Elephants in Equity Markets*

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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. Despite our sample's average coverage ratio being only 5%, our reconstructed equity holdings account for, on average, 89% of the time variation in over 20,000 individual stock returns and 96% of the fluctuations in 33 aggregate stock market returns. Using this decomposition, we present 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. 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 relies on observing only a sub-sample of equity holdings, specifically by asset managers, for the 2008-–2021 period. It is based 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 represent the behavior of all equity investors. Despite our sample's mean coverage ratio (observed asset managers' holdings relative to market capitalization) being only 5%, our reconstructed equilibrium holdings accounts for an average of 89% and 96% of the variation in over 20,000 individual stock returns and 33 aggregate stock market monthly returns, respectively.[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. 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 net-of-fee fund returns and also (iv) exchange rate valuation effects due to foreign investors being an important source of demand for many global equities. Components (i) and (ii)

[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 (see the Online Appendix).

are the main variables of interest in the vast majority of asset pricing models, as they represent a direct measure 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 and can themselves be driven by and affect equity holdings. For example, when an investor located in the US purchases a Brazilian equity stock denominated in BRL, indexed by j, she is simultaneously increasing the demand for BRL and for asset j, thereby putting some upward pressure on both prices to clear the market.[2]

The decomposition leads to new findings 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 stock price changes at the ISIN level for all countries, with active (non-ETF) funds being the main driver. Moreover, we further document that it is truly "stock picking", rather than "industry picking", that explains the bulk of ISIN-level equity price growth.

(ii) *Final inflows into funds push up prices of stocks held by the funds*, albeit explain a small fraction of stock price movements.

(iii) *Exchange rates play a crucial equilibrating role in nearly all stock markets*, with greater importance in more "open" stock markets. Currency movements generally reduce local stock market volatility, except in markets associated with "safe haven" currencies like the USD, CHF, and JPY, as well as those currencies pegged to the USD. For currencies outside this safe haven group, the exchange rate appreciates in response to higher equity holdings, implying that local-currency equity prices need to increase by less in order

[2]We further break our sub-components of equity holdings down in various ways such as ETFs vs active funds, local vs foreign investors etc. and we also provide an alternative decomposition which focuses only on the holdings of the "marginal" traders.

to clear the equity market.[3] Conversely, fluctuations of the USD, JPY and the CHF provide a hedge for foreign equity investors with respect to the stock market. They tend to depreciate when the stock market goes up and to appreciate in bad times.[4]

(iv) *The main drivers of individual stock price growth rates can differ significantly from those driving aggregate stock market returns 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 (EMs), 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 within the Brazilian market). This implies that, in EMs, portfolio weight changes is 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 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

[3]Another way to interpret this result is that, since the values 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 monthly but not at quarterly frequency, unlike the USD and JPY where the results are robust across frequencies.

only observable holdings would be close to impossible.[5] It may well be that global equity markets give us a unique opportunity to directly observe 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 ISINs, opening avenues for directly testing various existing asset pricing theories, and to deepen our understanding of both equity markets and exchange rates by providing many novel stylized facts.

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

2 Literature Review

Our paper closely aligns with a new class of empirical research that that places equity demand and characteristics-based investing at the heart of the empirical study of asset prices.[6] Koijen and Yogo (2019) introduce a novel framework, based on models of demand from the industrial organization literature, where they estimate demand elasticities from data on mutual fund holdings. Koijen et al. (forthcoming) apply this framework to study the impact of the

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

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. Our finding on the importance of the portfolio weight re-balancing 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 on both sides allocate their investment to firms at the top of the productivity distribution.[7]

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 and cannot interpret our results causally.

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 return for equity markets not only in the US but also in a large number of countries.

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 decomposition presents a whole new set of moments that need to be matched by theoretical models related to *quantities*. Some of the more prominent papers include Basak and Pavlova (2013) which provide a model of asset prices with institutional investors following benchmarks, Buffa et al. (2022) who provide a model allowing for a continuum of active versus

[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.

passive behavior by funds that generates novel asset pricing implications. 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] Since we split the funds in our decomposition into various categories such as ETFs vs active and funds that rebalance more or less frequently, our empirical results 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' holdings in fixed income markets to document an important currency bias. We document another novel fact related to the specialness of currencies: i.e. an interesting pattern of rebalancing of mutual funds across "currency borders" with the US, Japanese and Swiss stock market 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. 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 accompanying the easing of monetary policy during the global financial crisis led to higher risk aversion by markets. This ended up appreciating the USD against a number of currencies (besides JPY) by triggering 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 why this

[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.

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-Shiller decomposition (see Campbell and Shiller (1988)), which links 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.[9]

3 Market Clearing Decomposition

In this section, we present the theoretical underpinnings of our stock price decomposition as a function of equilibrium supply and holdings.

3.1 Individual Stock Returns Decomposition

We start with the market clearing condition for a single stock j at the ISIN level:

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

where W_t^i is the total invested wealth of investor i (or assets under management for asset managers), denominated in the currency of the investor's main operating region (or region of sale (ROS) for asset managers), 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. Further, I is the universe of investors that hold asset j. S_t^{l/c^i} is the nominal exchange rate defined as units of currency l needed to purchase one unit of currency c^i. Finally, P_t^j is the price of ISIN j denominated in currency c^j and Q_t^j is the outstanding shares of ISIN j. Based on these variable definitions, $\sum_{i \in I} \omega_t^{i,j} W_t^i S_t^{l/c^i}$ is the

[9]Moreover, unlike the Campbell-Shiller decomposition, which requires assumptions on how the marginal trader forms her beliefs, our decomposition relies on a milder set of assumptions.

total 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 transform the market clearing condition, (1), by linearizing with respect to $\omega_t^{i,j}$ and log-linearizing with respect to W_t^i, S_t^{l/c^i}, and P_t^j around some constant value:

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

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, ΔD_t^j, can be decomposed into three components. The first is a component associated with the changes of the portfolio weights of investors for asset j, $\sum_{i \in I} \widehat{W^i} \widehat{S}^{c^j/c^i} \left(\Delta \omega_t^{i,j} \right)$. This is the component of demand 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, $\sum_{i \in I} \widehat{W^i} \widehat{S}^{c^j/c^i} \left(\widehat{\omega}^{i,j} \Delta s_t^{c^j/c^i} \right)$. 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). The last component of the change in total holdings is associated with the growth rate of the investor's wealth, $\sum_{i \in I} \widehat{W^i} \widehat{S}^{c^j/c^i} \left(\widehat{\omega}^{i,j} \Delta w_t^i \right)$. 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, $Flow_t^i$. We use the law of motion of the wealth 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) provides the market clearing condition, linking the growth rate of the price of ISIN j,Δp_t^j, to the four components of holdings that can be summarized as exchange rate valuation effects, portfolio weight changes, investor-specific portfolio performance (net return valuation effects) and changes in total invested wealth/assets under management. It further links it to the change in shares issued, associated with ISIN j, due to certain corporate actions such as stock buy-backs.[10] Since new equity of a firm is usually issued under a new ISIN, and since our analysis is at the ISIN-level, we expect, and later confirm, that Δq_t^j does not play a substantial role in the analysis. Re-writing equation (2), we can express the price growth rate of ISIN j as:

$$\Delta p_t^j = \sum_{i \in I} \frac{\mu^{i,j}}{\widehat{P^j Q^j}} (\Delta s_t^{l/c^i} + \frac{\Delta \omega_t^{i,j}}{\widehat{\omega}^{i,j}} + r_t^{i,NF} + flow_t^i) - \Delta q_t^j \tag{4}$$

$$\text{where } \mu^{i,j} = \widehat{W}^i \widehat{S}^{l/c^i} \widehat{\omega}^{i,j}, \tag{5}$$

with $\mu^{i,j}$ being the sample average amount of ISIN j held by investor i, denominated in currency $c^j = l$.

This expression decomposes, at the *micro level*, total holdings for equity j into four components, reflecting changes due to: (i) exchange rate movements, which captures the fact that the investors need to convert their holdings denominated in their operating currency into the currency of issuance of the ISIN, (ii) changes in the portfolio weights of the investors holding this ISIN, (iii) reinvestment of (net-of-fee) portfolio returns measured in the operating currency of the investor (ROS currency of the asset manager), which acts as an amplification mechanism, and, finally, (iv) exogenous flows into the invested wealth of the investor (or into the fund when considering asset managers), measured in the operating currency.

[10]Note that we ensure to use a stock price adjusting for stock splits and, more broadly, for mechanical structural breaks in the price series and, as a result, our supply series are also adjusted for these events.

3.1.1 Empirical Methodology

Constructing the holdings sub-components in equation (4) requires data on the holdings of every single investor who owns ISIN j, which is unrealistic, even with the best available data. In order to circumvent this obstacle, we will scale our observed asset manager 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 as an average and a residual term, where we group the funds by type. In step two, we impose two assumptions related to the "representativeness" of our sample of equity holdings. The first representativeness assumption relates to the fact that the portfolio weight change, net of fee returns and final flows *population* averages can be well approximated by our equivalent *sample* averages. Second, we assume that we have ***"representative holdings ratios"*** in our sample for each sub-type of fund. We define the "representative holdings ratio" as for each type of fund, the ratio of average-over-time holdings of ISIN j we observe in our sample relative to the average-over-time population holdings of ISIN j being the same across all types of funds. 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 the funds for the ISIN, by the inverse of the coverage ratio, to obtain what we call the "common" equilibrium holdings sub-components of our market clearing decomposition. As we will show in the results section, the "common" equilibrium holdings sub-components will account for almost all of the equity price growth variation, thus validating this approach, and allowing us to reconstruct market clearing conditions using only observed holdings data, despite the low sample coverage.

In what follows, we explain the exact assumptions that allow us to construct the terms in the accounting identity in equation (4).

Funds Groups

We separate the change in the weight invested in asset j by every investor i into a "common"

component, which is the *arithmetic* average of portfolio weight changes within a narrowly defined group of investors, and an idiosyncratic residual term, $\varepsilon_t^{\omega,i,j}$:

$$\frac{\Delta\omega_t^{i,j}}{\widehat{\omega}^{i,j}} = \sum_{k\in\tau_i'} \frac{1}{|\tau_i'|} \frac{\Delta\omega_t^{k,j}}{\widehat{\omega}^{k,j}} + \varepsilon_t^{\omega,i,j}. \tag{6}$$

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 $\Upsilon' = Active \times Broad\ Strategy \times Freq\ Rebalance \times ROS\ Local\ Currency$ 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 ETF or not. Within non-ETFs, we further split the investors into more or less active traders. 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 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 operating currency (for funds, the predominant currency in which the fund sells shares to its final investors) is or is not the same as the currency of issuance of the ISIN.[11]

Similarly to the portfolio weight changes sub-component, we express the flows and the net-of-fee returns for each investor as averages within each investor type plus investor-specific

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

residuals as follows:

$$flow_t^i = \sum_{k \in \tau_i} \frac{flow_t^k}{|\tau_i|} + \varepsilon_t^{f,i} \tag{7}$$

$$r_t^{i,NF} = \sum_{k \in \tau_i} \frac{r_t^{k,NF}}{|\tau_i|} + \varepsilon_t^{r,i}, \tag{8}$$

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 we can use an even more granular grouping of investors, captured by $\tau \in \Upsilon$, where $\Upsilon = Active \times Size \times Broad\ Strategy \times Narrow\ Strategy \times Freq\ Rebalance \times ROS\ Currency$ and $\tau_i = \{k \in \tau | i \in \tau\}$ is the set of all investors of the same type as investor i. The three new sub-categories are "ROS Currency", "Size" and "Narrow Strategy".[12] "ROS Currency" is each investor's currency. We have three investor "Size" categories: " $\leq 100mil$", " $\leq 1bil$ and $\geq 100mil$" and "$\geq 1bil$". The "Narrow Strategy" categories 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 groupings ensures that it is always the case that $\tau \subseteq \tau'$ which we will utilize 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 $\tilde{I}^{miss} \equiv I \backslash \tilde{I}$ is the set of investors we do not observe. Intuitively, $\widehat{H}_{\tilde{I}}^{j,\tau}$ is the sample average holdings of ISIN j by all observed funds of type τ 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 $\widehat{H}_{\tilde{I}}^{j,m} \equiv \sum_{\{i|\ i \in \tilde{I} \cap c^i = m\}} \frac{\mu^{i,j}}{\widehat{P^j Q^j}}$ and $\widehat{H}_{\tilde{I}^{miss}}^{j,m} \equiv \sum_{\{i|\ i \in \tilde{I}^{miss} \cap c^i = m\}} \frac{\mu^{i,j}}{\widehat{P^j Q^j}}$ as the sample averages of holdings of ISIN j across all observed funds with ROS currency m and across the investors that we do not observe, respectively. Substituting equations (6),

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

(7), and (8) into equation (4) implies:

$$\begin{aligned}\Delta p_t^j = \quad & \sum_m \left(\widehat{H}_{\tilde{I}}^{j,m} + \widehat{H}_{\tilde{I}^{miss}}^{j,m}\right)\left(\Delta s_t^{l/m}\right) \\ & + \sum_{\tau\in\Upsilon}\left(\widehat{H}_{\tilde{I}}^{j,\tau} + \widehat{H}_{\tilde{I}^{miss}}^{j,\tau}\right)\left(\Delta\alpha_t^{f,\tau} + \alpha_t^{\omega,\tau,j} + \bar{r}_t^{NF,\tau}\right) \\ & + \sum_{i\in I}\frac{\mu^{i,j}}{\widehat{P^jQ^j}}\left(\varepsilon_t^{r,i} + \varepsilon_t^{f,i} + \varepsilon_t^{\omega,i,j}\right) - \Delta q_t^j,\end{aligned} \tag{9}$$

where

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

We further assume that:

$$\widehat{H}_{\tilde{I}^{miss}}^{j,\tau} = \kappa^j\widehat{H}_{\tilde{I}}^{j,\tau}, \tag{10}$$

where the scaling parameter κ^j depends on the ISIN but not on the group of funds. Since total holdings must equal the total market capitalization of ISIN j,

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

which implies

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

Thus, to compute the "common" sub-components of equilibrium holdings, aggregated across all investors, we must scale up our type-specific average sub-components by *a scaling factor that is the inverse of the total coverage ratio*, $\frac{\sum_{i\in\tilde{I}}\mu^{i,j}}{\widehat{P^jQ^j}}$, which is defined as the sample average holdings of ISIN j by all the investors in our sample as a fraction of the sample average market capitalization of the ISIN. Given that the set τ conditions on the ROS currency of

the fund, equation (10) also implies:

$$\widehat{H}^{j,m}_{\tilde{I}^{miss}} = \kappa^j \widehat{H}^{j,m}_{\tilde{I}}.$$

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

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

where

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

We proxy the population average net returns, flows, and portfolio weight change terms within each type of funds using sample averages.

Equation (11) implies that there are two valuation components of the "common" component of equity holdings, Δd^j_t. The first one refers to the fact that equity holdings are impacted by the overall performance of investors, $\Delta d^{r^{NF},j}_t$. Holding the other components of "common" equity holdings constant, higher net-of-fee portfolio returns get reinvested, which in turn, increases the holdings of equities and increases stock prices.

The second valuation component of "common" equity holdings, $\Delta d^{s,j}_t$, captures the fact that prices and exchange rates are jointly determined in equilibrium. Based on equation (11), a local currency depreciation, positive $\Delta d^{s,j}_t$, will increase the value of the local-currency stock

market, holding the other sub-components of "common" equity holdings fixed. Intuitively, conditional on given holdings, denominated in the currency of the investor, $\Delta d_t^{ROS,j}$, 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 component and local-currency stock prices, *conditional* on the other components of "common" holdings, captured by $\Delta d_t^{ROS,j}$, not adjusting. In contrast, for most ISINs, we would expect variation in equity holdings to generate an 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 have to be entirely absorbed by an increase of the local-currency stock market price.

The last two components of "common" equity holdings relate to the portfolio weight change of investors with respect to ISIN j, $\Delta d_t^{\omega,j}$, and to the decisions of the final investors who decide on the amount of invested wealth, $\Delta d_t^{f,j}$. 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 Returns Decomposition

In order to also study the key drivers of the aggregate stock market, we construct the average of equation (11) weighted by the sample average market capitalization of each ISIN relative to the total market capitalization of all ISINs in the stock market associated with a currency

l, $\nu^{j,l} = \frac{\widehat{P^j Q^j}}{\sum_{\{j:c^j=l\}} \widehat{P^j Q^j}}$. We can express this weighted-sum as:

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

where $\Delta p_t^{SM,l} = \sum_{\{j:c^j=l\}} \nu^{j,l} \Delta p_t^j$ and $D_t^{x,l} = \sum_{\{j:c^j=l\}} \nu^{j,l} \Delta d_t^{x,j}$.

We will construct the 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.

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, currency of issuance of the share class, and Fund Type.[13] For each asset at an ISIN/CUSIP level, we obtain data from Refinitiv/Eikon on prices, market capitalization, and characteristic including type of the asset (fixed income vs equity etc.), industry of the issuing firm, currency of issue, 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 total AUM where the difference represents the importance of ETFs. One can see that ETFs 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 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.

[13] Morningstar states that their data covers close to the universe of mutual funds.

[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.

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

As an external validity check of the quality of our data, at the total stock market level, we compare our monthly stock market return measures, 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.[16] 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 returns. The weighted coverage ratios range from 1% to 21% at the end of our monthly sample with the coverage being highest for the US, Eurozone, UK, and other advanced economies.[17]

Table 1 also reports the number of ISINs per stock market that we use to construct our stock 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 estimate the common-across-investors flow and net-of-fee returns 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" component of equity holdings at an ISIN level is 80.

[16] The list of stock indices is reported in the Data Appendix.

[17] The respective range for the quarterly data is 2–40% (see Table A.10 in the Online Appendix.).

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 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 "common" and idiosyncratic residual components of equations (6), (7) and (8). 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.[18] 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, 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 ETFs vs active funds and include the averages within these categories. The "common" component of equity holding due to portfolio weight changes across active and ETF funds is very similar even at the individual ISIN level. This result could be rationalized if stock prices respond strongly to the active "common" component of portfolio weight change. More specifically, if within the same ETF 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 ETFs in a direction consistent with the active funds.

Last but not least, another key observation that stands out is the very large volatility

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

of the idiosyncratic sub-components of equity holdings, $\varepsilon_t^{\omega,i,j}$, $\varepsilon_t^{f,i}$ and $\varepsilon_t^{r,i}$, or the differences between the fund level points in each figure and the average lines. In order for our "common" equity holdings measure to explain a sizable fraction of stock price movements, it has to be the case that these very volatile residual components of equity holdings, 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 subsection, we quantitatively assess the fit of our constructed aggregate equity holdings, given by equation (4), as well as the importance of each of the sub-components in our decomposition. We perform the following variance covariance decomposition.

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

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

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.

5.1.1 Total Observed "Common" Equity Holdings

The left panel of Figure 6 reports the distribution of $\beta^{p,\Delta d^j}$ across ISINs. We can see that the "common" component of equity holdings for a given stock explains a surprisingly large share of the variation in the price of that stock, 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, where the average scaled covariance is very high at 89 %. In summary, the "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.

As expected, the fit improves when we have a larger number of funds holding a given stock. Figure 9a 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 9b which plots $|1-\beta^{p,\Delta d^j}|$ against the median over time coverage per ISIN). Surprisingly, the "common" component of equity holdings still explains stock price growth 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 the funds in our sample are truly representative of the behavior of all investors that purchase this particular ISIN.

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 10 and 11, 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 (for example, Industrial and Commercial Bank of China Ltd, Petrobras, Rosneft, and Sberbank as shown in Figure 12 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.

Together, the low importance of both new issuance/buybacks and the idiosyncratic residual equity holdings term implies that the observed "common" equity holdings components explain most of individual equity price variation. We are seeing market clearing in action. Given the large volatility of the idiosyncratic components of equity holdings, the fact that it is the far-less-volatile "common" observed component of equity holdings 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, on average, receives 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.

5.1.2 Sub-components of Observed "Common" Equity Holdings

Next, we discuss the relative importance of the sub-components of the "common" equity holdings. Figure 7 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 8 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 ETFs vs active (i.e. non-ETF) funds and own currency vs other currency investors. The panel regression results are presented in Tables 3 and 4.[19] The sum of the ETF and active fund sub-components might not add up to the total estimated contribution as for some funds, there are no ETF holdings and, thus, we have sample differences across the regressions.[20]

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

[20]Finally, we also break down the importance of the equity holdings sub-components for select individual ISINs in Figures 10–12 and Figures A.29–A.34 presented in the Online Appendix.

Weights

From the panel regressions, it is clear that the portfolio weight change 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 ETFs are of lower importance and act as an amplifier. There are only two currencies for which the change in weights of ETFs is almost as important as the rebalancing of active investors: JPY and CNH. Hence, non-ETF investing and "stock-picking" seems alive and well. This finding is consistent with Bertaut et al. (2023) who find, using the granular US TIC data, that international equity investors tend to allocate capital towards the most productive firms.

Another important finding is that, while some stock markets exhibit very high currency home bias, with equity mostly held by local investors, we also see home bias in the portfolio weight change component of our holdings decomposition. For example, Table 4 shows that, for the US, almost all of the variation in the change in the weights subcomponent reflects portfolio rebalancing of investors whose ROS currency is the USD. Currency home bias is also important, but to a lesser degree, for the GBP, the 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" or "financial 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 active and passive 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 investor flows are positively correlated with the equity price growth rates and are statistically significant.

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 return component 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 component enters significantly and negatively for most currencies, indicating exchange rates appreciate when stock prices go up. 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.[21]

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

[21]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.

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-quality 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.[22] 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 "common" equity holdings component with respect to stock price growth rates at the micro level, for each individual ISIN, and analyzed the relative importance of each sub-component of equity holdings, 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

[22]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.

market, in order to understand the impact of policies on aggregate stock market returns, 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 "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 "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, safe haven countries, etc. As surprising as it may sound, we are able to construct equity holdings 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 condition and assumptions about similarity of behavior within narrowly defined investor types.

In what follows, we study the relative importance of the equity holdings 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 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 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, its contribution decreases significantly for advanced economies and even turns slightly negative for USD, JPY and CHF. The portfolio weight change component is always statistically significantly correlated with the stock price growth rate with the exception of CNH.

Intuitively, the negative estimated co-variances for USD, JPY and CHF are consistent with risk averse wealth that is parked in safe haven currencies rebalancing out of these currency areas *in aggregate* when global stock markets are doing well and flowing back into these safe haven stock markets after negative global shocks or when volatility increases. This is consistent with a global financial cycle of risk-averse wealth going in and out of safe haven currency areas. Having said that, the estimated negative portfolio weight change contributions are fairly small and only borderline statistically significant.

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 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 aggregate portfolio weight change 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 change 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 elasticity component 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 flow sub-component of equity holdings has gained some importance in the aggregate variance covariance decomposition. This sub-component always comoves positively with stock returns in a statistically significant way for 24 out of 33 stock markets. The average fraction of aggregate stock price movements explained by the final flows 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 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/financial multiplier", an increase in stock prices leads to the returns being rein-

vested 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 returns 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-fees fund returns and stock returns. 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 subcomponent. 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.[23] The contribution of the exchange rate 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

[23]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.

for the USD, JPY and CHF are 2%, 23% and 8%.[24] 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 returns 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 returns 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 seen from the fact that $Cov\left(\Delta D_t^{s,l}, \Delta D^{ROS,l}\right) < 0$ for all currencies but JPY, USD, and HKD.[25]

[24] 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.

[25] 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

Exploring further which ones of the sub-components of $\Delta D^{ROS,l}$ 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 $D^{s,l}$ on $D^{\omega,l}$ or $D^{f,l}$, 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 sub-components. Considering $D^{\omega,l}$, the relationship is statistically significant for all currencies but CNH and 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 $D^{f,l}$, the estimated coefficients are insignificant in 8 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 fixed income funds that invest in these currencies while equity funds that invest in these currencies, if anything, experience outflows.[26] Notice that portfolio weight changes into USD and JPY equities is still associated with an appreciation of these currencies, implying that,

between $\Delta D_t^{s,l}$ and $\Delta D^{ROS,l}$.

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

within equity markets, JPY and USD still have safe haven status. However, for all other currencies, we do find the expected negative unconditional correlation between changes in equity holdings for the currency and the exchange rate movement.

Finally, when considering patterns regarding the importance of the various 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 return volatility by more, the portfolio weight change 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 sub-component as a function of portfolio weight change sub-component, specific to a given industry and country, and an idiosyncratic portfolio weight change sub-component, specific to the individual stock, and backed out as a residual.

We re-write equation (6) as follows:

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

where $\gamma' \in \Gamma'$ captures the type of ISIN and $\Gamma' = Industry \times Currency\ of\ ISIN$ and $\gamma_j' = \{l \in \gamma' | j \in \gamma'\}$ is the set of all ISINs of type γ' such that ISIN j is also of type γ'. Finally, $|\gamma_j' \times \tau_i'|$ is the number of elements in the set $\gamma_j' \times \tau_i'$. Based on equation (13), we further decompose the portfolio weight change sub-component as:

$$\Delta d_t^{\omega,j} = \Delta d_t^{\omega,j,iid} + \Delta d_t^{\omega,j,Ind}, \quad (14)$$

where

$$\Delta d_t^{\omega,j,Ind} = \sum_{\tau \in \Upsilon} \frac{\sum_{\{i:\, i \in \tilde{I} \cap i \in \tau\}} \mu^{i,j}}{\sum_{i \in \tilde{I}} \mu^{i,j}} \alpha_t^{\omega,\tau,Ind,j}, \tag{15}$$

and

$$\alpha_t^{\omega,\tau,Ind,j} = \sum_{l \in \gamma_j'} \sum_{k \in \tau'} \frac{1}{|\gamma_j' \times \tau'|} \frac{\Delta \omega_t^{k,l}}{\widehat{\omega}^{k,l}} for\ all\ \tau \subseteq \tau'. \tag{16}$$

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

$$\Delta D^{\omega,l} = \Delta D^{\omega,l,iid} + \Delta D^{\omega,l,Ind}, \tag{17}$$

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 (15). It is clear that idiosyncratic stock picking is key in explaining individual stock returns, meaning it appears that ISIN specific portfolio weight change (due to potentially ISIN specific news), rather than industry level portfolio weight change (due to potentially 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 explains the importance of portfolio weight changes for aggregate stock market fluctuations.

7 Conclusion

Data on mutual funds holdings which account, on average, for as little as 5 % of individual ISIN equity market capitalization are informative enough to reconstruct equilibrium equity

holdings that can account for the bulk of individual level and aggregate stock market returns. *This is the central and highly surprising result of the paper.* Based on this novel decomposition of returns, we document numerous stylized facts that should motivate all asset pricing theories of equities, 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 find that exchange rates are a key equilibrating price for the vast majority of stock markets, besides the ones close to financial "autarky" such as the US, and that the safe haven currency status of the USD and JPY also plays an important role for equity markets. 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 can be used to express exchange rates as a function of the net supply of currencies and elasticities linked to the centrality of a currency for equity markets.

Our second key finding is that financial investors re-balance heterogeneously across and within "currency" borders, which generates very different dynamics with respect to what the key drivers of individual level vs aggregate stock returns are. While stock picking, as captured by portfolio weight changes, seems to explain most of the individual stock market returns, at the aggregate stock market level, "Keynesian" wealth effects dominate, as captured by the increasing importance of the net-of-fee returns component of equity holdings. Having said that, the importance of this wealth effect versus the portfolio weight change effect varies a lot across countries, depending on how substitutable stocks are within and across "currency borders".

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8 Appendix

8.1 Details on Cleaning 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.

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.

8.2 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 or if they are classified as Depository Receipts.
- "Price" measured in "Currency" – the price we download is the "Closing Price" which corrects for shares' splits but does not adjust for dividend payments, 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 from the Eikon and Morningstar price series where the monthly or quarterly price growth rate exceeds 100 percent in absolute value. The correlation between the price growth rates from the two 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 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 this variable bases on the Eikon variable "Country of Risk" and if missing, we proxy using of the following variables"Issuer Country", "Ultimate Parent" and "Country of Headquarters".

8.3 Stock Market Daily Indices

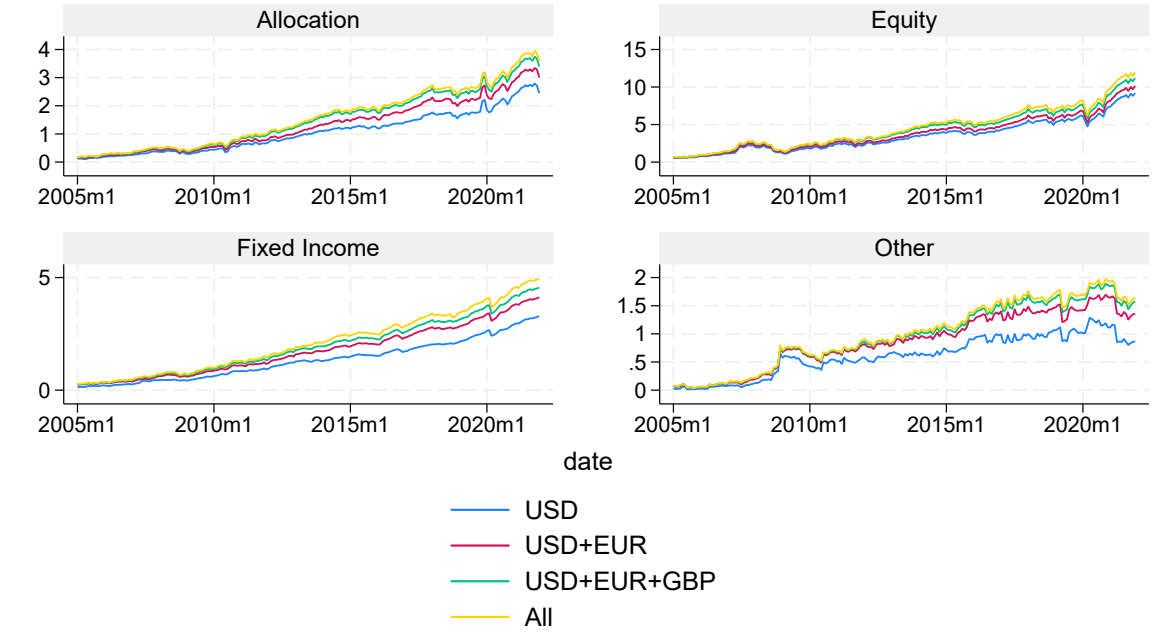
The data source is Global Financial Data and the list of stock market indices in local currency is:

- 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

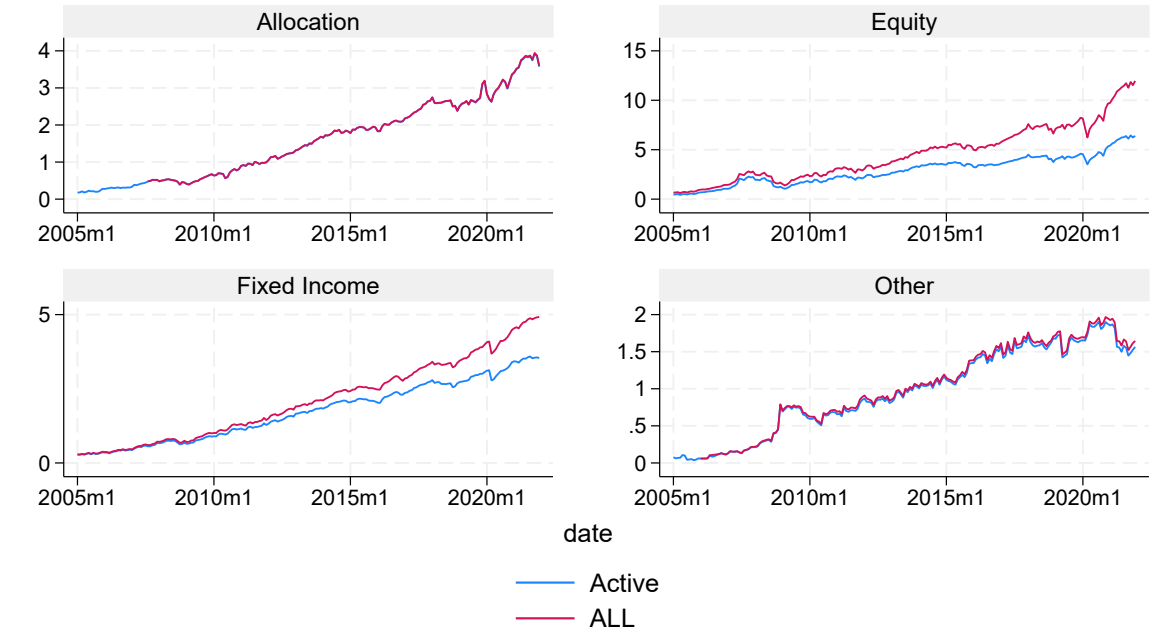
9 Tables and Figures

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



Graphs by Global Broad Category Group

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



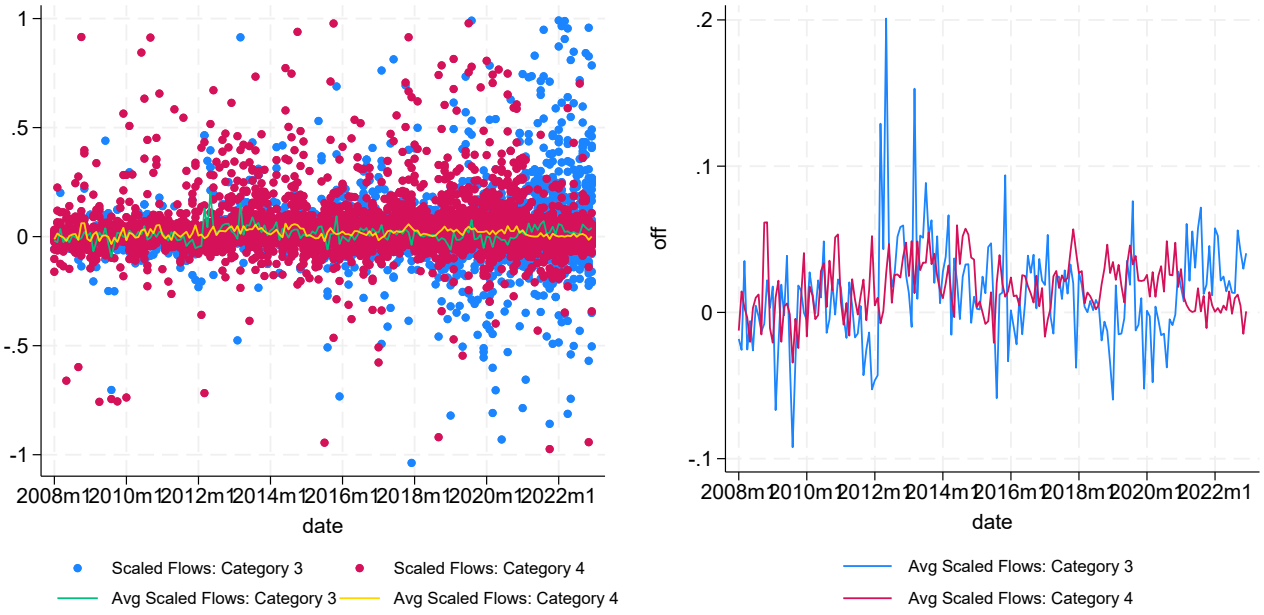
Graphs by Global Broad Category Group

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

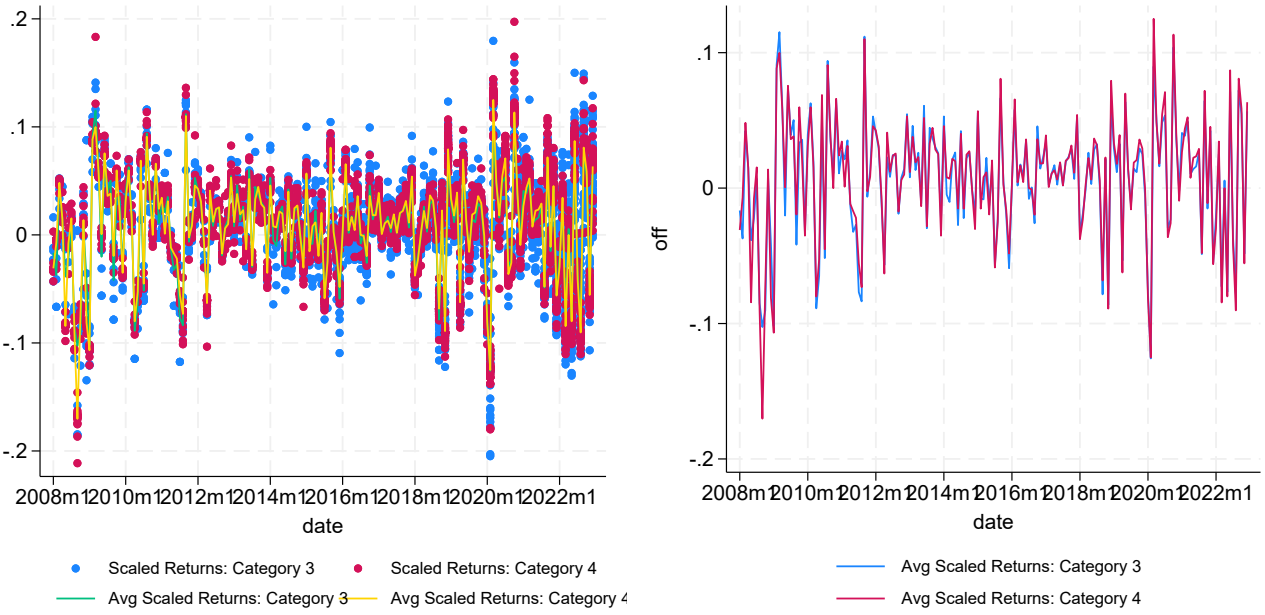
This table presents the sample average, starting date and ending date coverage ratios, weighted by the market capitalization of the ISIN. The coverage ratio for an ISIN is defined as total observed holdings of this ISIN in our data set over the market capitalization of the ISIN, translated in the same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



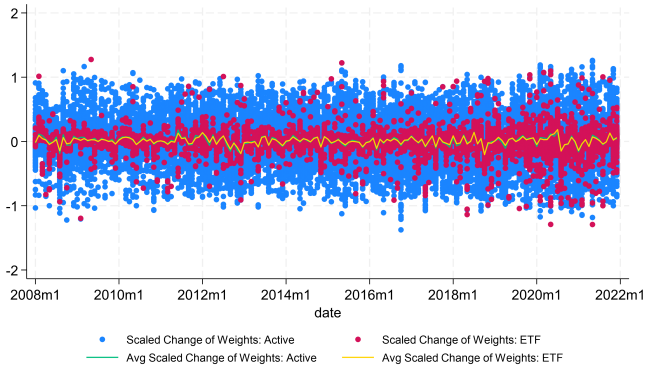
Equity Funds; USD ROS currency;
Category 3 : Active: more active; Freq Rebalance: re-balancing frequently; size of fund: <=100mil; GlobalCategory: US Equity Large Cap Blend
Category 4: Active: ETF; Freq Rebalance: re-balancing frequently; size of fund: >1bil; GlobalCategory: US Equity Large Cap Blend

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

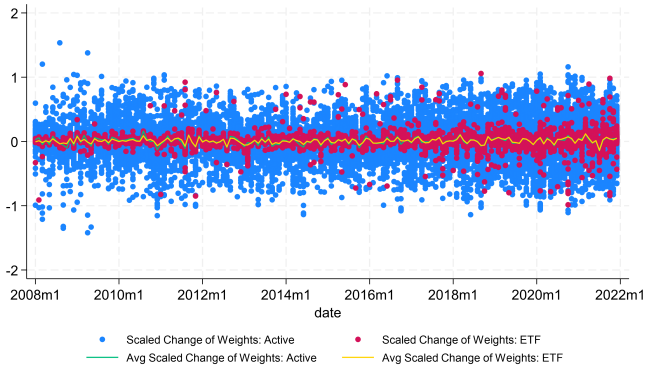


Equity Funds; USD ROS currency;
Category 3 : Active: more active; Freq Rebalance: re-balancing frequently; size of fund: <=100mil; GlobalCategory: US Equity Large Cap Blend
Category 4: Active: ETF; Freq Rebalance: re-balancing frequently; size of fund: >1bil; GlobalCategory: US Equity Large Cap Blend

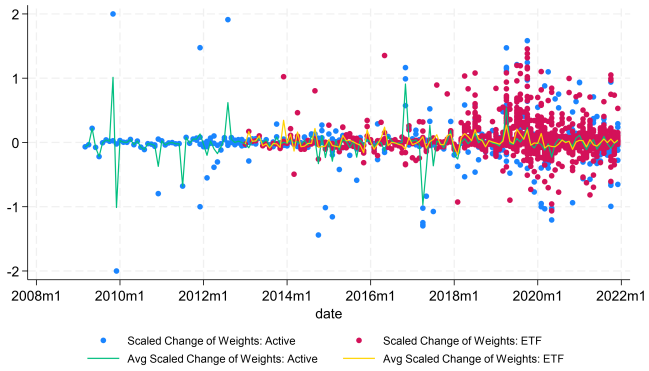
Figure 5: Portfolio Weight Change for Select Stocks



(a) Apple



(b) LVMH



(c) Industrial and Commercial Bank of China Ltd

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

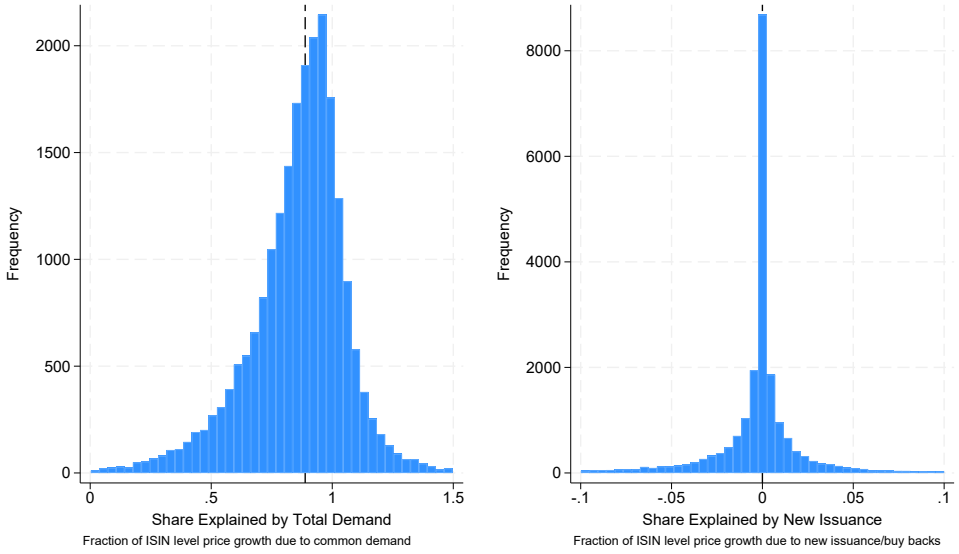


Figure 7: ISIN-Level Equity Price Growth Rate Decomposition: Equity Holdings Sub-Components

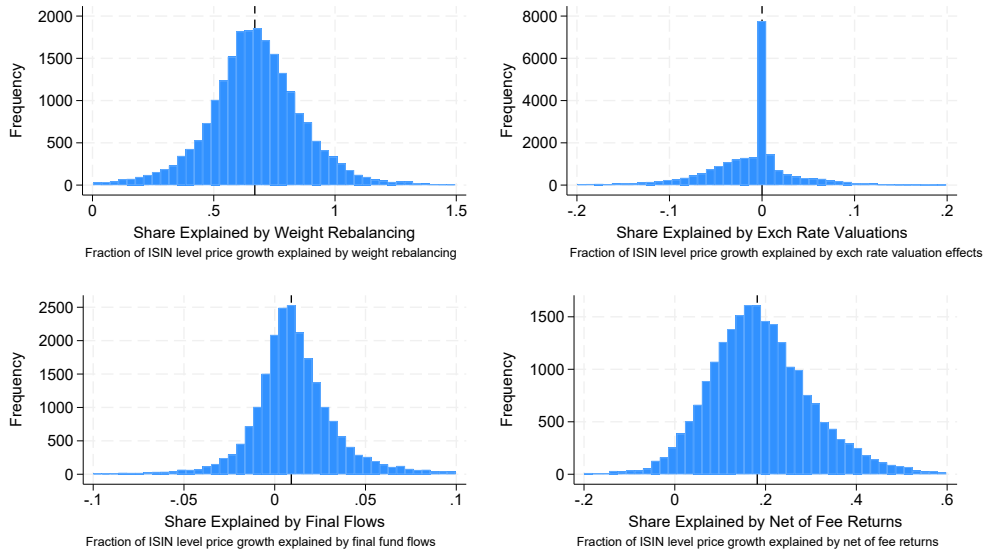


Figure 8: ISIN-Level Equity Price Growth Rate Decomposition: Panel Regression Estimates

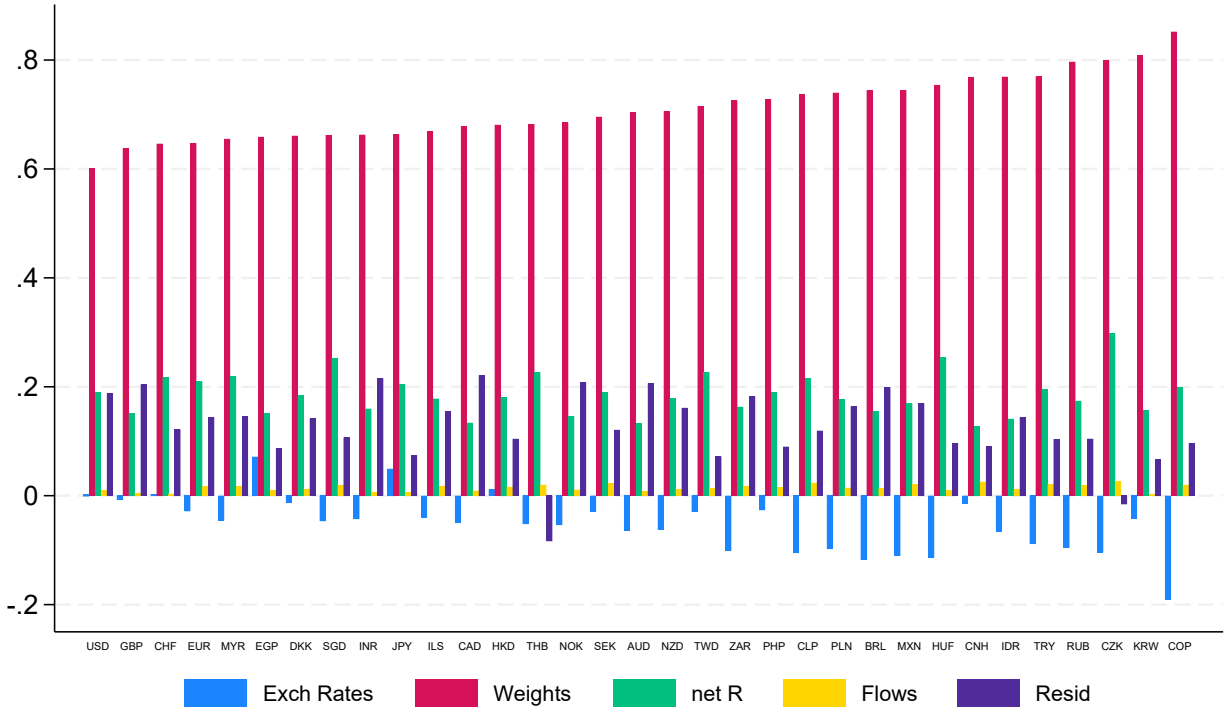
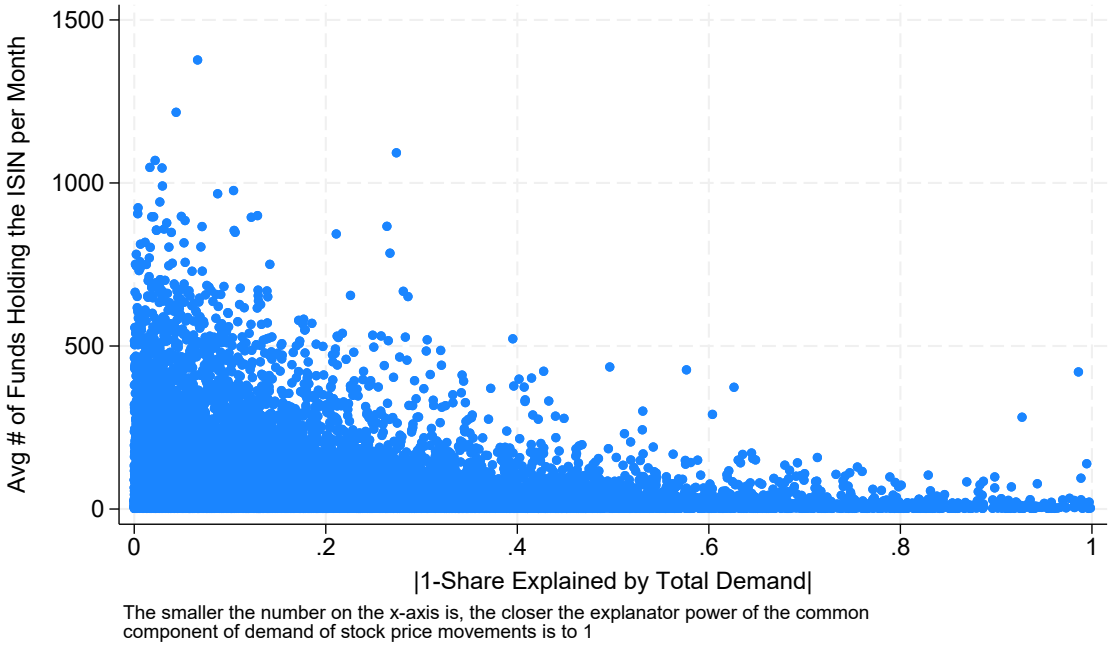


Table 2: ISIN-Level Equity Price Growth Rate Decomposition: Panel Regressions

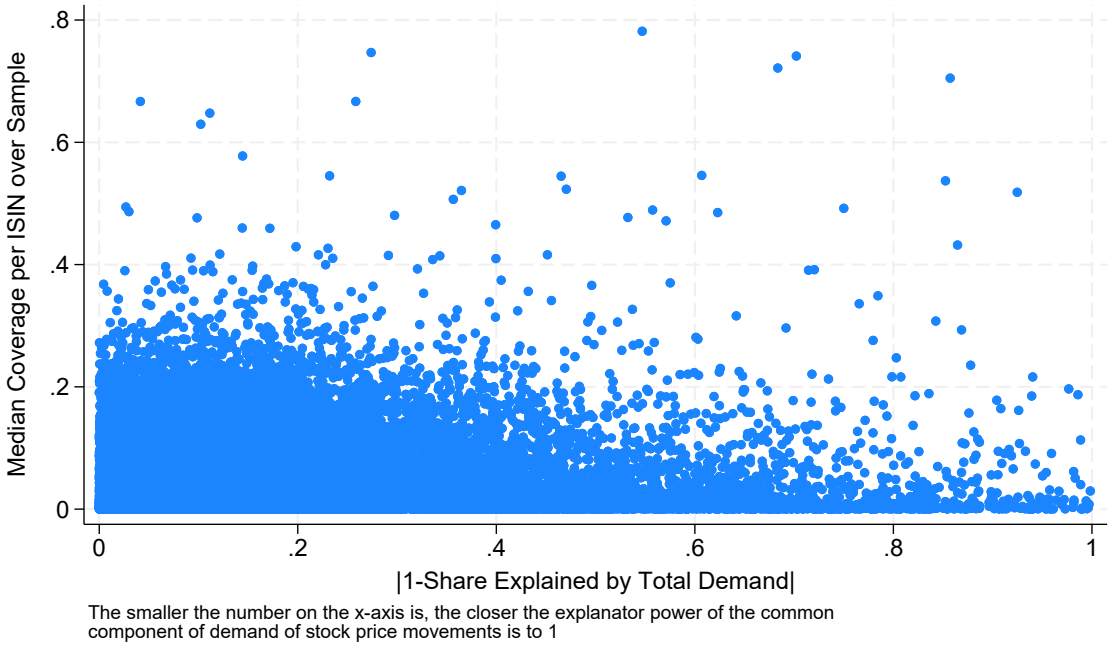
Currency	Δd_t^j	$\Delta d_t^{\omega,j}$	$\Delta d_t^{s,j}$	$\Delta d_t^{f,j}$	$\Delta d_t^{r^{NF},j}$	$\Delta d_t^{Resid,j}$	Δq_t^j
AUD	0.780***	0.704***	-0.064***	0.008***	0.133***	0.206***	-0.010***
BRL	0.795***	0.745***	-0.118***	0.013***	0.155***	0.199***	-0.007**
CAD	0.773***	0.678***	-0.049***	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 of panel regressions of the "common" component of equity holdings (or its sub-components) on Δp_t^j 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 9: ISIN Level Fit

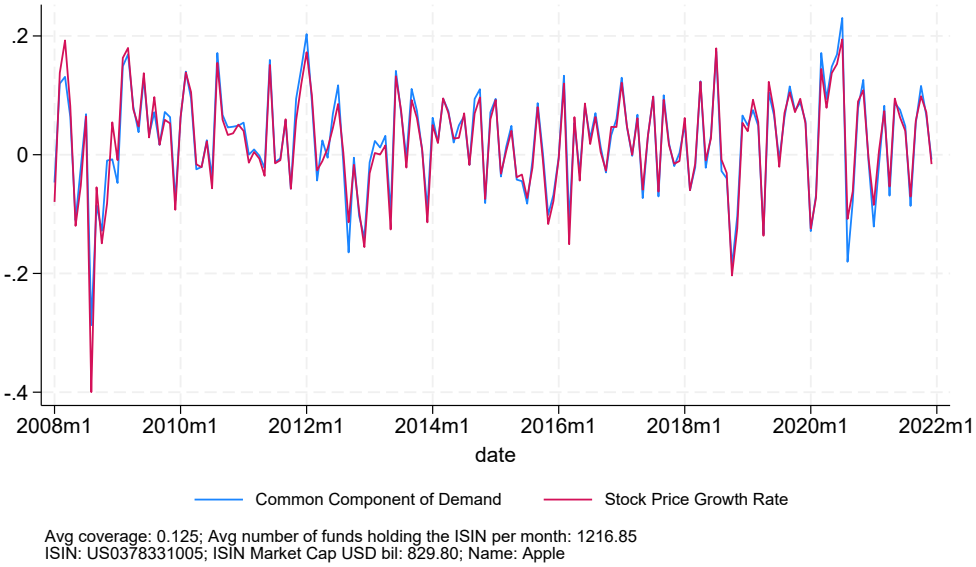


(a) Against Average Number of Funds



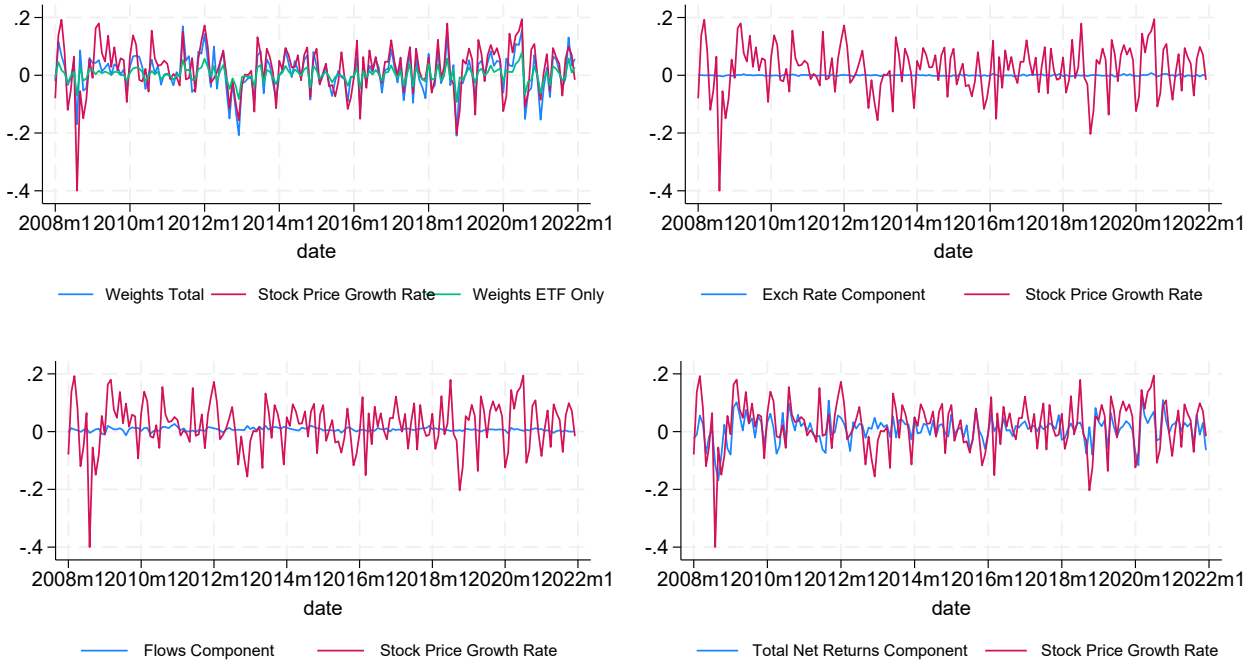
(b) Against Coverage

Figure 10: "Common" Equity Holdings Components: Apple



Avg coverage: 0.125; Avg number of funds holding the ISIN per month: 1216.85
ISIN: US0378331005; ISIN Market Cap USD bil: 829.80; Name: Apple

(a) Total



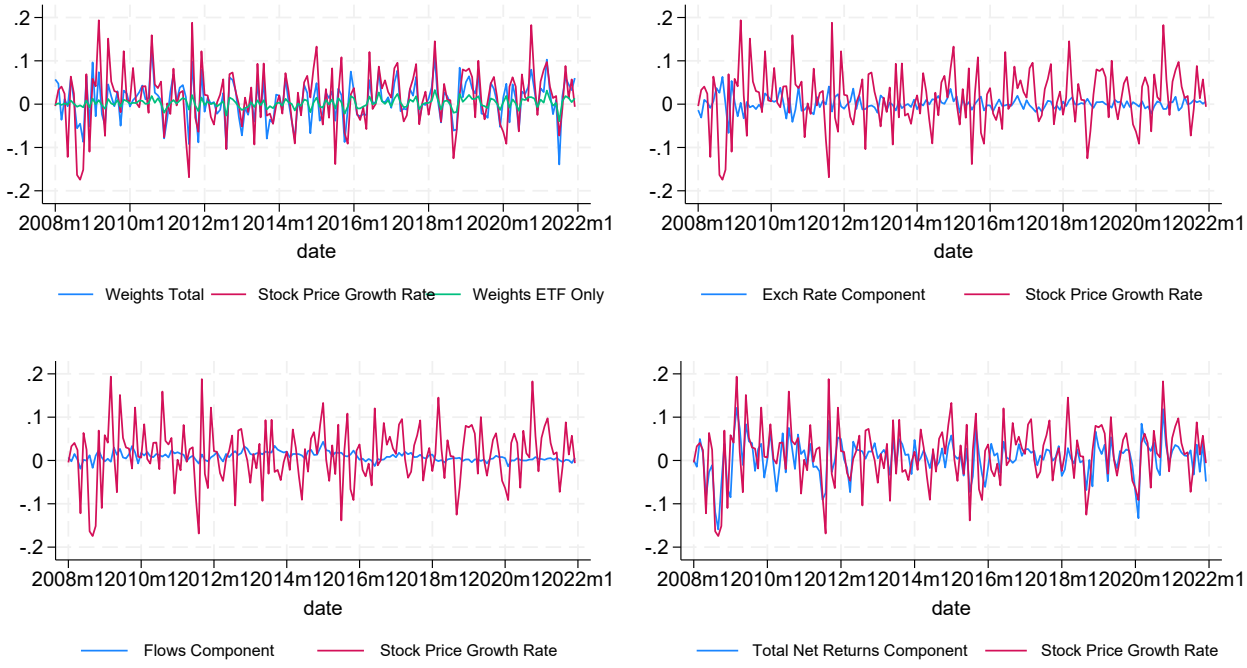
(b) Sub-components

Figure 11: "Common" Equity Holdings Components: LVMH



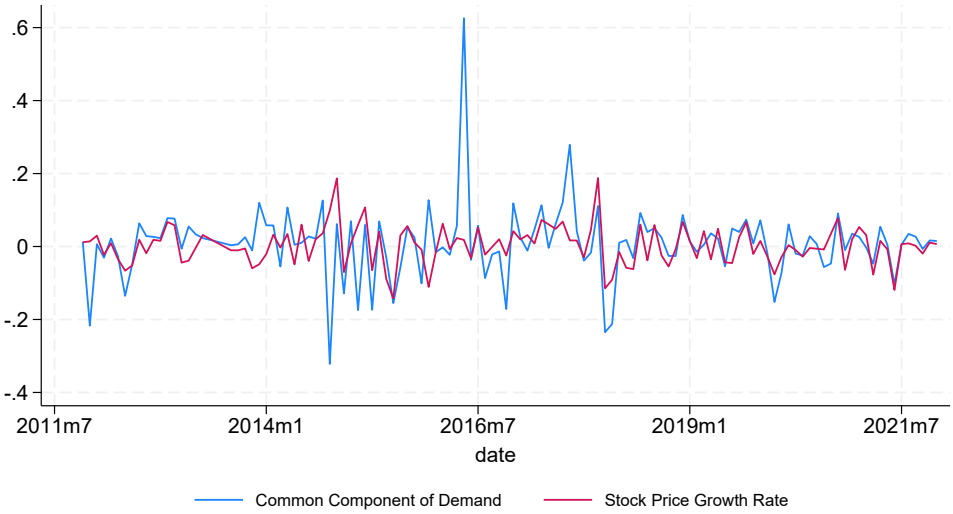
Avg coverage: 0.067; Avg number of funds holding the ISIN per month: 575.49
ISIN: FR0000121014; ISIN Market Cap USD bil: 141.55; Name: LVMH

(a) Total

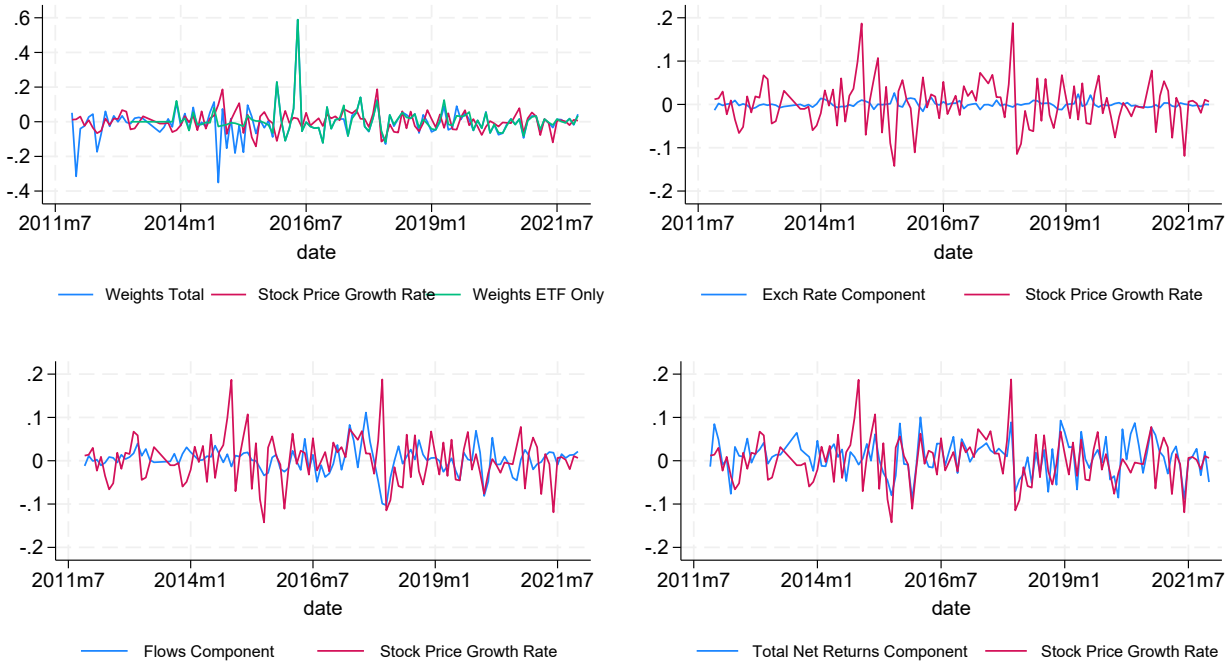


(b) Sub-Components

Figure 12: "Common" Equity Holdings Components: Industrial and Commercial Bank of China Ltd



(a) Total



(b) Sub-Components

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

Currency	$\Delta d^{\omega,j}_{ETF}$	$\Delta d^{\omega,j}_{Active}$	$\Delta d^{f,j}_{ETF}$	$\Delta d^{f,j}_{Active}$
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 active and passive 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

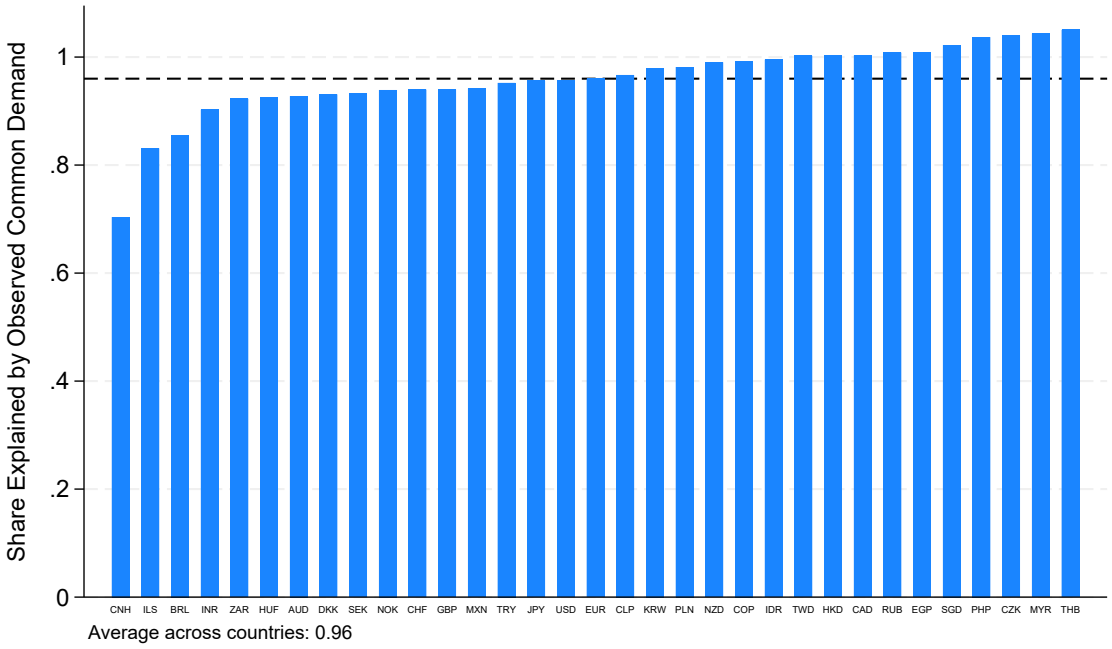


Figure 14: Aggregate Stock Market Price Growth Rate Decomposition

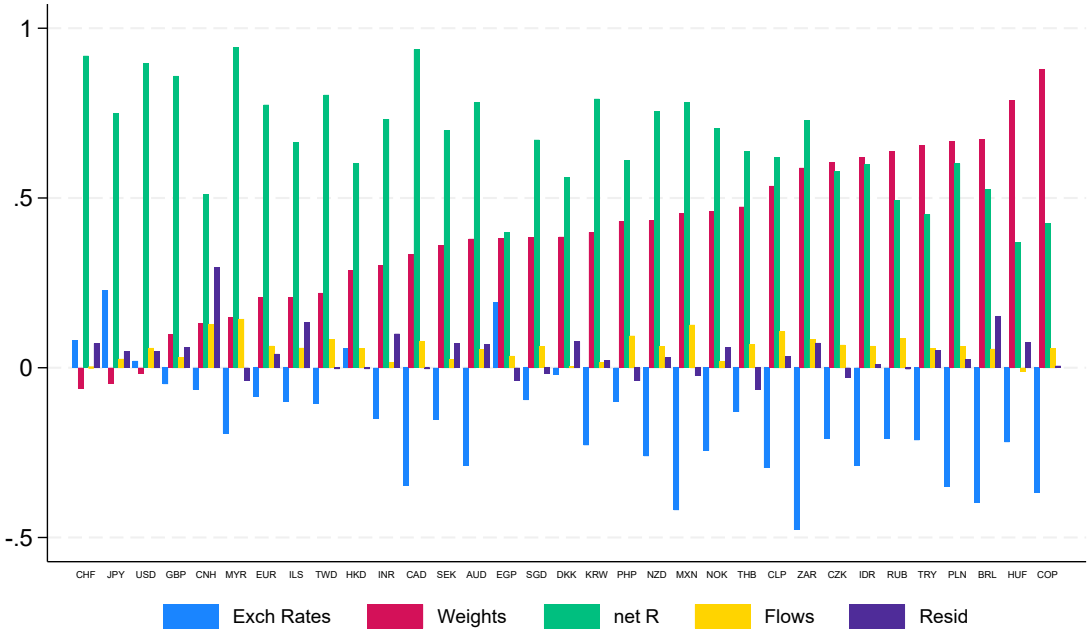
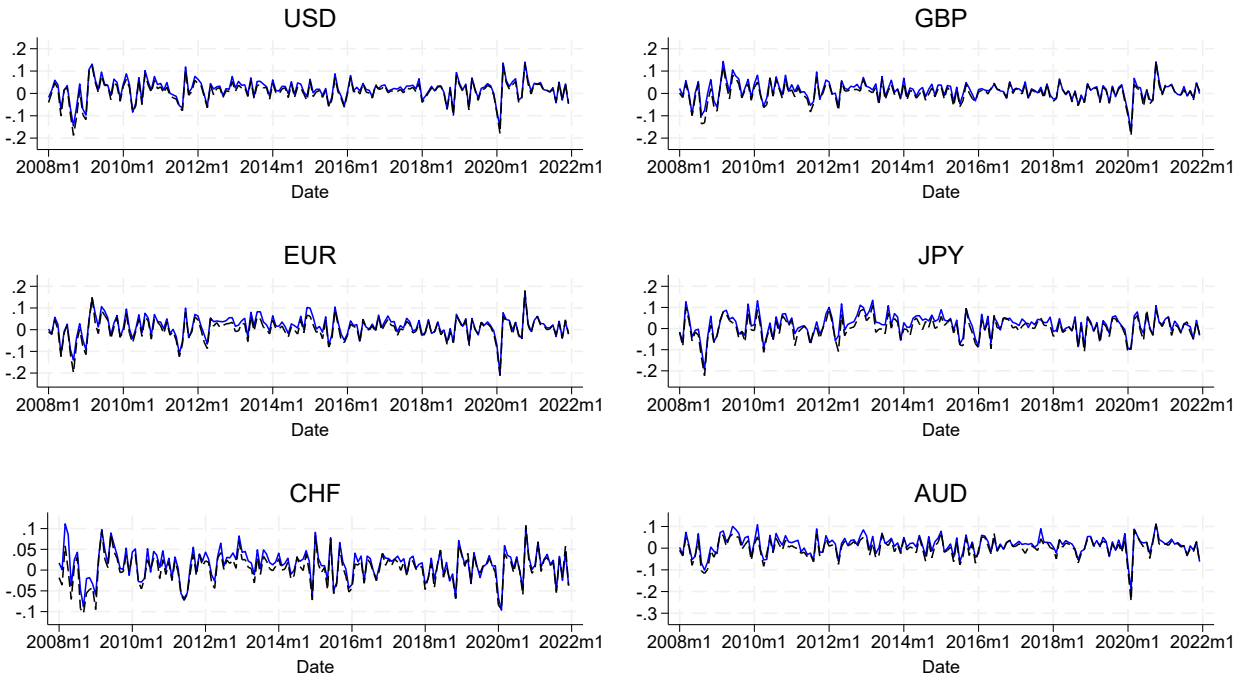


Table 5: Aggregate Stock Market Price Growth Rate Decomposition

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

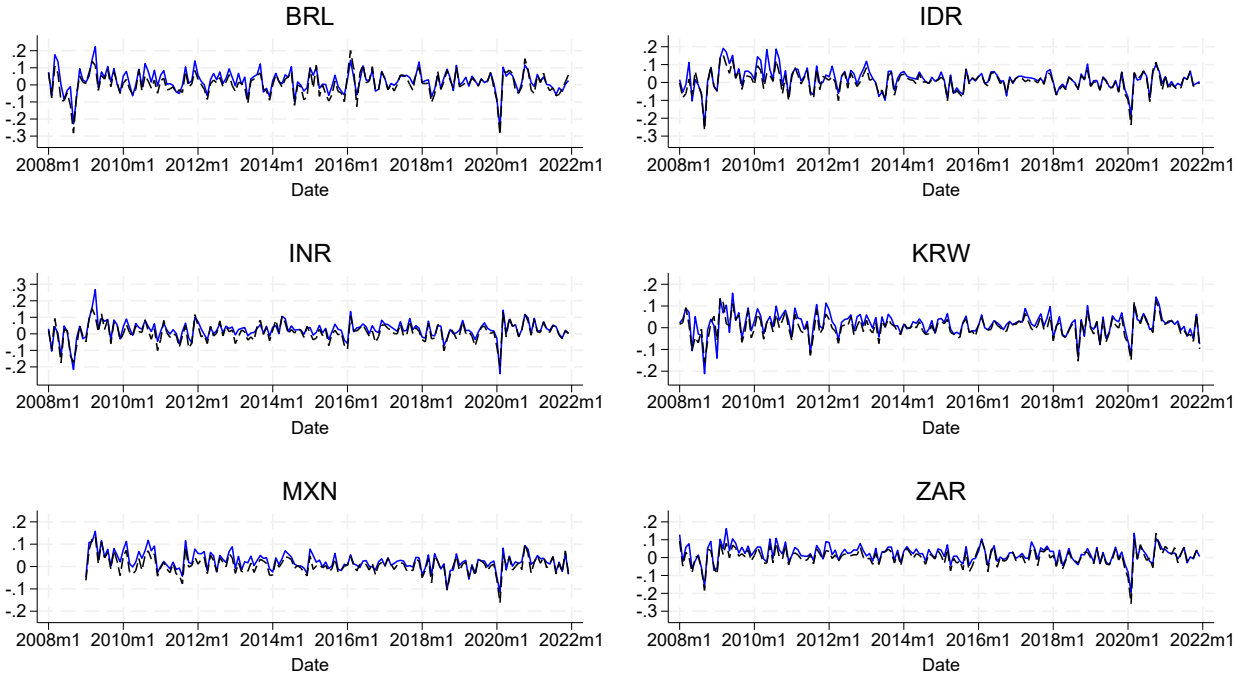
Note: In this table we report the coefficients from regressing the "common" component of equity holdings and its sub-components on the aggregate stock market price growth rate (where the stock market is denoted by the currency associated with that stock market). * – significant at 10%; ** – significant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

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



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

(a) Select Advanced Economies



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

(b) Select Emerging Markets

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

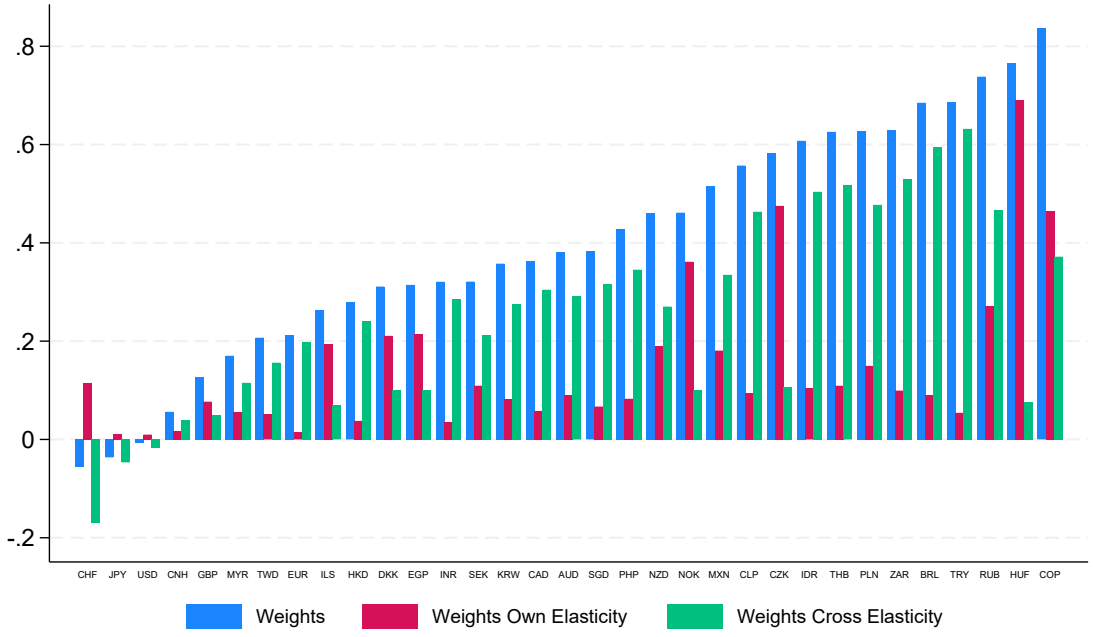


Figure 17: The Importance of Own vs Cross-Covariance Sub-components: Net-of-Fee Returns

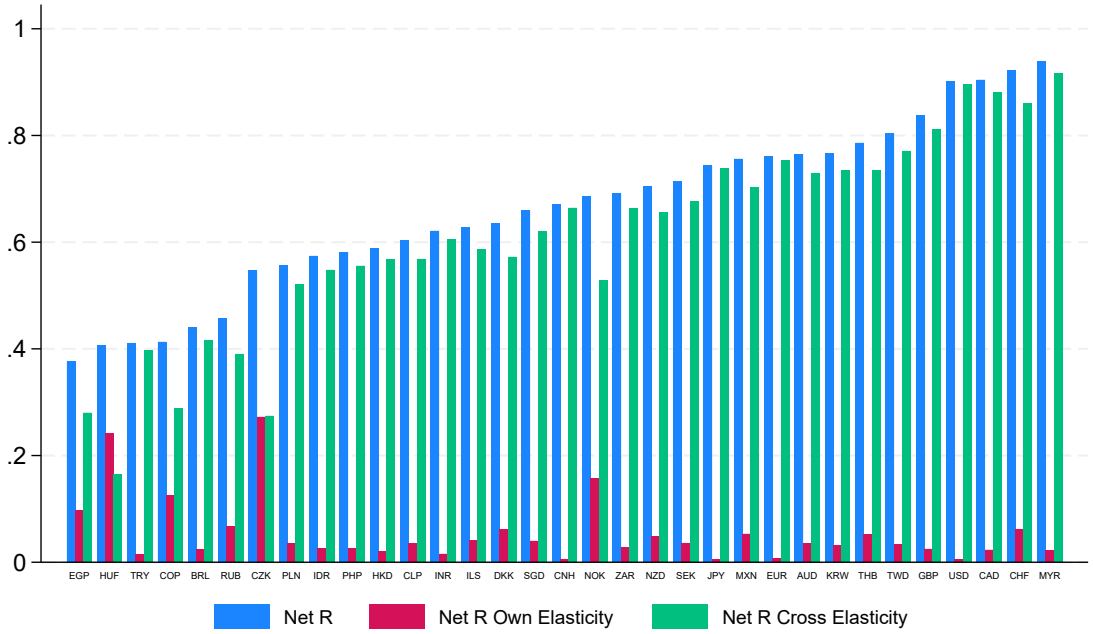
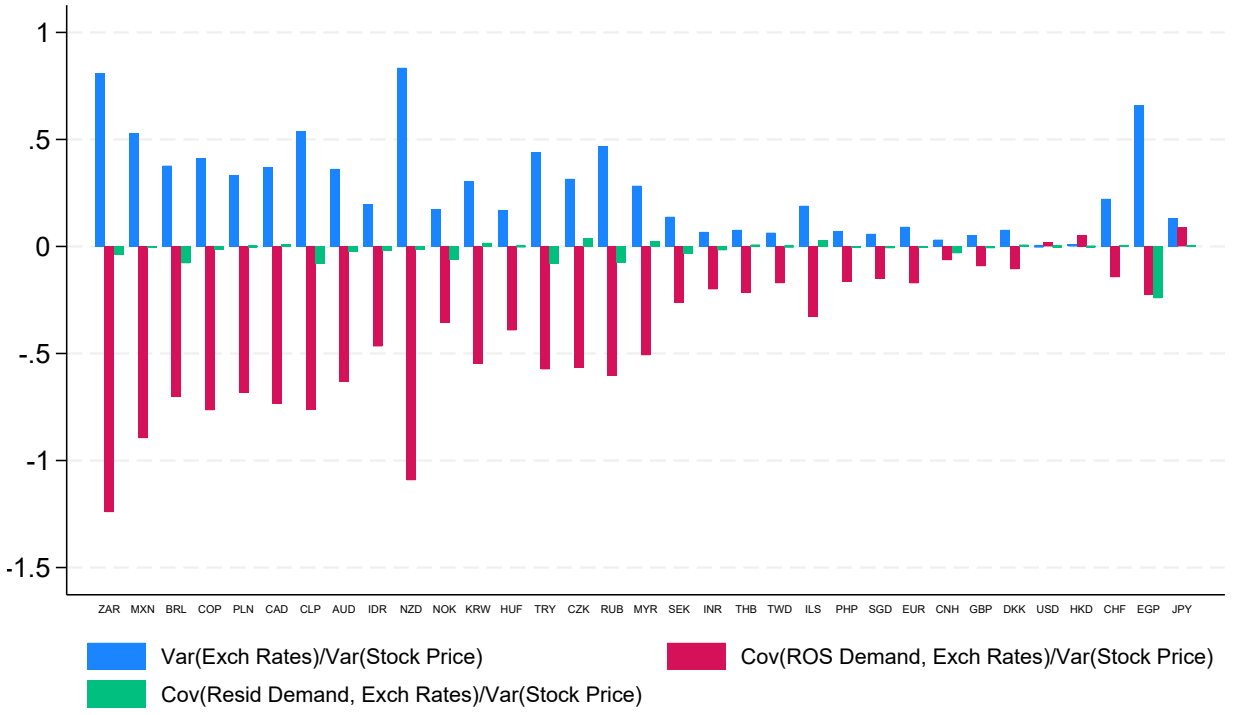


Figure 18: Further Decomposing $\beta^{p,D^{s,l}}$ Using Sub-components of Equity Holdings



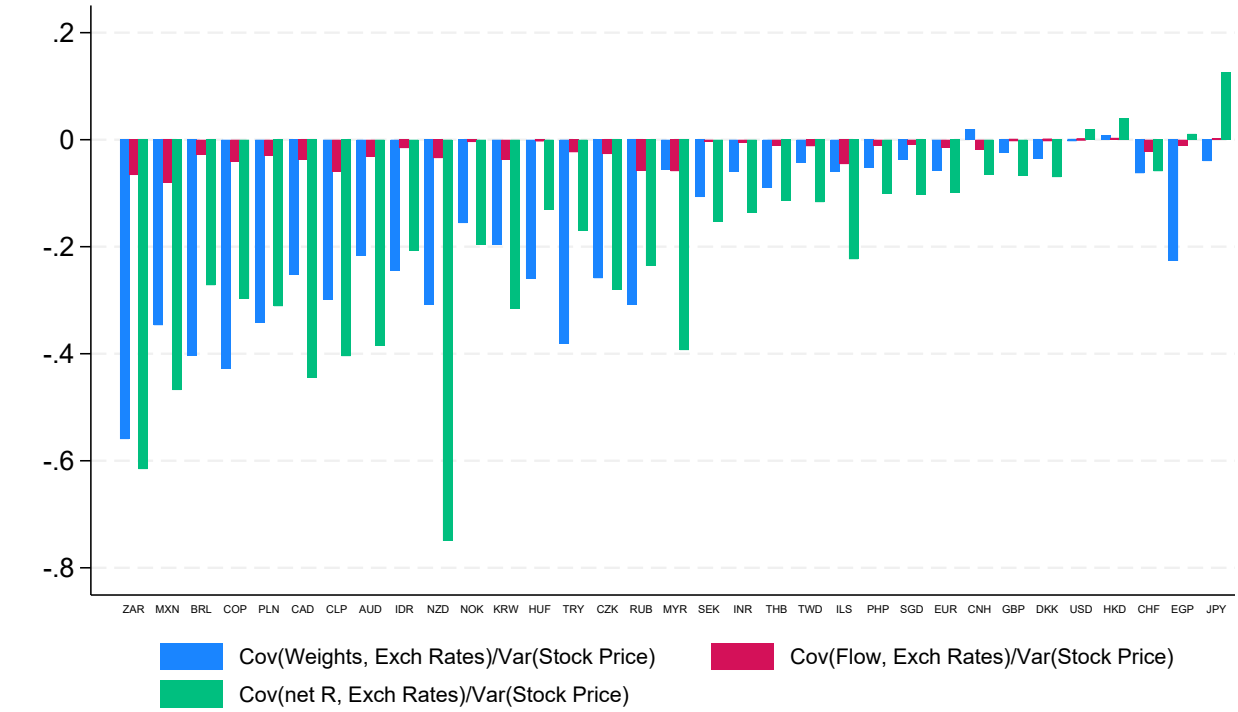


Table 6: Link Between Weighted-Average Exchange Rates and Portfolio Weight Changes or Flow Sub-Components

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***	0.430***	0.737***	0.532***	0.003	0.536***
CNH	0.116***	0.652***	0.768***	0.097	0.033	0.130
COP	0.552***	0.310***	0.852***	0.677***	0.203***	0.880***
CZK	0.615**	0.275	0.799***	0.561***	0.043***	0.604***
DKK	0.193***	0.468***	0.661***	0.343***	0.043	0.386***
EGP	0.308***	0.358***	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***	0.264***	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***	0.549***	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***	0.493***	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***	0.477***	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***	0.553***	0.725***	0.560***	0.028*	0.589***

Note: In this table we report the coefficients of panel regressions of the portfolio weight change sub-component on Δp_t^j by stock market (as denoted by the currency associated with that stock market). ISIN level panel regressions and stock market level regressions. For the panel level regressions we allow for ISIN level fixed effects and cluster the standard errors by ISIN. * – 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:

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

After scaling up the observed equity holdings using the inverse of the coverage ratio and expressing the equity holdings sub-components as simple averages and residuals, as in the text, we obtain the following expression for equity price growth rates:

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

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

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

The main difference with equation (11) from the main text is that now the holdings components will be scaled up by the factor $\frac{1}{\Theta^j}$ and we consider only the holdings of the marginal traders when constructing the "common" component 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.[27] That number is around 77% at quarterly frequency. The equivalent numbers for allocation funds are 63% at monthly and 79% at quarterly frequency.[28]

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 significant difference between the results from our benchmark decomposition vs these results from the decomposition based on only marginal traders' holdings.

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

[28] 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.19: IISIN-Level Equity Price Growth Rate Decomposition: Histograms (Marginal Traders)

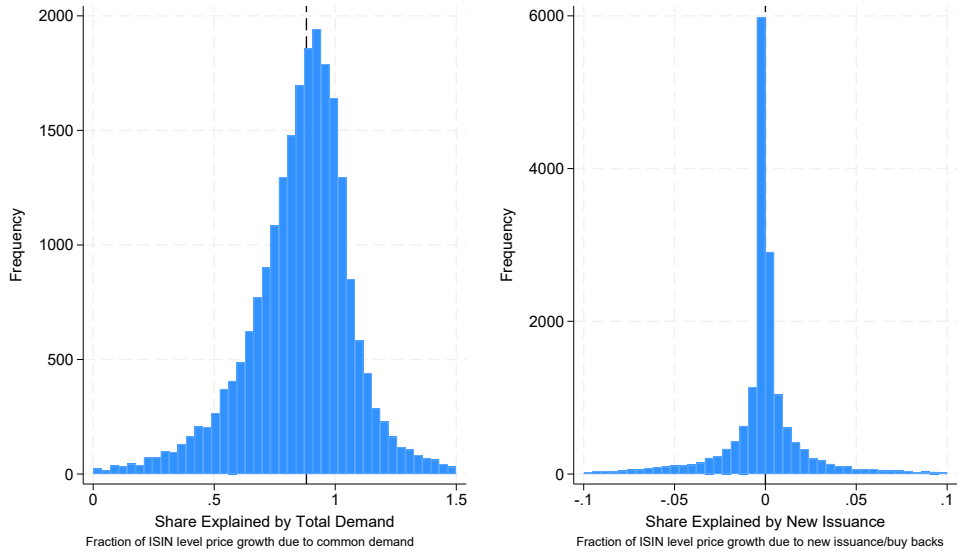


Figure A.20: ISIN-Level Equity Price Growth Rate Decomposition: Histograms Sub-Components (Marginal Traders)

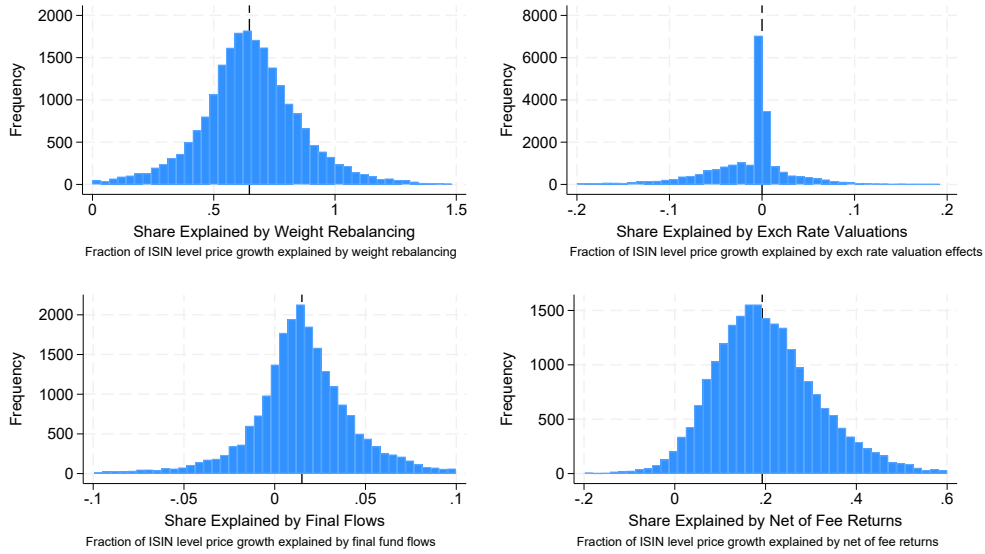


Figure A.21: ISIN-Level Equity Price Growth Rate Decomposition:: Panel Regressions (Marginal Traders)

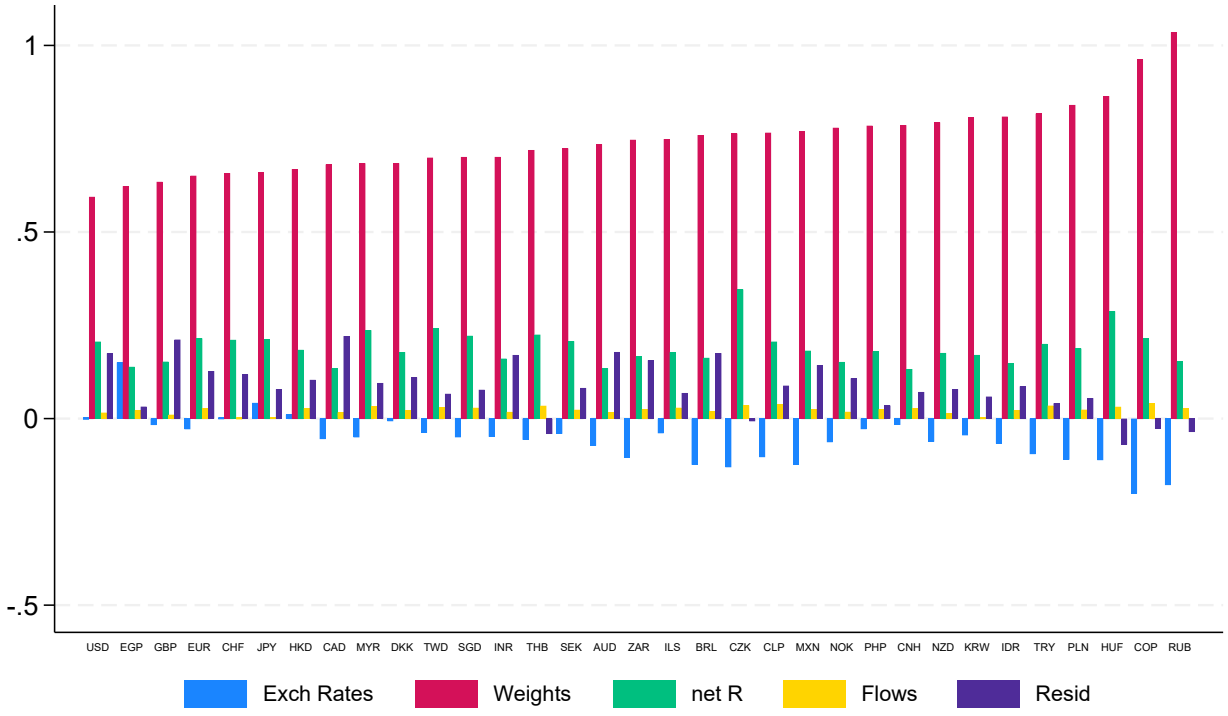


Table A.8: ISIN-Level Equity Price Growth Rate Decomposition: Panel Regressions (Marginal Traders)

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 of panel regressions of the total "common" component of equity holdings (or its sub-components) on Δp_t^j 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.22: Aggregate Stock Market Price Growth Rate Decomposition

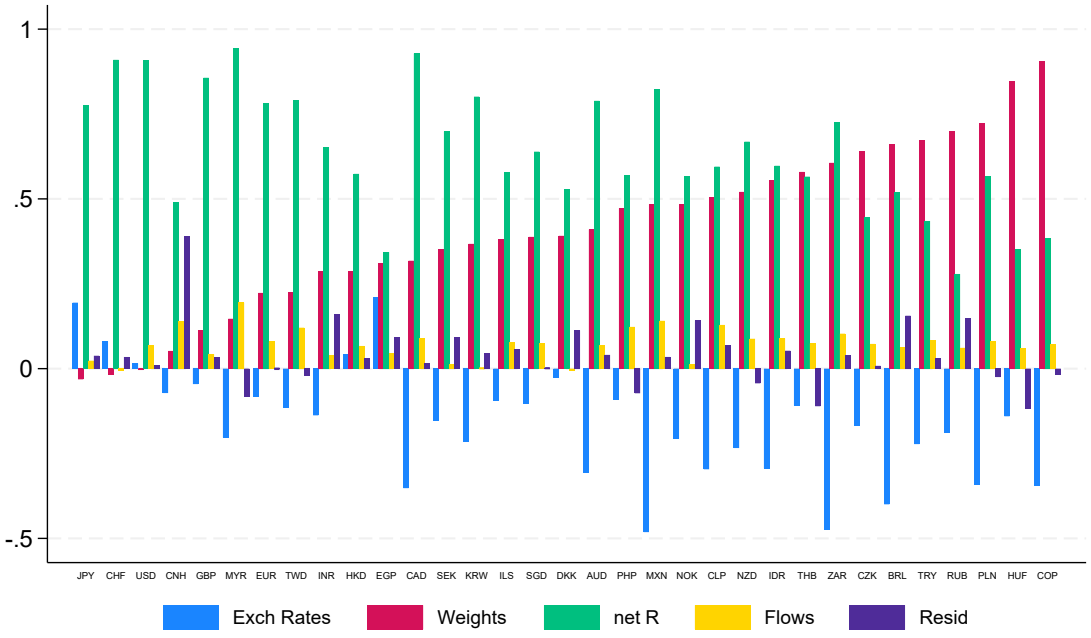


Table A.9: Aggregate Stock Market Price Growth Rate Decomposition

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	0.93***	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 coefficients from stock market regressions of the "common" component of equity holdings and its sub-components on the aggregate stock market price growth rate, by stock market (as denoted by the currency associated with that stock market). * – significant at 10%; ** – significant at 5% ; *** – significant at 1%

A.2 Additional Figures Using Monthly Sample

Figure A.23: Total AUM USD Trillions; Monthly

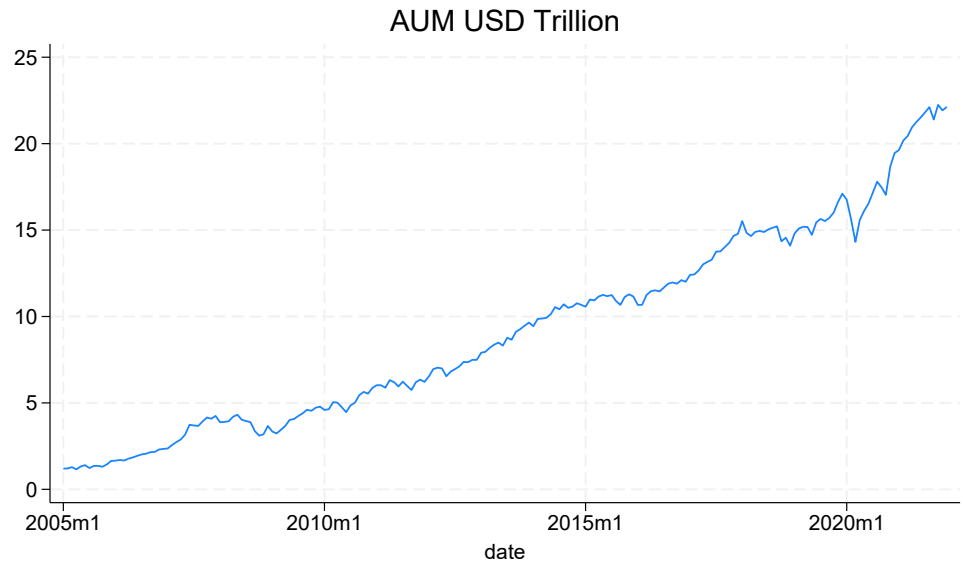


Figure A.24: Sample Aggregate vs Market Index Stock Return Correlations

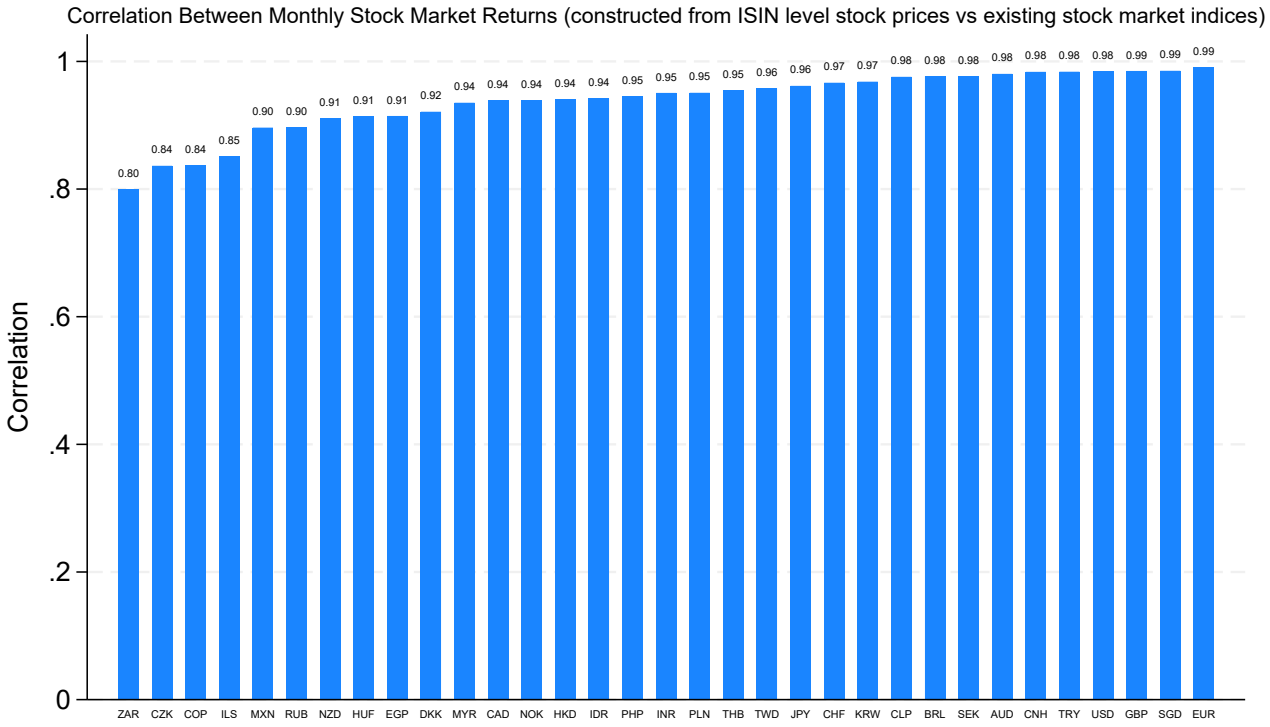


Figure A.25: Number of Funds Within Each Type (for Net-of-Fee Returns and Flows Components)

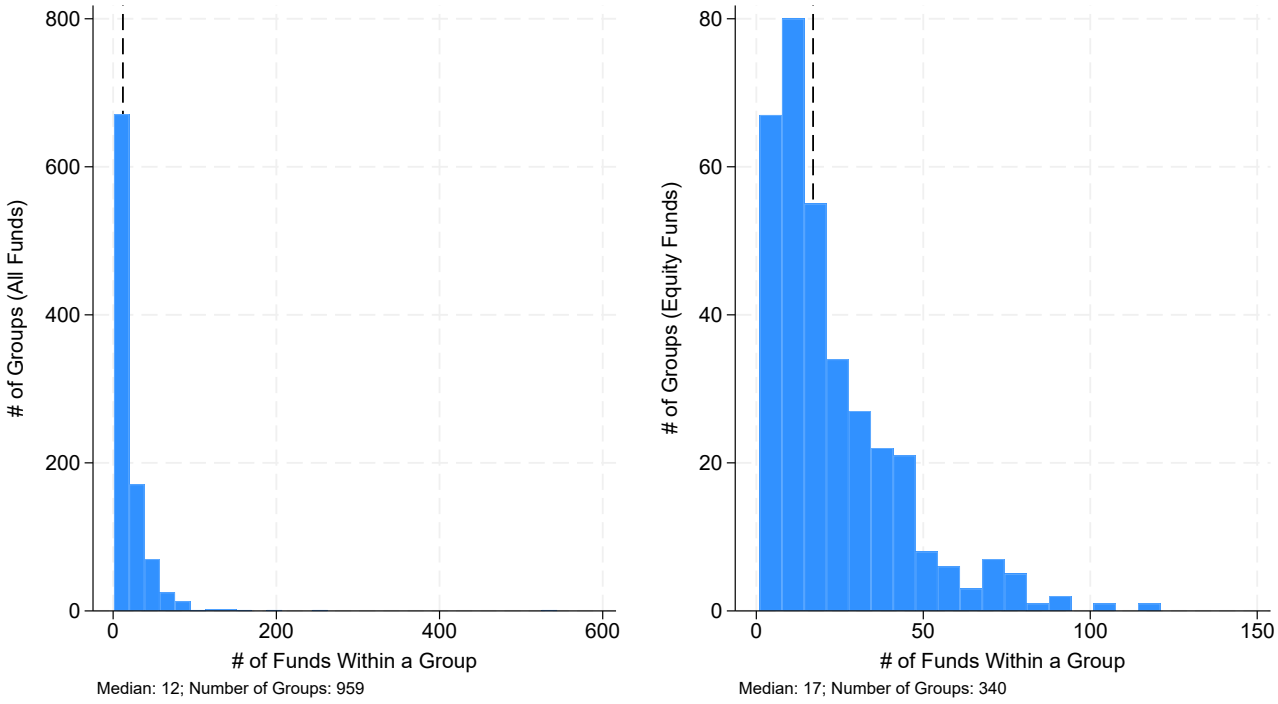
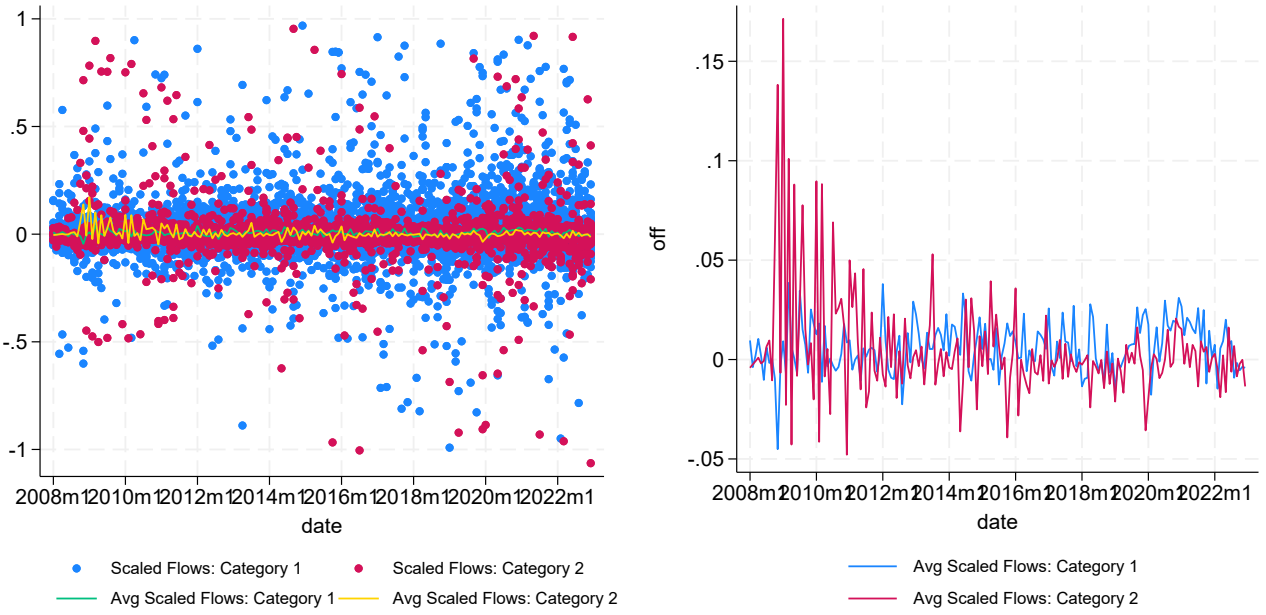
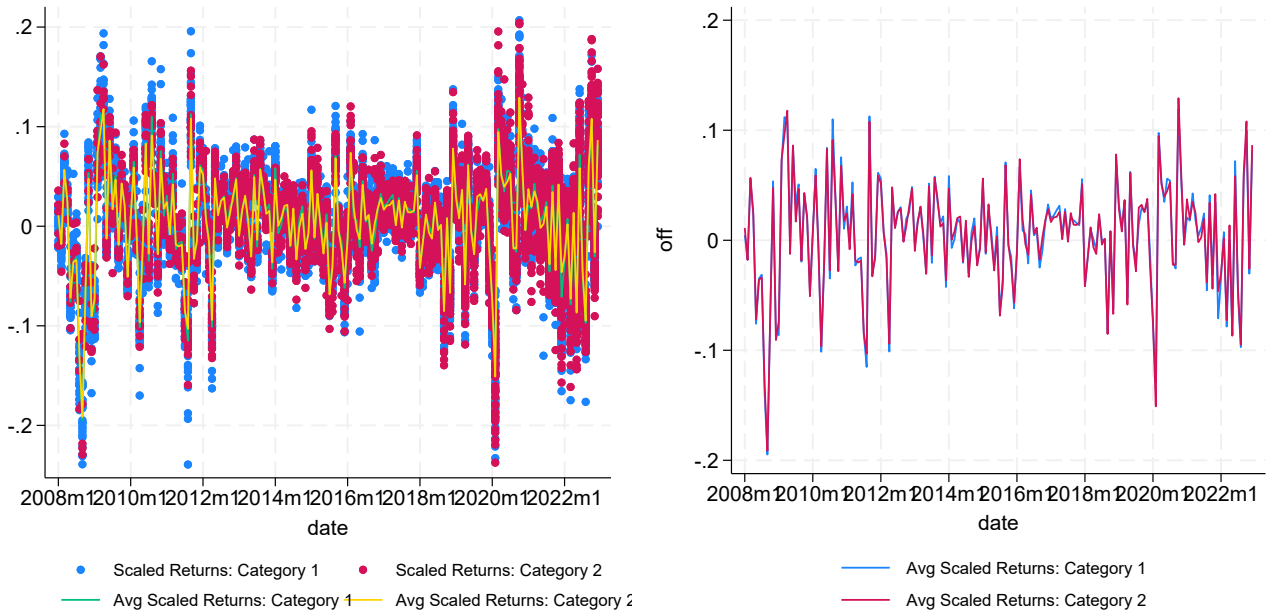


Figure A.26: Examples of Fund-level and Average Scaled Flows For Select Categories



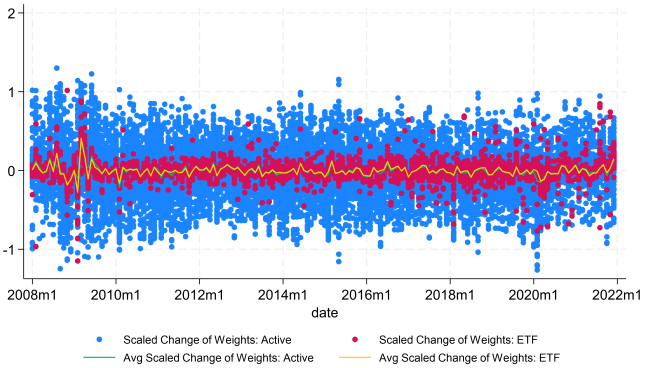
Equity Funds; USD ROS currency;
Category 1: Active: more active; Freq Rebalance: re-balancing frequently; size of fund: <=1bil and >100mil; GlobalCategory: Global Equity Large Cap
Category 2: Active: more active; Freq Rebalance: re-balancing less frequently; size of fund: <=100mil; GlobalCategory: Global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

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

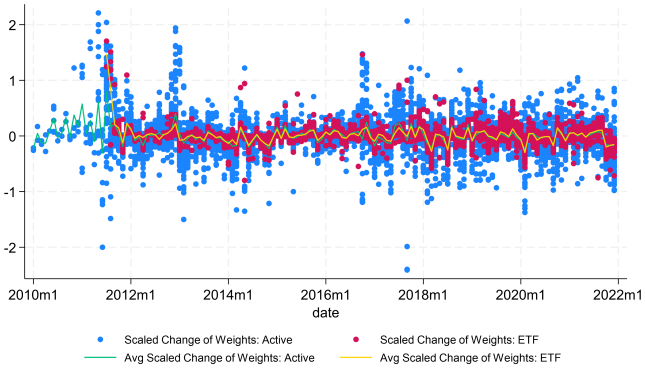


Equity Funds; USD ROS currency;
Category 1: Active: more active; Freq Rebalance: re-balancing frequently; size of fund: <=1bil and >100mil; GlobalCategory: Global Equity Large Cap
Category 2: Active: more active; Freq Rebalance: re-balancing less frequently; size of fund: <=100mil; GlobalCategory: Global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

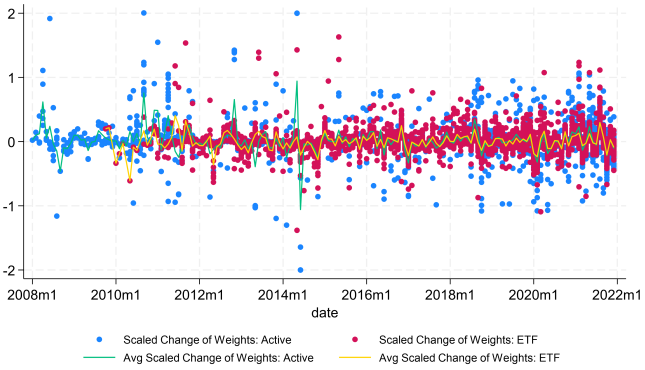
Figure A.28: Portfolio Weight Changes for Select Stocks



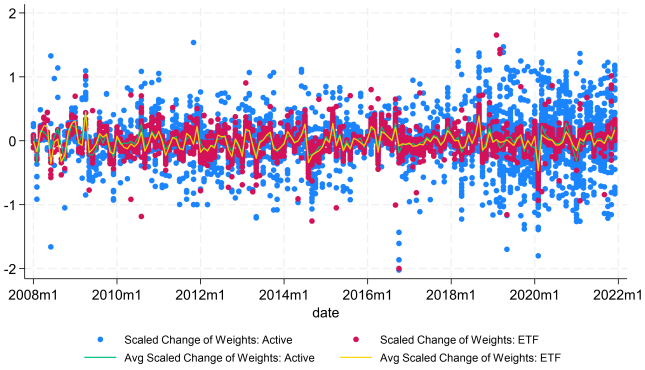
(a) HSBC



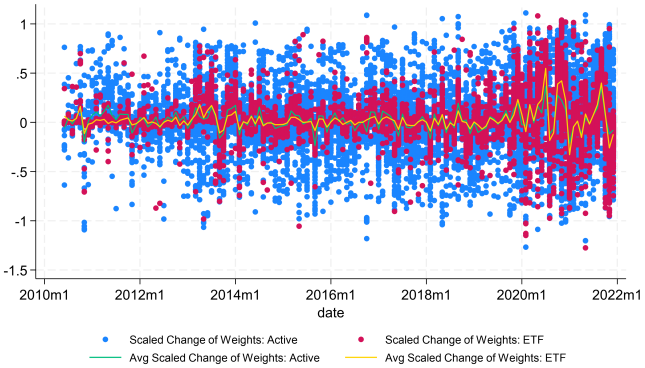
(b) Sberbank Rossii



(c) Rosneft

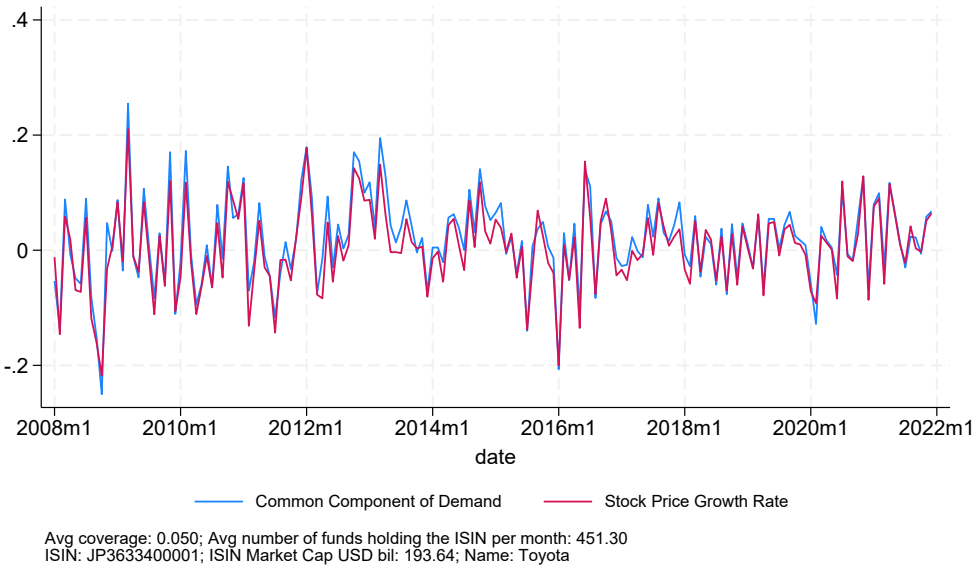


(d) Petrobras



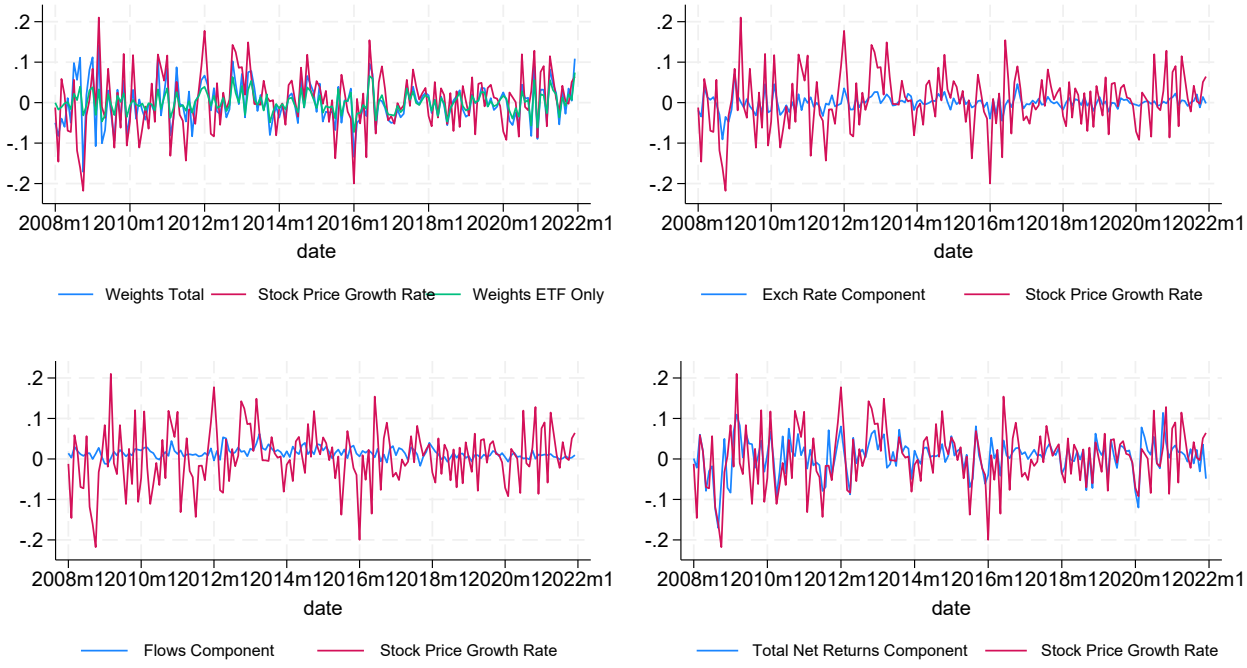
(e) Tesla

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



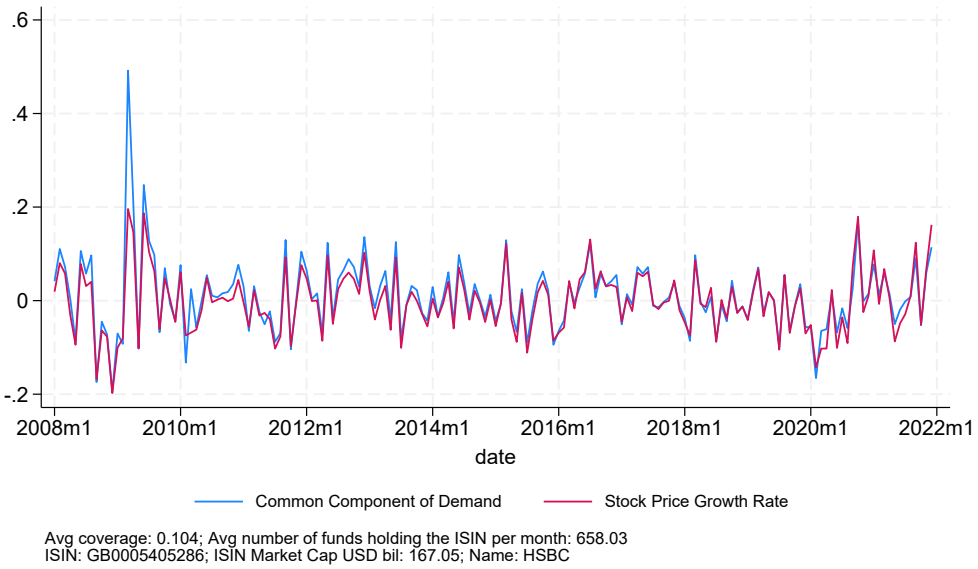
Avg coverage: 0.050; Avg number of funds holding the ISIN per month: 451.30
ISIN: JP3633400001; ISIN Market Cap USD bil: 193.64; Name: Toyota

(a) Total



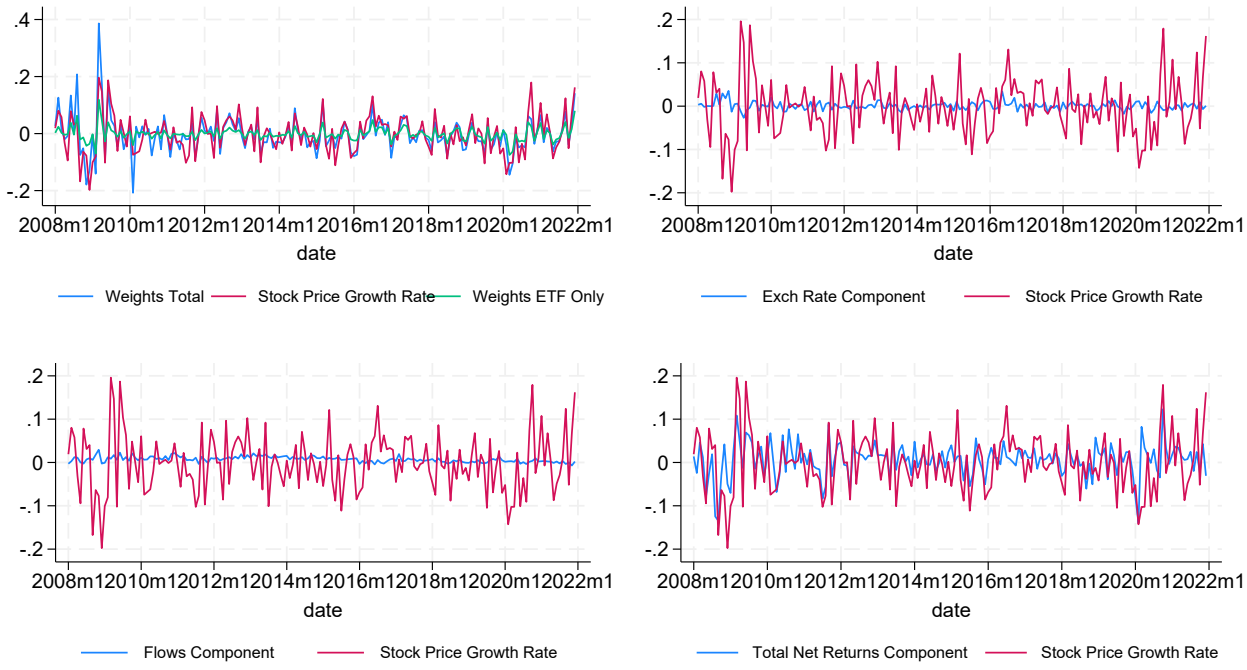
(b) Sub-Components

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



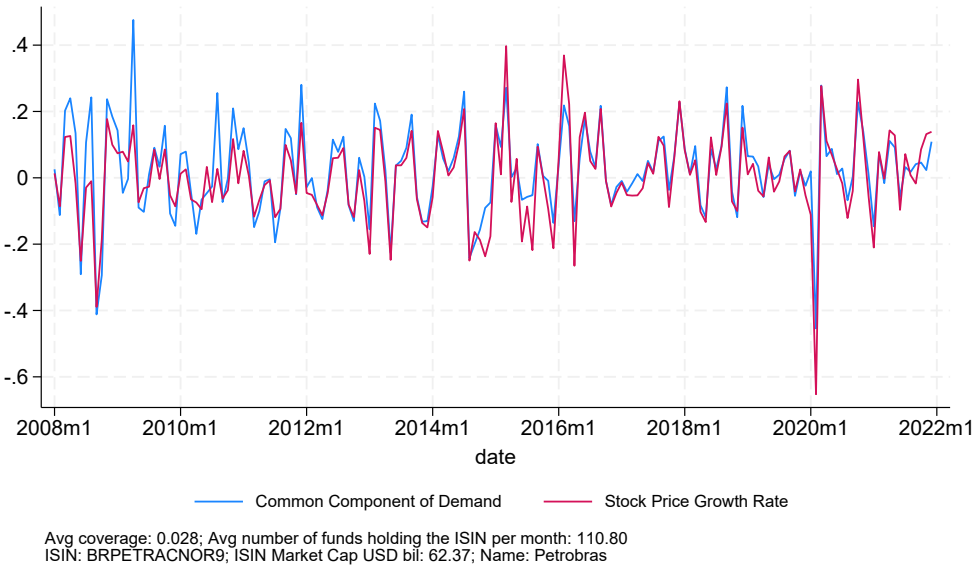
Avg coverage: 0.104; Avg number of funds holding the ISIN per month: 658.03
ISIN: GB0005405286; ISIN Market Cap USD bil: 167.05; Name: HSBC

(a) Total



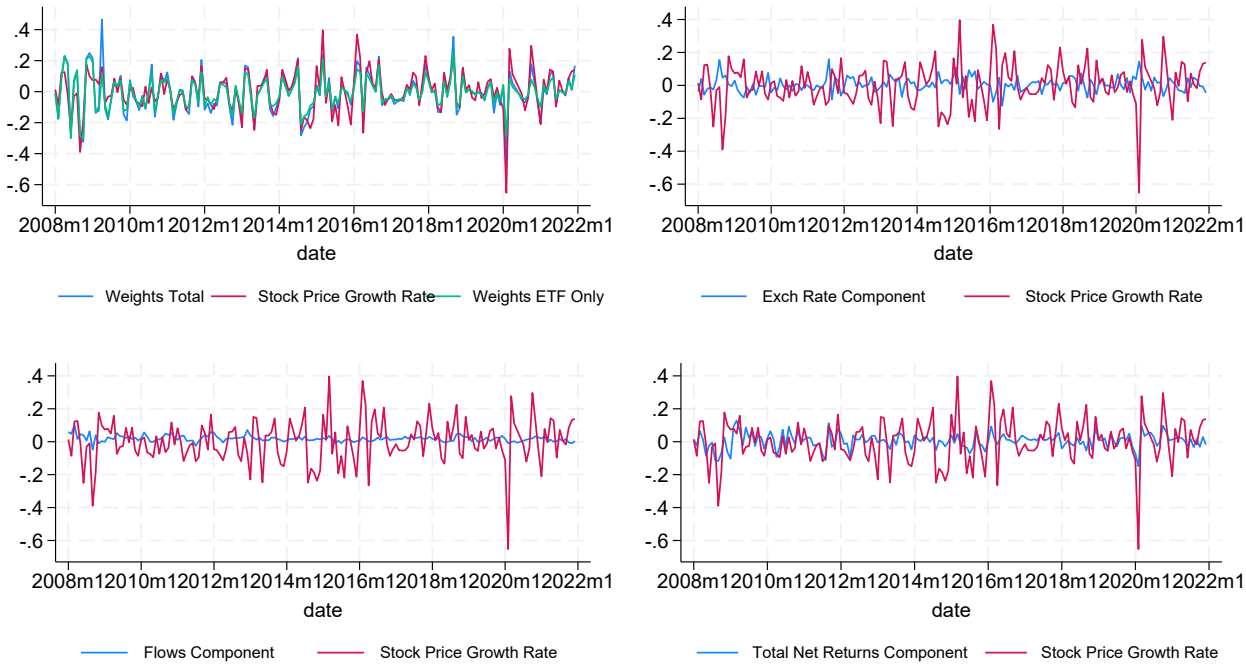
(b) Sub-Components

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



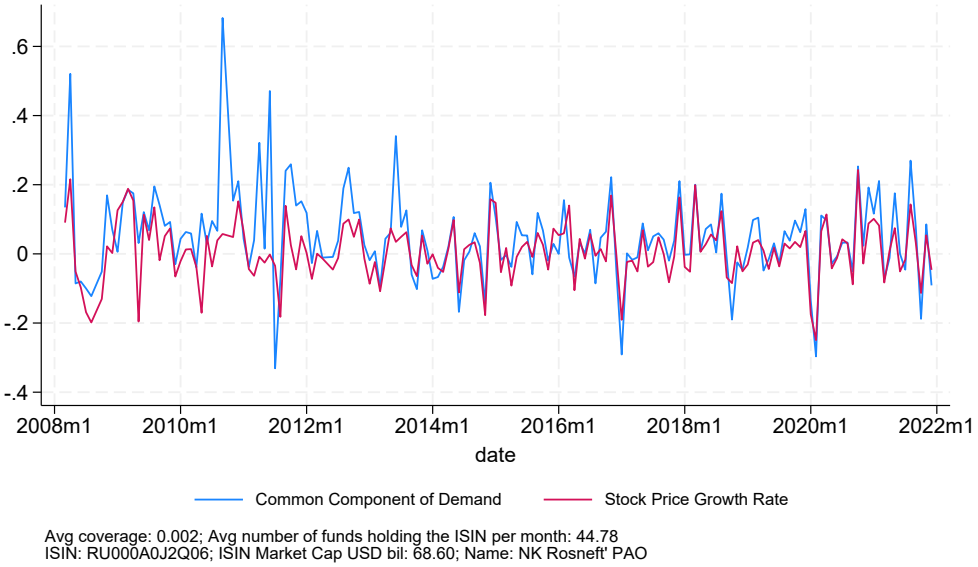
Avg coverage: 0.028; Avg number of funds holding the ISIN per month: 110.80
ISIN: BRPETRACNOR9; ISIN Market Cap USD bil: 62.37; Name: Petrobras

(a) Total



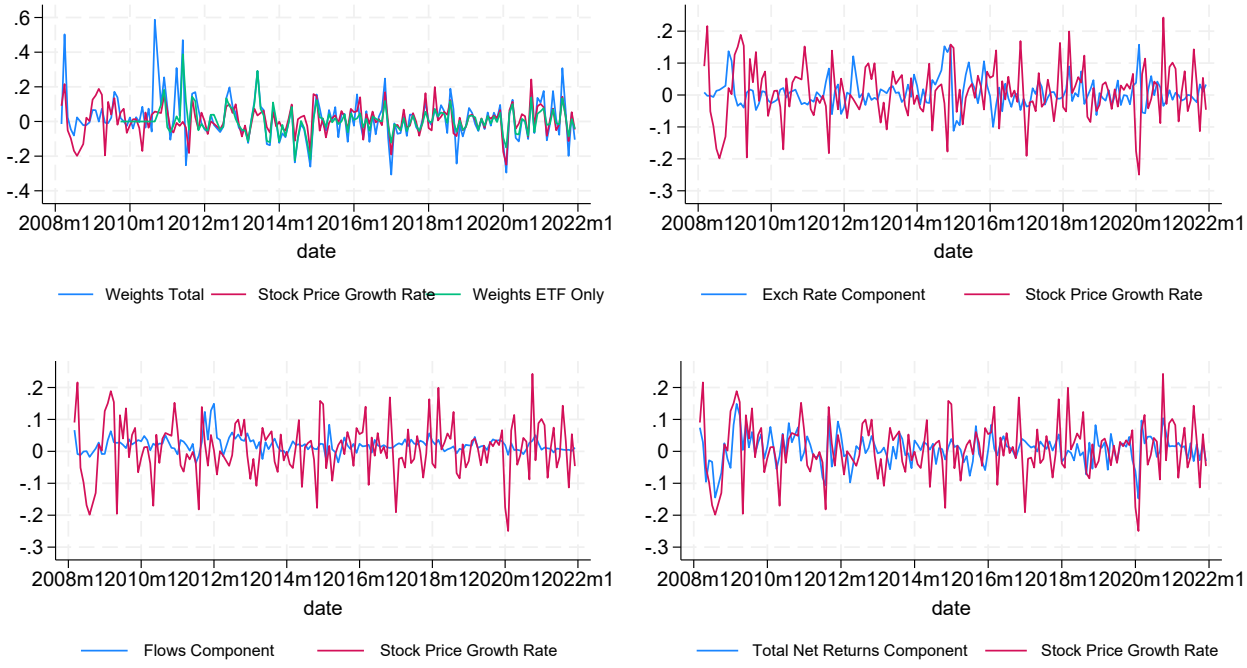
(b) Sub-Components

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



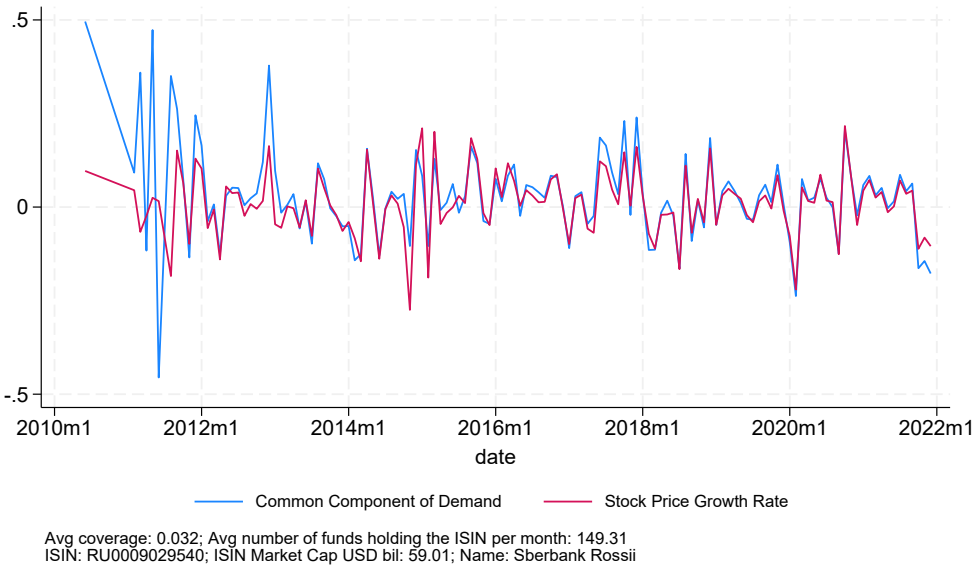
Avg coverage: 0.002; Avg number of funds holding the ISIN per month: 44.78
ISIN: RU000A0J2Q06; ISIN Market Cap USD bil: 68.60; Name: NK Rosneft' PAO

(a) Total



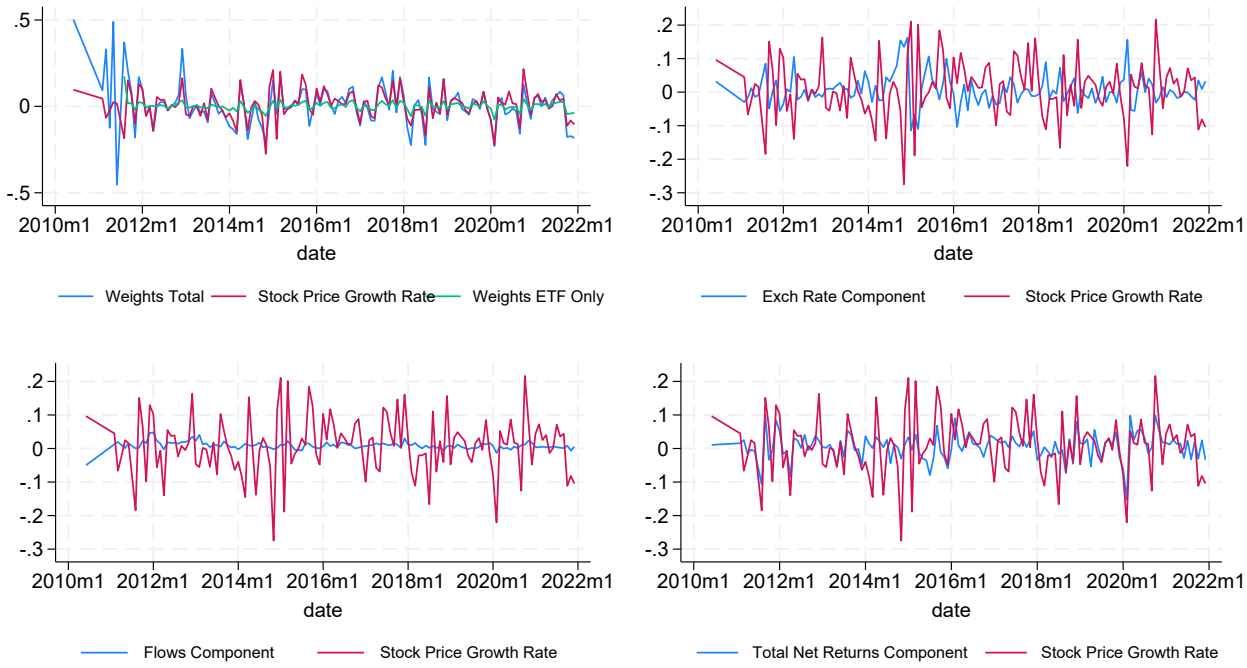
(b) Sub-Components

Figure A.33: "Common" Equity Holdings Components: Sberbank Rossii



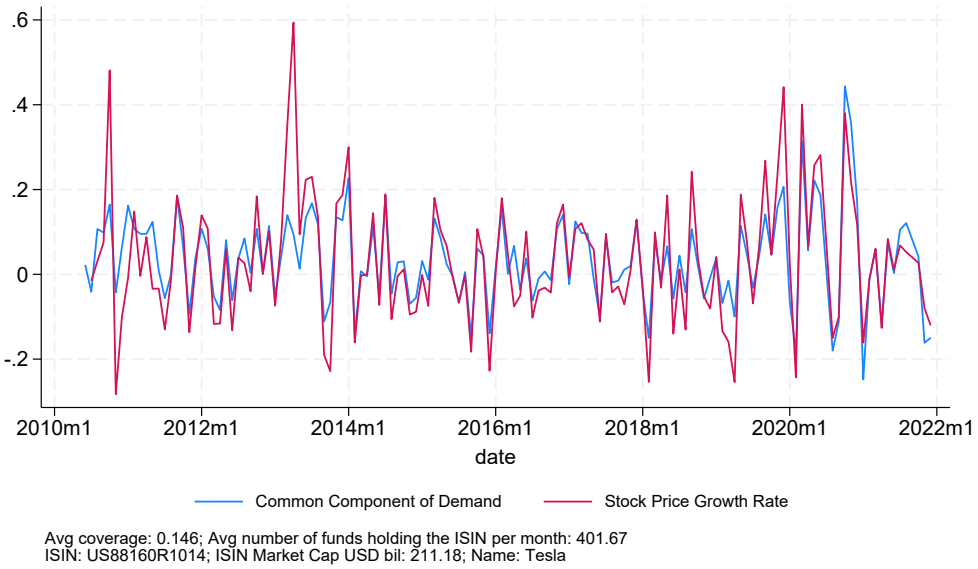
Avg coverage: 0.032; Avg number of funds holding the ISIN per month: 149.31
ISIN: RU0009029540; ISIN Market Cap USD bil: 59.01; Name: Sberbank Rossii

(a) Total



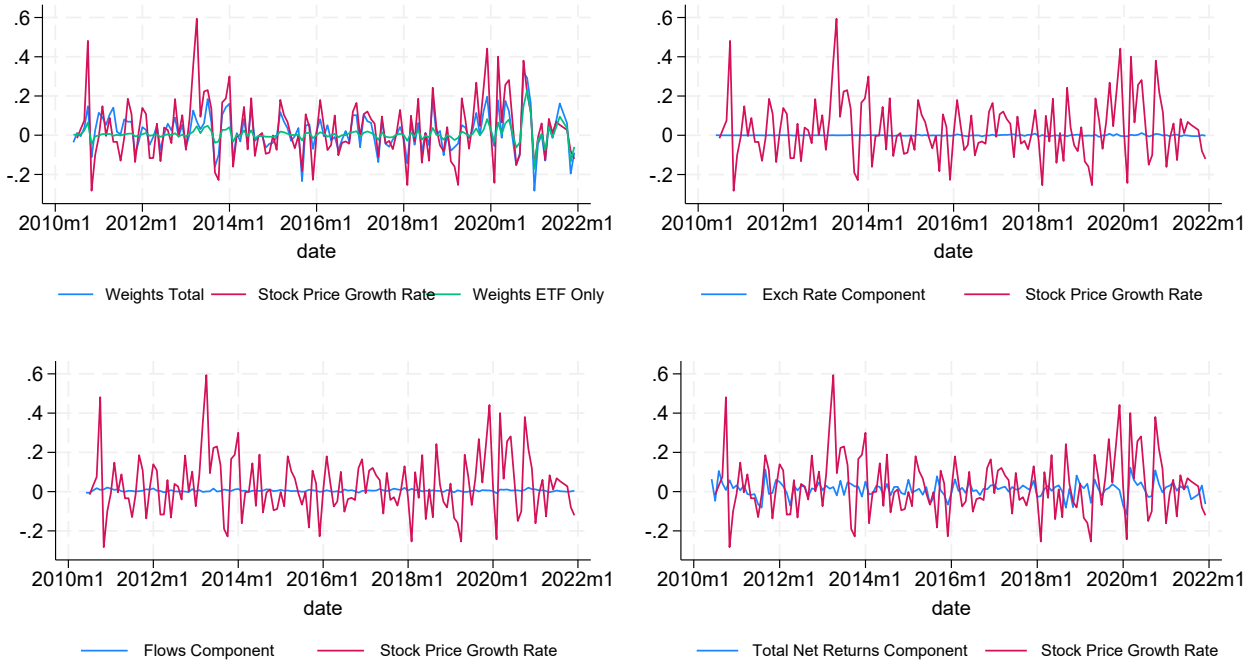
(b) Sub-Components

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



Avg coverage: 0.146; Avg number of funds holding the ISIN per month: 401.67
ISIN: US88160R1014; ISIN Market Cap USD bil: 211.18; Name: Tesla

(a) Total



(b) Sub-Components

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

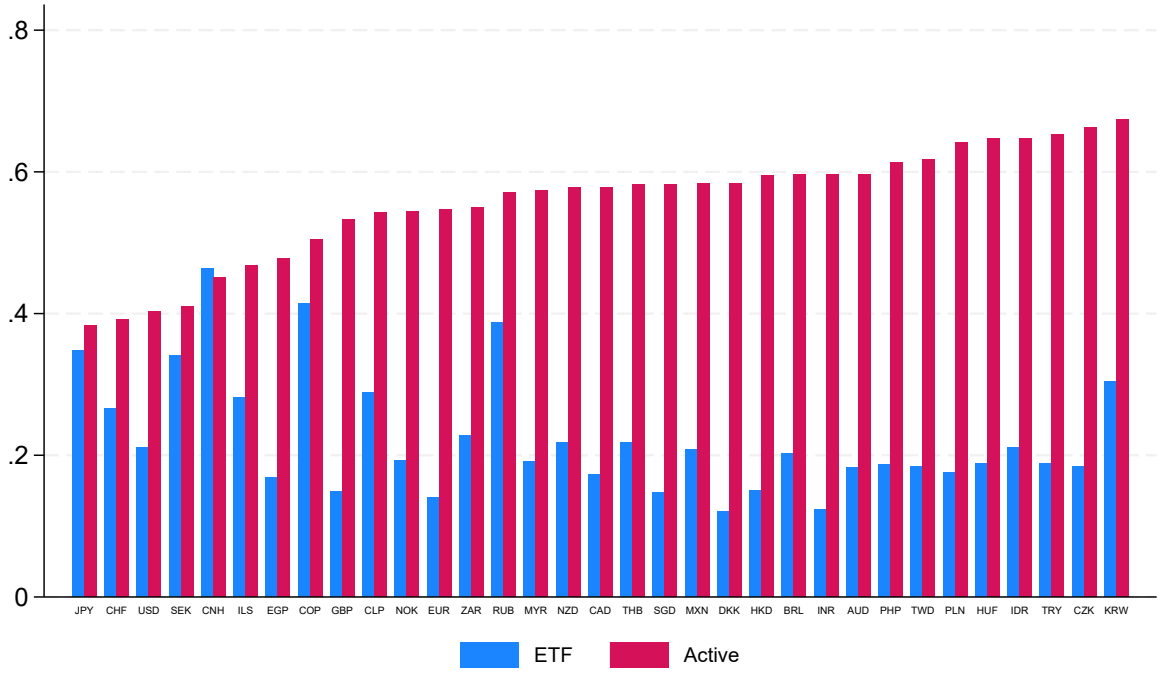


Figure A.36: ISIN-Level Equity Price Growth Rate Decomposition: ETF vs Active Flows: Panel Regressions

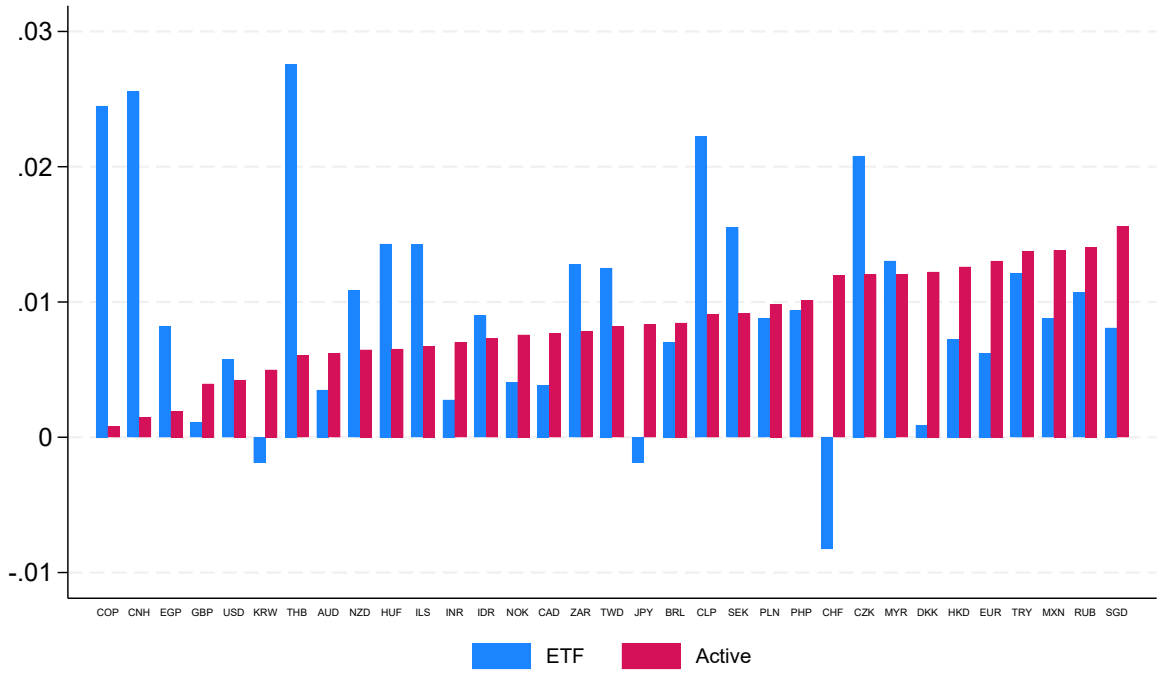


Figure A.37: ISIN-Level Equity Price Growth Rate Decomposition: Own vs Other Currency Investors Portfolio Weight Changes: Panel Regressions

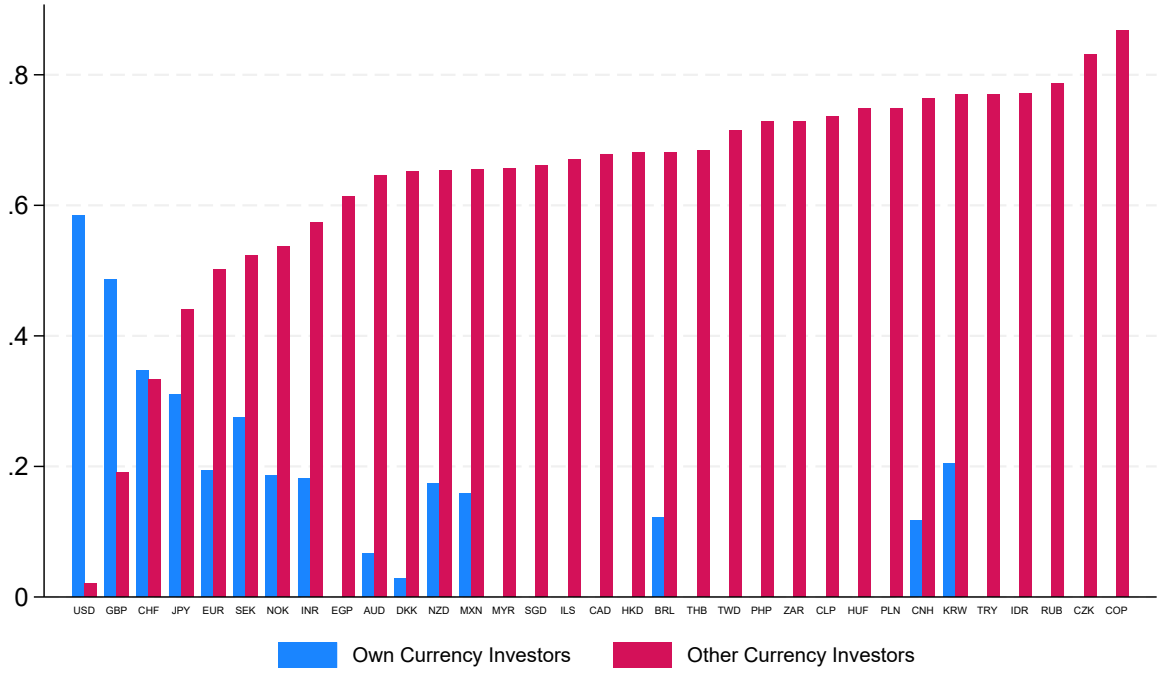


Figure A.38: ISIN Level Equity Price Growth Rate Decomposition: Own vs Other Currency Investors Flows: Panel Regressions

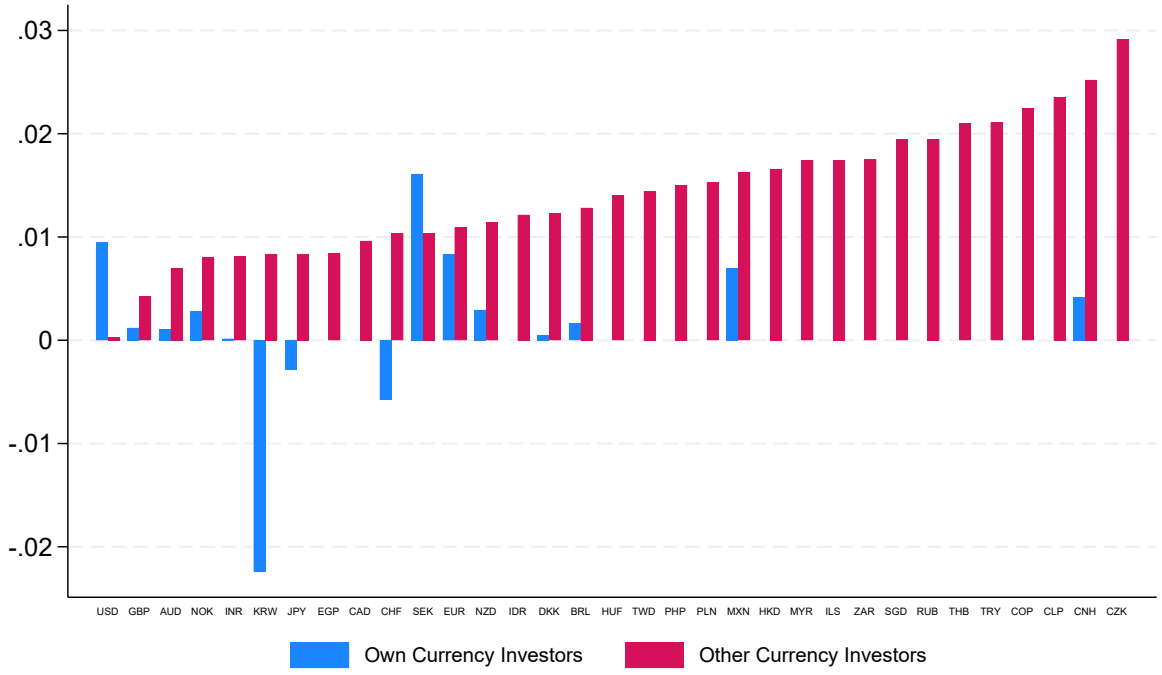
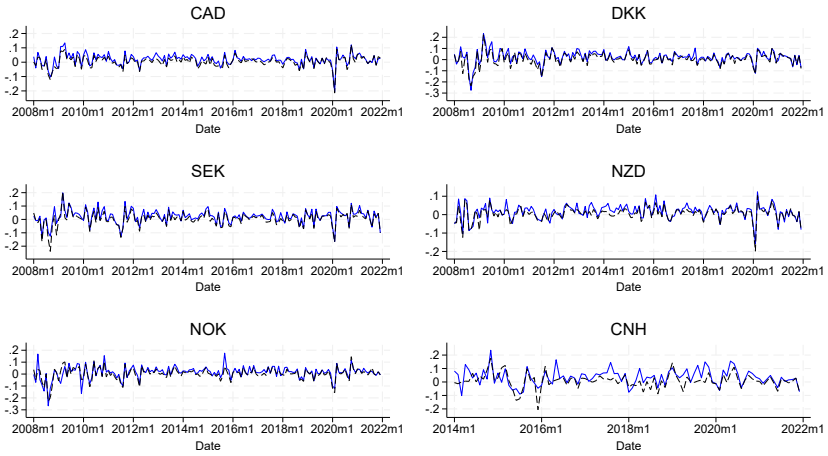
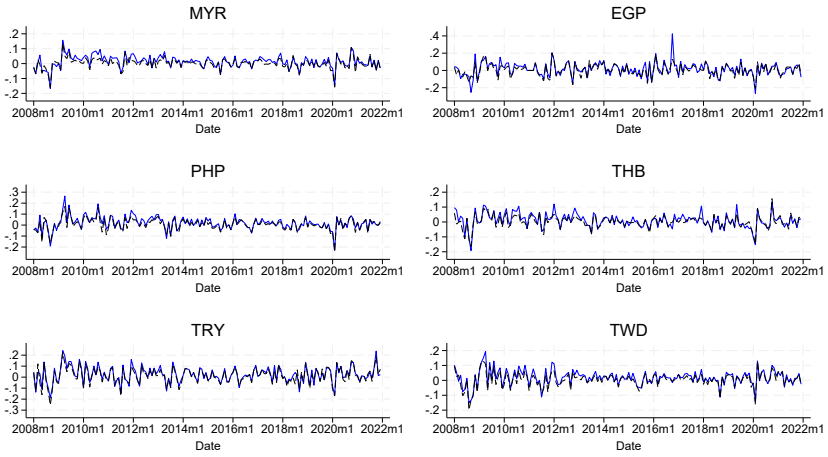


Figure A.39: Stock Market Price Growth Rate vs "Common" Component of Equilibrium Holdings



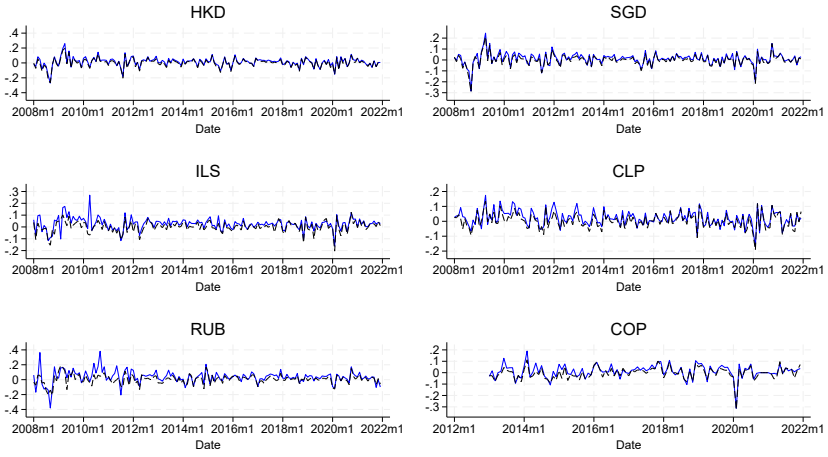
The black dashed line represents the stock price growth rate and the solid blue line is the change in common equity demand.

(a) Select Advanced Economies



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

(b) Select Emerging Markets



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

(c) Select Emerging Markets (cont.)

A.3 Quarterly Sample Results

Figure A.40: Total AUM USD Trillions; Quarterly

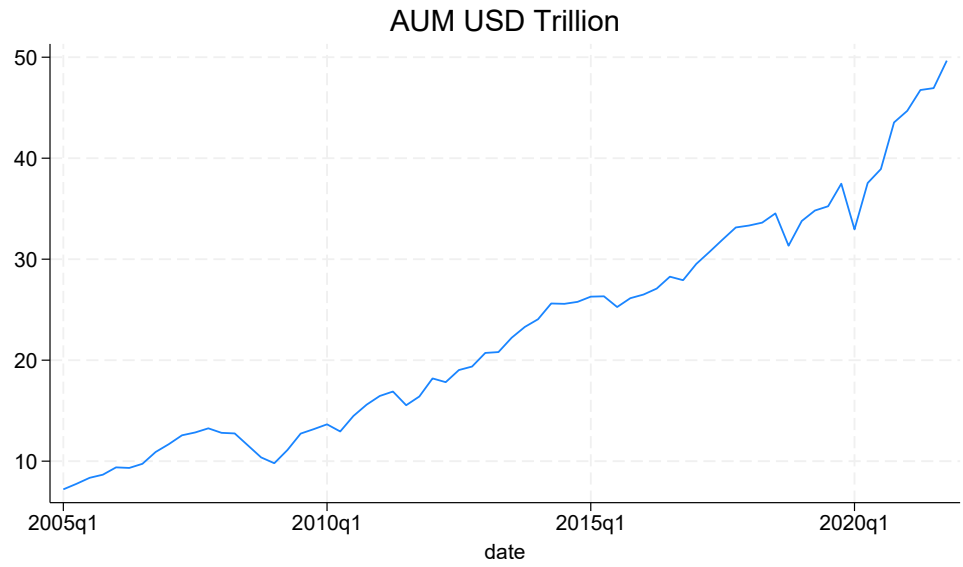


Figure A.41: AUM by Investment Type and ROS Currency (Quarterly Sample, USD Trillions)

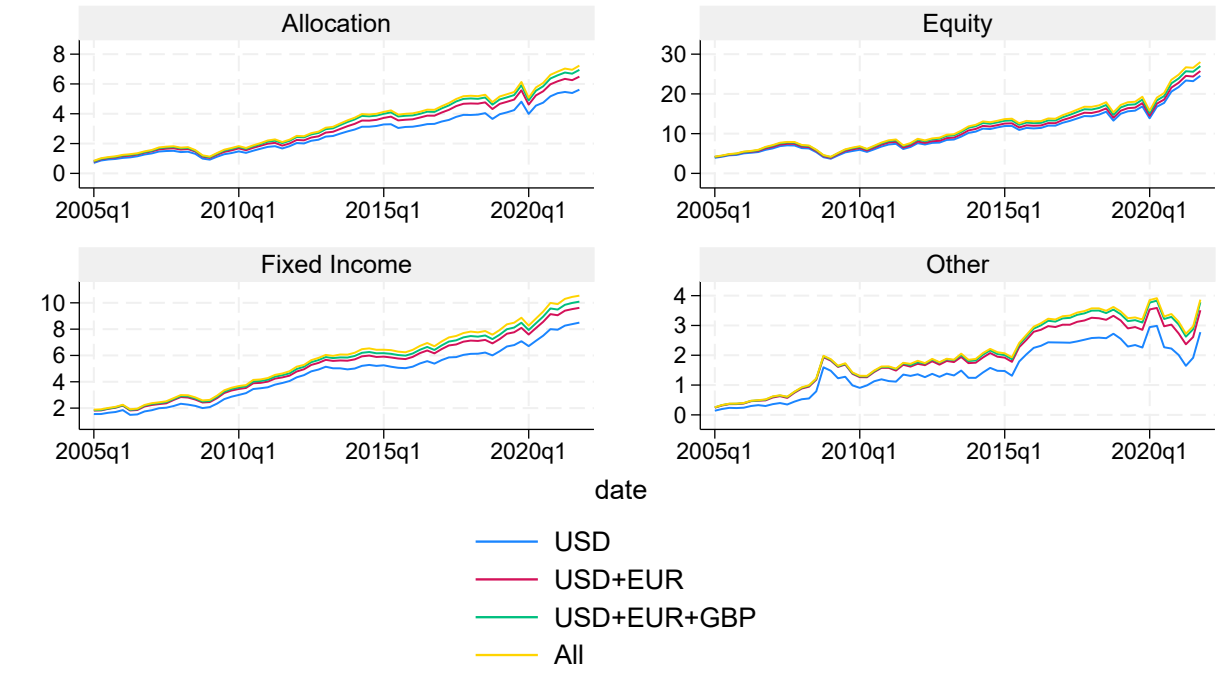


Figure A.42: AUM by Investment Type and Active/ETF (Quarterly Sample, USD Trillions)

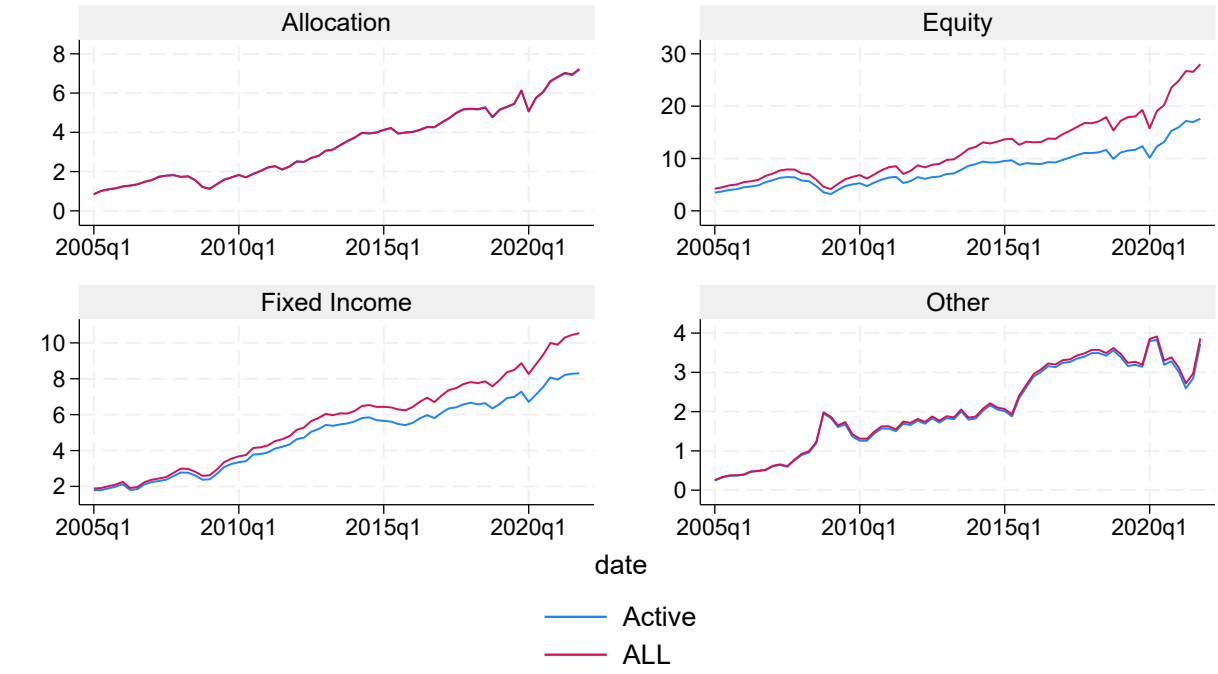


Table A.10: Coverage and Market Capitalization (Quarterly Sample)

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)

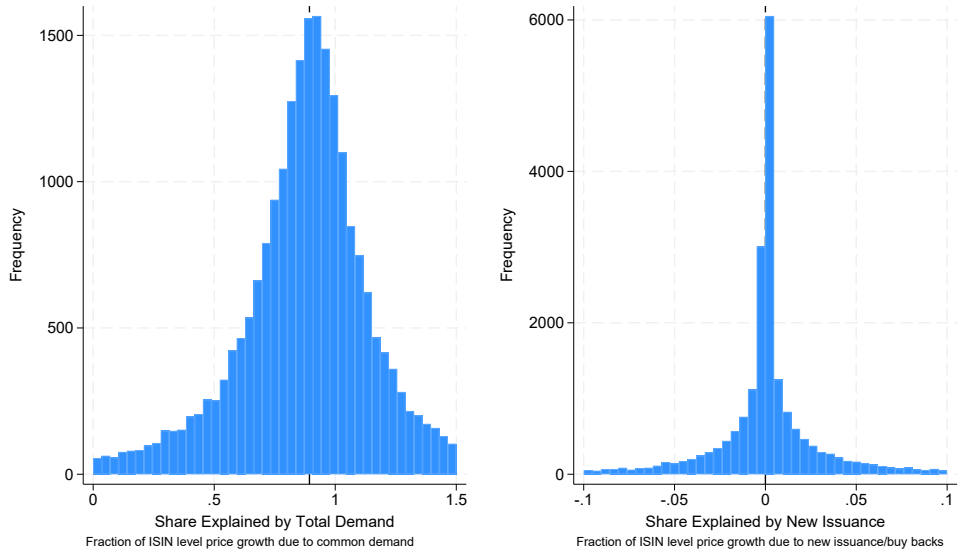


Figure A.44: ISIN-Level Equity Price Growth Rate Decomposition: Historgams Sub-Components (Quarterly Sample)

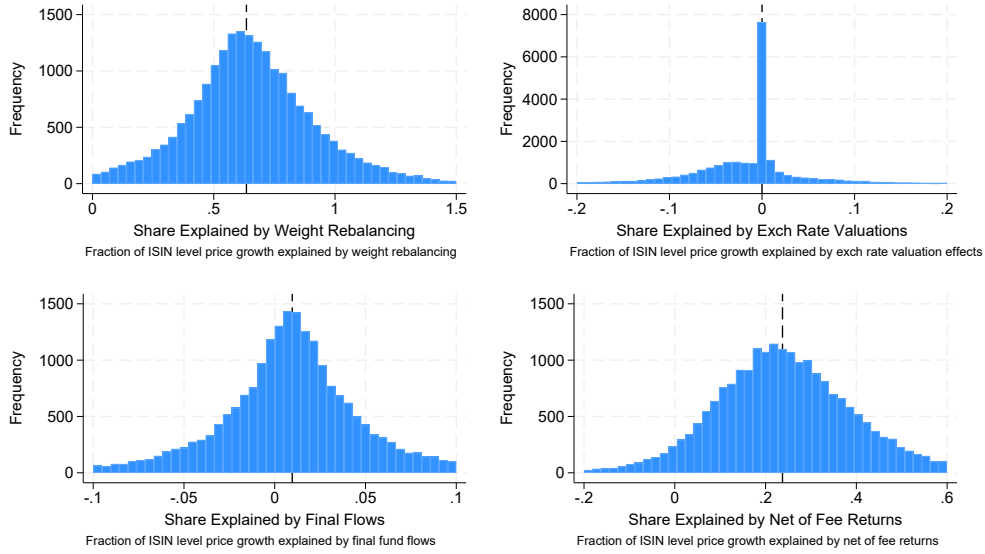


Table A.11: ISIN-Level Equity Price Growth Rate Decomposition: Panel Regressions (Quarterly Sample)

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 of panel regressions of the total "common" component of equity holdings (or its sub-components) on Δp_t^j 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.45: ISIN-Level Equity Price Growth Rate Decomposition: Panel Regressions (Quarterly Sample)

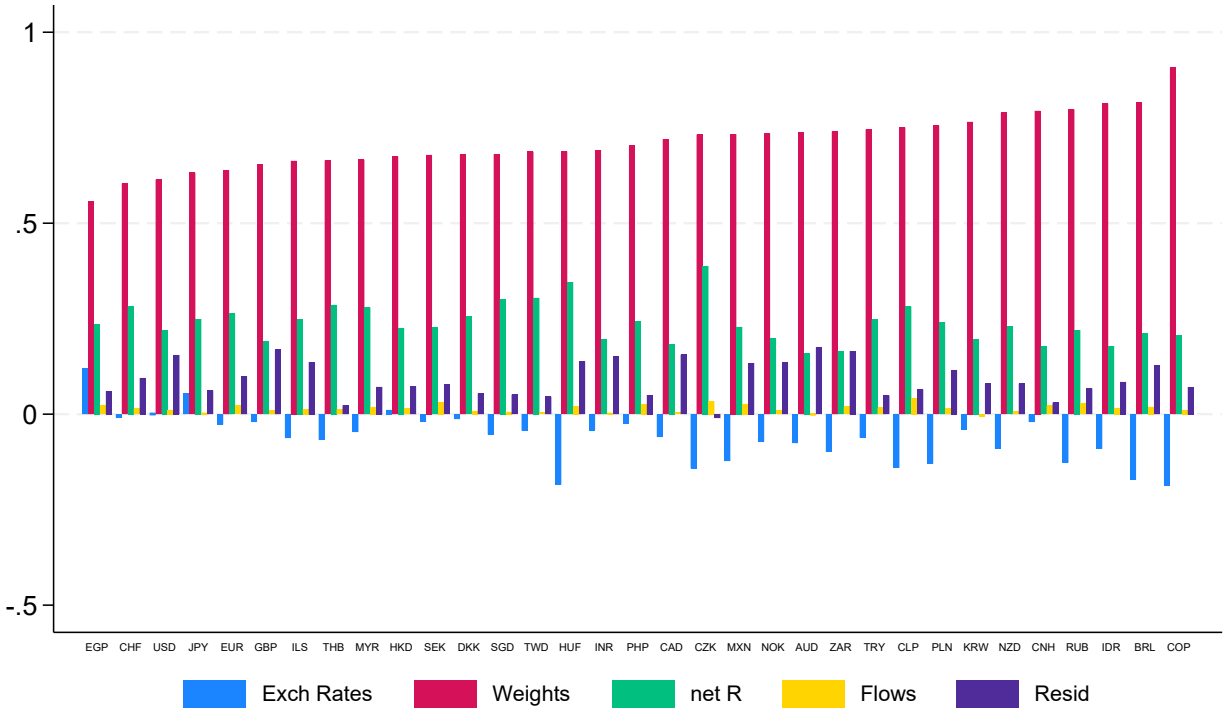


Table A.12: ISIN-Level Equity Price Growth Rate Decomposition: ETF vs Active Portfolio Weight Changes and Flows: Panel Regressions (Quarterly Sample)

Currency	$\Delta d^{\omega,j}_{ETF}$	$\Delta d^{\omega,j}_{Active}$	$\Delta d^{f,j}_{ETF}$	$\Delta d^{f,j}_{Active}$
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 subcomponents, broken down by active and passive 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)

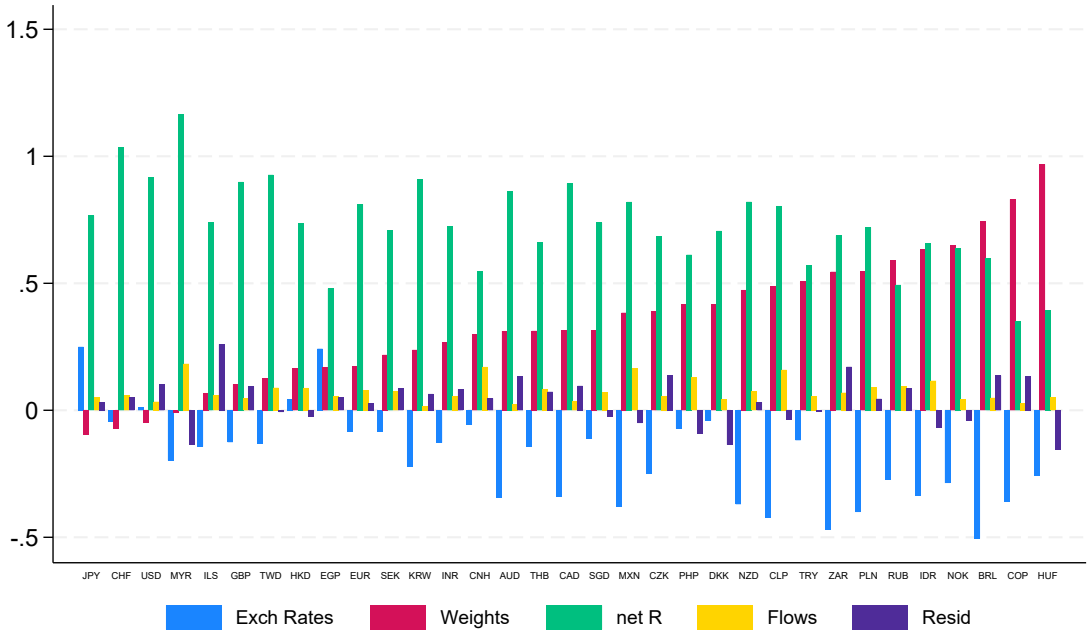


Table A.14: Aggregate Stock Market Price Growth Rate Decomposition (Quarterly Sample)

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 coefficients from stock market regressions of the "common" component of equity holdings and its sub-components on the aggregate stock market price growth rate, by stock market (as denoted by the currency associated with that stock market). * – 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)

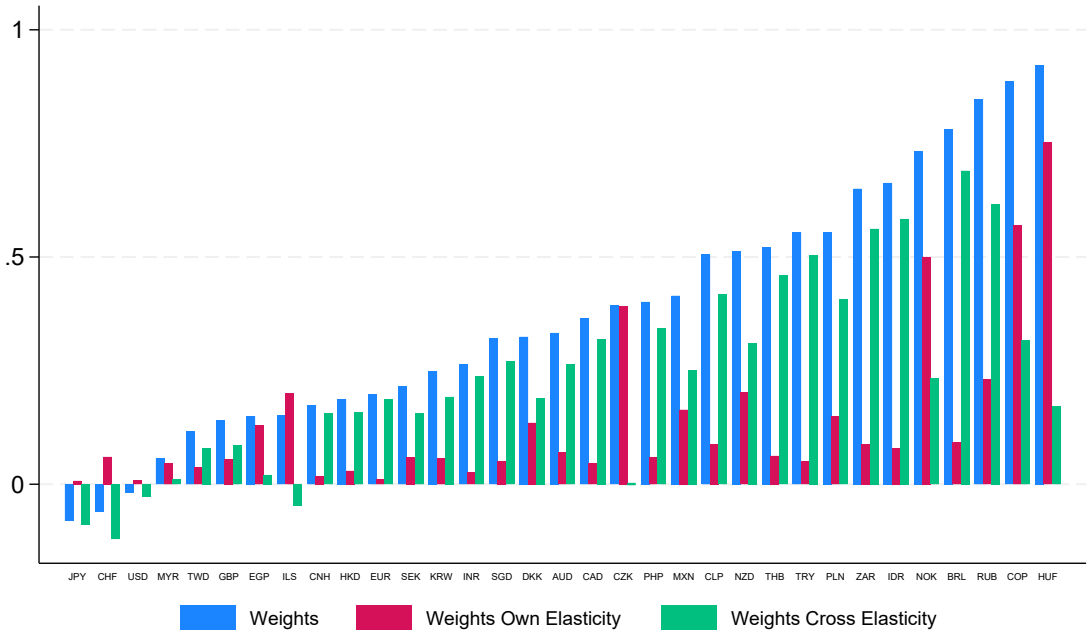


Figure A.48: The Importance of Own vs Cross-Covariance Sub-components: Net-of-Fee Returns (Quarterly Sample)

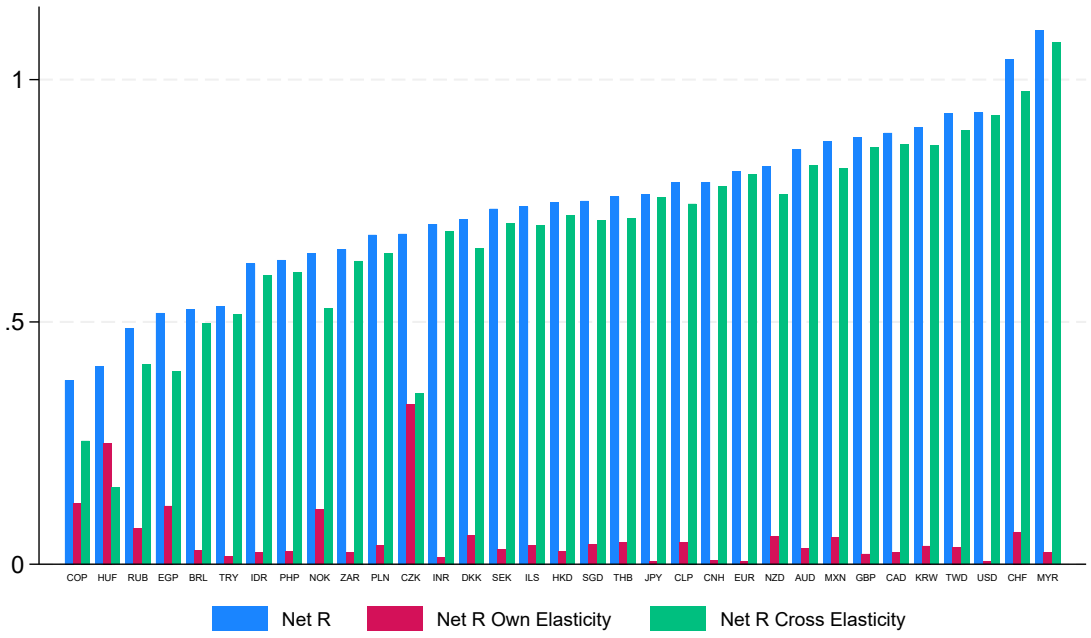


Table A.15: Stock Picking vs Industry Picking: Panel Regressions (Quarterly Sample)

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***	0.450***	0.750***	0.445***	0.043	0.488***
CNH	0.164***	0.630***	0.794***	0.370**	-0.072	0.298**
COP	0.642***	0.273***	0.907***	0.675***	0.156**	0.830***
CZK	0.625**	0.169	0.732***	0.390***	-0.001	0.388***
DKK	0.202***	0.479***	0.680***	0.312***	0.105**	0.417***
EGP	0.252***	0.313***	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***	0.128*	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***	0.530***	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***	0.586***	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***	0.558***	0.740***	0.454***	0.092**	0.545***

Note: In this table we report the coefficients of panel regressions of the portfolio weight change sub-component on Δp_t^j by stock market (as denoted by the currency associated with that stock market). ISIN level panel regressions and stock market level regressions. For the panel level regressions we allow for ISIN level fixed effects and cluster the standard errors by ISIN. * – significant at 10%; ** – significant at 5% ; *** – significant at 1%