	-0.47^{***}	0.47	0.55^{***}	0.39	0.69^{***}	0.47	0.07^{*}	0.02	0.17^{***}	0.11

Note: In this table we report the OLS coefficients from regressing the total "common" component of equity holdings and its sub-components on the aggregate stock market price growth rate (where the stock market is denoted by the currency associated with that stock market). We also report the equivalent regression for the residual holdings sub-component. Robust standard errors. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%

Figure A.47: The Importance of Own vs Cross-Covariance Sub-components: Portfolio Weight Changes (Quarterly Sample)

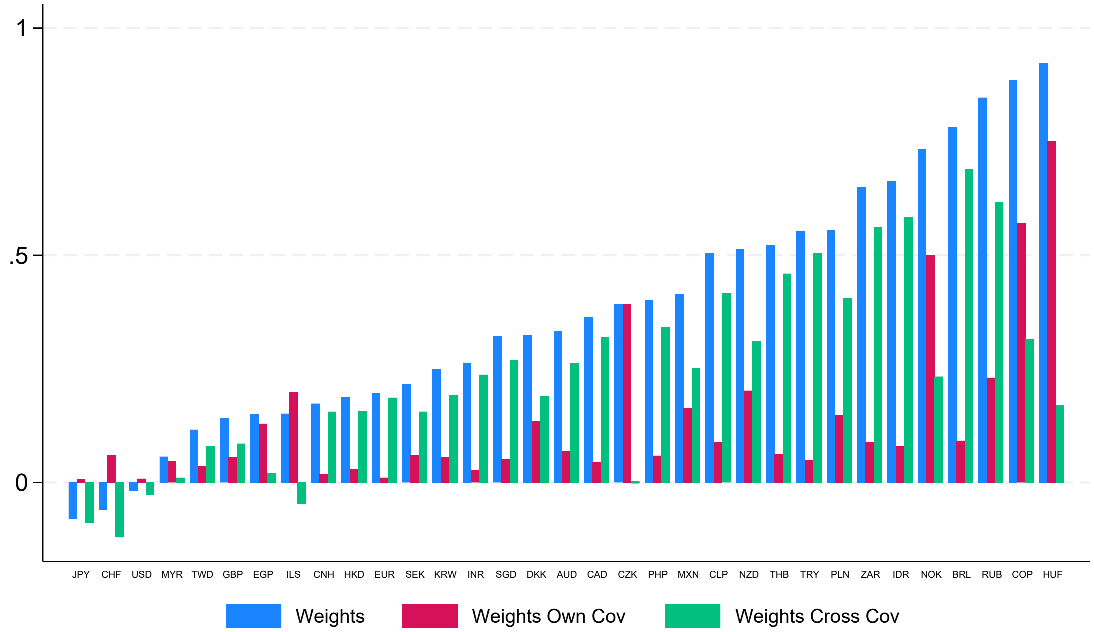


Figure A.48: The Importance of Own vs Cross-Covariance Sub-components: Net-of-Fee Returns (Quarterly Sample)

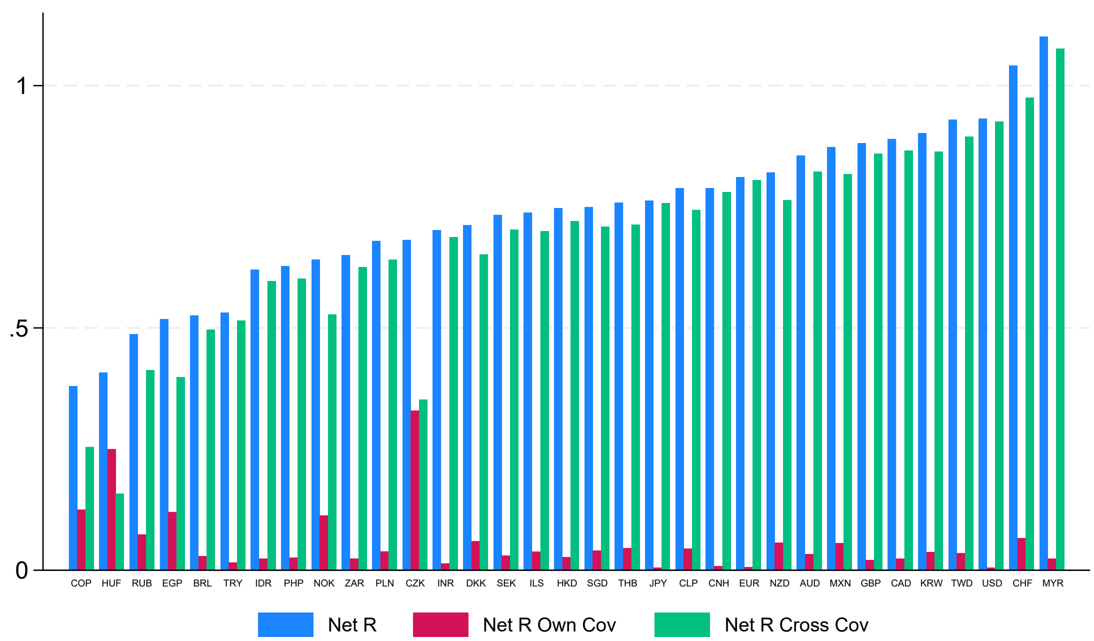


Table A.15: Stock Picking vs Industry Picking: Panel Regressions (Quarterly Sample)

Currency	$\Delta d_t^{\omega,j,Ind}$	$\Delta d^{\omega,j,iid}$	$\Delta d^{\omega,j}$	$\Delta D_t^{\omega,l,Ind}$	$\Delta D^{\omega,l,iid}$	$\Delta D^{\omega,l}$
AUD	0.123***	0.615***	0.738***	0.377***	-0.065	0.312***
BRL	0.314***	0.502***	0.816***	0.685***	0.058	0.743***
CAD	0.137***	0.583***	0.720***	0.397***	-0.083**	0.314***
CHF	0.065***	0.539***	0.604***	0.001	-0.073*	-0.072
CLP	0.304***	0.447***	0.750***	0.445***	0.043	0.488***
CNH	0.164***	0.630***	0.794***	0.370**	-0.072	0.298*
COP	0.642***	0.266***	0.907***	0.675***	0.156*	0.830***
CZK	0.625**	0.106	0.732***	0.390***	-0.001	0.388***
DKK	0.202***	0.478***	0.680***	0.312***	0.105	0.417***
EGP	0.252***	0.306***	0.558***	0.199	-0.031	0.168
EUR	0.084***	0.554***	0.638***	0.174***	-0.002	0.172***
GBP	0.064***	0.590***	0.654***	0.101	0.001	0.102*
HKD	0.085***	0.589***	0.674***	0.213**	-0.049	0.164
HUF	0.592***	0.096	0.688***	0.916***	0.052**	0.968***
IDR	0.276***	0.538***	0.813***	0.775***	-0.140*	0.635***
ILS	0.179***	0.484***	0.663***	0.040	0.028	0.068
INR	0.187***	0.503***	0.691***	0.411***	-0.143**	0.267***
JPY	0.008***	0.624***	0.632***	-0.110	0.013	-0.097
KRW	0.087***	0.679***	0.765***	0.153**	0.085***	0.238***
MXN	0.204***	0.529***	0.733***	0.275***	0.109	0.384***
MYR	0.083***	0.583***	0.666***	0.114	-0.124**	-0.010
NOK	0.237***	0.497***	0.734***	0.708***	-0.059	0.649***
NZD	0.205***	0.584***	0.789***	0.410***	0.064	0.474***
PHP	0.225***	0.478***	0.703***	0.450***	-0.034	0.416***
PLN	0.310***	0.446***	0.755***	0.632***	-0.085	0.546***
RUB	0.305***	0.493***	0.798***	0.460**	0.131	0.591**
SEK	0.113***	0.566***	0.679***	0.287***	-0.069*	0.218***
SGD	0.181***	0.500***	0.680***	0.352***	-0.036	0.316***
THB	0.228***	0.436***	0.664***	0.350***	-0.037	0.313***
TRY	0.248***	0.498***	0.745***	0.557***	-0.050*	0.507***
TWD	0.117***	0.570***	0.687***	0.252***	-0.125***	0.126**
USD	0.048***	0.566***	0.614***	0.053	-0.101***	-0.048
ZAR	0.183***	0.557***	0.740***	0.454***	0.092**	0.545***

Note: In this table we report the coefficients of panel regressions (for the ISIN level decomposition) and OLS regressions (for the stock market decomposition) of the "common" portfolio weight change sub-component, which is further broken down into industry and idiosyncratic components, on either the equity price growth rate or the stock market price growth rate, respectively. For the panel level regressions we allow for ISIN level fixed effects and cluster the standard errors by ISIN and for the OLS regressions we use robust standard errors. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%