Elephants in Equity and Currency Markets*

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Abstract

We develop a novel decomposition based on market clearing identities that allows us to study currency and equity price determination jointly through the prism of asset managers' demand. The *observed* components of our decomposition can explain almost all of equity and exchange rate variation for 26 countries/currencies. We further study the relative importance of the sub-components of demand and net supply as explanatory variables of equity price and currency fluctuations, respectively, and examine through what channels variation in risk aversion, macroeconomic news, and US news propagate to global equity prices. Finally, through the prism of our decomposition, we examine why the USD, and to a lesser degree, the EUR, and the US and Eurozone stock markets, play central roles in equity price and exchange rate determination, providing a microfoundation for the *centrality* of these currencies and stock markets.

*The views expressed are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Boston or the Federal Reserve System.

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1 Introduction

In this paper, we confront two of the central questions in international finance: (1) whose demand determines equity price and exchange rate fluctuations and (2) what makes the USD and the US stock market, and, to a lesser degree, the EUR and the Eurozone stock market, *central* for global equity and exchange rate determination.

Exchange rates are ubiquitous in the international economy. They help clear many global markets : bonds, equities, goods and services. We focus on equity markets for two reasons. The first is that equity markets are truly global, while fixed income markets tend to be concentrated in a few key currencies. The second is that a well identified set of investors, asset managers, for which granular data can be obtained, hold the bulk of issued global equity. Hence, we can construct a good measure of supply and demand at the ISIN level.

This is in contrast to fixed income markets for which multiple players with different objectives play a role and detailed data is harder to come by.[1] We show empirically that mutual funds are key for equity and exchange rate determination: they are the elephants in the market[2]

One cannot study equity price determination without studying exchange rate determination as both prices move in response to shocks to equilibrate the market for equity and foreign exchange. To be more specific, we start from the simple observation that when an investor located in the US purchases a Brazilian equity denominated in BRL, indexed by j, she is simultaneously increasing the demand for BRL (increasing the supply of USD) and for asset j and putting upward pressure on both prices. Furthermore, the existing network of global equity demand, especially the dominance of USD funds and the substantial exposure of mutual funds to US equities, underscores the significant roles played by the USD and the US stock market in influencing fluctuations in both exchange rates and equity prices. The

[1] In particular for fixed income markets, market makers hold significant amount of inventories. In contrast, equities are traded on an exchange which implies that market makers play no such role.

[2] However, we are not claiming that demand shocks originating in other markets, such as fixed income markets of the real economy, do not play a role for exchange rate determination.

same goes for the EUR and the Eurozone stock market but to a much lesser degree. [3]

To capture these ideas, we develop a novel accounting identity based on market clearing conditions that allows us to study the joint determination of equity prices and exchange rates, using very granular demand and supply data. In addition to studying the importance of the various components of demand, for equity determination, and net supply, for exchange rate determination, we also analyze how movements in risk aversion (proxied by the VIX), macroeconomic news and US news propagate to equity markets through the various components of demand.[4]

More specifically, we start with the market clearing condition *for a single stock*, indexed by its ISIN, and express the growth rate of the price of this stock as a function of changes in demand.[5] We then decompose total demand into four components reflecting changes due to – (1) weight re-balancing of the funds holding this ISIN, (2) exogenous flows into the funds holding this ISIN measured in the currency of the fund's region of sale (ROS), (3) reinvestment of net-of-fee portfolio returns measured in the currency of the ROS (a valuation effect which acts as an amplification mechanism) and, finally, (4) exchange rate movements, which captures the fact that the funds need to translate their demand for the stock from the currency of the ROS into the currency of issuance of the ISIN. We refer to the last two components, (3) and (4), as the valuation components of demand. We further break down these demand components by the contribution of each type of funds, equity versus allocation, passive versus active and according to the fund's currency of the ROS.

We do not observe the universe of each stock's investors which is needed to construct the sub-components of demand. We circumvent this problem in two steps. First, we extract the *common* component of equity demand for each sub-component 1) - 3) by taking the sample

[3] See Figures 4 and 5.

[4] We focus on movements of the VIX and macroeconomic news indices, which impact either the local currency stock market or the US stock market, as we find that they explain a very large fraction of stock market movements and, thus, are a key driver of equity prices. On average, these variables explain 26 percent, 44 percent and 24 percent of stock market fluctuations, respectively.

[5] The price growth rate is also a function of new issuance which, at the ISIN level, is close to zero so we abstract from it.

average within a narrowly defined group of funds and/or ISINs, assuming a single factor structure. Second, we make an assumption regarding the representativeness of our sample, which covers mutual funds with total assets under management of over 60 trillion USD with data available at a quarterly frequency and 25 trillion USD at a monthly frequency. Based on this representativeness assumption, we can directly construct, for a given ISIN, the total *common* components of our 3 demand measures, capturing weight rebalancing, exogenous flows and reinvestment of the net-of-fee returns and also the exchange rate component of demand. We aggregate our ISIN-level market clearing decomposition to the level of the stock market of a given country; we end up with 26 stock markets, associated with 26 currencies. We focus on the period from Jan 2008 till Dec 2021 and for most of the analysis study monthly frequency, while providing robustness checks with the quarterly frequency.

Based on a variance covariance decomposition, we find that the sum of all four of our *observed common* demand components explains, on average, 91 percent of the stock price variation. The smallest fraction explained is 76 percent and the largest is 106 percent [6], with the numbers for the US and the Eurozone stock markets being 97 and 92 percent, respectively. So indeed our measure of mutual funds' equity *common* demand explains almost all of equity price variation, which validates our representativeness assumption.We can thus refer to these scaled up *common* demand components as the *observed common* demand components.

Next, we turn to studying the importance of the various sub-components of *observed common* equity demand and discuss how one can think of the USD and EUR currencies, and the US and Eurozone stock markets, as *central* for global equity and exchange rates determination. We start with the sub-component (4) which captures the exchange rate valuation effects. This is the most direct way to measure the centrality of the USD and EUR for global equity price determination as most assets under management globally are denominated in

[6] Numbers can exceed 100% since the idiosyncratic component, which is always small may co-move negatively with the common component.

EUR and USD with an especially large pool of assets in USD. When US investors purchase, for example, Brazilian equity denominated in BRL, they exchange USD for BRL and the BRL/USD currency movement will impact their final equity demand denominated in BRL, and thus the Brazilian stock market return measured in BRL. We find that the exchange rate component of common demand explains, on average, -14 percent of stock price movements, implying that it dampens stock market volatility. The range across stock markets is from -50 to 31 percent. The exchange rate component plays an amplifying role for the stock market volatility only for very few countries. Those are the "safe haven" currencies, such as the USD and JPY, that appreciate, rather than depreciate, when their stock market is doing poorly.

Another component of *common* demand that directly captures the centrality of the US and Eurozone stock markets is the demand due to the reinvested net-of-fee portfolio returns, component (3). As most global investors hold primarily USD- and EUR-denominated equities, given that most of the global market capitalization is denominated in these currencies, then the net-of-fees portfolio returns component of demand will co-move very strongly with the US and Eurozone stock markets. We show that this net-of-fee return component of demand explains most of the variation of all stock market prices, on average 71 percent. Most interestingly, it is also the main channel through which US macroeconomic news transmit to global equity markets.

Next, we turn to the flow component of *common* equity demand, component (2), which captures the influence of exogenous flows into or out of equity funds. We find that this component explains, on average, 6 percent of stock price fluctuations and is largely driven by fluctuations in both risk aversion (VIX) and macroeconomic news. Macroeconomic news that appreciate the US or the local stock markets increase inflows into equity funds which, in turn, increase demand for global equity and appreciate global equity prices [7]. In contrast, higher risk aversion is associated with outflows from equity funds and lower demand for

[7]These flows may come for example from investors' portfolios which were previously in fixed income

global equity, as a result, which decreases equity valuations.

The weight re-balancing component of *common* equity demand (1) also plays a very important role, by explaining on average 27 percent of equity price fluctuations with the maximum value being 52 percent. It is a significantly more important driver of stock market prices for emerging market stocks than for advanced economies. Good macroeconomic news for the US stock market can benefit some countries' stock markets while hurting others, as we see re-balancing out of some stock markets into others in response to these news. We observe a similar pattern for the VIX where a higher VIX leads to equity funds investing more in Japanese stocks and moving out of emerging market stocks, for example[8].

The next part of the paper focuses on exchange rate determination. Using the same accounting identity as before, and focusing on the component of equity demand which translates demand from the currency of ROS of the fund into local currency, we can solve out jointly for all currency crosses against the USD.

More specifically, we can express the exchange rate as a function of the change in net equity supply components, defined as the change in the market capitalization of the stock market in local currency minus the change in the *common* demand for local equity, denominated in the currency of the funds' ROS.[9] For example, excess supply of BRL means that the market valuation of the Brazilian stock market, measured in BRL, is higher than the demand for Brazilian equity as measured in the currency of the ROS. Thus the BRL will have to depreciate in order to allow for the equity market to clear in BRL. Hence higher excess net supply of BRL will depreciate the BRL against the USD. The opposite is true with respect to excess net supply of USD. Because BRL-denominated equities are purchased by funds in multiple ROS, the equilibrium solution for the BRL/USD cross does not depend only on the USD and BRL net supply but also on the EUR net supply, given the importance of the

[8]Equity funds hold very little cash.

[9]We focus on net supply rather than supply and demand separately as the non-exchange rate components of demand already explain most of the growth rate of the market capitalization, implying the two variables are very highly correlated.

EUR as a ROS currency for many funds. We find that the net supply components of local currency, USD and EUR explain, on average, a remarkable 90 percent of exchange rate variation.

Based on this decomposition, we can define and measure the *elasticity* of exchange rates with respect to the net equity supply of a given currency, holding the net equity supply of other currencies constant.[10] We estimate the elasticity of the USD net equity supply to be negative and large and of the local currency net equity supply to be positive, but smaller in absolute value than the elasticity of the USD net supply, as would be consistent with the conventional wisdom. The EUR net supply elasticity is estimated to be positive, which implies that an increase in EUR net equity supply depreciates the local currency against the USD.

However, one cannot conclude based on this result, that the USD net supply is a more important determinant of exchange rates than local currency net supply as the overall importance depends on both these elasticities and the variance of the net supplies. In fact, local currency net equity supply matters much more for movements in exchange rates against the USD than USD net equity supply, due to the small volatility of the USD net equity supply. This last result is due to the fact that most of the US stocks are held by US funds; i.e. the US stock market is the closest stock market to autarky in our sample. This is despite the fact that foreigners hold a lot of US equity simply because most assets under management are denominated in USD globally. The last part of the paper focuses on the transmission of macro news and VIX fluctuations on stock returns and exchange rates. The US stock market centrality plays a key role. Positive news in the US leads to more inflows into funds and local stock market returns tend to go up. It also leads to an appreciation of local currency exchange rates for most countries though the rebalancing of portfolios (changes in weights) exhibit some heterogeneity. To investigate this further we provide a decomposition

[10] We define the elasticity as the partial derivative that tells us by how much the exchange rate will move if the net equity supply of USD, for example, increases by one due to an exogenous shock, holding the net equity supply of other currencies constant.

between active and passive rebalancing of equity funds. When the VIX goes up, there are outflows from equity funds and reshuffling of positions out of the equity of some countries and into others. The USD and the JPY tend to appreciate while most of the other currencies depreciate.

Section 2 provides a literature review, sections 3 and 4 present the granular accounting identities and teh assumptions on which we build our analysis and explains our concept of centrality. Section 5 discusses the data and section 6 show our results regarding both the equity markets and the forex decompositions while section 7 investigates the transmission of macroeconomic news and VIX fluctuations on equity markets and exchange rates. Finally section 8 concludes.

2 Literature Review

Our paper is related to the very large literature on exchange rate determination and asset markets. Early on, the literature on portfolio balance models in international finance (i.e. Kouri (1976), Branson and Henderson (1985)) have sought to derive jointly the behaviour of asset prices -stocks and bonds- and exchange rates, assuming imperfect substitutability across domestic and foreign assets. Strikingly, that literature featured at its heart deviations from uncovered interest parity and rich exchange rate dynamics. Recent papers have revived this approach for international bond markets such as Gabaix and Maggiori (2015) who introduces a financial intermediary with a capital constraint arbitraging between domestic and foreign bonds to facilitate international trade in goods. Market segmentation and reliance on intermediaries with limited capital or risk aversion is also a key element in Gourinchas et al. (2022) and Greenwood et al. (2023) who present models of currency and bond markets with preferred-habitat investors and global arbitrageurs. They derive interesting implications for the links between exchange rates and term premia. While all the recent literature above studies fixed income markets and exchange rates the close link between exchange rates and equity markets has been emphasized by Hau and Rey (2004) and Hau and Rey (2006). Camanho et al. (2022) models jointly the dynamics of international equity prices and of the exchange rate in a two-country partial equilibrium model with optimal portfolio choice. From an empirical point of view, Camanho et al. (2022) studies the rebalancing behaviour of equity funds[11] and identifies the causal effect of cross border net equity flows on exchange rates via a granular instrument. Compared to that literature, we present a detailed characterisation of the links between equity markets and exchange rates without making any assumptions on investors' behaviour. We rely on granular accounting identities and observed components of demand to provide robust stylized facts on the links between equity markets and exchange rates for a wide cross section of countries. In this sense, any theoretical model of asset markets and exchange rate should be compatible with the set of stylized facts that we uncover.

On the empirical front, there are many papers focusing on exchange rate predictability, covered and uncovered interest rate parity (for a recent survey see Du and Schreger (2022)[12]) but relatively little linking exchange rates and equity markets. Lustig et al. (2011) and Verdelhan (2018) show that two global factors -a carry factor and a USD factor- explain an important share of the variation in bilateral exchange rates. Following a more structural approach, Richmond (2019) shows that countries which are more central in the global trade network tend to have lower interest rates and currency risk premia. In his model, central countries' consumption growth is more exposed to global consumption growth shocks, which causes their currencies to appreciate in bad global states and explains their lower currency premia[13]. Lustig and Richmond (2020) relate the risk characteristics of currencies to systematic differences across countries such as physical, cultural or institutional distance. Those

[11]Some recent empirical papers focus on the currency composition of holdings of bond portfolios (Maggiori et al. (2020)) and the correlations between the USD and bond flows post 2008 (Lilley et al. (2022)).

[12]For interesting DSGE models featuring shocks to the UIP conditions or a convenience yield on US assets see i.e.Itskhoki and Mukhin (2021), Kekre and Lenel (Forthcoming), Jiang et al. (Forthcoming), Valchev (2020)

[13]For the role of country size see Hassan (2013)

determine the patterns of co-variations of bilateral exchange rates. These empirical results are compatible with ours but unlike those papers we rely on accounting identities and emphasize the network links through equity investment in mutual funds rather than through trade in goods.

More directly related to some of our results, is Bruno et al. (2022) which shows that higher local currency stock returns are associated with a weaker dollar. They also find evidence that the "dollar beta" of emerging markets (sensitivity of stock returns to changes in the broad dollar index) is positively correlated with the average returns of their stock indices. These findings are consistent with ours. 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. Stavrakeva and Tang (2024a) show the importance of flight to safety for the Dollar exchange rate and interesting cross-sectional heterogeneity: currencies more sensitive to global bad states depreciates more vis a vis the dollar when a surprise cut in US monetary policy triggers a flight to safety. Koijen and Yogo (2020) estimate a demand system to study exchange rates jointly with short term rates, long term yields and equity prices across 37 countries using portfolio holdings data. Their coverage of type of asset markets is larger than ours but they use aggregate asset holdings (rather than granular data like us) and rely on a structural IO model and instrumental variables to decompose variations in exchange rate and equity prices. Instead we exploit observed demands and market clearing conditions which allows us to account for the role of wealth (valuation) changes in the determination of exchange rates and asset prices[14]. Boehm and Kroner (2023) show that US macroeconomic news have large effects on stock market indices of 27 countries. At the quarterly frequency,

[14]For a partial equilibrium model of asset prices and institutional investors following benchmarks and allowing for wealth effects see Basak and Pavlova (2013). They show that good cash flow news tilt the distribution of wealth towards institutional investors and decrease the Sharpe ratio of the stock market. Bacchetta et al. (2022) provides a two-country DSGE model with bonds and equities in which investors make infrequent portfolio decisions and derive the price impact of financial flows using US equity mutual funds data.

they explain about a quarter of their variation and affect investors' risk taking capacity. Hence macroeconomic news in the US have a large effect on the Global Financial Cycle. Stavrakeva and Tang (2024b) show that most of the variation in exchange rates at the monthly and quarterly frequencies can be explained by macroeconomic news, in particular lagged ones. Our results are consistent with theirs. In addition we show that a specific transmission channel via the equity holdings of mutual funds and the centrality of US assets can explain these findings.

3 Market Clearing Decomposition

In this section, we present the theoretical underpinnings of our stock price and exchange rate decompositions as a function of supply and demand. We start with the market clearing condition for a single stock j at an 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 are the assets under management of fund i, denominated in the currency of its main region of sale (ROS), 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 fund i invested in ISIN j. Further, I is the universe of funds that hold asset j. S_t^{l/c^i} is the nominal exchange rate defined as units of currency l needed to purchase one unit of currency c^i. Finally, P_t^j is the price of ISIN j denominated in currency c^j and Q_t^j is the outstanding shares of ISIN j. Based on these variable definitions, $\sum_{i \in I} \omega_t^{i,j} W_t^i S_t^{l/c^i}$ is the total demand 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:

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

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

Equation (2) implies that the change in total demand for ISIN j, ΔD_t^j, can be decomposed into a component associated with the changes of the portfolio weights that fund managers place on asset j in their portfolios, $\sum_{i\in I}\widehat{W^i}\widehat{S}^{c^j/c^i}\left(\Delta\omega_t^{i,j}\right)$. This is the component of demand that fund managers have direct control over and if one were to write a model of optimal equity demand, it is often the case that the optimal first order condition (i.e. the Euler equation), in these models, would determine precisely the weight that a particular fund manager places on a given ISIN in her overall portfolio. 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 funds whose ROS currency, c^i, differs from c^j).

The last component of the change in total demand is associated with the growth rate of the fund's assets under management, $\sum_{i\in I}\widehat{W^i}\widehat{S}^{c^j/c^i}\left(\widehat{\omega}^{i,j}\Delta w_t^i\right)$. We decompose Δw_t^i further into components associated with the net-of-fee net portfolio returns of asset manager i, $R_t^{i,NF}-1$, and the net flows, $Flow_t^i$, into the fund. We begin with the law of motion of the assets under management of fund i, 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 the assets under management of fund i :

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

Plugging in expression (3) in equation (2) provides an accounting identity, linking the growth rate of the price of ISIN j, Δp_t^j, to the four components of demand that can be summarized as exchange rate valuation effects, weight re-balancing, fund-specific portfolio performance (net return valuation effects) and final fund inflows (outflows if negative). It further links it to the change in shares issued, associated with ISIN j, due to certain corporate actions such as stock splits, reverse splits, mergers, acquisitions, or other corporate restructuring events.[15] Granted that whenever a firm issues new equity, it usually does so under a new ISIN, and since our analysis is at the ISIN level, we would expect, and later confirm, that Δq_t^j would play no substantial role in the analysis. Re-writing equation (2), we can express the price growth rate of ISIN j as:

$$\begin{aligned}
\Delta p_t^j \quad &= \quad \sum_{i \in I} \frac{\mu^{i,j}}{\widehat{P^j Q^j}} \Delta s_t^{l/c^i} + \sum_{i \in I} \frac{\mu^{i,j}}{\widehat{P^j Q^j}} \frac{\Delta \omega_t^{i,j}}{\widehat{\omega}^{i,j}} \qquad (4) \\
&\quad + \sum_{i \in I} \frac{\mu^{i,j}}{\widehat{P^j Q^j}} r_t^{i,NF} + \sum_{i \in I} \frac{\mu^{i,j}}{\widehat{P^j Q^j}} flow_t^i - \Delta q_t^j \\
\text{where } \mu^{i,j} \quad &= \quad \widehat{W}^i \widehat{S}^{l/c^i} \widehat{\omega}^{i,j}, \qquad (5)
\end{aligned}$$

and $\mu^{i,j}$ is the sample average amount of ISIN j held by fund i, denominated in currency $c^j = l$. We will further decompose the demand components in equation (4) by types of funds such as active versus passive, ROS or investment style.

However, constructing the demand 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 assume that we observe a representative sample of investors that own asset j, which have similar investment styles, portfolios and final flows, within a narrowly defined type. As we will show later on in the results section, where we discuss the fit of our demand measures, this will turn out to be a very realistic assumption.

Next, we explain the exact assumptions that allow us to construct the terms in the

[15]Notice that we ensure to use a stock price adjusting for such events and for mechanical structural breaks in the price series.

accounting identity in equation (4). We assume that the scaled change in the weight invested in asset j by investor i can be decomposed as:

$$\frac{\Delta\omega_t^{i,j}}{\widehat{\omega}^{i,j}} = \alpha_t^{\omega,\gamma,\tau,c^i} + \varepsilon_t^{\omega,i,j}, \tag{6}$$

where $\alpha_t^{\omega,\gamma,\tau,c^i}$ is a common component and $\varepsilon_t^{\omega,i,j}$ is the idiosyncratic component. We construct the common component as the average $\frac{\Delta\omega_t^{i,j}}{\widehat{\omega}^{i,j}}$ within a given group of ISINs and funds, captured by $\{\gamma, \tau, c^i\}$. We define fund type based on the currency of the ROS, whether the fund is active vs passive, the size of the fund, captured by the sample average assets under management of the fund, and the investment strategy of the fund. The last three characteristics are summarized by $\tau \in \Upsilon$, where $\Upsilon = active \times size \times strategy$. The asset type is captured by $\gamma \in \Gamma$, where $\Gamma = sector \times size \times owncurr \times currency$. We condition on the currency of the asset, whether the asset is issued in the same currency as the currency of the main region of operation of the firm, size of the firm issuing the asset (captured by the sample average market capitalization of the ISIN), and the sector of the firm issuing the asset.[16] Details of the categories are provided in the Data Section.[17]

Similarly, we assume that the flows and the net-of-fee returns also have common components within the same fund type:

$$flow_t^i = \alpha_t^{f,\tau,c^i} + \varepsilon_t^{f,i} \tag{7}$$

$$r_t^{i,NF} = \bar{r}_t^{NF,\tau,c^i} + \varepsilon_t^{r,i}, \tag{8}$$

where α_t^{f,τ,c^i} and $\bar{r}_t^{NF,\tau,c^i}$ are the common components, once again, constructed as the average $flow_t^i$ and $r_t^{i,NF}$ within a fund type, $\{\tau, c^i\}$, and $\varepsilon_t^{f,i}$ and $\varepsilon_t^{r,i}$ are the idiosyncratic components.

[16] Since we will aggregate the ISIN-level decomposition to the stock market level, we only keep ISINs issued in the currency of the main region of operation of the firm issuing the asset, to capture local stock markets rather than non-US firms issuing in USD, for example.

[17] The results are robust to assuming that the common component is a function only of the ISIN, i.e. we define the common component as $\alpha_t^{\omega,j}$, which would imply that all funds re-balance their portfolios with respect to a given ISIN in a similar way.While this specification allows for ISIN-specific news, we do not use this as our benchmark specification because we have insufficient observations within ISIN-specific cells for some ISINs of emerging markets and smaller economies that are held only by a handful of funds in our sample. Also, this specification would not allow us to control for fund characteristics for the same reason.

Next, we define the following coverage ratios $\widehat{H}_{\tilde{I}}^{j,\tau,m} = \sum_{\{i:\, i\in\tilde{I}\cap i\in\tau\cap c^i=m\}} \frac{\mu^{i,j}}{\widehat{P^jQ^j}}$ and $\widehat{H}_{\tilde{I}^{miss}}^{j,\tau,m} = \sum_{\{i:\, i\in\tilde{I}^{miss}\cap i\in\tau\cap c^i=m\}} \frac{\mu^{i,j}}{\widehat{P^jQ^j}}$, where $\tilde{I}$ is the set of funds we observe in our sample which hold ISIN j and $\tilde{I}^{miss} = I \setminus \tilde{I}$ is the set of funds we don't observe. $\widehat{H}_{\tilde{I}}^{j,\tau,m}$ is the sample average holdings of ISIN j by all observed funds of type $\{\tau, c^i = m\}$ as a fraction of the sample average market value of this ISIN. $\widehat{H}_{\tilde{I}^{miss}}^{j,\tau,m}$ is the same variable but summed across the funds that we do not observe in our sample. Substituting equations (6), (7) and (8) into equation (4), we can re-write equation (4) as

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

We further assume that, for a given ISIN, we have a representative sample of final investors, an assumption that we model as:

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

Since total holdings must equal the total market value,

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

which implies

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

Thus, the scaling factor is the inverse of the total coverage ratio, $\frac{\sum_{i\in\tilde{I}} \mu^{i,j}}{\widehat{P^jQ^j}}$, defined as the sample average holdings of ISIN j by all the investors in our sample as a fraction of the sample average market value of the ISIN. Thus equation (9) can be re-written as

$$\begin{aligned}\Delta p_t^j + \Delta q_t^j = & \sum_m \sum_{\tau\in\Upsilon} \sum_{\{i:\, i\in\tilde{I}\cap i\in\tau\cap c^i=m\}} \frac{\mu^{i,j}}{\sum_{i\in\tilde{I}} \mu^{i,j}} \left(\Delta s_t^{l/m} + \alpha_t^{f,\tau,m} + \alpha_t^{\omega,\gamma,\tau,m} + \bar{r}_t^{NF,\tau,m}\right) \\ & + \sum_{i\in I} \frac{\mu^{i,j}}{\widehat{P^jQ^j}}\left(\varepsilon_t^{r,i} + \varepsilon_t^{f,i} + \varepsilon_t^{\omega,i,j}\right).\end{aligned} \tag{10}$$

We will not perform the analysis at the ISIN level but we will sum up across a group of ISINs, where the group is indexed by k, which could be, for example, the overall stock market of the country or a sector in a country. For the remainder of the paper, the group k will refer to all ISINs within the stock market of a given country. Therefore, we construct the average of equation (10) weighted by the sample average market value of each ISIN relative to the total market value of all ISINs within group k, $w^{j,p,l,k} = \frac{\widehat{P^jQ^j}}{\left(\sum_{\{j:c^j=l\cap j\in k\}} \widehat{P^jQ^j}\right)}$.

We can re-write the weighted sum across ISINs of type $\{k,l\}$ as:

$$
\begin{aligned}
\sum_{\{j:c^j=l\cap j\in k\}} w^{j,p,l,k}\Delta p_t^j &= \underbrace{\Delta D_t^{s,l,k} + \underbrace{\Delta D_t^{f,l,k} + \Delta D_t^{\omega,l,k} + \Delta D_t^{r^{NF},l,k}}_{\Delta D_t^{ROS,l,k}}}_{\Delta D_t^{l,k}} + D_t^{Resid,l,k} \\
&\quad - \sum_{\{j:c^j=l\cap j\in k\}} w^{j,p,l,k}\Delta q_t^j, \qquad (11) \\
\text{where } \Delta D_t^{s,l,k} &= \sum_m \left(\Delta s_t^{l/m}\right) \sum_{\{j:c^j=l\cap j\in k\}} w^{j,p,l,k}\nu^{m,j,l,k}, \\
\Delta D_t^{f,l,k} &= \sum_{\{j:c^j=l\cap j\in k\}} w^{j,p,l,k} \sum_m \sum_{\tau\in\Upsilon} \nu^{m,\tau,j,l,k}\alpha_t^{f,\tau,m}, \\
\Delta D_t^{\omega,l,k} &= \sum_{\{j:c^j=l\cap j\in k\}} w^{j,p,l,k} \sum_m \sum_{\tau\in\Upsilon} \nu^{m,\tau,j,l,k}\alpha_t^{\omega,\gamma,\tau,m}, \\
\Delta D_t^{r^{NF},l,k} &= \sum_{\{j:c^j=l\cap j\in k\}} w^{j,p,l,k} \sum_m \sum_{\tau\in\Upsilon} \nu^{m,\tau,j,l,k}\bar{r}_t^{NF,\tau,m}, \\
D_t^{Resid,l,k} &= \sum_{i\in I} \frac{\mu^{i,j}}{\widehat{P^jQ^j}} \left(\varepsilon_t^{r,i} + \varepsilon_t^{f,i} + \varepsilon_t^{\omega,i,j}\right),
\end{aligned}
$$

where $\nu^{m,j,l,k} = \frac{\sum_{\{i:\ i\in\tilde{I}\cap c^i=m\}} \mu^{i,j}}{\sum_{i\in\tilde{I}} \mu^{i,j}}$ is the sample average holdings of asset j by funds located in the ROS with currency m relative to the sample average holdings of asset j by all funds in our sample. This share reflects the importance of the ROS currency m for the demand of asset j. $\nu^{m,\tau,j,l,k} = \frac{\sum_{\{i:\ i\in\tilde{I}\cap i\in\tau\cap c^i=m\}} \mu^{i,j}}{\sum_{i\in\tilde{I}} \mu^{i,j}}$ is a similar share but summing across funds located in the ROS with currency m and also of type τ.

Equation (11) implies that there are two valuation components of the common component of equity demand, $\Delta D_t^{l,k}$. The first one refers to the fact that demand would be impacted by the overall performance of the funds, $\Delta D_t^{r^{NF},l,k}$. Holding the other components of common equity demand constant, higher net-of-fee portfolio returns get reinvested, which in turn, increases the demand for equities and increases stock prices. Granted that the vast majority of global funds are located in the US and the Eurozone and that they are heavily exposed to the US and Eurozone stock markets, we would expect that this valuation component of demand will be an important propagation mechanism for monetary policy and macroeconomic shocks, originating in the US and the Eurozone, to other stock markets and currency crosses. It further captures the importance, i.e. centrality, of US and Eurozone stock market performance for global equity performance.

The second valuation component of common equity demand, $\Delta D_t^{s,l,k}$, captures the fact that prices and exchange rates are jointly determined in equilibrium. Based on equation (11), local currency depreciation, positive $\Delta D_t^{s,l,k}$, will appreciate the local currency stock market, holding the other components of common demand fixed. Intuitively, conditional on a given demand by "foreign funds", measured in the ROS currency and captured by $\Delta D_t^{ROS,l,k}$, local currency depreciation implies larger equity demand by foreigners, as measured in local currency. As a result, a larger local-currency stock market price increase will be needed in order for the stock market to equilibrate.

Notice that this is the *conditional* relationship between the exchange rate valuation component and local currency stock prices. We would expect the *unconditional* relationship to be, in most cases, the opposite, meaning local currency appreciation to be associated with a local-currency stock market price increase as higher equity demand, measured in the currency of the ROS of the funds, will increase both prices. In other words, we would expect $Cov(\Delta D_t^{s,l,k}, \Delta D_t^{ROS,l,k}) < 0$, generating a negative covariance between $\Delta D_t^{s,l,k}$ and the local currency stock price movements for most stock markets and currencies.

The last two components of common equity demand relate to the weight rebalancing of the fund managers, $\Delta D_t^{\omega,l,k}$, or to the investment decisions of the final mutual fund investors, who decide how much to save and also how to allocate their savings, $\Delta D_t^{f,l,k}$. A higher weight placed by portfolio managers on the equities of the currency l stock market or more inflows into equity funds will both increase the price of stocks denominated in currency l, all else constant.

As the investment decisions of fund managers are tightly linked to macroeconomic and monetary policy news and to swings in their own risk aversion, we would expect that the weight rebalancing component will play a key role in the propagation of macroeconomic news and VIX movements to stock markets. Similarly, the savings of final investors and their savings allocations will react to changes in the state of the economy which is captured by macroeconomic news. Moreover, risk aversion shocks would impact the final investors' investment in equity funds vs other safer asset classes. As a result, we would expect that the flows components of common equity demand to also play a key role in the propagation of macroeconomic news and VIX fluctuations to asset prices.

Since most mutual funds are located in the US or the Eurozone, flows into these funds would be disproportionately more sensitive to developments in the US and the Eurozone, which could explain the importance of US and Eurozone macroeconomic news for global equity prices. Similarly, we would expect that the weight rebalancing component of common equity demand to be disproportionately more sensitive to US and Eurozone news due to the oversized exposure of mutual funds to the US and Eurozone stock markets and cross equity substitution effects.[18]

4 Exchange Rate Change Decomposition

In this section, we develop an exchange rate decomposition based on equation (11), where we will express exchange rate changes only as a function of nominal equity supply (market value

[18] More concretely, if one were to write a general equilibrium model where equity prices are endogenously determined, it would indeed be the endogenous movements of portfolio weights and fund flows in response to macroeconomic, risk aversion, or equity demand shocks that would entirely explain the propagation of these shocks to equity prices, holding exchange rates fixed. Writing and estimating such a model, consistent with the common equity demand components we construct in this paper, is left for future work.

of the stock market in a given country) and equity demand denominated in the currency of the ROS. We start by re-writing equation (11) as:

$$\begin{aligned}\sum_m \Delta s_t^{l/m}\nu^{m,l,k} + \Delta D_t^{ROS,l,k} &\approx \Delta MC_t^{l,k}, \\ \text{where } \nu^{m,l,k} &\approx \sum_{\{j:c^j=l\cap j\in k\}} w^{j,p,l,k}\nu^{m,j,l,k}, \\ \Delta MC_t^{l,k} &= \sum_{\{j:c^j=l\cap j\in k\}} w^{j,p,l,k}\Delta p_t^j + \sum_{\{j:c^j=l\cap j\in k\}} w^{j,p,l,k}\Delta q_t^j.\end{aligned} \tag{12}$$

We abstract from $D_t^{Resid,l,k}$ to simplify the mathematical expressions. $\nu^{m,l,k}$ is the sample average holdings of equities denominated in currency l by funds with ROS currency m relative to the sample average holding of all funds in our sample of equities denominated in currency l. If, for example, Eurozone funds hold a large share of BRL-denominated equity relative to other funds in our sample, then $\nu^{EUR,BRL,k}$ will be large and the BRL/EUR cross will be an important currency cross for the equilibration of the Brazilian stock market. Furthermore, $\Delta D_t^{ROS,l,k}$ is the change in the *common* demand, measured in the currency of the funds' ROS and $\Delta MC_t^{l,k}$ is the change in the market capitalization of the stock market associated with currency l, i.e. change in the nominal supply of currency l.

If all equity denominated in currency l is held by investors located in ROS with currency l, then $\nu^{m,l,k} = 0$ if $l \neq m$, and all the exchange rate terms will disappear. This is an intuitive result as, without cross-border equity demand, then we are in the case of financial autarky with respect to equities and exchange rates no longer play an equilibrating role for equity markets.

Note that $\Delta s_t^{l/m} = \Delta s_t^{l/z} - \Delta s_t^{m/z}$ and $\sum_{m\in M}\nu^{m,l,k} = 1$ and that, if $l = z$, then $-\sum_{m\in M}\Delta s_t^{m/z}\nu^{m,z,k} = \Delta MC_t^{z,k} - \Delta D_t^{ROS,z,k}$. As a result, we can re-write equation (12) and express $\Delta s_t^{l/z}$ as a function of *net* supply defined as nominal equity supply minus demand measured in the currency of the ROS and exchange rate fluctuations of other currency crosses as follows:

$$\Delta s_t^{l/z} \approx \sum_{m \in M \setminus l} \Delta s_t^{m/z} \frac{\left(\nu^{m,l,k} - \nu^{m,z,k}\right)}{\left(1 - \nu^{l,l,k} + \nu^{l,z,k}\right)} + \frac{\left(\Delta MC_t^{l,k} - \Delta D_t^{ROS,l,k}\right)}{\left(1 - \nu^{l,l,k} + \nu^{l,z,k}\right)} - \frac{\left(\Delta MC_t^{z,k} - \Delta D_t^{ROS,z,k}\right)}{\left(1 - \nu^{l,l,k} + \nu^{l,z,k}\right)}. \tag{13}$$

In our analysis of exchange rate determination, we focus on movements of net supply, given the high correlation between $\Delta D_t^{ROS,n,k}$ and $\Delta MC_t^{n,k}$, as higher demand for a given equity, measured in the ROS currency, also increases its price and, therefore, its market value. In other words, when we study currencies, we are interested in how much supply increases relative to demand, measured in the currency of the ROS, as this is the relevant "excess" supply measure that tells us by how much exchange rates need to adjust to equilibrate equity markets.

Let's take, for example, the case where $z = USD$ and $l = BRL$. It will always be the case that $\left(1 - \nu^{BRL,BRL,k} + \nu^{BRL,USD,k}\right) > 0$. Holding all else constant, equation (13) implies that the exchange rate change defined as $\Delta s_t^{BRL/USD}$ increases (i.e. the BRL depreciates) if (1) the BRL net supply increases (i.e. the market value of the BRL stock market, measured in local currency, increases by more than the demand for BRL equity, measured in the currency of the ROS of the funds); (2) USD net supply decreases; or (3) the exchange rates associated with the non-USD major ROS currencies, $\Delta s_t^{m/USD}$, depreciate against the USD.

Point number (3) is conditional on $\nu^{m,BRL,k} > \nu^{m,USD,k}$. Since USD equities are held by US funds while BRL equities are mostly held by foreign investors, we indeed expect that, in most cases, $\nu^{m,BRL,k} > \nu^{m,USD,k}$. This term captures the "centrality" of the $\Delta s_t^{m/USD}$ cross for the determination of other currency crosses. As we are going to document in the empirical section, when studying exchange rate movements against the USD, the main "central" currency cross will be the EUR/USD. Moreover, the larger $\nu^{m,BRL,k} - \nu^{m,USD,k}$ is in absolute value, the more *central* the m/USD currency cross is for BRL/USD. The reason why the m/USD currency cross appears in the solution for the BRL/USD currency cross is because fluctuations of the BRL/m exchange rate will also impact the Brazilian equity demand of funds located in the ROS with currency m, when it is measured in BRL, and we can further decompose BRL/m into movements of the m/USD and BRL/USD currency crosses.

Next, we solve for exchange rates as a function only of net supply. We do that by representing the joint currency solution in matrix notation. For $l \neq z$:

$$\tilde{\mathbf{A}}^{k,z} \underbrace{\begin{bmatrix} \Delta s_t^{GBP/z} \\ .. \\ \Delta s_t^{EUR/z} \end{bmatrix}}_{\mathbf{\Delta s}_t^{\mathbf{l}/z}} \approx \underbrace{\begin{bmatrix} \Delta MC_t^{GBP,k} - \Delta D_t^{ROS,GBP,k} \\ .. \\ \Delta MC_t^{EUR,k} - \Delta D_t^{ROS,EUR,k} \end{bmatrix}}_{\tilde{\mathbf{\Pi}}_t^{l,k}} - \underbrace{\begin{bmatrix} \Delta MC_t^{z,k} - \Delta D_t^{ROS,z,k} \\ .. \\ \Delta MC_t^{z,k} - \Delta D_t^{ROS,z,k} \end{bmatrix}}_{\tilde{\mathbf{\Pi}}_t^{z,k}}$$

$$\text{where } \tilde{\mathbf{A}}^{k,z} = \begin{bmatrix} 1 - \nu^{GBP,GBP,k} + \nu^{GBP,z,k} & .. & -\nu^{EUR,GBP,k} + \nu^{EUR,z,k} \\ ... & ... & .. \\ -\nu^{GBP,EUR,k} + \nu^{GBP,z,k} & ... & 1 - \nu^{EUR,EUR,k} + \nu^{EUR,z,k} \end{bmatrix}$$

This system allows us to solve for $\mathbf{\Delta s}_t^{\mathbf{l}/z}$ as a function of the net supply of all currencies and not just l and z:

$$\mathbf{\Delta s}_t^{\mathbf{l}/z} \approx \left(\tilde{\mathbf{A}}^{k,z}\right)^{-1} \left(\tilde{\mathbf{\Pi}}_t^{l,k} - \tilde{\mathbf{\Pi}}_t^{z,k}\right). \tag{14}$$

By being able to directly measure all the entries in $\left(\tilde{\mathbf{A}}^{k,z}\right)^{-1}$, we can measure the elasticities of exchange rates with respect to net supply.

To gain more intuition, we consider a special case. Consider funds with ROS currencies USD and EUR, which comprise the majority of assets under management, as well as the local currency funds, which will capture the home bias holdings.[19] The exchange rate change

[19] We also provide the solution for the case where we also consider the UK funds in Appendix.

in this case can be expressed as:

$$\Delta s_t^{l/USD} \approx \sum_{j=\{l,USD,EUR\}} \xi^{l,j} \left(\Delta MC_t^{j,k} - \Delta D_t^{ROS,j,k}\right) \tag{15}$$

where if $l \neq EUR$

$$\begin{aligned} \xi^{l} &= \xi^{l,l} = \frac{1}{(1-\nu^{l,l,k})} > 0 \\ \xi^{l,USD} &= -\frac{1}{(1-\nu^{l,l,k})}\left(\frac{1-\nu^{EUR,EUR,k}+\nu^{EUR,l,k}}{1-\nu^{EUR,EUR,k}+\nu^{EUR,USD,k}}\right) < 0 \\ \xi^{l,EUR} &= \frac{1}{(1-\nu^{l,l,k})}\frac{\left(\nu^{EUR,l,k}-\nu^{EUR,USD,k}\right)}{(1-\nu^{EUR,EUR,k}+\nu^{EUR,USD,k})} \end{aligned} \tag{16}$$

and if $l = EUR$

$$\xi^{EUR,EUR} = -\xi^{EUR,USD} = \frac{1}{(1-\nu^{EUR,EUR,k}+\nu^{EUR,USD,k})} > 0.$$

$\xi^{l}, \xi^{l,US}$ and $\xi^{l,EUR}$ are the elastictities of the l/USD currency cross with respect to local currency net supply, USD and EUR net supply. It will be always the case that $\xi^{l} > 0$ and $\xi^{l,USD} < 0$ so that higher local currency net supply depreciates currency l against the USD and higher USD net supply appreciates the local currency against the USD. With respect to $\xi^{l,EUR}$, it is unclear what the sign would be and would depend on the sign of $\nu^{EUR,l,k} - \nu^{EUR,USD,k}$ since the other terms are positive. As a result $\xi^{l,EUR}$, will be positive if the EUR funds are more important for the currency l stock market rather than for the US stock market (i.e. they hold a larger fraction of the equities in the currency l stock market than of the equities in the US market). We would expect indeed that to be the case given that most of US equities are held by USD funds.

Notice that $\xi^{l}, \xi^{l,USD}$, and $\xi^{l,EUR}$ are partial derivatives. For example, the parameter ξ^{USD} is the response of the exchange rate change to an exogenous unit shock to the USD net supply of equities, $\Delta MC_t^{USD,k} - \Delta D_t^{ROS,USD,k}$, holding the net supply for all other currencies fixed. The total effect of an exogenous shock, ϕ_t^{us} for example, normalized to have a unit effect on the USD net supply, is given by the following total derivative:

$$\xi^{l,USD} + \xi^{l}\frac{\partial\left(\Delta MC_t^{l,k} - \Delta D_t^{ROS,l,k}\right)}{\partial \phi_t^{us}} + \xi^{l,EUR}\frac{\partial\left(\Delta MC_t^{EUR,k} - \Delta D_t^{ROS,EUR,k}\right)}{\partial \phi_t^{us}}.$$

Estimates of $\frac{\partial\left(\Delta MC_t^{l,k} - \Delta D_t^{ROS,l,k}\right)}{\partial \phi_t^{us}}$ and $\frac{\partial\left(\Delta MC_t^{EUR,k} - \Delta D_t^{ROS,EUR,k}\right)}{\partial \phi_t^{us}}$ can be model- and shock-specific and will require introducing many more assumptions and additional data. However, conditional on one having such estimates, one can calculate the total effect by using our partial elasticities, even without having access to the mutual funds data we use.

5 Data Description and Summary Statistics

We start with a total of 45246 mutual funds reporting in the Morningstar database. The funds we have are selected partially based on size, where we have all US funds, and most Eurozone and UK funds.[20] For details on the AUM and number of funds by the currency of the main region of sale see Tables XX and XX in the Appendix for the monthly and quarterly data, respectively.

We have fund-level information such as ISIN-level positions, assets under management, net-of-fee portfolio returns, and fund flows. We also obtain various fund characteristics. We use information from Refinitiv Eikon to classify all ISINs held by our sample of funds into equity, corporate debt, government debt and cash-like assets, and obtain additional ISIN-level information including region of operation of the issuer, currency of issuance, market capitalization, split-adjusted prices, and industry of the firm. This paper focuses only on equities and our final sample includes 21,290 individual equity ISINs. When we condition on issuer size we refer to the market value of the total issuance of the ISIN in USD.

Some funds report monthly data on positions while others report quarterly and a few only annually. From the monthly series, we exclude funds that do not have continuous monthly series; i.e. for more than 10 percent of the dates for which they are in the sample they are missing data. In the paper, we report results based on funds that report only monthly, which is 20746 funds, but the results are robust to using quarterly frequency, which is 45002 funds.

[20] According to the Morningstar data provider, their data covers close to the universe of mutual funds.

Our data covers 26 stock markets and the associated currencies in these stock markets where the abbreviation we use in the paper is with respect to the currency. The list of currencies are: AUD, BRL, CAD, CHF, CLP, CNH, DKK, EGP, EUR, GBP, HKD, IDR, ILS, INR, JPY, KRW, MXN, MYR, NOK, NZD, PHP, THB, TRY, TWD, USD, and ZAR. Given the smaller size of the mutual fund industry prior to the Global Financial Crisis of 2008, we focus on the period starting Jan 2008. More specifically, our sample is Jan 2008 through Jan 2022. For the stock market decomposition, the samples for JPY and CNH start later, in Jan 2010 and Jan 2012, respectively. For the exchange rate change decomposition, the samples for CHF and THB start in June 2008, and we exclude the currencies pegged against the USD: HKD, CNH, EGP, and DKK. We perform additional steps to clean the data such as winsorizing outliers or removing funds with significant data inconsistencies across the various data series provided by Morningstar.

As a gauge of representativeness, we compare our weighted average monthly stock market return measure, constructed using ISIN-level information, $\sum_{\{j:c^j=l\cap j\in k\}} w_t^{j,p,l,k}\Delta p_t^j$, to stock market returns based on stock indices in the different countries, where we obtain the data for these indices from Global Financial Data.[21] The monthly return correlation between our weighted average stock market series and the returns based on these stock market indices ranges between 70 percent and 98 percent with a mean and a median of 91 and 93 percent respectively. With respect to the US, EU and UK stock markets, the correlations are 95, 98, and 96 percent respectively. Note that we have more ISINs than the ones used to calculate the stock market indices we use from GFD but our stock market return measure is size-weighted where we use the market cap as the weight which accounts for the high correlation and reassures us regarding the quality of our data.

We define fund type using three main characteristics. First is the currency of the final investors which is constructed using information on the region of sale (ROS) and domicile, available at the more disaggregated share class level. We primarily use the ROS, but we

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

use the domicile variable when ROS is missing or is one of the following broad categories: Global Cross-Border, European Cross-Border, Nordic Cross-border, Pure Offshore, Asian Cross-Border. Then, for a given fund and date, we construct the fraction of the assets under management held by investors in each country, based on the fraction of assets under management in each share class. We then define the currency of the final investors of the fund as the one in which, for a majority of time periods, the fund sold over 50 percent of its shares to countries with that particular currency. If a fund ends up being classified as selling shares primarily to one of the following offshore countries: Cayman Islands, Jersey, Liechtenstein, Guernsey, Bermuda, Bahrain, Channel Islands, Brunei Darussalam, Macao, we assume the currency of the final investor is USD.

Another fund characteristic that we use is the investment strategy given by the Morningstar variable Global Broad Category Group where we focus on these most important classifications: "Allocation", "Fixed Income", "Equity", etc. For USD, EUR, and GBP funds, we interact this Global Category variable with a more narrow investment strategy classification, given by the Global Category variable, that includes a total of 82 categories with one example being "Global Emerging Markets Equity".

Finally, we construct an active vs passive investment style classification that consists of three groups based on the size of a fund's tracking error with respect to a benchmark portfolio. We construct the return of the benchmark portfolio as the average return of the funds in our sample within the same Global Category. The tracking error is the average absolute difference between the monthly realized fund return and the monthly benchmark portfolio return, both measured in USD. We classify funds based on the sample average tracking error with funds being passive if the error is below one percent; medium-passive if it's between one and two percent, a group that captures almost 50 percent of funds; and active if the error exceeds two percent. Exchange rates are obtained from Global Financial Data.

Figures 1, 2, and 3 in the Data Appendix, we have plotted the time series of the USD

AUM of our funds broken down by type of fund for our monthly data, and the equivalent graphs for the quarterly data are presented in the Appendix in Figures 17, 18 and 19. In the monthly data, total assets under management peaks at 25 trillion USD, towards the end of the sample, and the equivalent number for the quarterly data is above 60 trillion USD.

Breaking down by investment strategy, Equity funds have the most assets under management, reaching a peak of 30 trillion USD in the quarterly data, followed by Fixed Income funds, which reach a peak of about 13 trillion USD, and by Allocation funds, which peak at 8 trillion USD. The numbers for our monthly data are 14 trillion USD for Equity funds, about 5 trillion USD for Fixed Income funds and 4 trillion USD for Allocation funds. Focusing on Equity and Allocation funds, as these are the funds that hold the majority of global equities, it is clear that funds with USD ROS vastly dominate (more so than for Fixed Income funds where funds with EUR ROS plays also an important role). The second most important ROS currency is, of course, the EUR, followed by GBP and all the rest.

Further disaggregating by investment style, passive and medium-passive funds are most prominent within the Equity and Allocation funds in the monthly data while active funds seem to be more important in the Fixed Income space. In the quarterly series, one can see that active funds are also prominent within the Equity and Allocation categories. However, note that some differences between the monthly and quarterly analysis can be due to the fact that our definition of active vs passive investment styles is frequency-specific as for the quarterly series, we construct a quarterly tracking error.

6 Variance Covariance Decomposition and Elasticities

In this section we first present how well our estimates of demand explain both stock market fluctuations and exchange rate fluctuations and decompose the importance of the various components of demand as drivers of these asset prices. We document a lot of novel facts related to the channels through which equity demand impacts equity prices and exchange rates.

6.1 Stock Market

First, we start by plotting the stock market decomposition, given by equation (11). In Figures 6 and 7, we plot our measures of the common component of demand, $\Delta D_t^{l,k}$, against the stock market price growth rate for a number of advanced economies and emerging markets. The plots for the other stock markets are provided in the Online Appendix. The difference between the two series represents idiosyncratic demand, and potentially measurement error, $D_t^{Resid,l,k}$, and the new issuance at ISIN level, $\sum_{\{j:c^j=l\cap j\in k\}} w^{j,p,l,k}\Delta q_t^j$. We can see that the fit between the two series is almost perfect and indeed our measure of the common component of demand explains stock price movements almost entirely.

Next we perform the following variance covariance decomposition:

$$1 \approx \sum_{x=\left\{\Delta D^{s,l,k},\Delta D^{f,l,k},\Delta D^{\omega,l,k},\Delta D^{r^{NF},l,k},D^{Resid,l,k}\right\}} \beta^{p,x}, \text{ where}$$

$$\beta^{p,y} = \frac{Cov\left(y_t, p_t^{SM,l}\right)}{Var\left(\Delta p_t^{SM,l}\right)}$$

$$\text{and } y = \left\{\Delta D^{s,l,k}, \Delta D^{f,l,k}, \Delta D^{\omega,l,k}, \Delta D^{r^{NF},l,k}, D^{Resid,l,k}, \Delta D^{l,k}\right\}$$

$$\text{and } \Delta p_t^{SM,l} = \sum_{\{j:c^j=l\cap j\in k\}} w^{j,p,l,k}\Delta p_t^j$$

We abstract from $\sum_{\{j:c^j=l\cap j\in k\}} w^{j,p,l,k}\Delta q_t^j$ granted that this term, as we will show, explains close to zero of the variation of the stock market prices. We also construct $D_t^{Resid,l,k}$ as a residual from equation (11). We present the results in Figure 8 and Table 2. In Figures 25-36, in the Online Appendix, we further break down each one of our demand components into the role of the different types of funds and perform the same variance covariance decomposition. The classification of funds are according to the currency of the ROS of the fund: USD, EUR, GBP and Other; the size of the tracking error of the fund where we group the funds into passive, medium-passive and active; and the investment type: equity funds, mixed allocation funds and others. For example, if we take the ROS break down, essentially we decompose $\beta^{p,x} = \beta^{p,USD,x} + \beta^{p,EUR,x} + \beta^{p,GBP,x} + \beta^{p,Other,x}$ for every x. We estimate $\beta^{p,x}$ by regressing x on $\Delta p_t^{SM,l}$ where in Table 2 we report also the adjusted R^2 from this regression and the significance of the estimated coefficients, with one star we indicate significance at 10 percent, two starts indicating significant results at 5 percent and three starts at 1 percent.

Turning to Table 2 first, in the last column, we report $\beta^{p,\Delta D^{l,k}}$, which captures the importance of the common component of demand, also plotted in Figures 6 and 7. We find that $\Delta D_t^{l,k}$ explains, on average, 91 percent of the stock price variation. The smallest fraction explained is 76 percent and the largest is 106 percent, with the numbers for the US and the Eurozone stock markets being 97 and 92 percent, respectively. In contrast the idiosyncratic component of demand, $D_t^{Resid,l,k}$, explains on average, 8 percent of the stock market price variation with the minimum and maximum values being -9 and 24 percent. This implies that the observed component of common demand plays a much more important role in explaining stock market prices at monthly frequency than idiosyncratic demand. This result should come as no surprise, given the similar investment strategies employed by the mutual fund industry. In total, both components of demand $\beta^{p,\Delta D^{l,k}} + \beta^{p,D^{Resid,l,k}}$, explain on average 99 of the total stock market price variation, indeed confirming that we can abstract from $\sum_{\{j:c^j=l\cap j\in k\}} w^{j,p,l,k}\Delta q_t^j$ for the rest of the analysis.

Regarding the importance of the various common demand sub-components, which we construct directly from the Morningstar Data, we can see that the most important component is the net of fees fund level portfolio return component. $\beta^{p,\Delta D^{r^{NF},l,k}}$ explains on average 71 percent of the variation of the stock market with the minimum and the maximum numbers being 37 and 102 percent respectively. In other words, as the funds generate positive or negative returns on their overall portfolios, they increase or decrease their demand for the equity of a particular country, proportional to their steady state exposure to that equity instrument, and this is one of the most important components of common demand, and, as a result, one of the most important drivers of equity prices. Granted that these returns are themselves linked to equity prices, one can think of this channel as an amplification effect. Delving deeper into the sub-components of $\beta^{p,\Delta D^{r^{NF},l,k}}$, reported in the Online Appendix in Figures 31, 32 and 33, we observe strong equity home bias for the EUR, GBP, JPY, CHF and of course USD, where the returns associated with the portfolios of local funds play a disproportionately larger role.[22] It is clear that the USD funds dominate the overall net return component of demand, granted that they have the largest assets under management. At the same time, the US equity funds are very heavily exposed to the US stock market. This implies that one of the key reasons why US monetary and macroeconomic news might transmit to other stock markets globally is due to the oversized importance of USD funds and their heavy exposure to USD equities prices, which are, in turn, driven by these news. We will explore this hypothesis formally in Section 7.

Having said that, EUR funds also play an important role as contributing to the overall importance of the net return *common* demand component (they explain on average 15 percent of the overall stock markets fluctuations via their contribution to the net return demand component, while the USD funds explain on average 47 percent). The importance of GBP and Other funds is significantly smaller. Considering the break down into other type of funds, it is clear that equity funds are the main holder of equities and so are medium passive funds for advanced economies with passive funds playing more important role for certain emerging market economies. Active funds play a disproportionate role as drivers of the Chinese stock market which is consistent with the fact that the Chinese stock market does not enter most standard global stock market benchmark indices. From Table 2, we can also see that the $\beta^{p,\Delta D^{r^{NF},l,k}}$s are all statistically significant at one percent with the average adjusted R^2 from regressing the net return demand component on the respective stock market growth being 62 percent. The adjusted R^2 would be higher if most of the local equity stock market is owned by domestic funds who also invest most of their assets domestically. Indeed, the adjusted R^2 is the highest for the US at 97 percent and second highest R^2 is for

[22]The JPY funds appear in the Other category and, in general, the Other category for all stock markets is dominated by funds with ROS in local currency.

the Eurozone at 91 percent.

Next we turn to the fund flow component of common demand, which captures the inflows/outflows of the final investors into a given fund, scaled by the steady state exposure of this fund with respect to a given equity. On average, this term explains 6 percent of the total stock market variation with minimum number being 0 and the maximum 15 percent. The numbers for the USD and EUR stock markets are 3 and 5 percent, respectively. Notice that despite the low explanatory power all estimated $\beta^{p,\Delta D^{f,l,k}}$ coefficients are statistically significant with the exception of 3 stock markets with the average adjusted R^2 from the regression being 13 percent (minimum of -1 and maximum of 34 percent), implying strong co-movement between flows and stock market returns. We find that fund flows play a more important role for emerging markets' stock markets than advanced economies' stock markets; i.e. inflows and outflows are a more important driver of overall demand for funds that invest more heavily into emerging markets, which would be consistent with the portfolio returns of these funds also being riskier. In Figure 35, we also consider the break down of $\beta^{p,\Delta D^{f,l,k}}$ into passive vs active type of funds and we see that on average all types of funds matter equally for the size of the explanatory power of the flow components but there is significant heterogeneity across stock markets. When we consider the importance of the different funds, grouped according to ROS, in Figure 34, the USD funds again dominate in terms of importance and the USD and EUR fund flow sub-components of demand always contribute positively to the overall stock market movement, i.e. when the demand of USD and EUR funds for a given stock market increases/decreases due to more inflows/outflows into these funds, that stock market price increases. Finally, once again it's equity funds that drive almost all of the explanatory power.[23]

[23]Interestingly, for a few stock markets such as JPY, and to a lesser degree GBP, CHF and DKK, the relationship with respect to local fund flows is reversed implying that inflows into these local funds, appropriately scaled by the steady state exposure to local equities, correlates with a decrease of the local stock market. For Japan, in particular, we find that this surprising result is driven by passive equity funds where the final flows of active funds co-move positively with the stock market. If Japanese passive funds are a preferred investment option for collective investment vehicles that want to target a certain Japanese stock market exposure, this negative covariance can be easily explained.

When we consider the common component of demand due to weight re-balancing, we find significantly more heterogeneity in its explanatory power of stock market returns across different countries. From Table 2 one can see that the average $\beta^{p,\Delta D^{\omega,l,k}}$ is 27 percent with the minimum and maximum values being -2 percent and 52 percent. Notice that all the $\beta^{p,\Delta D^{\omega,l,k}}$ but for 4 stock markets are statistically significant, implying that rebalancing into a particular stock market is associated with a statistically significant appreciation of that stock market. The average adjusted R^2 is 20 percent, with a minimum of -1 percent and a maximum of 49 percent, which implies a strong correlation between the weight re-balancing component of equity demand and stock returns. There is a clear sorting regarding the importance of weight rebalancing as a driver of overall stock price movements, where this component plays a disproportionately more important role for emerging markets and advanced economies commodity exporters than for other advanced economies. Looking into the breakdown by type of funds with respect to the ROS, Figure 28, we can once again see the oversized importance of USD funds followed by EUR funds where the covariances are always positive with the exception of Japan and local currency funds. In terms of the importance of passive vs active funds, which can be seen in Figure 29 we can see that it's the medium passive funds that matter the most. Active funds play a role too and so do passive funds as passive funds still have a tracking error of up to one percent and for some stock markets they are the most important source of equity demand. Once again equity funds play dis-proportionally the most important role in explaining the overall importance of the weight re balancing component.[24]

Finally, the last component of common demand is associated with the valuation effects due to exchange rate movements. Funds that invest globally have to transact in currencies and their overall equity demand, measured in local currency, is a function of exchange rate fluctuations. The sign of $\beta^{p,\Delta D^{s,l,k}}$ varies across stock markets but is, on average, negative and

[24] We find that increasing the weight placed of Japanese funds on Japanese equities co-moves is associated with lower returns of the Japanese stock market. The surprising negative coefficient for the Japanese funds with respect to the Japanese stock market is driven by passive Japanese equity funds and can be potentially rationalized with them wanting to target certain Japanese stock market exposure.

equal to -14 percent, with the minimum being -50 percent and the maximum 31 percent. It is intuitive that $\beta^{p,\Delta D^{s,l,k}}$ would tend to be negative, meaning the valuation effects due to currency movements are such that they lower the volatility of the stock market price in local currency. To give a concrete example, an increased demand for Brazilian equity, for example, as measured in the currency of the ROS of the final investor, will both appreciate the BRL and the Brazilian stock market price. If the BRL appreciation is large, then the same amount of demand, measured in the currency of the ROS, will imply lower demand measured in BRL, thus, requiring a smaller increase in the price of the Brazilian stock market, in order to ensure that the equity market clears, i.e. demand and supply, as measured in local currency, are the same. The absolutely value of $\beta^{p,\Delta D^{s,l,k}}$ tends to be small for stock markets where a large fraction of total demand is internal, such as the US, where USD funds hold most of the market cap of the US stock market or which are pegged to the USD or EUR as USD and EUR funds play a disproportionate role in global demand. For these stock markets, exchange rates do no present as important of an equilibrating mechanism and the market clears in response to demand shocks by fluctuations of the local currency stock market price.

Delving deeper into which are the stock markets with positive rather than negative $\beta^{p,\Delta D^{s,l,k}}$, we see that these are the stock markets associated with the USD, JPY and CHF and also currencies pegged to the USD such as HKD and EGP over this period, where $\beta^{p,\Delta D^{s,l,k}}$ is most positive for JPY. Positive $\beta^{p,\Delta D^{s,l,k}}$ means that the currencies associated with these stock markets appreciate against the USD, EUR and the GBP, which are the main ROS currencies, when their stock markets are doing poorly. This is in line with the USD, JPY and CHF having "safe heaven" currency status. If we study our break down of the importance of the exchange rate valuation component by type of funds, starting with the ROS breakdown, represented in Figure 25, it is clear that the appreciation of the JPY when the Japanese market is doing poorly is with respect to all currencies associated with the regions of sales we capture. When we study the USD stock market, the USD also appreciates against all currencies when the US stock market is doing poorly. In contrast the

CHF appreciates against all currencies but the USD when the Swiss stock market is doing poorly.[25] When we consider the break down by passive vs active funds, all types of funds matter for the relationship observed while it's once again only Equity funds that dominate the sample.

To examine further what drives the relationship between the exchange rate change component of equity demand and stock price returns we perform the following decomposition of $\beta^{p,\Delta D^{s,l,k}}$ as:

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

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

Figures 9 and 10 in the Appendix report the results from this decomposition. It is clear that the unconditional negative correlation between the exchange rate change valuation component of equity demand and stock market returns is due to the fact that higher equity demand, as measured in the currency of the ROS of the funds, appreciates not only the price of equity in local currency but also the local currency as well. This can be seen from the fact that $Cov\left(\Delta D_t^{s,l,k}, \Delta D^{ROS,l,k}\right) < 0$ for all currencies but JPY and USD and also HKD which is pegged for the USD.[26]

Exploring further which ones of the sub-components of $\Delta D^{ROS,l,k}$ drive the negative unconditional covariance, it is the case that for all stock markets, increasing the weight funds place on the local stock market leads to an appreciation of the local currency. This is the case also for the final flows component of equity demand with the exception of the

[25]Finally for the HKD, which is pegged against the USD, the positive sign we observe is due to all ROS currencies and so is the case for the EGP which is also pegged against the USD.

[26]The fact that the EGP appreciates when the stock market does poorly can be explained by the high variance of the EGP exchange rate component which swamps the negative co-variances of the other equity demand components with the exchange rate component.

USD and JPY where the estimated co-varainces are slightly positive. Finally, the covariance between the exchange rate component and the net of fee returns equity demand component is also negative in all cases but for the USD, HKD, JPY and EGP.

With respect to the JPY and USD, we do not observe a negative unconditional correlation between equity demand, as measured in the currency of the ROS of the fund, and the exchange rate component of demand. This is because most likely the "flight-to-safety" demand in fixed income markets for USD and JPY is a relatively more important driver of this unconditional relationship. More specifically, demand for USD and JPY fixed income assets tends to be higher when the stock market performs poorly which appreciates the currency when the stock markets perform poorly. However for all other currencies we do find that equity demand does generate the expected negative unconditional correlation between demand for the currency and the movement of the currency.

Finally, when considering any patterns regarding the importance of the various components of demand, we observe a very strong negative correlation between $\beta^{p,\Delta D^{s,l,k}}$ and $\beta^{p,\Delta D^{\omega,l,k}}$ of -68 percent. It is the case that for countries for which the exchange rate valuation channel dampens the overall stock market return volatility by more, the weight rebalancing component of demand explains a larger fraction of the overall stock market price fluctuation.

6.2 Exchange Rates

In this sub-section, we present the results from the exchange rate change decompositions, given by equations 13 and 15. We focus on the USD base. Equation (13) links the exchange rate change to local currency and USD net equity supply and to the movement of other currencies against the USD, associated with the largest amount of assets under management. Equation (15) expresses the exchange rate change as a function of local currency USD and EUR net equity supply. Net equity supply is defined as the the market capitalization in local currency minus the common component of demand, denominated in the currency of the ROS. The results from the case where we also consider the GBP net equity supply are presented in the Online Appendix.

In Figures 11 and 12, we start by plotting the sum of all the components on the right hand side of equations (13) and (15) against the exchange rate change itself, where the plots for the other currency crosses are presented in the Online Appendix. We can see that considering only the net equity supply of local currency, USD and EUR is sufficient to explain most of the exchange rate change variation. The fit is almost identical to the more general specification in equation (13), in which the only missing components are the idiosyncratic demand component and the new issuance at the ISIN level, which, as we documented, does not play an important role.

Next, in Table 3, we present the exchange rate elasticities with respect to net equity supply presented in equation 16, $\xi^{l}, \xi^{l,USD}$ and $\xi^{l,EUR}$, the interpretation of which is discussed below equation (16). We present the results from the specification where the GBP is also a central currency in Table 9 in the online Appendix. We construct the reported elasticities as averages over time over the period Jan 2012 till Dec 2021, over which we have the most balanced panel. One can see that the elasticities are positive with respect to the local currency net supply and negative with respect to the USD net supply, as one would expect. This implies that excess supply in local currency will depreciate the local currency against the USD, allowing for the market to equilibrate so that demand and supply, as measured in local currency, are the same. The opposite is true if the USD net supply increases. The elasticity of the exchange rate change with respect to the EUR net supply is positive which captures the fact that European funds are relatively more important for non US stock markets rather than the US stock market, as can be seen from equation (16). It also implies that excess EUR net equity supply will depreciate the local currency against the USD. If we allow for the GBP to be a central currency as well we also see that excess GBP net equity supply will, on average, depreciate the local currency against the USD, albeit the elasticities are much smaller.

In absolute value, the elasticities with respect to the USD net equity supply are larger than the elasticity of the local currency net supply. Having said that, the overall importance of the various net supplies measures, as drivers of exchange rate change movements, depends not only on these elasticities but also on the volatilities of the net supply components. For that reason, we perform a similar variance covariance decomposition to the one presented in the previous sub-section:

$$1 = \sum_{j=\{l,USD,EUR\}} \beta^{s,NS_j} + \beta^{s,Resid}, \text{ where}$$

$$\beta^{s,NS_j} = \frac{Cov\left(\Delta s_t^{l/USD}, \xi^{l,j}\left(\Delta MC_t^{j,k} - \Delta D_t^{ROS,j,k}\right)\right)}{Var\left(\Delta s_t^{l/USD}\right)} \text{ and } j = \{l, USD, EUR\}$$

The contribution of the residual component, constructed as, $\beta^{s,Resid} = 1 - \sum_{j=\{l,USD,EUR\}} \beta^{s,NS_j}$ captures the importance of idiosyncratic demand, measurement error, issuance at the ISIN level and the net supply of other currencies. The results for the VCV decomposition of equation (15) are presented in Table 4 and Figure 13. The results for the case where we allow the GBP to be also a central currency are presented in Table 10 and Figure 39 in the Online Appendix.

Starting from Table 4, the last column presents what fraction of the exchange rate change variation is explained by our measures of net supply, $\sum_{j=\{l,USD,EUR\}} \beta^{s,NS_j}$. The number is, on average, 90 percent, but there is significant variation, where for some currency crosses, such as NOK/USD, the explanatory power is 60 percent while for the GBP/USD 144 percent, where the latter implies that the net supply components are more volatile than the exchange rate. Allowing for the GBP to be a central currency makes a difference for a number of currency crosses such as the EUR/USD where the explanatory power increases from 78 to 84 .

Next we discuss the importance of the various net equity supply components. One can see that the local currency net supply component explains the vast majority of exchange rate change variation for all currency crosses and is the most important net supply component (with the exception of NOK). β^{s,NS_l}, on average, explains 75 percent of exchange rate change movements, with the values ranging from 45 percent to 120 percent. From Table 4 we can see that the adjusted R^2 from regressing $\xi^l\left(\Delta MC_t^{j,k} - \Delta D_t^{ROS,l,k}\right)$ on $\Delta s_t^{l/USD}$ is on average 47 percent with the minimum and maximum values being 16 and 79 percent. Further, β^{s,NS_l} is always very statistically significant.

Turning to the USD net supply component, we can see that while it is an important driver of exchange rates, it explains a smaller fraction of exchange rate variation. More specifically, it explains, on average, 10 percent of exchange rate variation with the minimum and maximum values being 3 and 20 percent, respectively. This is despite the fact that the USD net supply elasticities were in absolute value larger than the local currency net supply elasticity and reflects the result that US net equity supply is less volatile than the local currency net equity supply. This is the case as most US equities are owned by US funds, and as we saw, exchange rate valuations play a very small role in equilibrating the US stock market, thus making USD net supply less important for exchange rate movements, holding the other currencies' net supply components constant. Having said that, fluctuations in the US stock market will be still very important for the net supply of all currencies granted that the net of fee return component of demand is the most important driver of equity demand and US funds hold the vast majority of global assets. $\beta^{s,NS_{USD}}$ is statistically significant for all currency crosses but 1 and the average adjusted R^2 from the corresponding regression is 5 percent with a minimum of 1 percent and a maximum of 12 percent.

Finally, turning to the EUR net supply, we find that it explains on average 5 percent of the exchange rate variation against the USD base (excluding the EUR/USD cross) with a minimum of zero and a maximum of 18 percent. The $\beta^{s,NS_{EUR}}$ is statistically significant in all but 3 cases and the adjusted R^2 from the corresponding regression is on average 9 percent with the range being from 0 to 26 percent.

7 Transmission of Macroeconomic News and Risk Aversion

In this section we study how fluctuation in the VIX, which has been used as a proxy for risk aversion, and also macroeconomic news transmit to stock market returns.

We estimate and decompose the response of the local stock market returns to a one percentage change in the VIX and to an increase of the local or US stock market due to macroeconomic news by one percent. The last two variables are macroeconomic news indices we construct in this paper by building on the work of Stavrakeva and Tang (2024) and, as we will show, they will explain a large fraction of stock market volatility. More specifically we perform the following decomposition:

$$
\begin{aligned}
\gamma_g^p &= \frac{Cov\left(\Delta p_t^{SM,l}, g_t\right)}{Var\left(g_t\right)} = \sum_{x=\left\{\Delta D^{s,l,k},\Delta D^{f,l,k},\Delta D^{\omega,l,k},\Delta D^{r^{NF},l,k},D^{Resid,l,k}\right\}} \gamma_g^{p,x} \\
\gamma_g^{p,x} &= \frac{Cov\left(g_t, x_t\right)}{Var\left(g_t\right)} \\
\text{where } g_t &= \left\{\Delta vix_t, \Delta\widehat{p}_t^{agg,US}, \Delta\widehat{p}_t^{agg,l}\right\}.
\end{aligned}
$$

$\gamma_g^{p,x}$ is estimated by regressing x_t on g_t, vix stands for the log VIX . $\Delta\widehat{p}_t^{agg,US}$and $\Delta\widehat{p}_t^{agg,l}$ are macroeconomic news indices, where $\Delta\widehat{p}_t^{agg,US}$ captures the response of the US stock market to US macroeconomic news and shocks while $\Delta\widehat{p}_t^{agg,l}$ captures the response of the local stock market to US and local macroeconomics news and shocks, where we have local news for most advanced economies but not emerging markets.

As in Stavrakeva and Tang (2024), we follow a two stage procedure in order to construct $\Delta\widehat{p}_t^{agg,US}$ and $\Delta\widehat{p}_t^{agg,l}$, where in the first stage we regress the daily return of a local stock market index on contemporaneous and lagged US and local, if available, macroeconomic news. The list of macroeconomic news and shocks we use is in the Data Appendix. We include the following daily lags $t_d = 0, 1, 2, 30, 60, 90, 120, 150, 180$.[27] We then construct the

[27]We use the same daily stock market indices as the ones discussed in Section 5. Note that our weighted

fitted values from this regression, and sum them up to monthly frequency in order to obtain a macro news index. $\Delta\widehat{p}_t^{agg,US}$ is constructed the same way as $\Delta\widehat{p}_t^{agg,l}$, but for the US stock market.

Figure 14 and Table 5 present the responses of the local currency stock market returns and their sub-components to one percent contemporaneous increase in the VIX. The first column of table 14 presents the coefficients $\gamma^p_{\Delta vix}$. The average $\gamma^p_{\Delta vix}$ is -10 percent over our sample with the minimum effect being -15 percent and the largest effect -5 percent. The negative coefficient implies that an increase of the VIX is associated with a decrease of equity prices globally. The estimated coefficients are all very statistically significant and the average adjusted R^2 is 26 percent with a minimum of 6 percent and a maximum of 49 percent, implying that the VIX co-moves strongly with equity prices at monthly frequency.

Decomposing $\gamma^p_{\Delta vix}$, we can see that the most important component is $\gamma^{p,D^{r^{NF}},l,k}_{\Delta vix}$, which is expected, given the importance of the net return component of demand as a driver of overall demand and stock prices. where we interpret the importance of $\gamma^{p,D^{r^{NF}},l,k}_{\Delta vix}$ as an amplification effect. The average $\gamma^{p,D^{r^{NF}},l,k}_{\Delta vix}$ is -12 percent, where all coefficients are statistically significant, and the average adjusted R^2 associated with this regression is 41 percent. Next we turn to the second common demand component which captures valuation effects due to exchange rate movements, $\gamma^{p,\Delta D^{s,l,k}}_{\Delta vix}$. We find that an increase of the VIX ends up depreciating most currencies besides most of the "safe heaven" currencies, discussed earlier, i.e $\gamma^{p,\Delta D^{s,l,k}}_{\Delta vix} > 0$ for most currencies. The exchange rate depreciation for these countries ameliorates the decrease of local currency stock market returns. The average $\gamma^{p,\Delta D^{s,l,k}}_{\Delta vix}$ is 2 percent with the minimum being -4 percent and the maximum 7 percent. $\gamma^{p,\Delta D^{s,l,k}}_{\Delta vix}$ is statistically significant for all but 3 countries and the average adjusted R^2 from the associated regression is 8 percent, with a maximum of 22 percent.

Turning to $\gamma^{p,D^{f,l,k}}_{\Delta vix}$ we find that higher VIX leads to lower stock returns due to a decrease

average stock market indices constructed from ISIN level data are only monthly and for this exercise we need daily data.

in equity demand driven by outflows from equity funds. If we interpret the VIX as a proxy for risk aversion, this result implies that risk averse investors leave equity funds and presumably re-balance into safer asset classes when risk aversion increases. What is interesting is that the flow component of demand plays a more important role, i.e. $\gamma_{\Delta vix}^{p,D^{f,l,k}}$ is more negative, for emerging markets than advanced economies which is most likely due to specialization of equity funds into emerging market and advanced economy funds and a riskier return associated with emerging market equity funds relative to advanced economies' equity funds. The averge $\gamma_{\Delta vix}^{p,D^{f,l,k}}$ is -1 percent with the minimum being -1 percent and the largest effect zero percent. $\gamma_{\Delta vix}^{p,D^{f,l,k}}$ is statistically significant for all countries but 7 and the average adjusted R^2 associated with this regression is 3 percent, with a maximum of 8 percent.

The second non-valuation component of demand, $\gamma_{\Delta vix}^{p,\Delta D^{\omega,l,k}}$, which captures the change in demand due to weight re-balancing, in some cases amplifies the stock price decrease due to higher VIX due to funds re-balancing out of the equity of the particular country, and, in some cases, the reverse is true. It's interesting that $\gamma_{\Delta vix}^{p,\Delta D^{\omega,l,k}}$ is positive for about half the countries and negative for the other half. Granted that equity demand is dominated by equity funds, rather than mixed allocation funds, the margin of adjustment by portfolio managers is either to sell one stock and buy another or to increase/decrease the buffer of cash-like assets. It appears that higher VIX leads to higher weight placed on some stock markets such as Japan and lower weight placed on others, such as US and Brazil, for example. This implies that the margin of adjustment is not just in and out of cash-like assets in response to a higher risk aversion. $\gamma_{\Delta vix}^{p,\Delta D^{\omega,l,k}}$ is on average 0 , with the minimum being -5 percent and the maximum 4 percent. $\gamma_{\Delta vix}^{p,\Delta D^{\omega,l,k}}$ is statistically significant for all countries besides 16 , and the average adjusted R^2 associated with this regression is 2 percent, with a maximum of 10 percent.

Moving onto answering the question how macroeconomic news transmit to global stock markets, we focus both on the transmission of US news via movements of the US stock market, which is captured by $\widehat{p}_t^{agg,US}$, and the transmission of news via movements of the local stock market $\Delta\widehat{p}_t^{agg,l}$. For a number of advanced economies we have also local news, which are captured in the latter measure, while for the rest of the countries we use only US news (See Data Appendix). The results are presented in Tables 6 and 7 and Figures 15 and 16.

Starting with $\gamma^{p}_{\Delta\widehat{p}^{agg,l}}$, we can see that, on average, it's 82 percent. Notice that it is not exactly one hundred percent, as the daily stock market returns that we use to construct the local stock market macro news index often have much fewer stocks than our weighted average stock market index derived from ISIN level data. What is noticeable though is that macroeconomic news explain, on average 44 percent of the variation of local stock market returns, as can be elicited from the average adjusted R^2 from this regression, with a minimum of 32 and a maximum of 58 . Looking at which components play the most important role in explaining the relationship, indeed we find, once again, that the portfolio return component plays the most important role. The average $\gamma^{p,D^{r^{NF}},l,k}_{\Delta\widehat{p}^{agg,l}}$ is 69 percent, all estimated coefficients are statistically significant and the average adjusted R^2 from this regression is 37 percent. The second valuation component due to exchange rate movements, $\gamma^{p,\Delta D^{s,l,k}}_{\Delta\widehat{p}^{agg,l}}$, once again, is, on average, negative and equal to -13 percent, dampening the appreciation of the local stock market. There is once again heterogeneity across the stock markets. This estimated coefficient is statistically significant in all but 5 cases and the average adjusted R^2 from this regression is 9 percent, with a maximum of 32 percent.

Moving to the non-valuation component of demand due to fund flows, we find that the relationship between macroeconomic news that appreciate the local stock market and fund flows is positive and very statistically significant. The average effect is 6 percent with a maximum of 16 and the estimated coefficients are significant in all but 3 cases. The average adjusted R^2 from this regression is 6 percent, with a maximum of 14 percent. This implies that macroeconomic news that appreciate the local stock market trigger more equity fund inflows, which, in turn, leads to higher equity prices.

A similar pattern is present for the weight re-balancing component of demand which is also positive, on average, 13 percent, with a maximum of 40 , and significant in all but 11 cases.

This result implies that macroeconomic news which appreciate the local stock market also propagate via higher weights being place on the equities of these stock markets by portfolio managers. The average adjusted R^2 from this regression is 6 percent, with a maximum of 23 percent. The adjust R^2 from this regression signifies how much of the portfolio weight rebalancing can be explained by macroeconomic news that appreciate the local stock market by one percent.

Finally, we consider how US macro news that appreciate the US stock market transmit to other stock markets. This effect is captured by the coefficient $\gamma^{p}_{\Delta\widehat{p}^{agg,US}}$. It is on average positive and equal to 68 percent, it is always significant and the average adjusted R^2 from this regression is 24 percent, with a maximum of 43 percent. These results imply that US macroeconomic news that appreciate the US stock market have significant impact on global stock markets.

Next we decompose the channels through which these spill overs take place. The main channel is due to the fact that the net portfolio return of US and Eurozone funds are determined mostly by the performance of the US stock market given the disproportionately large holdings of US equities by these funds. The average $\gamma^{p,D^{r^{NF},l,k}}_{\Delta\widehat{p}^{agg,US}}$ is 77 percent, all estimated coefficients are statistically significant and the average adjusted R^2 from this regression is 36 percent. This result is a reflection of the global dominance of the USD, defined as the majority of the global equity market capitalization being denominated in USD and most assets under management globally originating from funds located in the US or with ROS currency which is the USD.

Moving onto the importance of the exchange rate valuation component. It is on average negative, -16 percent, once again, dampening the appreciation of the local currency market, with the estimated coefficient being statistically significant for all but 8 countries. The smallest and the largest effects are -45 and 12 , respectively. The "flight-to-safety" is present also conditionally for the JPY and the USD, for example, where instead of appreciating, these currencies depreciate when the US stock market is doing well in response to US macroeconomic news, and the other way round.

Next, we turn to the non-valuation components. The fund flow component of demand is on average positive, 5 percent, and significant in all but 4 cases, indicating that macroeconomic news that appreciate the US stock market are associated with more inflows into equity funds, as one might expect. The average adjusted R^2 from this regression is 4 percent, with a maximum of 8 percent. These results imply that US macroeconomic news that appreciate the US stock market lead to higher equity demand due to more fund inflows.

Finally, regarding the weight re-balancing component, we find that US macroeconomic news that appreciate the US stock market prompt equity funds to re-balance into some countries and out of others, with the mix between positive and negative coefficients being roughly equal. The minimum and maximum effects are -34 percent and 32 , respectively, with the estimated coefficients being statistically significant in all but 13 cases. The average adjusted R^2 from this regression is 2 percent, with a maximum of 14 percent. A lot of the stock markets that equity funds rebalance out of are located in Asia and potentially are associated with economies that are less correlated with the US economy. In contrast, a lot of the stock markets they rebalance into are located in Latin America or in advanced economies which tend to have economies more correlated with the US economy.

8 Conclusion

TO BE COMPLETED

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9 Appendix

9.1 Derivations

Here we derive the expression linking the exchange rate change to local currency, USD, EUR and GBP net supply.

$$\Delta s_t^{l/z} - \sum_{m\in\{USD,EUR,GBP,l\}} \Delta s_t^{m/z} \nu^{m,l,k} = \Delta MC_t^{l,k} - \Delta D_t^{l,k} + \underbrace{\sum_{m\in M\setminus\{USD,EUR,GBP,l\}} \Delta s_t^{m/z} \nu^{m,l,k}}_{\Delta s_t^{l,W}}$$

where we assume the terms $\underbrace{\sum_{m\in M\setminus\{USD,EUR,GBP,l\}} \Delta s_t^{m/z} \nu^{m,l,k}}_{\Delta s_t^{l,W}}$ will be second order for all currencies and we will omit them from now on.

$$\Delta s_t^{l/z} \left(1 - \nu^{l,l,k}\right) - \sum_{m\in\{USD,EUR,GBP\}} \Delta s_t^{m/z} \nu^{m,l,k} \approx \Delta MC_t^{l,k} - \Delta D_t^{l,k}$$

Combining the equation above with the equation $l = z$

$$\begin{aligned} &\Delta s_t^{l/z} \left(1 - \nu^{l,l,k}\right) - \sum_{m\in\{USD,EUR,GBP\}} \Delta s_t^{m/z} \left(\nu^{m,l,k} - \nu^{m,z,k}\right) \\ \approx\; &\left(\Delta MC_t^{l,k} - \Delta MC_t^{z,k}\right) - \left(\Delta D_t^{l,k} - \Delta D_t^{z,k}\right) \end{aligned}$$

Assume $z = USD$

$$\begin{aligned} &\Delta s_t^{l/USD} \left(1 - \nu^{l,l,k}\right) - \sum_{m\in\{EUR,GBP\}} \Delta s_t^{m/USD} \left(\nu^{m,l,k} - \nu^{m,USD,k}\right) \\ \approx\; &\left(\Delta MC_t^{l,k} - \Delta MC_t^{USD,k}\right) - \left(\Delta D_t^{l,k} - \Delta D_t^{USD,k}\right) \end{aligned}$$

$$\tilde{\mathbf{A}}^{k,USD} \begin{bmatrix} \Delta s_t^{GBP/z} \\ \Delta s_t^{EUR/z} \end{bmatrix} \approx \underbrace{\begin{bmatrix} \Delta MC_t^{GBP,k} - \Delta MC_t^{USD,k} \\ \Delta MC_t^{EUR,k} - \Delta MC_t^{USD,k} \end{bmatrix}}_{\tilde{\boldsymbol{\pi}}_t^{k,MC}} - \underbrace{\begin{bmatrix} \Delta D_t^{GBP,k} - \Delta D_t^{USD,k} \\ \Delta D_t^{EUR,k} - \Delta D_t^{USD,k} \end{bmatrix}}_{\tilde{\boldsymbol{\pi}}_t^{k,D}}$$

$$\begin{bmatrix} \Delta s_t^{GBP/z} \\ \Delta s_t^{EUR/z} \end{bmatrix} \approx \left(\tilde{\mathbf{A}}^{k,z}\right)^{-1} \left(\tilde{\mathbf{\Pi}}_t^{k,MC} - \tilde{\mathbf{\Pi}}_t^{k,D}\right)$$

If $z = USD$

$$\begin{aligned} \tilde{\mathbf{A}}^{k,USD} &= \begin{bmatrix} 1-\nu^{GBP,GBP,k}+\nu^{GBP,USD,k} & -\nu^{EUR,GBP,k}+\nu^{EUR,USD,k} \\ -\nu^{GBP,EUR,k}+\nu^{GBP,USD,k} & 1-\nu^{EUR,EUR,k}+\nu^{EUR,USD,k} \end{bmatrix} \\ &= \begin{bmatrix} \tilde{\mathbf{A}}_{GBP,GBP}^{k,USD} & \tilde{\mathbf{A}}_{EUR,GBP}^{k,USD} \\ \tilde{\mathbf{A}}_{GBP,EUR}^{k,USD} & \tilde{\mathbf{A}}_{EUR,EUR}^{k,USD} \end{bmatrix} \end{aligned}$$

$$\left(\tilde{\mathbf{A}}^{k,USD}\right)^{-1} = \frac{1}{\tilde{\mathbf{A}}_{GBP,GBP}^{k,USD}\tilde{\mathbf{A}}_{EUR,EUR}^{k,USD} - \tilde{\mathbf{A}}_{GBP,EUR}^{k,USD}\tilde{\mathbf{A}}_{EUR,GBP}^{k,USD}} \begin{bmatrix} \tilde{\mathbf{A}}_{EUR,EUR}^{k,USD} & -\tilde{\mathbf{A}}_{EUR,GBP}^{k,USD} \\ -\tilde{\mathbf{A}}_{GBP,EUR}^{k,USD} & \tilde{\mathbf{A}}_{GBP,GBP}^{k,USD} \end{bmatrix}$$

$$\begin{aligned} \begin{bmatrix} \Delta s_t^{GBP/USD} \\ \Delta s_t^{EUR/USD} \end{bmatrix} &= \left(\tilde{\mathbf{A}}^{k,USD}\right)^{-1} \left(\tilde{\mathbf{\Pi}}_t^{k,MC} - \tilde{\mathbf{\Pi}}_t^{k,D}\right) \\ &= \begin{bmatrix} \frac{\tilde{\mathbf{A}}_{EUR,EUR}^{k,USD}}{\mathbf{\Theta}} & -\frac{\tilde{\mathbf{A}}_{EUR,GBP}^{k,USD}}{\mathbf{\Theta}} \\ -\frac{\tilde{\mathbf{A}}_{GBP,EUR}^{k,USD}}{\mathbf{\Theta}} & \frac{\tilde{\mathbf{A}}_{GBP,GBP}^{k,USD}}{\mathbf{\Theta}} \end{bmatrix} \begin{bmatrix} \Delta MC_t^{GBP,k} - \Delta D_t^{GBP,k} \\ \Delta MC_t^{EUR,k} - \Delta D_t^{EUR,k} \end{bmatrix} \\ &\quad - \begin{bmatrix} \frac{\tilde{\mathbf{A}}_{EUR,EUR}^{k,USD}}{\mathbf{\Theta}} & -\frac{\tilde{\mathbf{A}}_{EUR,GBP}^{k,USD}}{\mathbf{\Theta}} \\ -\frac{\tilde{\mathbf{A}}_{GBP,EUR}^{k,USD}}{\mathbf{\Theta}} & \frac{\tilde{\mathbf{A}}_{GBP,GBP}^{k,USD}}{\mathbf{\Theta}} \end{bmatrix} \begin{bmatrix} \Delta MC_t^{USD,k} - \Delta D_t^{USD,k} \\ \Delta MC_t^{USD,k} - \Delta D_t^{USD,k} \end{bmatrix} \end{aligned}$$

where $\Theta = \tilde{\mathbf{A}}_{GBP,GBP}^{k,USD}\tilde{\mathbf{A}}_{EUR,EUR}^{k,USD} - \tilde{\mathbf{A}}_{GBP,EUR}^{k,USD}\tilde{\mathbf{A}}_{EUR,GBP}^{k,USD}$

$$\begin{aligned} &\Delta s_t^{l/USD}\left(1-\nu^{l,l,k}\right) \\ \approx\ &\left(\Delta MC_t^{l,k} - \Delta MC_t^{USD,k}\right) - \left(\Delta D_t^{l,k} - \Delta D_t^{USD,k}\right) \\ &+ \begin{bmatrix} -\tilde{\mathbf{A}}_{GBP,l}^{k,USD} & -\tilde{\mathbf{A}}_{EUR,l}^{k,USD} \end{bmatrix} \left(\tilde{\mathbf{A}}^{k,USD}\right)^{-1} \left(\tilde{\mathbf{\Pi}}_t^{k,MC} - \tilde{\mathbf{\Pi}}_t^{k,D}\right) \end{aligned}$$

where

$$\begin{bmatrix} -\tilde{\mathbf{A}}_{GBP,l}^{k,USD} & -\tilde{\mathbf{A}}_{EUR,l}^{k,USD} \end{bmatrix} \left(\tilde{\mathbf{A}}^{k,USD}\right)^{-1}$$

$$= \begin{bmatrix} \frac{\tilde{\mathbf{A}}_{EUR,l}^{k,USD}\tilde{\mathbf{A}}_{GBP,EUR}^{k,USD}-\tilde{\mathbf{A}}_{GBP,l}^{k,USD}\tilde{\mathbf{A}}_{EUR,EUR}^{k,USD}}{\tilde{\mathbf{A}}_{GBP,GBP}^{k,USD}\tilde{\mathbf{A}}_{EUR,EUR}^{k,USD}-\tilde{\mathbf{A}}_{GBP,EUR}^{k,USD}\tilde{\mathbf{A}}_{EUR,GBP}^{k,USD}} & \frac{\tilde{\mathbf{A}}_{GBP,l}^{k,USD}\tilde{\mathbf{A}}_{EUR,GBP}^{k,USD}-\tilde{\mathbf{A}}_{EUR,l}^{k,USD}\tilde{\mathbf{A}}_{GBP,GBP}^{k,USD}}{\tilde{\mathbf{A}}_{GBP,GBP}^{k,USD}\tilde{\mathbf{A}}_{EUR,EUR}^{k,USD}-\tilde{\mathbf{A}}_{GBP,EUR}^{k,USD}\tilde{\mathbf{A}}_{EUR,GBP}^{k,USD}} \end{bmatrix}$$

$$\begin{aligned}
\tilde{\mathbf{A}}_{GBP,GBP}^{k,USD} &= 1-\nu^{GBP,GBP,k}+\nu^{GBP,USD,k} \\
\tilde{\mathbf{A}}_{EUR,EUR}^{k,USD} &= 1-\nu^{EUR,EUR,k}+\nu^{EUR,USD,k} \\
\tilde{\mathbf{A}}_{EUR,GBP}^{k,USD} &= -\nu^{EUR,GBP,k}+\nu^{EUR,USD,k} \\
\tilde{\mathbf{A}}_{GBP,EUR}^{k,USD} &= -\nu^{GBP,EUR,k}+\nu^{GBP,USD,k} \\
\tilde{\mathbf{A}}_{GBP,l}^{k,USD} &= -\nu^{GBP,l,k}+\nu^{GBP,USD,k} \\
\tilde{\mathbf{A}}_{EUR,l}^{k,USD} &= -\nu^{EUR,l,k}+\nu^{EUR,USD,k}
\end{aligned}$$

9.2 Data Appendix

9.2.1 Details on Cleaning the Morningstar Data

For the set of of funds we have, we pull all holdings, shares held and portfolio weights, as well as the ISIN and CUSIP for each asset held.

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 over 2 million ISINs or CUSIP. These are classified into types of assets and additional characteristics, which we pull from Refinitiv/Eikon (see section 9.2.2 for details). 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 holdings data reports only ISIN or only CUSIP, we use the available identifier to map this particular holding to the Refiniv data. However, if the Morningstar holdings data has both ISIN and

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 2002 to April 2008 then we assume that the fund purchased stock i for first time in March 2002 so the holdings end of Feb 2002 are zero and similarly we assume the holdings end of May 2008 are zero as by then the asset is sold. This way we ensure we don't throw away relevant information.

Regarding the construction of flows and net returns, we combine a number of different variables reported by Morningstar in order to improve the coverage.

9.2.2 Refinitiv Eikon

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"; We end up with 21,290 ISINs.
- "Currency" of the ISIN – this is the currency of issuance of the ISIN. We cross check the currency reported in Eikon for a given ISIN and the mode currency reported for that same ISIN by the funds reporting in Morningstar. We remove the ISINs with discrepancies.
- "Market capitalization" measured in "Currency"
- "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 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 over 93 percent. Notice that we supplement the Eikon series with Morningstar prices only if the Eikon price is not available for any date or if it is available for some dates but not for all for which we have prices from Morningstar we ensure that we combine the two series only if on overlapping dates, the average deviation between the two series is no more than 10 percent (in absolute value) of the Eikon price.

- "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" and "TRBC Economic Sector Name".
- "Country 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".

9.2.3 Macroeconomic Announcement Surprises

We use surprises for the following indicators for each country. When both Bloomberg and Informa Global Markets (IGM) publish expectations for the same indicator, we choose the source based on data availability. In a few rare cases in which indicators are discontinued, we splice the surprise series with a close substitute.

- Australia: (Inflation) CPI all groups goods component; (Activity) employment change, unemployment rate, GDP, building approvals, retail sales; (External) trade balance, (Monetary) RBA cash rate target

- Canada: (Inflation) CPI; (Activity) unemployment rate, GDP; (External) trade balance; (Monetary) Bank of Canada overnight lending rate
- Euro area:
  - Germany: (Activity) ifo Business Climate Index, industrial production, total manufacturing new orders, manufacturing PMI, ZEW Indicator of Economic Sentiment
  - Euro area: (Inflation) CPI; (Activity) GDP, manufacturing PMI; (External) current account balance, (Monetary) ECB main refinancing operations announcement rate, 3-month and 10-year interest rate futures
- Japan: (Inflation) Tokyo core CPI, PPI; (Activity) unemployment rate, industrial production, GDP, core machinery orders, tertiary industry activity, manufacturing PMI, (External) current account balance; (Monetary) M2 money supply, 10-year interest rate futures
- New Zealand: (Inflation) CPI; (Activity) GDP, unemployment rate, (External) trade balance, (Monetary) Reserve Bank of New Zealand official cash rate
- Norway: (Inflation) CPI; (Activity) unemployment rate; (Monetary) Norges bank deposit rate
- Sweden: (Inflation) CPI; (Activity) unemployment rate; (External) trade balance; (Monetary) Sweden repo rate, 3-month and 10-year interest rate futures
- Switzerland: (Inflation) CPI; (Activity) procure.ch PMI; (External) trade balance; (Monetary) policy rate (LIBOR target rate spliced with the interest rate on sight deposits), 3-month and 10-year interest rate futures
- United Kingdom: (Inflation) CPI; (Activity) claimant count rate, GDP, industrial production; (External) trade balance; (Monetary) Bank of England official bank rate,

3-month and 10-year interest rate futures

- United States: (Inflation) CPI, core CPI, core PPI; (Activity) capacity utilization, Conference Board consumer confidence, University of Michigan consumer sentiment, new home sales, initial jobless claims, industrial production, leading indicators index, nonfarm payrolls, ISM manufacturing index, unemployment rate, GDP, retail sales; (External) trade balance, , oil surprises from **?**; (Monetary) federal funds target rate, 3-month fed funds rate futures, 4-quarter eurodollar futures, and 10-year Treasury yields

9.2.4 Stock Market Daily Indices

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

- AUD – AORDD ; Australia ASX All-Ordinaries
- MXN – BMXD; Mexico Banamex-30 Index
- BRL – IBXD; Rio de Janeiro IBX-100 Index
- INR – BSE500D; Mumbai BSE-500 Index
- CNH – CSI300D; Shanghai-Shenzhen CSI-300 Return Index Stock Indices
- EGP – EGX30D; Egypt EGX-30 Index Large Cap
- GBP – FTASD; UK FTSE All-Share Index
- HKD – HSID; Hong Kong Hang Seng Composite Index
- IDR – ID1; Dow Jones Indonesia Stock Index
- CLP – IGPAD; Santiago SE SP CLX Indice General de Precios de Acciones
- ZAR – JALSHD; FTSE/JSE All-Share Index
- MYR – KLSED; Malaysia KLSE Composite
- KRW – KS11D; Korea SE Stock Price Index (KOSPI)
- JPY – N500D; Japan Nikkei 500 Index

- NZD – NZCID; New Zealand SE SP/NZX All-Share Capital Index
- DKK – OMXCPID; OMX Copenhagen All-Share Price Index
- NOK – OSEAXD; Oslo SE All-Share Index Total Return Indices
- PHP – PSID; Manila SE Composite Index
- THB – SET100D; Thailand SET-100 Index
- CAD – SPTSECP; SP/TSX 60 Large Cap Capped Index
- USD – SPXD ; SP 500/Cowles Composite Price Index
- CHF – SSMID; Swiss Market Index
- EUR – STOXXE; EuroStoxx Price Index
- ILS – TAALLSD; Tel Aviv All-Share Price Index
- TWD – TSE50D; Taiwan FTSE/TSE-50 Price Index
- TRY – XU100D; Istanbul SE IMKB-100 Price Index

9.2.5 Summary Statistics Figures

Figure 1: Total AUM USD Trillions; Monthly

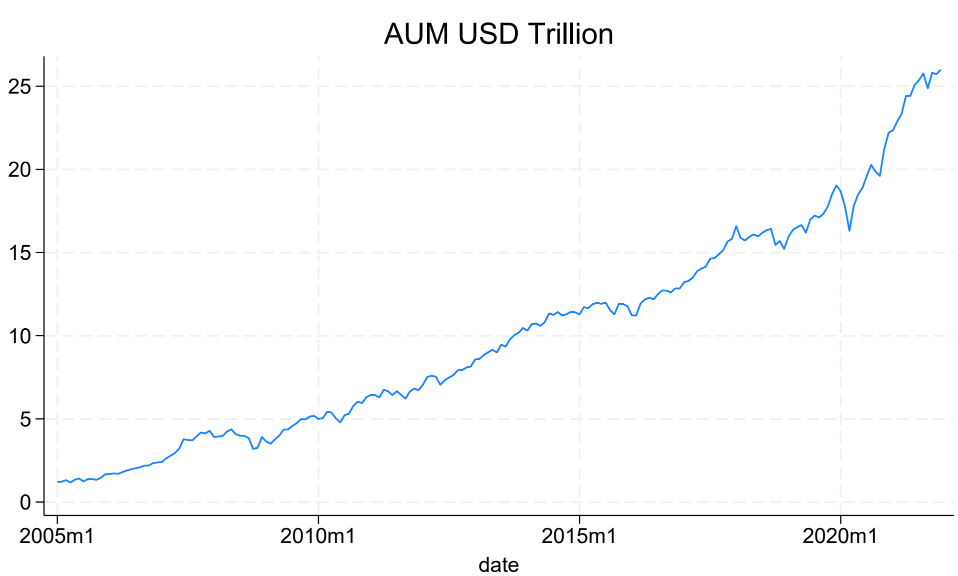


Figure 2: Total AUM USD Trillions by investment type and ROS; Monthly

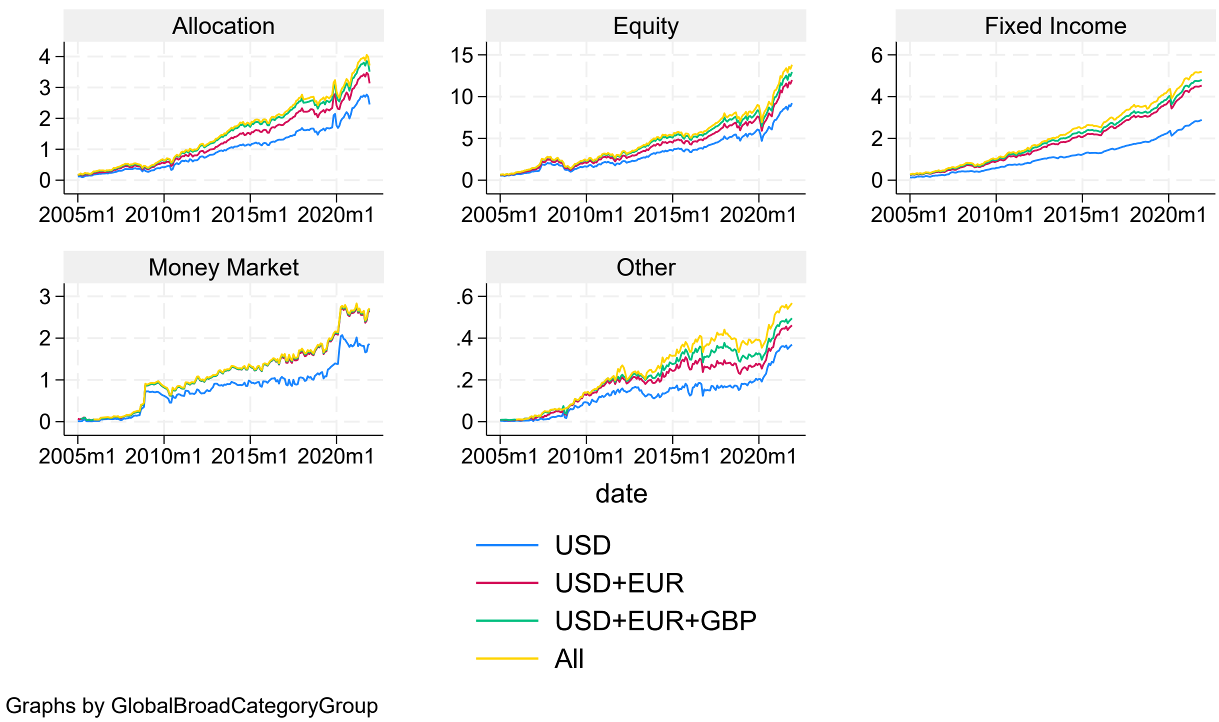


Figure 3: Total AUM USD Trillions by investment type and active/passive; Monthly

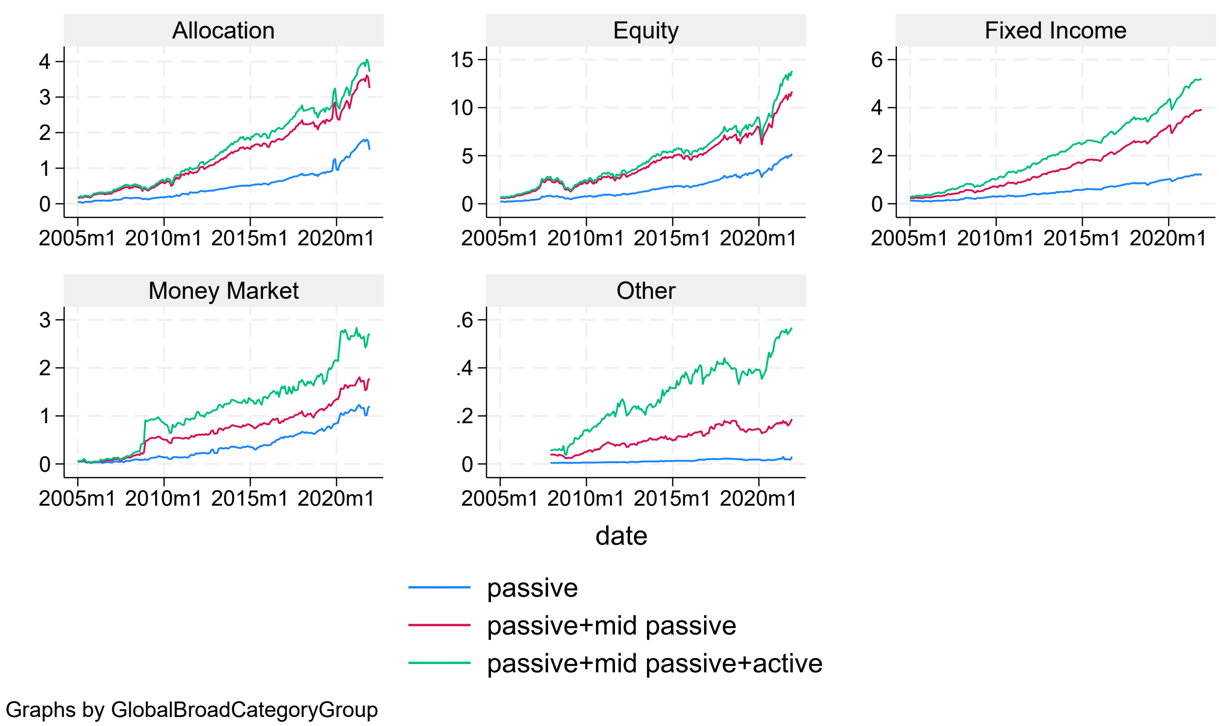
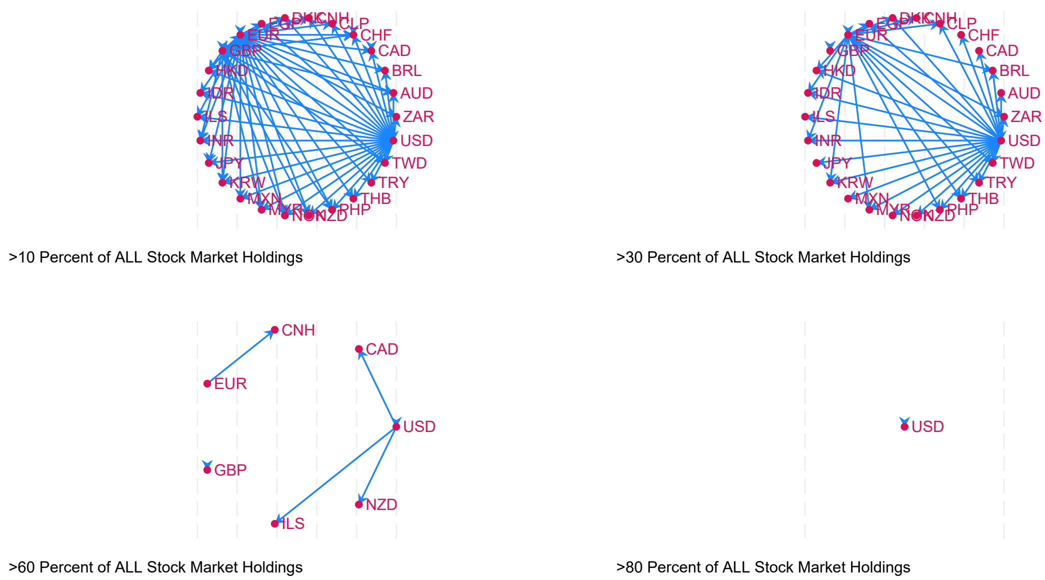


Table 1: Coverage and Market Capitalization; Monthly

Currency	*AvgCoverage*	*CoverageStart*	*CoverageEnd*	*AvgMarketCapUSDbil*	*MarketCapStartUSDbil*	*MarketCapEndUSDbil*	*ISINs*
AUD	0.04	0.03	0.06	295.33	213.67	568.89	622.00
BRL	0.04	0.02	0.04	504.58	424.73	567.80	293.00
CAD	0.04	0.03	0.06	532.88	459.98	875.06	692.00
CHF	0.07	0.04	0.10	482.63	327.11	805.25	185.00
CLP	0.02	0.00	0.02	91.35	78.02	62.15	52.00
CNH	0.00	0.00	0.01	4183.93	537.56	9725.52	1793.00
DKK	0.06	0.02	0.12	116.13	53.31	262.52	100.00
EGP	0.02	0.01	0.02	31.17	58.66	27.05	62.00
EUR	0.06	0.02	0.09	3130.43	2446.48	5590.11	1739.00
GBP	0.10	0.04	0.16	914.61	912.00	1363.11	1128.00
HKD	0.03	0.02	0.04	418.03	269.27	494.79	496.00
IDR	0.03	0.01	0.05	188.77	47.85	318.97	217.00
ILS	0.02	0.01	0.03	67.07	30.00	178.88	148.00
INR	0.03	0.02	0.04	1311.01	518.85	3189.60	1021.00
JPY	0.07	0.02	0.17	2654.40	1542.12	3781.17	2558.00
KRW	0.04	0.02	0.05	636.64	376.49	1122.56	1548.00
MXN	0.03	0.02	0.04	195.42	113.13	259.73	109.00
MYR	0.02	0.02	0.02	267.12	161.99	270.37	424.00
NOK	0.04	0.01	0.07	154.17	171.98	290.01	159.00
NZD	0.03	0.01	0.04	24.16	7.12	52.73	59.00
PHP	0.03	0.03	0.02	116.75	36.80	161.90	116.00
THB	0.01	0.00	0.01	459.03	137.25	853.41	507.00
TRY	0.03	0.02	0.03	89.14	71.91	70.11	141.00
TWD	0.05	0.02	0.07	836.05	489.56	1759.39	1144.00
USD	0.12	0.07	0.16	6073.89	4348.37	12502.75	5881.00
ZAR	0.05	0.02	0.06	157.94	129.62	181.67	109.00

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.

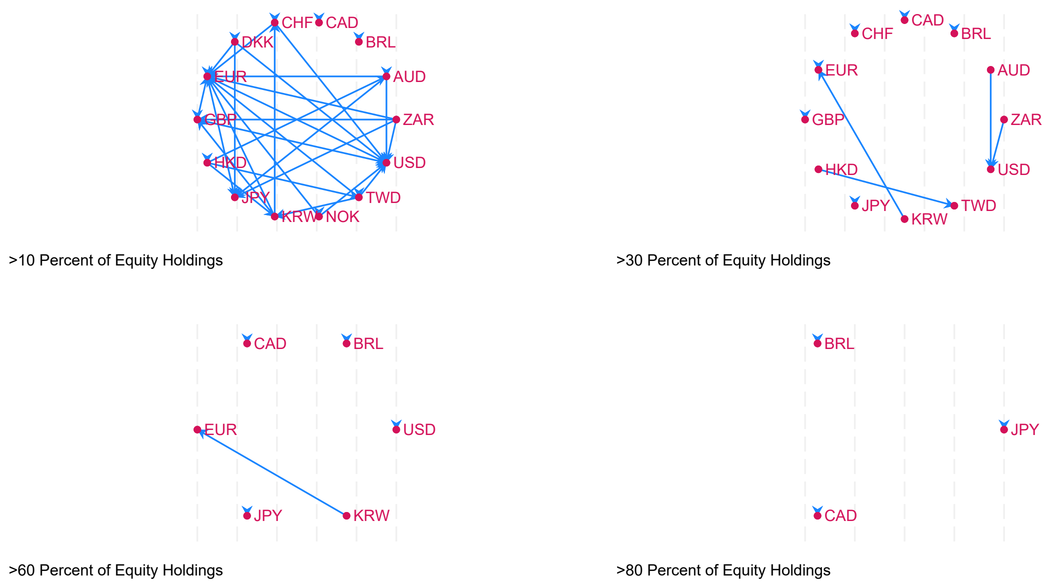
Figure 4: Importance of the Final Investor for the Local Stock Market (Sample Average); Monthly



The arrow is present if more than X percent of all stock market holdings associated with a given currency (end node) are held by funds with a given ROS currency (starting node).

In the different graphs we plot a different threshold for the importance of the final investor for a given stock market based on the variable $\tilde{f}_{inv}$. $\tilde{f}_{inv}$ is the sample average fraction of all observed holdings of stock market associated with currency i held by funds with a ROS currency j. The case $i = j$ is denoted with the arrow pointing onto the same node and captures the home equity bias.

Figure 5: Portfolio Concentration Of Final Investors (Sample Average); Monthly

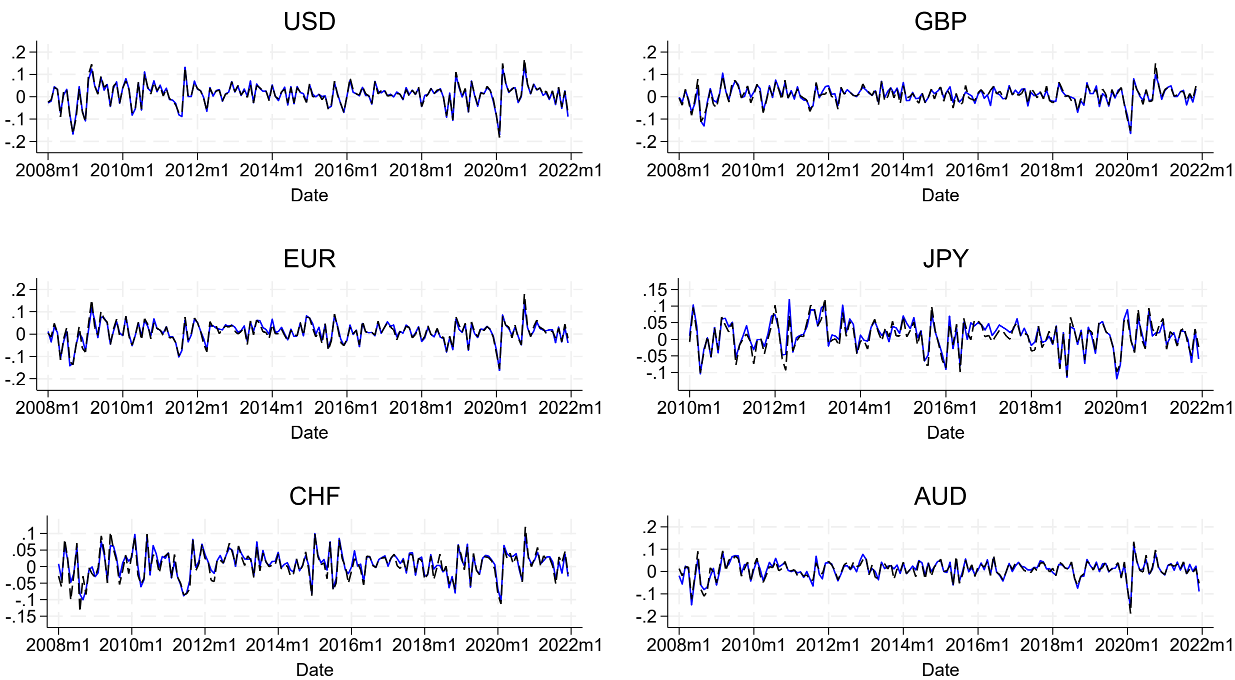


The arrow is present if more than X percent of all equity holdings of funds with a given ROS currency (starting node) are invested in the stock market associated with a given currency (end node).

In the different graphs we plot a different threshold for the portfolio concentration of the final investor categorized by the currency of the ROS, based on the variable $\tilde{f}_{conc}$. $\tilde{f}_{conc}$ is the sample average fraction of all observed holdings of equities denominated in currency j by funds with a ROS currency i relative to all equity holdings by funds with a ROS currency i. The case $i = j$ is denoted with the arrow pointing onto the same node and captures the local stock market portfolio concentration.

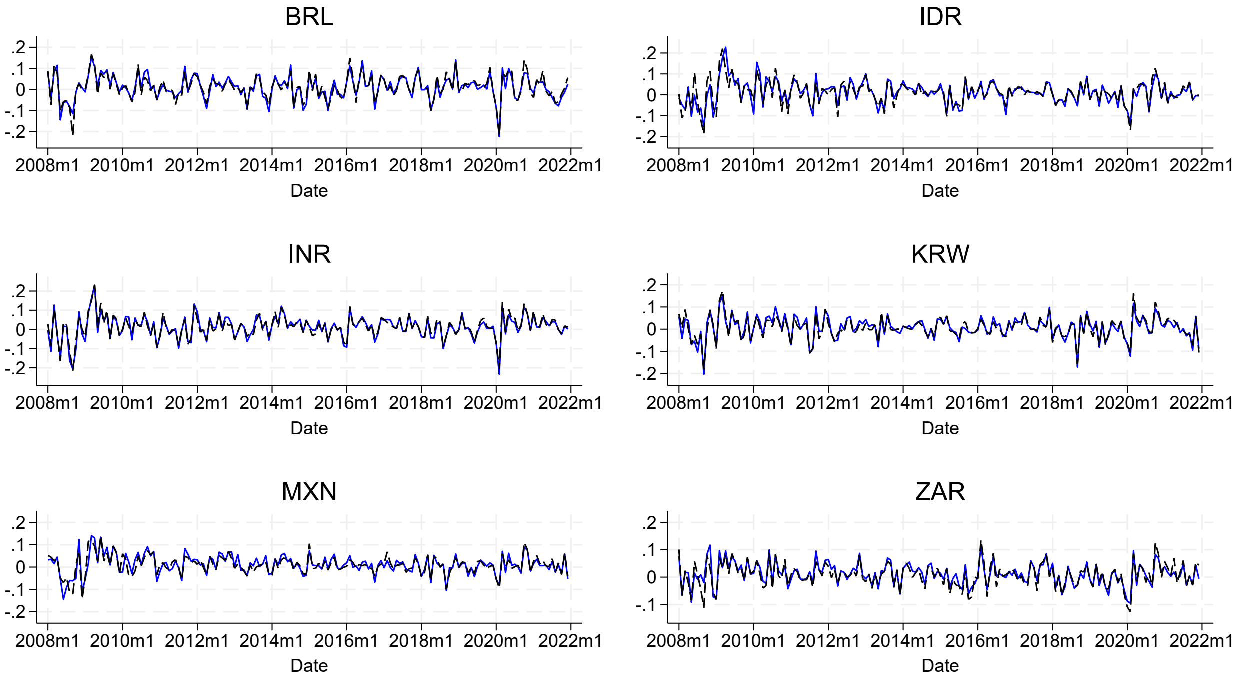
9.3 Decomposition Graphs and Tables

Figure 6: Log Stock Market Price Change vs Common Component of Demand Change



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

Figure 7: Log Stock Market Price Change vs Common Component of Demand Change



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

Figure 8: Log Stock Market Price Change: VCV Decomposition; All Components

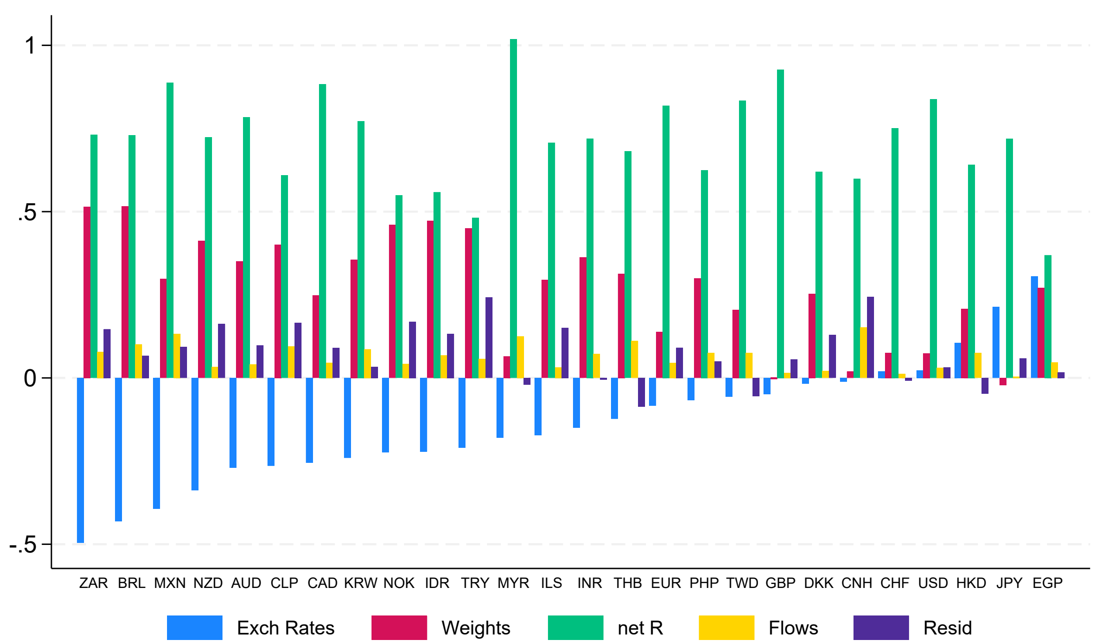


Table 2: Stock Market Variance Covariance Decomposition

Currency	*ExchRates*	R^2	*Weights*	R^2	*netR*	R^2	*Flows*	R^2	*Resid*	R^2	*ShareObsComps*
AUD	-0.27^{***}	0.11	0.35^{***}	0.37	0.78^{***}	0.53	0.04^{***}	0.10	0.10^{***}	0.06	0.91
BRL	-0.43^{***}	0.37	0.52^{***}	0.49	0.73^{***}	0.74	0.10^{***}	0.26	0.07^{*}	0.01	0.92
CAD	-0.26^{***}	0.30	0.25^{***}	0.25	0.88^{***}	0.79	0.05^{***}	0.08	0.09^{***}	0.05	0.92
CHF	0.02	-0.00	0.08^{**}	0.02	0.75^{***}	0.71	0.01	0.01	-0.01	-0.01	0.86
CLP	-0.26^{***}	0.15	0.40^{***}	0.25	0.61^{***}	0.39	0.09^{***}	0.21	0.17^{***}	0.13	0.84
CNH	-0.01	-0.01	0.02	-0.01	0.60^{***}	0.56	0.15^{***}	0.13	0.24^{***}	0.09	0.76
DKK	-0.02	-0.00	0.25^{***}	0.16	0.62^{***}	0.61	0.02^{**}	0.02	0.13^{**}	0.03	0.88
EGP	0.31^{***}	0.17	0.27^{***}	0.14	0.37^{***}	0.39	0.05^{***}	0.09	0.02	-0.00	0.99
EUR	-0.08^{***}	0.06	0.14^{***}	0.25	0.82^{***}	0.91	0.05^{***}	0.11	0.09^{***}	0.11	0.92
GBP	-0.05^{**}	0.02	-0.00	-0.01	0.93^{***}	0.85	0.02	0.01	0.06	0.00	0.89
HKD	0.11^{***}	0.29	0.21^{***}	0.23	0.64^{***}	0.77	0.07^{***}	0.34	-0.05^{***}	0.04	1.03
IDR	-0.22^{***}	0.25	0.47^{***}	0.39	0.56^{***}	0.50	0.07^{***}	0.19	0.13^{***}	0.06	0.88
ILS	-0.17^{***}	0.17	0.29^{***}	0.18	0.71^{***}	0.52	0.03^{**}	0.03	0.15^{***}	0.10	0.86
INR	-0.15^{***}	0.19	0.36^{***}	0.37	0.72^{***}	0.75	0.07^{***}	0.13	-0.00	-0.01	1.00
JPY	0.21^{***}	0.43	-0.02	-0.00	0.72^{***}	0.83	0.00	-0.01	0.06	0.01	0.91
KRW	-0.24^{***}	0.17	0.36^{***}	0.27	0.77^{***}	0.64	0.09^{***}	0.21	0.03	0.00	0.97
MXN	-0.39^{***}	0.25	0.30^{***}	0.13	0.89^{***}	0.55	0.13^{***}	0.17	0.09^{**}	0.02	0.92
MYR	-0.18^{***}	0.11	0.07	-0.00	1.02^{***}	0.53	0.13^{***}	0.20	-0.02	-0.00	1.03
NOK	-0.22^{***}	0.34	0.46^{***}	0.39	0.55^{***}	0.60	0.04^{***}	0.16	0.17^{***}	0.09	0.83
NZD	-0.34^{***}	0.13	0.41^{***}	0.18	0.72^{***}	0.39	0.03^{***}	0.05	0.16^{***}	0.05	0.83
PHP	-0.07^{***}	0.06	0.30^{***}	0.16	0.62^{***}	0.49	0.08^{***}	0.19	0.05^{**}	0.02	0.93
THB	-0.12^{***}	0.20	0.31^{***}	0.22	0.68^{***}	0.60	0.11^{***}	0.15	-0.09	0.01	0.98
TRY	-0.21^{***}	0.08	0.45^{***}	0.35	0.48^{***}	0.46	0.06^{***}	0.18	0.24^{***}	0.26	0.78
TWD	-0.06^{***}	0.04	0.20^{***}	0.09	0.83^{***}	0.67	0.08^{***}	0.15	-0.06^{**}	0.02	1.06
USD	0.02^{***}	0.17	0.07^{***}	0.16	0.84^{***}	0.97	0.03^{***}	0.14	0.03^{***}	0.03	0.97
ZAR	-0.50^{***}	0.30	0.51^{***}	0.28	0.73^{***}	0.44	0.08^{***}	0.12	0.15^{***}	0.11	0.83

Figure 9: Decomposing $\beta^{p,D^{s,l,k}}$ into effects due to $\Delta D^{ROS,l,k}$ and $D^{Resid,l,k}$ components of equity demand

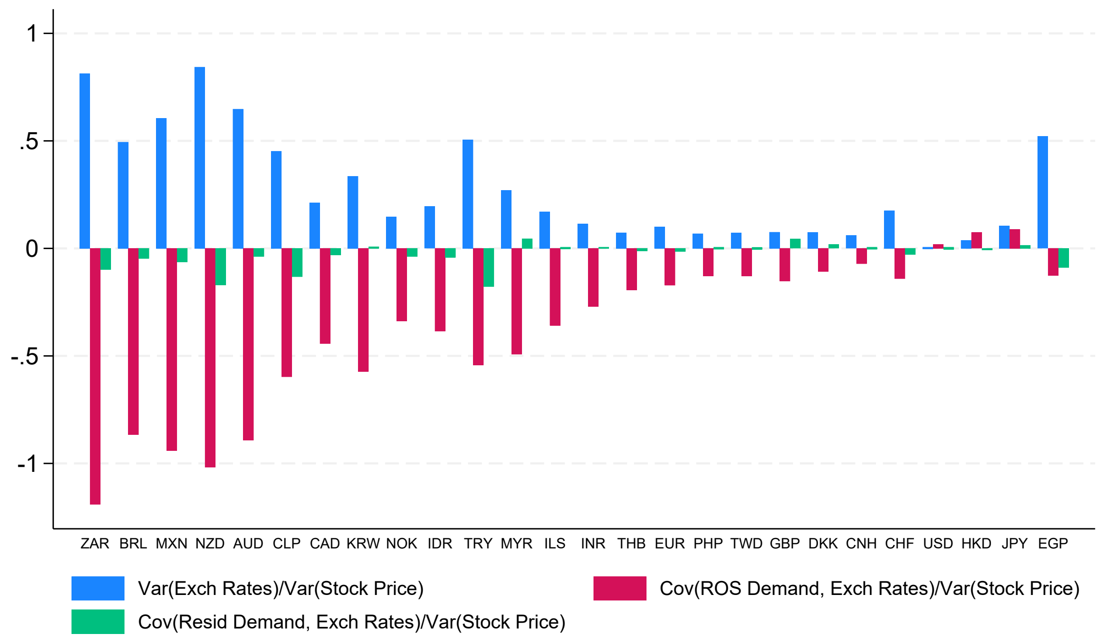
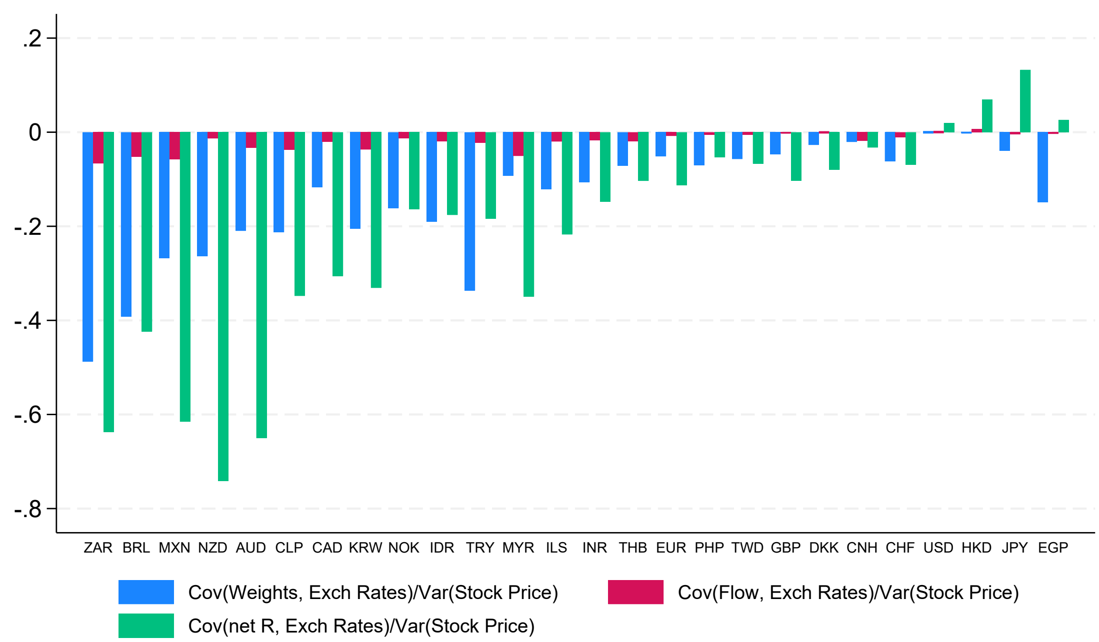
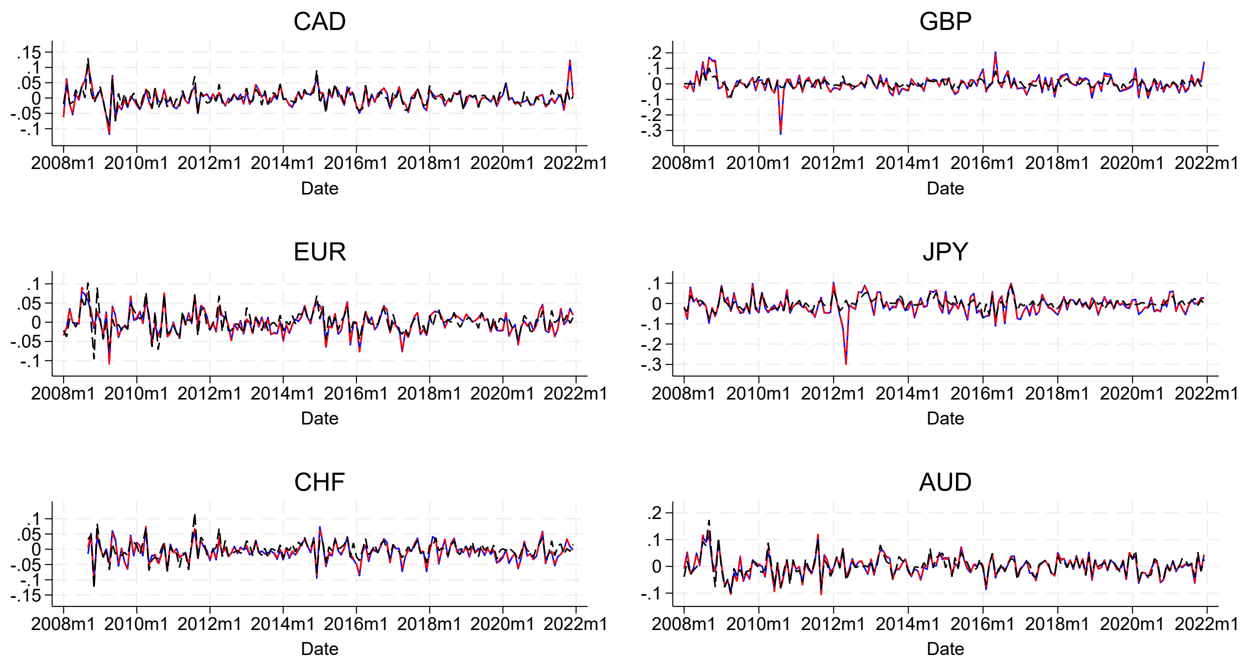


Figure 10: Decomposing $\beta^{p,D^{s,l,k}}$ into effects due to $\Delta D^{f,l,k}, \Delta D^{\omega,l,k}$ and $\Delta D^{r^{NF},l,k}$ components of equity demand



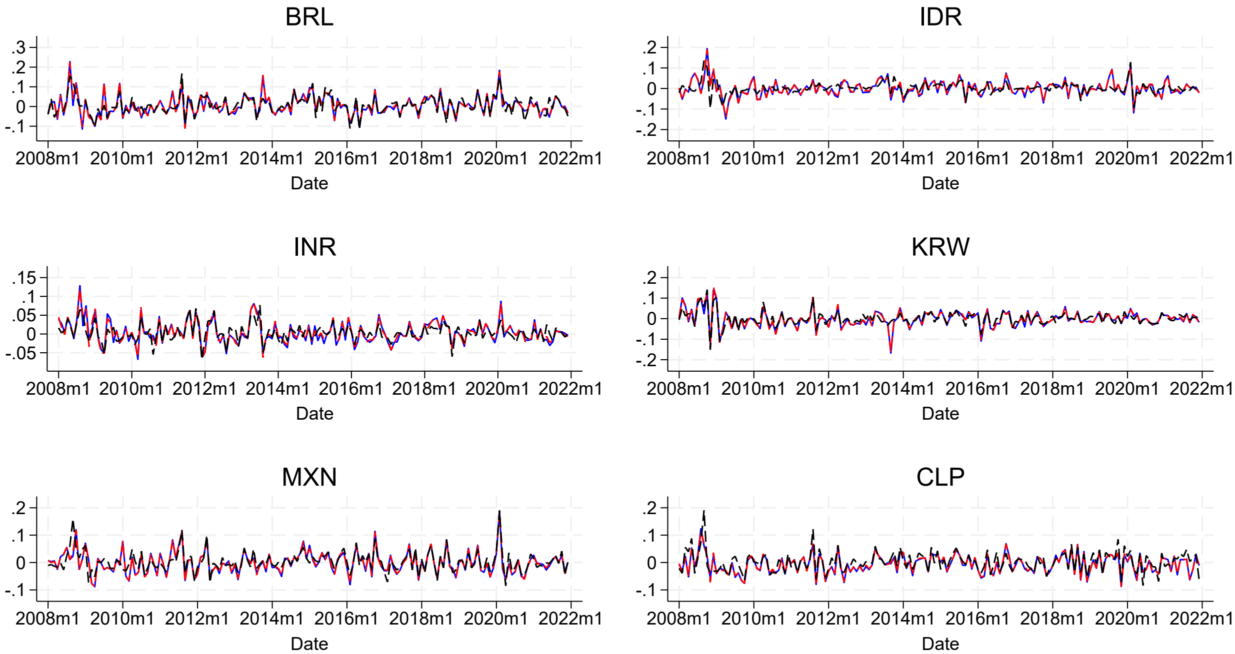
9.4 Exchange Rate Decomposition Graphs and Tables

Figure 11: Exchange Rate Growth Rate vs Common Component of Demand Change



The black dashed line represents the exch rate growth rate, the solid blue line is the specification with only USD, EUR and local currency net supply while the red dashed line is the case with net USD and local supply and other exchange rates.

Figure 12: Exchange Rate Growth Rate vs Common Component of Demand Change



The black dashed line represents the exch rate growth rate, the solid blue line is the specification with only USD, EUR and local currency net supply while the red dashed line is the case with net USD and local supply and other exchange rates.

Figure 13: Exchange Rate Change: VCV Decomposition; Net Supply (LC, USD, EUR)

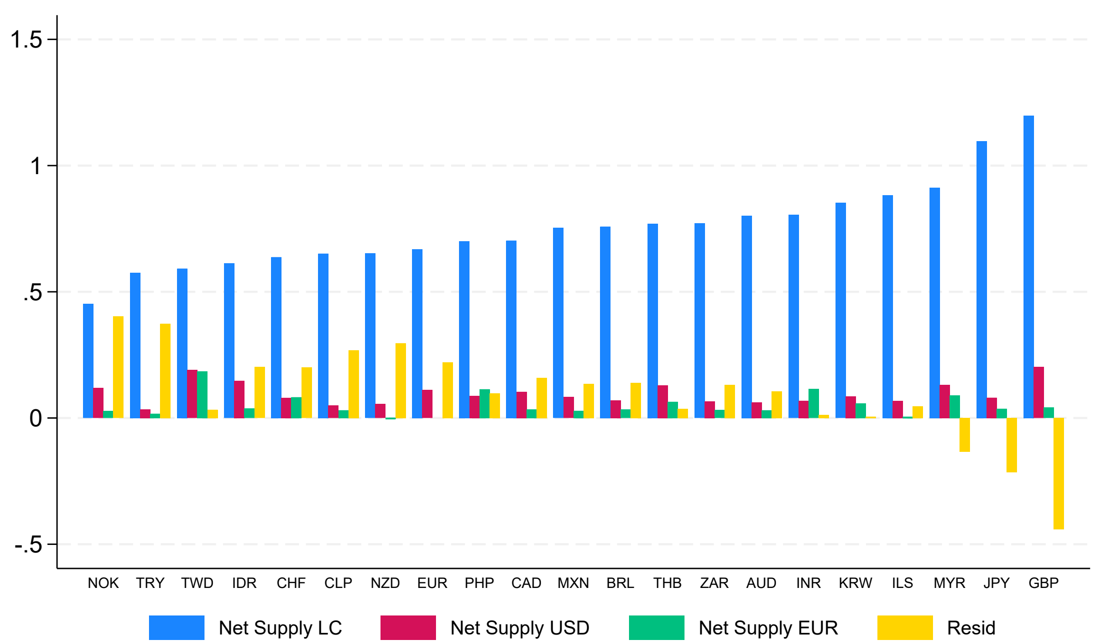


Table 3: Exchange Rate Elasticities with respect to Net Supply

Currency	ϵ	ϵ_{USD}	ϵ_{EUR}
AUD	1.02	-1.18	0.16
BRL	1.00	-1.32	0.32
CAD	1.19	-1.33	0.15
CHF	1.35	-1.63	0.29
CLP	1.00	-1.20	0.20
EUR	1.50	-1.50	.
GBP	2.09	-2.28	0.19
IDR	1.00	-1.38	0.38
ILS	1.00	-1.02	0.02
INR	1.00	-1.42	0.42
JPY	1.51	-1.79	0.28
KRW	1.00	-1.32	0.32
MXN	1.00	-1.26	0.26
MYR	1.00	-1.30	0.30
NOK	1.23	-1.41	0.18
NZD	1.00	-1.02	0.02
PHP	1.00	-1.32	0.32
THB	1.00	-1.34	0.34
TRY	1.00	-1.26	0.26
TWD	1.00	-1.35	0.35
ZAR	1.00	-1.33	0.33

Note: We construct the average elasticities over the period Jan 2012 to Dec 2021.

Table 4: Exchange Rates Variance Covariance Decomposition: Net Supply; LC USD EUR

Currency	NS_{LC}	R^2	NS_{USD}	R^2	NS_{EUR}	R^2	$Resid$	R^2	$ShareObsComps$
AUD	0.80^{***}	0.79	0.06^{***}	0.05	0.03^{***}	0.17	0.11^{***}	0.05	0.89
BRL	0.76^{***}	0.56	0.07^{***}	0.08	0.03^{***}	0.07	0.14^{***}	0.04	0.86
CAD	0.70^{***}	0.54	0.10^{***}	0.06	0.03^{***}	0.12	0.16^{***}	0.05	0.84
CHF	0.64^{***}	0.49	0.08^{**}	0.02	0.08^{***}	0.26	0.20^{***}	0.07	0.80
CLP	0.65^{***}	0.58	0.05^{**}	0.02	0.03^{***}	0.07	0.27^{***}	0.17	0.73
EUR	0.67^{***}	0.52	0.11^{***}	0.05	0.67^{***}	0.52	0.22^{***}	0.09	0.78
GBP	1.20^{***}	0.35	0.20^{***}	0.06	0.04^{***}	0.12	-0.44^{***}	0.07	1.44
IDR	0.61^{***}	0.25	0.15^{***}	0.12	0.04^{**}	0.02	0.20^{**}	0.03	0.80
ILS	0.88^{***}	0.42	0.07^{**}	0.02	0.00	0.00	0.05	-0.00	0.95
INR	0.80^{***}	0.51	0.07^{*}	0.01	0.11^{***}	0.12	0.01	-0.01	0.99
JPY	1.10^{***}	0.39	0.08^{*}	0.01	0.04^{***}	0.04	-0.21^{**}	0.02	1.21
KRW	0.85^{***}	0.64	0.09^{***}	0.06	0.06^{***}	0.11	0.00	-0.01	1.00
MXN	0.75^{***}	0.59	0.08^{***}	0.08	0.03^{***}	0.06	0.14^{***}	0.03	0.86
MYR	0.91^{***}	0.51	0.13^{***}	0.06	0.09^{***}	0.13	-0.13^{*}	0.01	1.13
NOK	0.45^{***}	0.16	0.12^{***}	0.11	0.03^{***}	0.07	0.40^{***}	0.13	0.60
NZD	0.65^{***}	0.55	0.06^{***}	0.05	-0.00	0.01	0.30^{***}	0.19	0.70
PHP	0.70^{***}	0.24	0.09	0.01	0.11^{***}	0.09	0.10	-0.00	0.90
THB	0.77^{***}	0.24	0.13^{**}	0.03	0.06^{**}	0.03	0.04	-0.01	0.96
TRY	0.58^{***}	0.53	0.03^{**}	0.02	0.02^{***}	0.03	0.37^{***}	0.33	0.63
TWD	0.59^{***}	0.19	0.19^{***}	0.05	0.18^{***}	0.17	0.03	-0.01	0.97
ZAR	0.77^{***}	0.75	0.07^{***}	0.06	0.03^{***}	0.06	0.13^{***}	0.07	0.87

9.5 Response of Stock Market Return to VIX and Macroeconomic News

Figure 14: Local Stock Market Return Response to Percentage Change in VIX

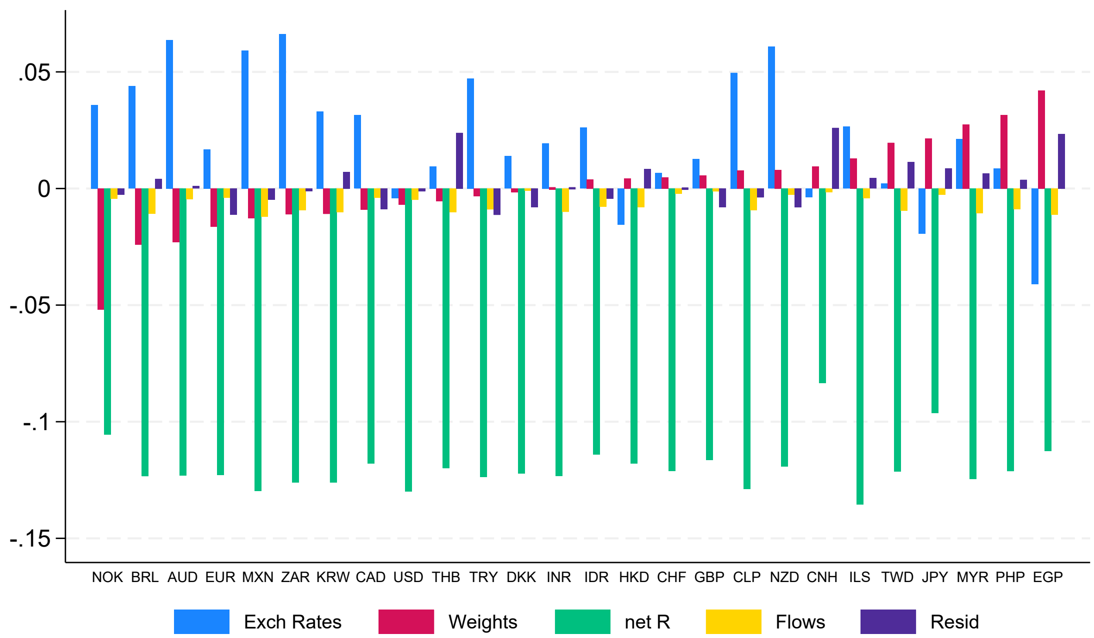


Figure 15: Local Stock Market Return Response to US stock market macro news index

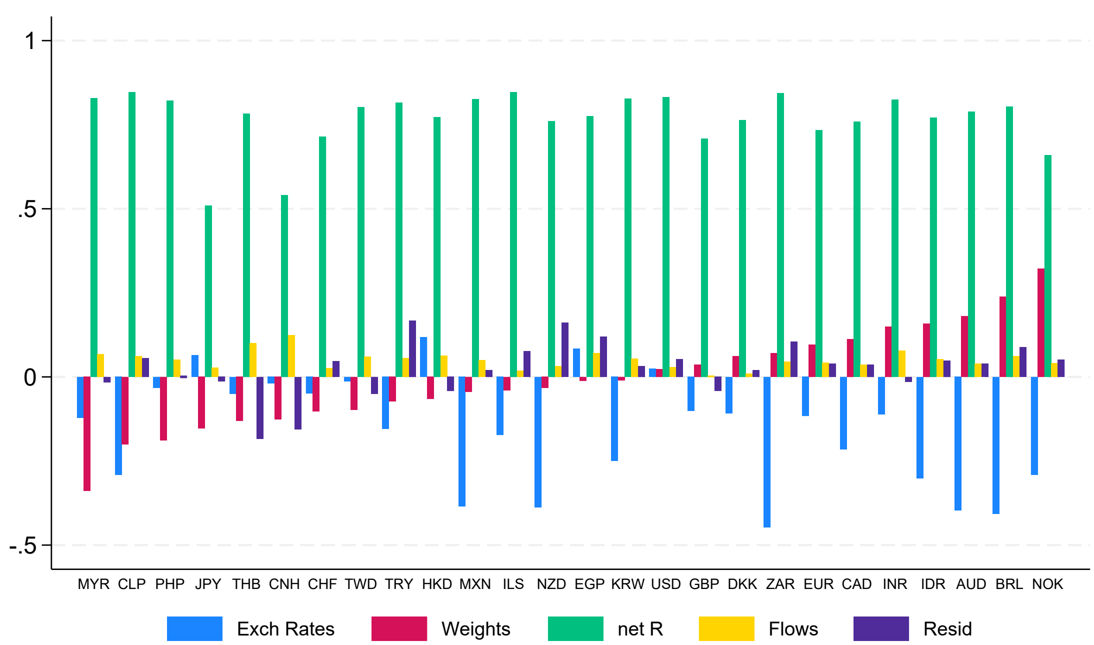


Table 5: Local Stock Market Return Response to Percentage Change in VIX

Currency	*LocalStockMarket*	R^2	*ExchRates*	R^2	*Weights*	R^2	*netR*	R^2	*Flows*	R^2	*Resid*	R^2
AUD	-0.09***	0.27	0.06***	0.22	-0.02***	0.05	-0.12***	0.47	-0.00***	0.04	0.00	-0.01
BRL	-0.12***	0.21	0.04***	0.06	-0.02*	0.01	-0.12***	0.34	-0.01***	0.04	0.00	-0.00
CAD	-0.10***	0.38	0.03***	0.16	-0.01	0.01	-0.12***	0.51	-0.00*	0.02	-0.01*	0.02
CHF	-0.12***	0.43	0.01	0.00	0.00	-0.00	-0.12***	0.54	-0.00	0.01	-0.00	-0.01
CLP	-0.09***	0.16	0.05***	0.11	0.01	-0.00	-0.13***	0.38	-0.01***	0.04	-0.00	-0.00
CNH	-0.05***	0.06	-0.00	-0.00	0.01	0.00	-0.08***	0.24	-0.00	-0.01	0.03*	0.02
DKK	-0.12***	0.30	0.01***	0.05	-0.00	-0.01	-0.12***	0.50	-0.00	-0.01	-0.01	-0.00
EGP	-0.11***	0.10	-0.04**	0.02	0.04**	0.03	-0.11***	0.35	-0.01***	0.05	0.02*	0.01
EUR	-0.14***	0.47	0.02***	0.07	-0.02**	0.09	-0.12***	0.52	-0.00***	0.02	-0.01***	0.04
GBP	-0.11***	0.44	0.01***	0.07	0.01	0.00	-0.12***	0.51	-0.00	-0.00	-0.01	0.00
HKD	-0.13***	0.28	-0.02***	0.10	0.00	-0.00	-0.12***	0.42	-0.01***	0.06	0.01*	0.02
IDR	-0.09***	0.13	0.03***	0.05	0.00	-0.01	-0.11***	0.35	-0.01***	0.04	-0.00	-0.00
ILS	-0.09***	0.21	0.03***	0.09	0.01	0.00	-0.14***	0.46	-0.00	0.01	0.00	-0.00
INR	-0.11***	0.20	0.02***	0.05	0.00	-0.01	-0.12***	0.35	-0.01***	0.03	0.00	-0.01
JPY	-0.09***	0.24	-0.02***	0.09	0.02***	0.08	-0.10***	0.41	-0.00	-0.00	0.01	0.00
KRW	-0.11***	0.26	0.03***	0.07	-0.01	-0.00	-0.13***	0.38	-0.01***	0.06	0.01	0.00
MXN	-0.10***	0.31	0.06***	0.17	-0.01	0.00	-0.13***	0.37	-0.01***	0.04	-0.00	-0.00
MYR	-0.08***	0.31	0.02***	0.07	0.03***	0.03	-0.12***	0.37	-0.01***	0.06	0.01	0.00
NOK	-0.13***	0.35	0.04***	0.18	-0.05***	0.10	-0.11***	0.46	-0.00**	0.03	-0.00	-0.01
NZD	-0.06***	0.15	0.06***	0.19	0.01	-0.00	-0.12***	0.49	-0.00	0.01	-0.01	0.00
PHP	-0.09***	0.15	0.01*	0.01	0.03**	0.03	-0.12***	0.36	-0.01***	0.05	0.00	-0.00
THB	-0.13***	0.30	0.01*	0.02	-0.01	-0.00	-0.12***	0.35	-0.01**	0.02	0.02*	0.01
TRY	-0.10***	0.12	0.05***	0.05	-0.00	-0.01	-0.12***	0.39	-0.01***	0.05	-0.01	0.00
TWD	-0.10***	0.25	0.00	-0.00	0.02*	0.02	-0.12***	0.36	-0.01***	0.06	0.01**	0.03
USD	-0.15***	0.49	-0.00	0.12	-0.01*	0.03	-0.13***	0.51	-0.00**	0.08	-0.00	-0.00
ZAR	-0.08***	0.19	0.07***	0.14	-0.01	-0.00	-0.13***	0.35	-0.01***	0.04	-0.00	-0.01

Figure 16: Local Stock Market Return Response to local stock market macro news index

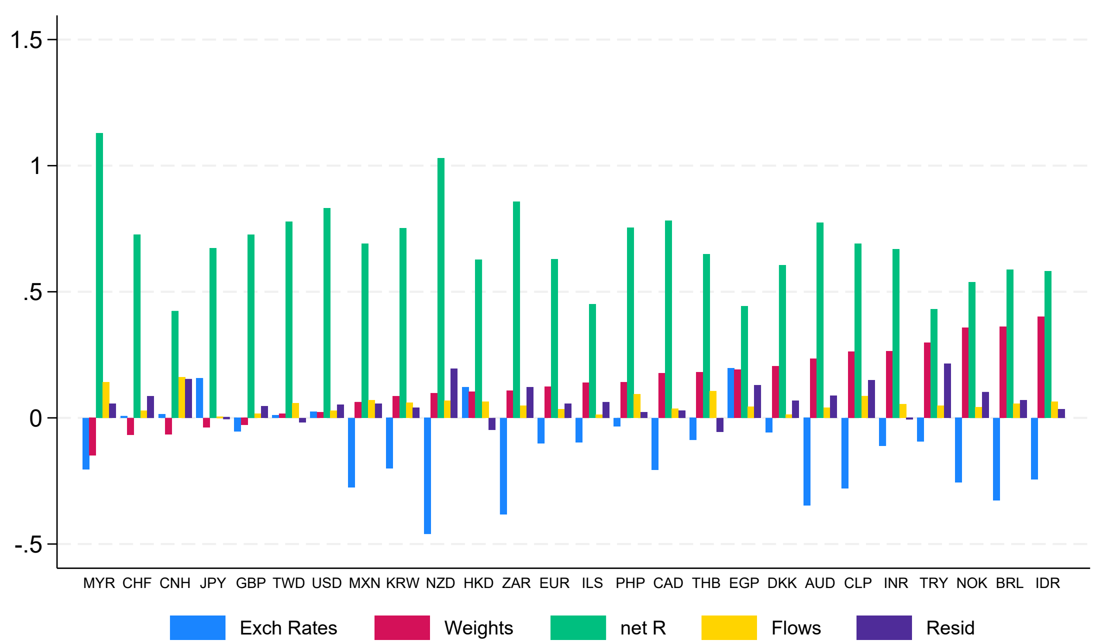


Table 6: Local Stock Market Return Response to US stock market macro news index

Currency	$LocalStockMarket$	R^2	$ExchRates$	R^2	$Weights$	R^2	$netR$	R^2	$Flows$	R^2	$Resid$	R^2
AUD	0.64***	0.32	-0.40***	0.18	0.18***	0.08	0.79***	0.41	0.04***	0.07	0.04	0.00
BRL	0.81***	0.24	-0.41***	0.11	0.24**	0.03	0.80***	0.32	0.06**	0.03	0.09	0.01
CAD	0.75***	0.43	-0.21***	0.17	0.11***	0.04	0.76***	0.45	0.04***	0.06	0.04	0.00
CHF	0.59***	0.22	-0.05	0.00	-0.10**	0.03	0.71***	0.41	0.03**	0.03	0.05	-0.00
CLP	0.47***	0.10	-0.29***	0.09	-0.20**	0.03	0.85***	0.36	0.06***	0.04	0.06	0.00
CNH	0.37***	0.05	-0.02	-0.01	-0.13*	0.02	0.54***	0.17	0.12**	0.03	-0.16	0.01
DKK	0.75***	0.26	-0.11***	0.07	0.06	-0.00	0.76***	0.42	0.01	-0.00	0.02	-0.01
EGP	1.01***	0.21	0.08	-0.00	-0.01	-0.01	0.78***	0.36	0.07***	0.04	0.12	0.00
EUR	0.80***	0.34	-0.12***	0.07	0.10	0.06	0.73***	0.40	0.04**	0.05	0.04	0.01
GBP	0.65***	0.34	-0.10*	0.10	0.04	0.00	0.71***	0.40	0.00	-0.01	-0.04	-0.00
HKD	0.88***	0.27	0.12***	0.12	-0.07	0.00	0.77***	0.40	0.06***	0.08	-0.04	0.01
IDR	0.73***	0.20	-0.30***	0.17	0.16*	0.01	0.77***	0.36	0.05***	0.04	0.05	-0.00
ILS	0.68***	0.24	-0.17***	0.09	-0.04	-0.00	0.85***	0.39	0.02	-0.00	0.08	0.01
INR	0.92***	0.30	-0.11**	0.03	0.15*	0.02	0.82***	0.34	0.08***	0.05	-0.01	-0.01
JPY	0.44***	0.08	0.06	0.01	-0.15***	0.07	0.51***	0.19	0.03	-0.00	-0.01	-0.01
KRW	0.68***	0.23	-0.25***	0.09	-0.01	-0.01	0.83***	0.36	0.05***	0.04	0.03	-0.00
MXN	0.48***	0.15	-0.39***	0.16	-0.04	-0.00	0.83***	0.32	0.05*	0.01	0.02	-0.01
MYR	0.42***	0.17	-0.12***	0.05	-0.34***	0.14	0.83***	0.36	0.07***	0.05	-0.02	-0.01
NOK	0.79***	0.29	-0.29***	0.26	0.32***	0.09	0.66***	0.39	0.04***	0.07	0.05	-0.00
NZD	0.49***	0.24	-0.39***	0.17	-0.03	-0.00	0.76***	0.42	0.03***	0.04	0.16***	0.06
PHP	0.66***	0.18	-0.03	0.00	-0.19**	0.03	0.82***	0.36	0.05**	0.03	0.00	-0.01
THB	0.71***	0.20	-0.05	0.01	-0.13	0.01	0.78***	0.32	0.10***	0.05	-0.18**	0.02
TRY	0.77***	0.16	-0.15	0.01	-0.07	-0.00	0.81***	0.37	0.06***	0.04	0.17**	0.03
TWD	0.70***	0.28	-0.01	-0.00	-0.10	0.01	0.80***	0.35	0.06***	0.05	-0.05	0.01
USD	0.96***	0.43	0.02***	0.09	0.02	0.00	0.83***	0.45	0.03	0.05	0.05***	0.05
ZAR	0.64***	0.24	-0.45***	0.14	0.07	-0.00	0.84***	0.35	0.05**	0.02	0.10**	0.03

Table 7: Local Stock Market Return Response to local stock market macro news index

Currency	$LocalStockMarket$	R^2	$ExchRates$	R^2	$Weights$	R^2	$netR$	R^2	$Flows$	R^2	$Resid$	R^2
AUD	0.78^{***}	0.45	-0.35^{***}	0.13	0.23^{***}	0.13	0.77^{***}	0.39	0.04^{***}	0.07	0.09^{**}	0.03
BRL	0.79^{***}	0.46	-0.33^{***}	0.15	0.36^{***}	0.17	0.59^{***}	0.34	0.06^{***}	0.06	0.07	0.01
CAD	0.83^{***}	0.51	-0.21^{***}	0.14	0.18^{***}	0.10	0.78^{***}	0.46	0.04^{***}	0.06	0.03	-0.00
CHF	0.75^{***}	0.35	0.01	-0.01	-0.07	0.01	0.73^{***}	0.41	0.03^{***}	0.04	0.09	0.00
CLP	0.91^{***}	0.36	-0.28^{***}	0.07	0.26^{***}	0.05	0.69^{***}	0.22	0.09^{***}	0.08	0.15^{***}	0.05
CNH	0.69^{***}	0.37	0.01	-0.00	-0.06	0.01	0.42^{***}	0.22	0.16^{***}	0.12	0.15^{*}	0.02
DKK	0.81^{***}	0.50	-0.06^{**}	0.03	0.20^{***}	0.08	0.61^{***}	0.44	0.01	0.00	0.07	0.00
EGP	0.96^{***}	0.51	0.20^{***}	0.04	0.19^{***}	0.04	0.44^{***}	0.31	0.04^{***}	0.04	0.13^{**}	0.03
EUR	0.74^{***}	0.58	-0.10^{***}	0.10	0.12	0.23	0.63^{***}	0.58	0.03	0.07	0.06^{***}	0.04
GBP	0.71^{***}	0.50	-0.05^{*}	0.03	-0.03^{**}	-0.00	0.73^{***}	0.52	0.02	0.01	0.05	0.00
HKD	0.90^{***}	0.42	0.12^{***}	0.20	0.10^{**}	0.03	0.63^{***}	0.38	0.06^{***}	0.13	-0.05^{**}	0.02
IDR	0.82^{***}	0.45	-0.24^{***}	0.19	0.40^{***}	0.19	0.58^{***}	0.35	0.06^{***}	0.11	0.03	-0.00
ILS	0.57^{***}	0.32	-0.10^{***}	0.05	0.14^{**}	0.03	0.45^{***}	0.24	0.01	0.01	0.06^{*}	0.02
INR	0.87^{***}	0.48	-0.11^{***}	0.06	0.26^{***}	0.12	0.67^{***}	0.40	0.06^{***}	0.04	-0.01	-0.01
JPY	0.83^{***}	0.48	0.16^{***}	0.16	-0.04	0.00	0.67^{***}	0.52	0.00	-0.01	-0.00	-0.01
KRW	0.75^{***}	0.35	-0.20^{***}	0.07	0.09	0.00	0.75^{***}	0.37	0.06^{***}	0.06	0.04	0.00
MXN	0.60^{***}	0.34	-0.28^{***}	0.11	0.06	-0.00	0.69^{***}	0.31	0.07^{***}	0.04	0.06	0.00
MYR	0.94^{***}	0.44	-0.20^{***}	0.07	-0.15	0.01	1.13^{***}	0.32	0.14^{***}	0.12	0.06	-0.00
NOK	0.78^{***}	0.47	-0.26^{***}	0.32	0.36^{***}	0.18	0.54^{***}	0.42	0.04^{***}	0.12	0.10^{**}	0.02
NZD	0.88^{***}	0.39	-0.46^{***}	0.11	0.10	-0.00	1.03^{***}	0.38	0.07^{***}	0.10	0.20^{***}	0.04
PHP	0.98^{***}	0.46	-0.03	0.00	0.14^{*}	0.01	0.75^{***}	0.34	0.09^{***}	0.14	0.02	-0.00
THB	0.89^{***}	0.48	-0.09^{***}	0.06	0.18^{***}	0.04	0.65^{***}	0.33	0.11^{***}	0.08	-0.05	-0.00
TRY	0.86^{***}	0.48	-0.09	0.01	0.30^{***}	0.10	0.43^{***}	0.23	0.05^{***}	0.08	0.22^{***}	0.13
TWD	0.85^{***}	0.45	0.01	-0.01	0.02	-0.01	0.78^{***}	0.36	0.06^{***}	0.05	-0.02	-0.00
USD	0.96^{***}	0.43	0.02^{***}	0.09	0.02	0.00	0.83^{***}	0.45	0.03^{***}	0.05	0.05^{***}	0.05
ZAR	0.77^{***}	0.32	-0.38^{***}	0.09	0.11	0.00	0.86^{***}	0.32	0.05^{**}	0.02	0.12^{***}	0.04

10 Online Appendix

Figure 17: Total AUM USD Trillions; Quarterly

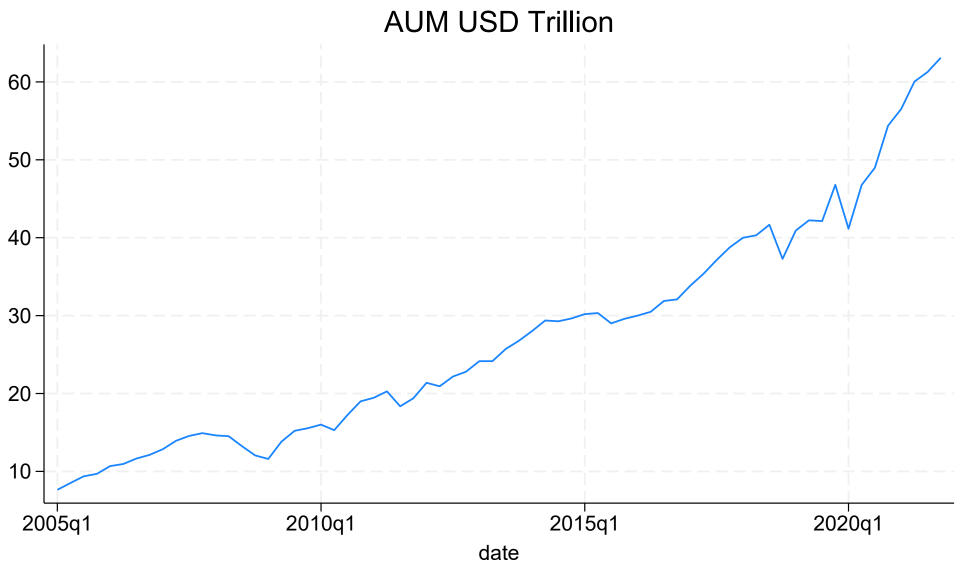


Figure 18: Total AUM USD Trillions by investment type and ROS; Quarterly

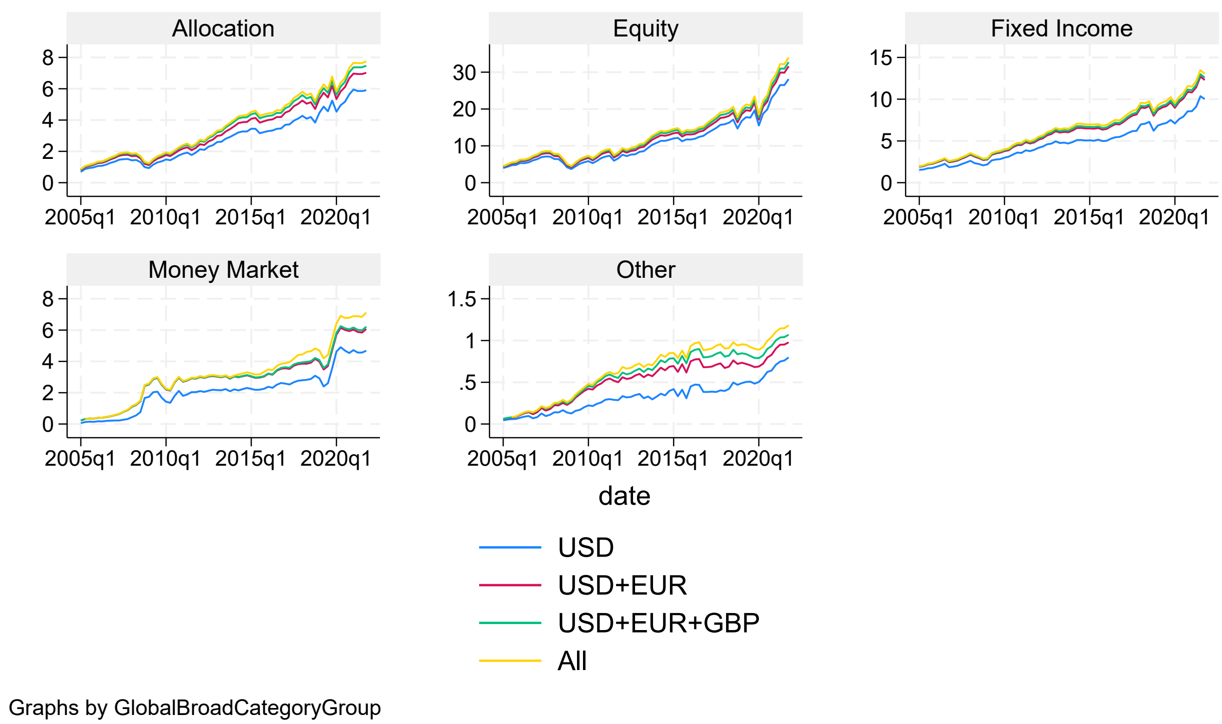


Figure 19: Total AUM USD Trillions by investment type and active/passive Q

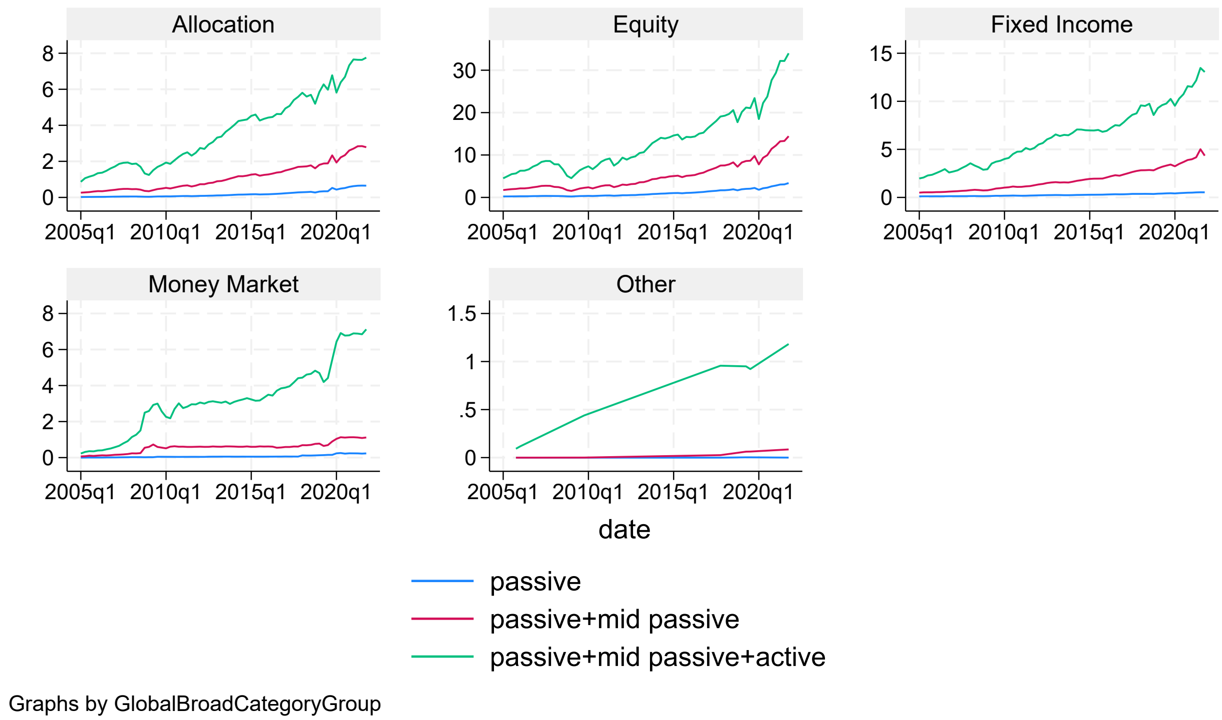
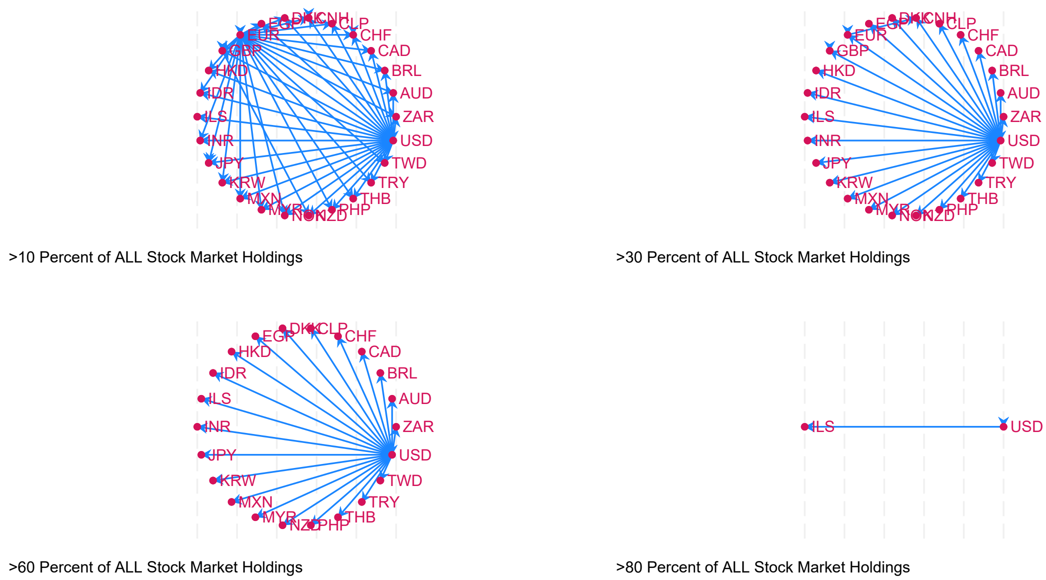


Table 8: Coverage and Market Capitalization; Quarterly

Currency	*AvgCoverage*	*CoverageStart*	*CoverageEnd*	*AvgMarketCapUSDbil*	*MarketCapStartUSDbil*	*MarketCapEndUSDbil*	*ISINs*
AUD	0.09	0.06	0.12	323.16	252.17	620.21	710.00
BRL	0.07	0.04	0.11	537.16	437.84	673.66	320.00
CAD	0.10	0.07	0.17	573.32	463.82	960.79	941.00
CHF	0.13	0.09	0.19	516.52	416.21	810.76	188.00
CLP	0.03	0.01	0.04	92.92	84.19	66.88	55.00
CNH	0.01	0.00	0.02	5037.92	1100.83	9756.52	2499.00
DKK	0.15	0.06	0.25	133.21	71.10	265.31	106.00
EGP	0.05	0.04	0.05	32.96	64.53	25.29	77.00
EUR	0.12	0.06	0.19	3373.68	3094.20	5233.25	1946.00
GBP	0.15	0.06	0.26	1062.56	1017.38	1405.72	1231.00
HKD	0.07	0.06	0.08	442.76	314.41	489.42	522.00
IDR	0.07	0.02	0.09	203.41	80.31	381.33	240.00
ILS	0.03	0.02	0.05	71.03	25.34	193.89	158.00
INR	0.07	0.03	0.09	1416.94	813.97	2975.63	1103.00
JPY	0.12	0.05	0.22	2830.54	1764.36	3586.41	2703.00
KRW	0.07	0.05	0.10	669.54	415.35	1196.04	1640.00
MXN	0.06	0.04	0.10	224.54	167.75	275.10	115.00
MYR	0.04	0.03	0.04	276.04	155.59	296.51	462.00
NOK	0.06	0.04	0.15	174.39	197.52	199.29	184.00
NZD	0.04	0.01	0.07	26.62	6.59	57.76	68.00
PHP	0.06	0.05	0.06	119.84	46.80	153.97	118.00
THB	0.02	0.01	0.01	497.84	158.59	931.52	565.00
TRY	0.07	0.07	0.04	94.08	71.23	71.14	160.00
TWD	0.11	0.07	0.17	864.27	621.88	1749.74	1188.00
USD	0.33	0.18	0.44	6590.43	5461.50	12669.44	6849.00
ZAR	0.11	0.07	0.13	161.23	125.07	220.39	116.00

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.

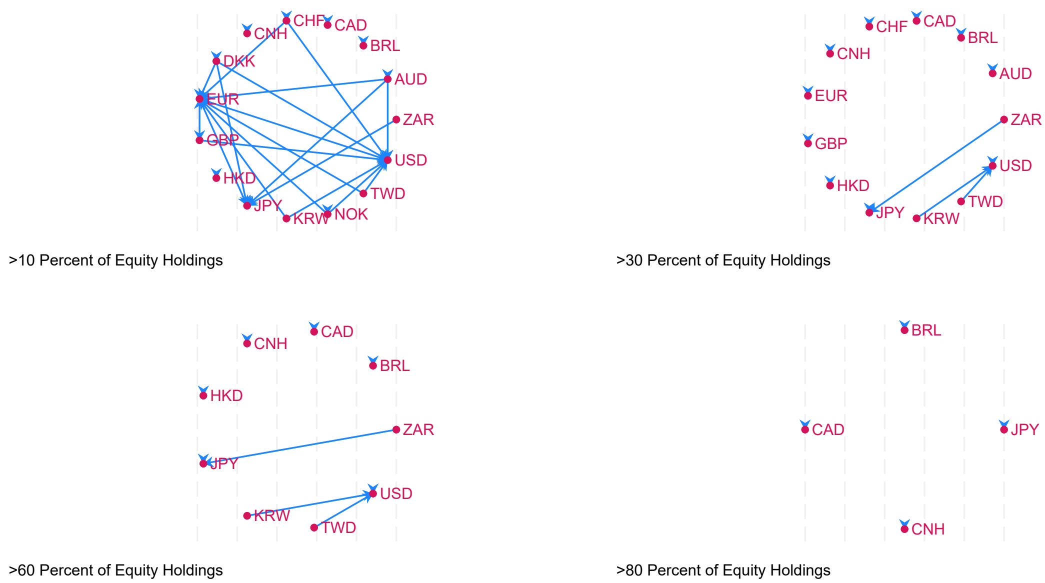
Figure 20: Importance of the Final Investor for the Local Stock Market (Sample Average); Quarterly



The arrow is present if more than X percent of all stock market holdings associated with a given currency (end node) are held by funds with a given ROS currency (starting node).

In the different graphs we plot a different threshold for the importance of the final investor for a given stock market based on the variable $\tilde{f}_{inv}$. $\tilde{f}_{inv}$ is the sample average fraction of all observed holdings of stock market associated with currency i held by funds with a ROS currency j. The case $i = j$ is denoted with the arrow pointing onto the same node and captures the home equity bias.

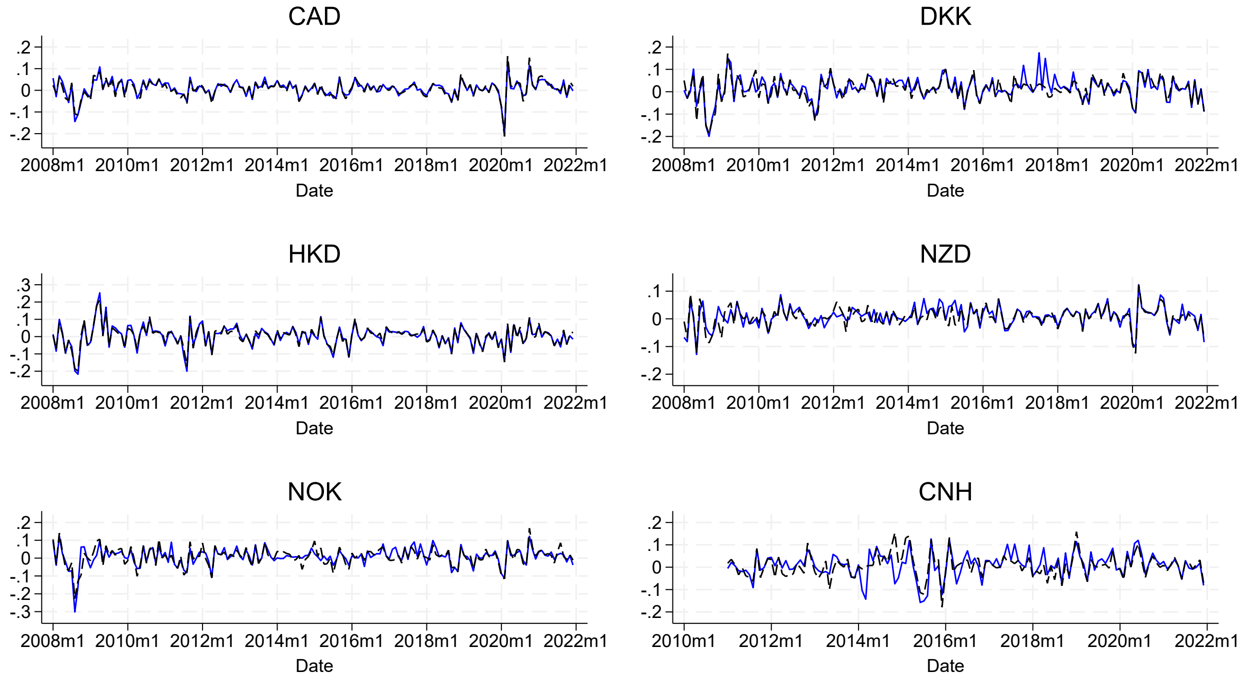
Figure 21: Portfolio Concentration Of Final Investors (Sample Average); Quarterly



The arrow is present if more than X percent of all equity holdings of funds with a given ROS currency (starting node) are invested in the stock market associated with a given currency (end node).

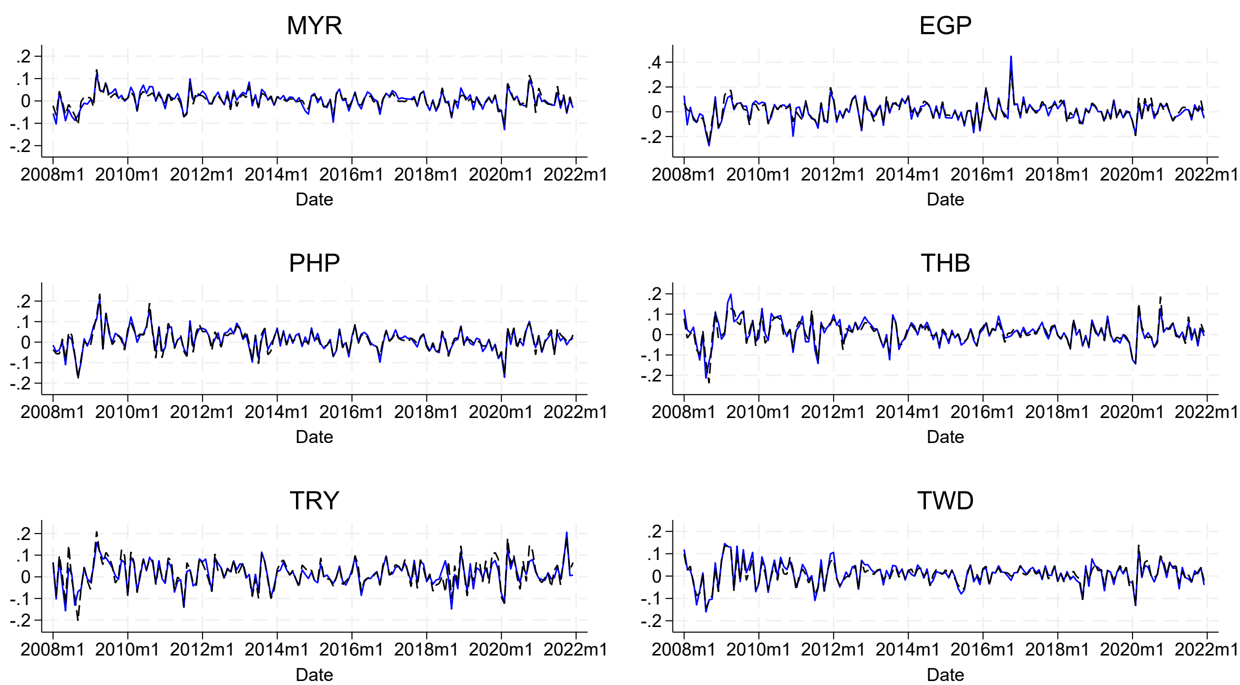
In the different graphs we plot a different threshold for the portfolio concentration of the final investor categorized by the currency of the ROS, based on the variable $\tilde{f}_{conc}$. $\tilde{f}_{conc}$ is the sample average fraction of all observed holdings of equities denominated in currency j by funds with a ROS currency i relative to all equity holdings by funds with a ROS currency i. The case $i = j$ is denoted with the arrow pointing onto the same node and captures the local stock market portfolio concentration.

Figure 22: Log Stock Market Price Change vs Common Component of Demand Change



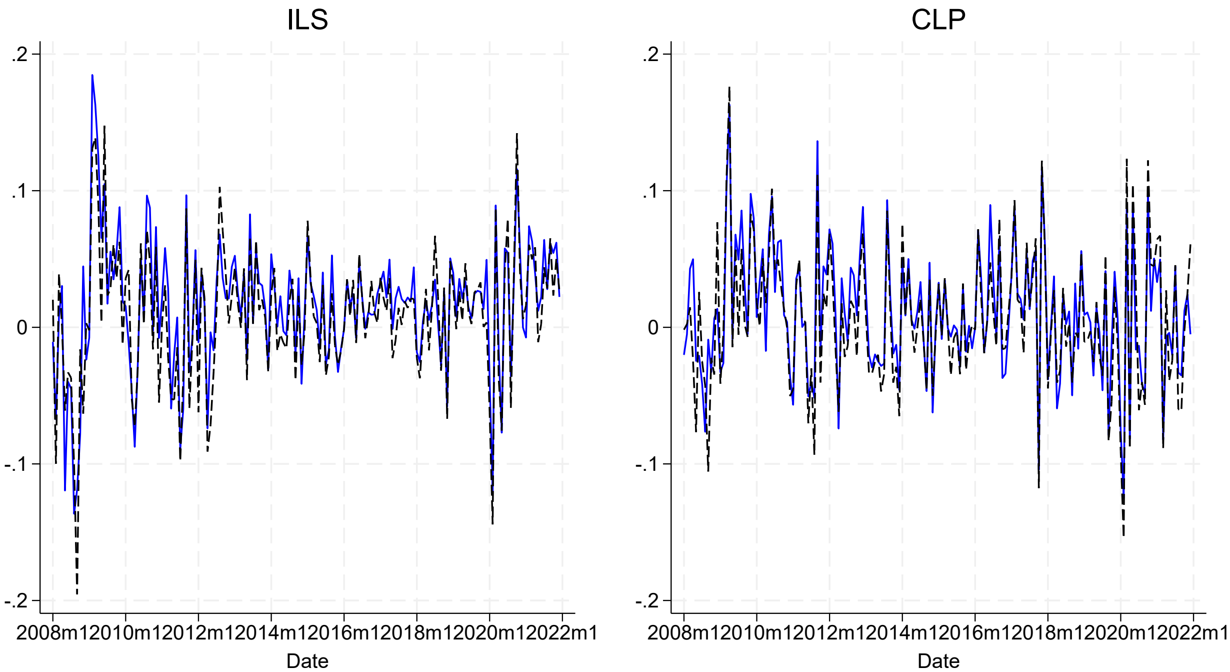
The black dashed line represents the stock price growth rate and the solid blue line is the change in common equity demand.

Figure 23: Log Stock Market Price Change vs Common Component of Demand Change



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

Figure 24: Log Stock Market Price Change vs Common Component of Demand Change



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

Figure 25: Log Stock Market Price Change: VCV Decomposition; Exchange Rate Component; ROS

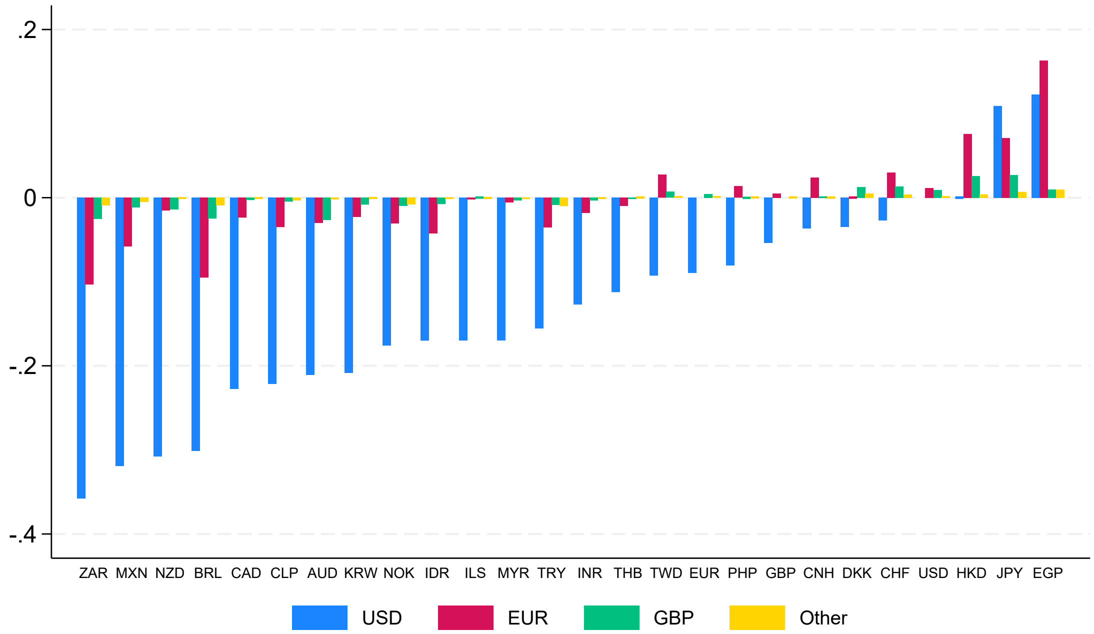


Figure 26: Log Stock Market Price Change: VCV Decomposition; Exchange Rate Component; Passive

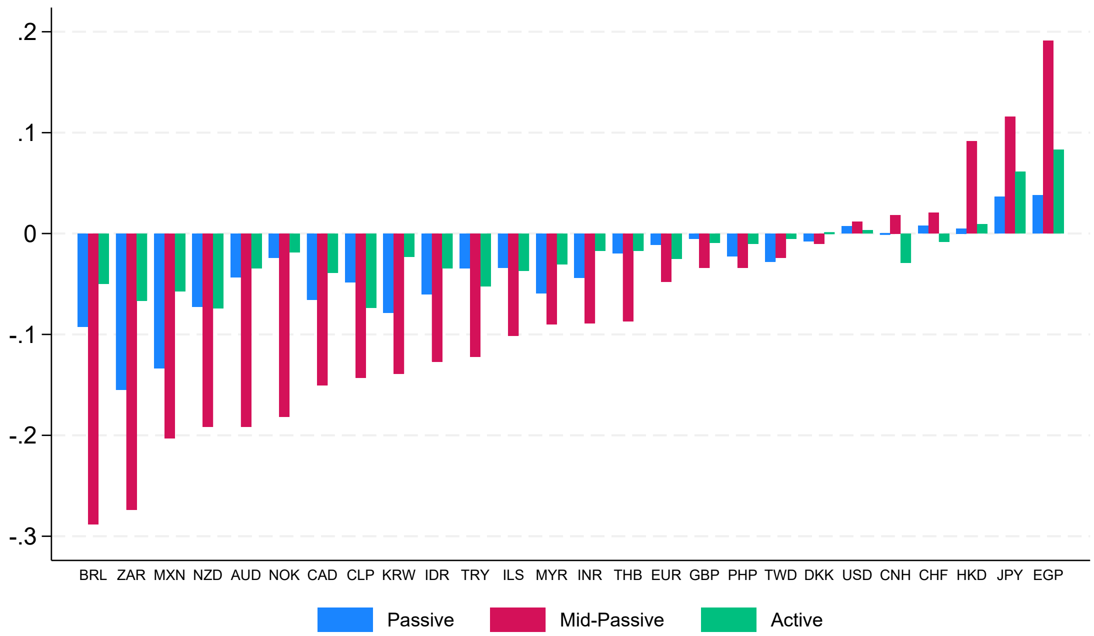


Figure 27: Log Stock Market Price Change: VCV Decomposition; Exchange Rate Component; Investment Style

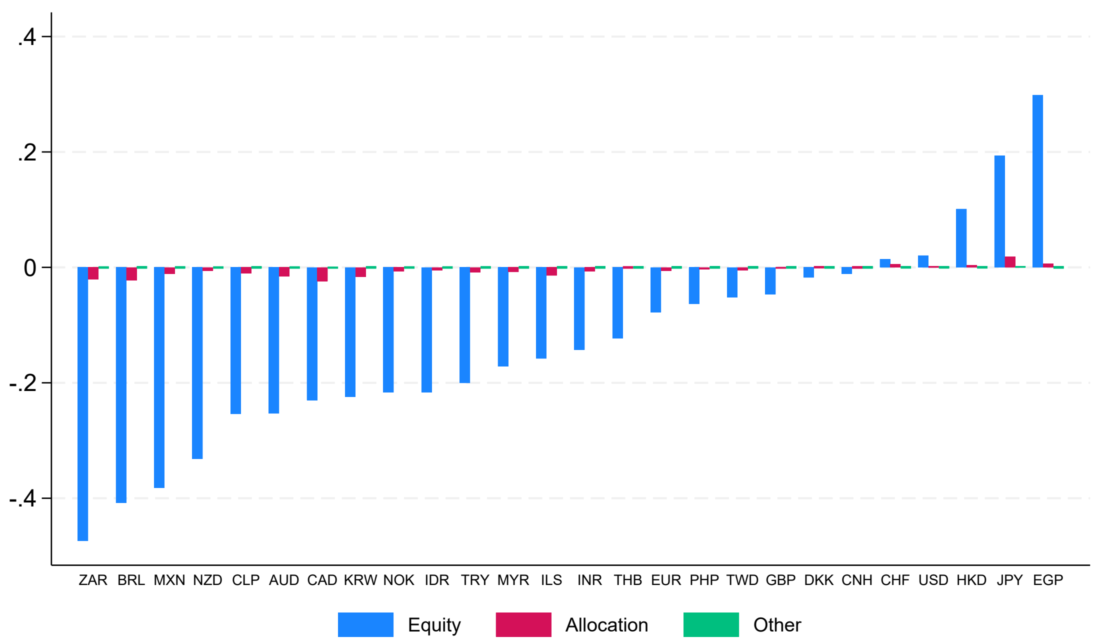


Figure 28: Log Stock Market Price Change: VCV Decomposition; Weight Rebalancing Component; ROS

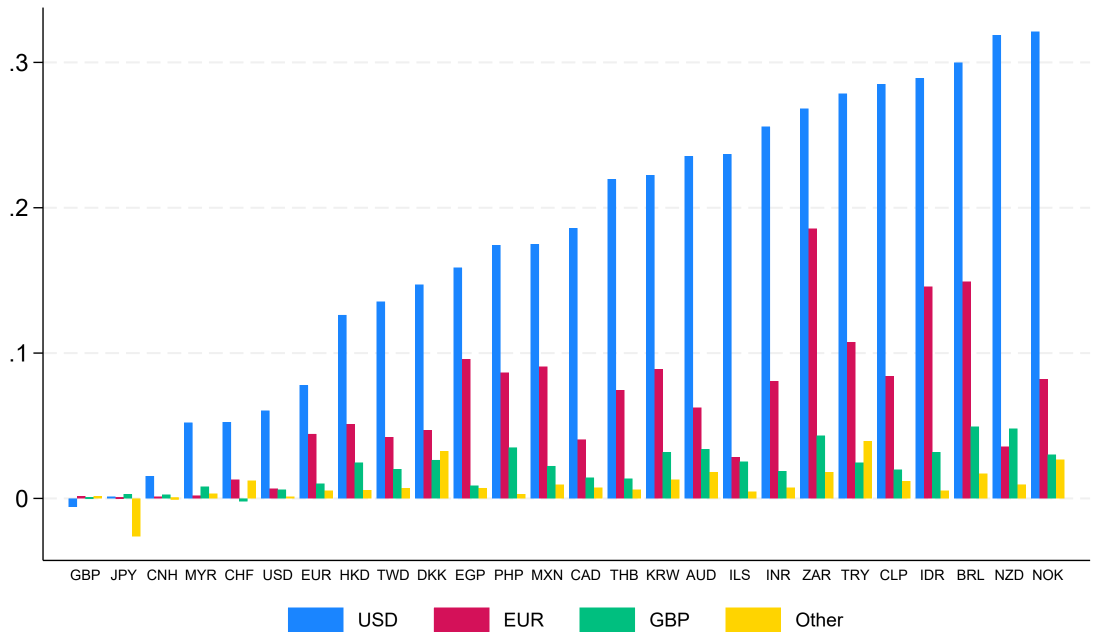


Figure 29: Log Stock Market Price Change: VCV Decomposition; Weight Rebalancing Component; Passive

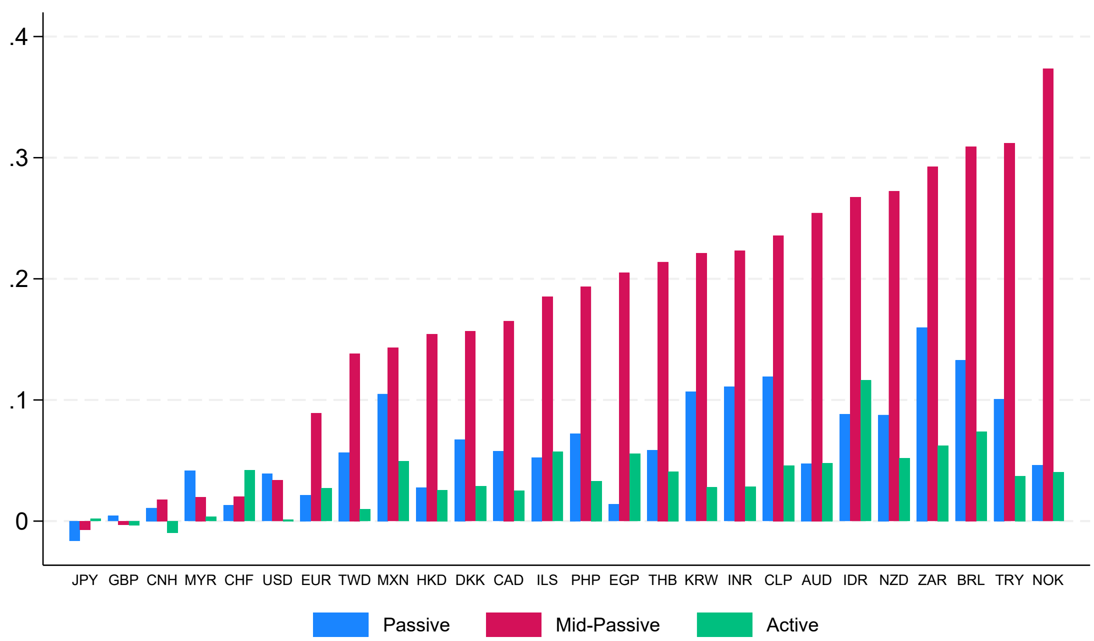


Figure 30: Log Stock Market Price Change: VCV Decomposition; Weight Rebalancing Component; Investment Style

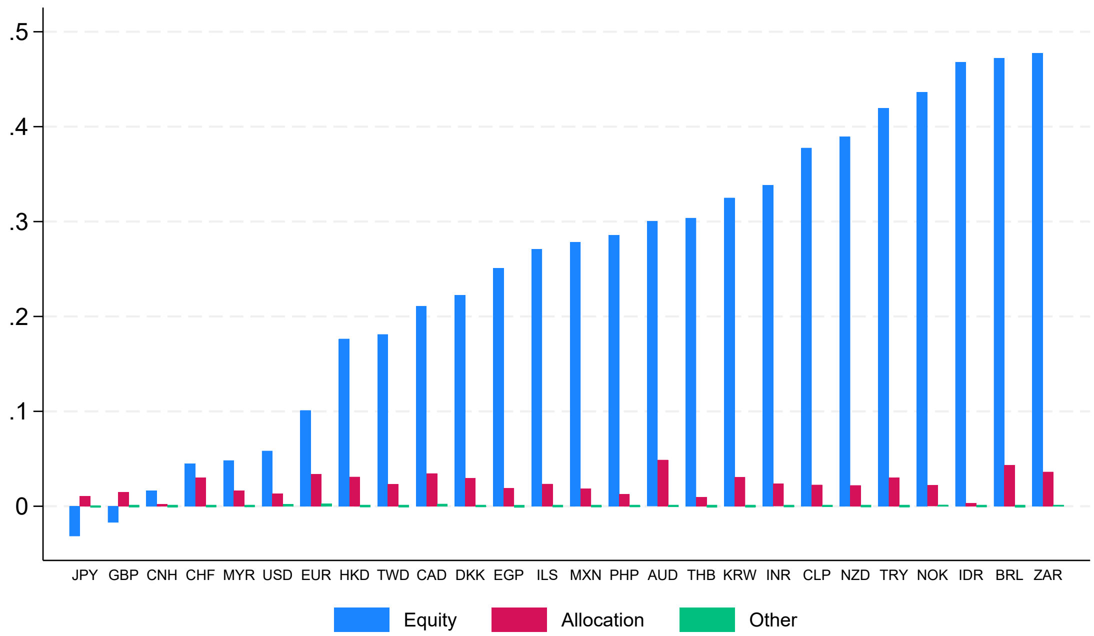


Figure 31: Log Stock Market Price Change: VCV Decomposition; Portfolio Return Component; ROS

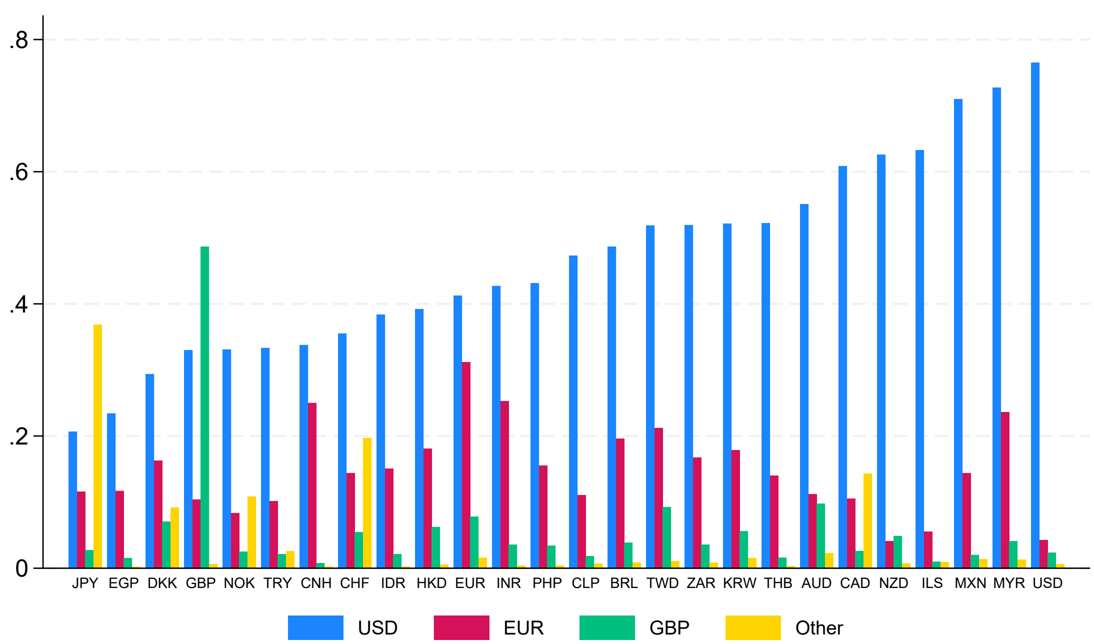


Figure 32: Log Stock Market Price Change: VCV Decomposition; Portfolio Return Component; Passive

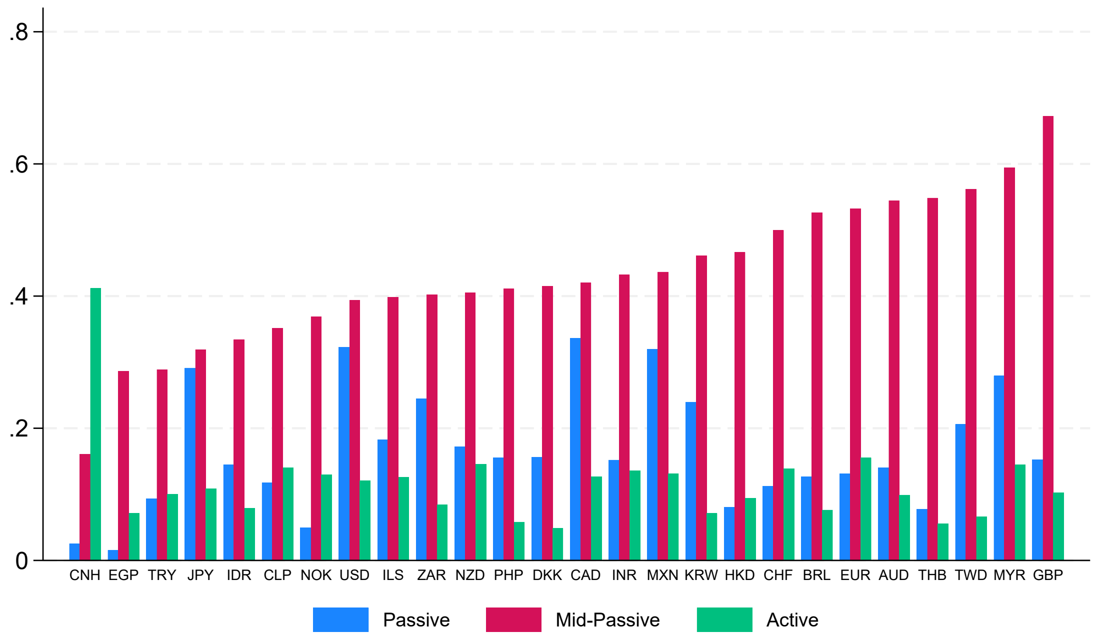


Figure 33: Log Stock Market Price Change: VCV Decomposition; Portfolio Return Component; Investment Style

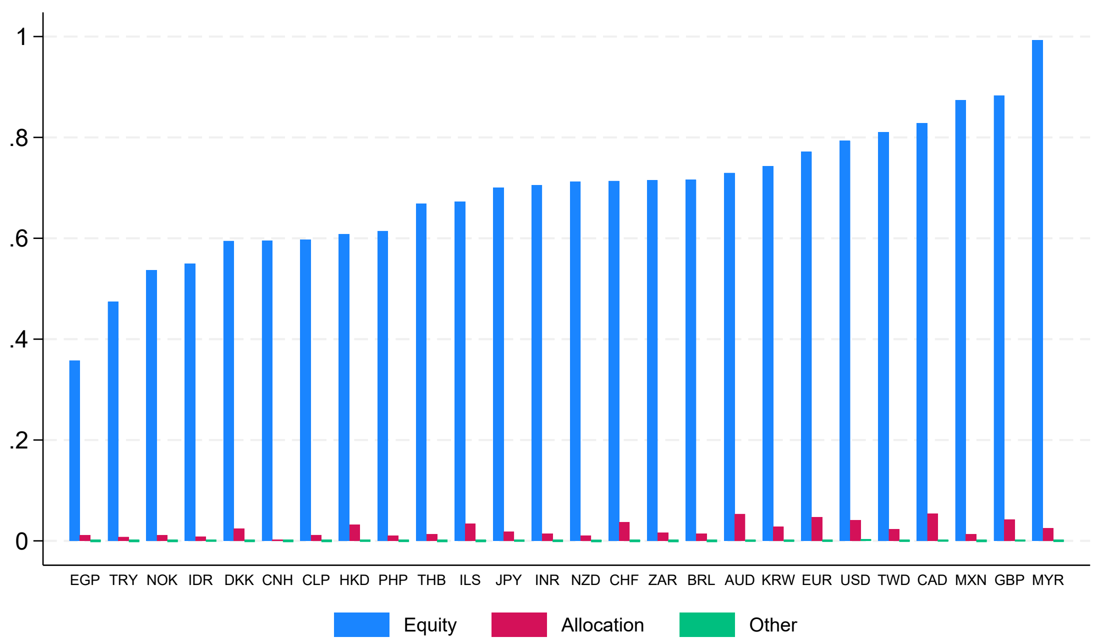


Figure 34: Log Stock Market Price Change: VCV Decomposition; Flows Component; ROS

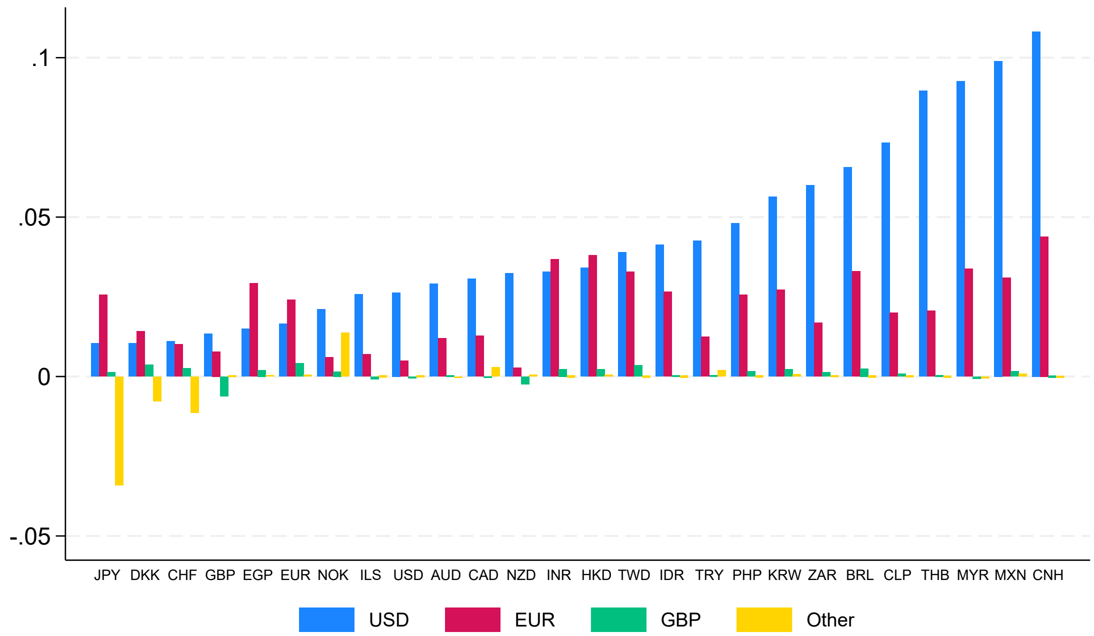


Figure 35: Log Stock Market Price Change: VCV Decomposition; Flows Component; Passive

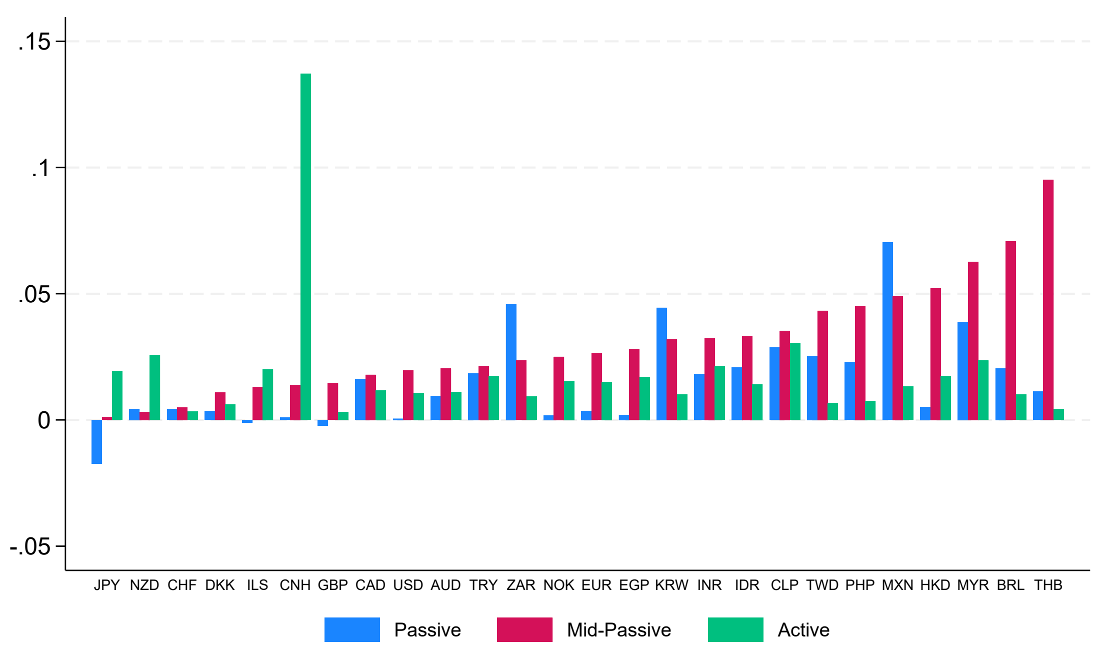


Figure 36: Log Stock Market Price Change: VCV Decomposition; Flows Component; Investment Style

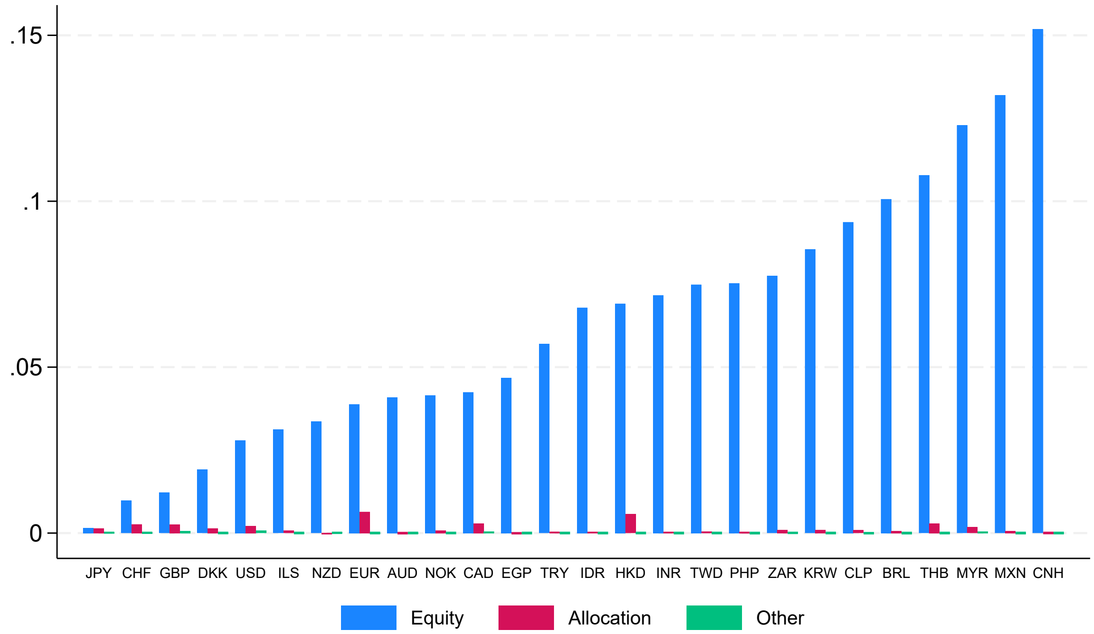
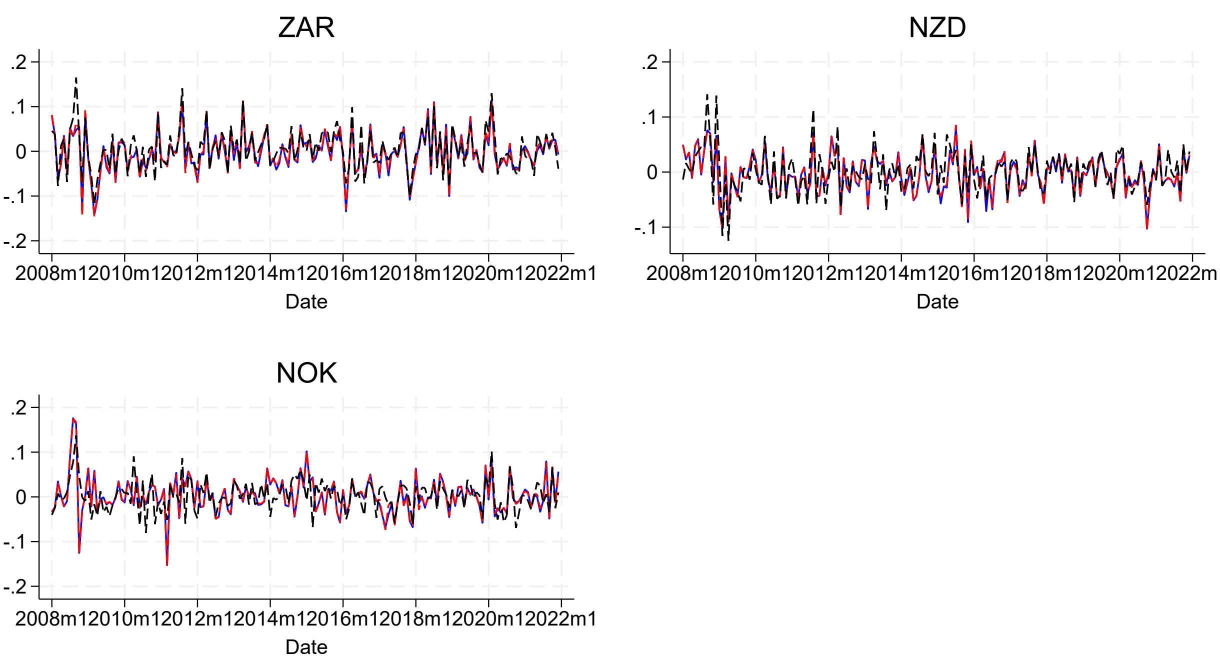
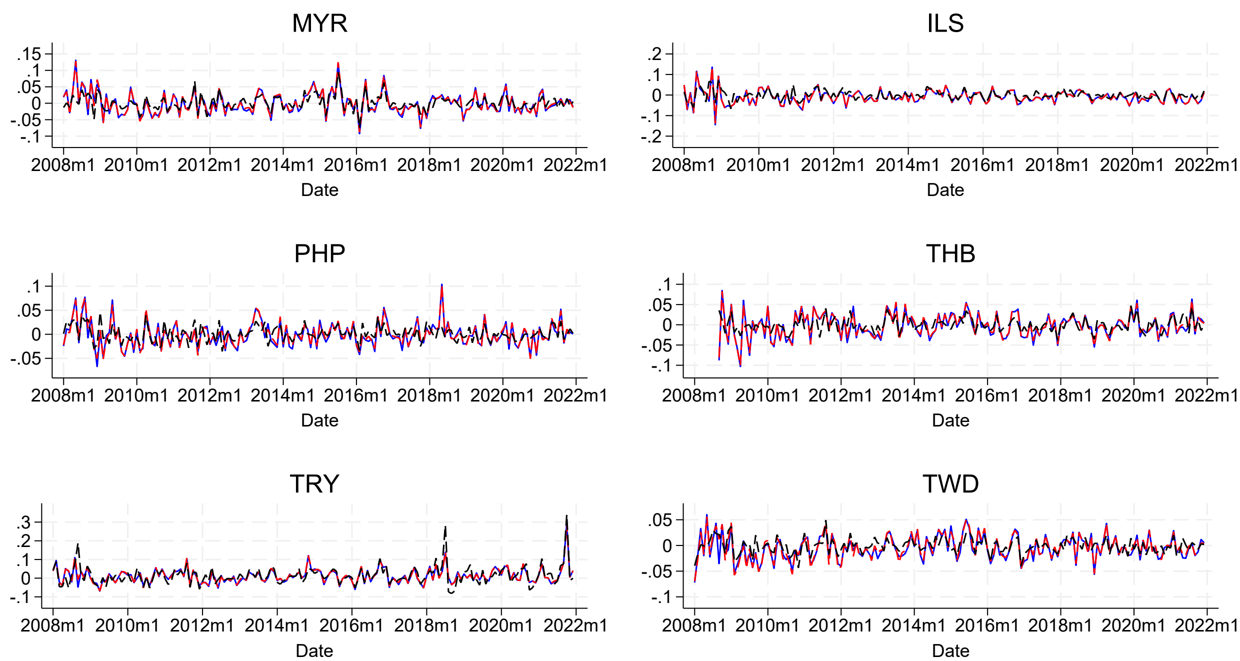


Figure 37: Exchange Rate Growth Rate vs Common Component of Demand Change



The black dashed line represents the exch rate growth rate, the solid blue line is the specification with only USD, EUR and local currency net supply while the red dashed line is the case with net USD and local supply and other exchange rates.

Figure 38: Exchange Rate Growth Rate vs Common Component of Demand Change



The black dashed line represents the exch rate growth rate, the solid blue line is the specification with only USD, EUR and local currency net supply while the red dashed line is the case with net USD and local supply and other exchange rates.

Figure 39: Exchange Rate Change: VCV Decomposition; Net Supply (LC, USD, EUR, GBP)

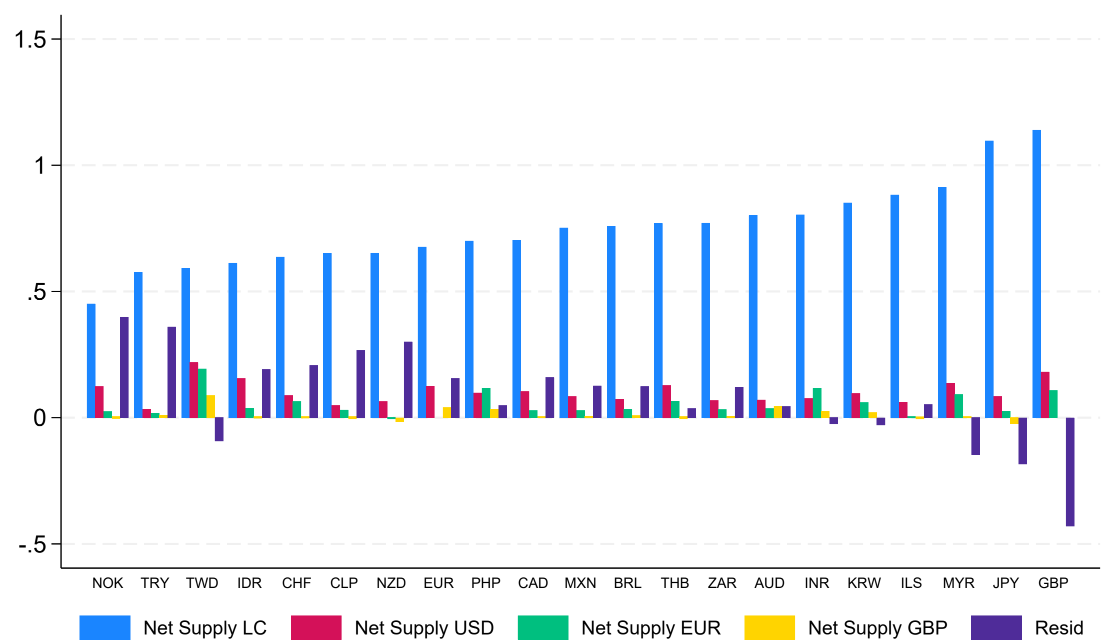


Table 9: Exchange Rate Elasticities with respect to net Supply

Currency	ϵ	ϵ_{USD}	ϵ_{EUR}	ϵ_{GBP}
AUD	1.02	-1.38	0.18	0.19
BRL	1.00	-1.43	0.33	0.10
CAD	1.19	-1.35	0.13	0.01
CHF	1.35	-1.75	0.22	0.08
CLP	1.00	-1.22	0.21	0.02
EUR	1.52	-1.70	.	0.18
GBP	1.93	-2.11	0.18	.
IDR	1.00	-1.47	0.39	0.08
ILS	1.00	-1.00	0.02	-0.01
INR	1.00	-1.54	0.43	0.11
JPY	1.51	-1.88	0.19	0.06
KRW	1.00	-1.43	0.33	0.11
MXN	1.00	-1.30	0.26	0.03
MYR	1.00	-1.38	0.30	0.07
NOK	1.23	-1.48	0.15	0.05
NZD	1.00	-1.13	0.03	0.09
PHP	1.00	-1.43	0.33	0.10
THB	1.00	-1.38	0.34	0.04
TRY	1.00	-1.33	0.27	0.06
TWD	1.00	-1.52	0.36	0.16
ZAR	1.00	-1.44	0.34	0.10

Note: We construct the average elasticities over the period Jan 2012 to Dec 2021.

Table 10: Exchange Rates Variance Covariance Decomposition: Net Supply; LC USD EUR GBP

Currency	NS_{LC}	R^2	NS_{USD}	R^2	NS_{EUR}	R^2	NS_{GBP}	R^2	$Resid$	R^2	$ShareObsComps$
AUD	0.80***	0.79	0.07***	0.05	0.04***	0.18	0.05***	0.08	0.05	0.00	0.95
BRL	0.76***	0.56	0.07***	0.08	0.03***	0.08	0.01	0.01	0.12**	0.03	0.88
CAD	0.70***	0.54	0.10***	0.05	0.03***	0.12	0.01*	0.01	0.16***	0.05	0.84
CHF	0.64***	0.49	0.09**	0.02	0.07***	0.27	0.00	-0.01	0.21***	0.08	0.79
CLP	0.65***	0.58	0.05**	0.02	0.03***	0.07	0.00	-0.01	0.27***	0.16	0.73
EUR	0.68***	0.52	0.13***	0.05	0.68***	0.52	0.04***	0.05	0.16***	0.04	0.84
GBP	1.14***	0.35	0.18***	0.06	0.11***	0.33	1.14***	0.35	-0.43***	0.06	1.43
IDR	0.61***	0.25	0.16***	0.12	0.04**	0.02	0.00	-0.01	0.19**	0.02	0.81
ILS	0.88***	0.42	0.06**	0.02	0.00	0.00	-0.00	-0.01	0.05	-0.00	0.95
INR	0.80***	0.51	0.08*	0.01	0.12***	0.11	0.03**	0.03	-0.02	-0.01	1.02
JPY	1.10***	0.39	0.09*	0.01	0.03**	0.03	-0.02***	0.03	-0.18*	0.01	1.18
KRW	0.85***	0.64	0.10***	0.07	0.06***	0.11	0.02*	0.01	-0.03	-0.00	1.03
MXN	0.75***	0.59	0.08***	0.08	0.03***	0.06	0.01**	0.02	0.13**	0.03	0.87
MYR	0.91***	0.51	0.14***	0.06	0.09***	0.13	0.00	-0.00	-0.15*	0.01	1.15
NOK	0.45***	0.16	0.12***	0.11	0.02***	0.07	0.00	-0.01	0.40***	0.13	0.60
NZD	0.65***	0.55	0.07***	0.06	-0.00	-0.00	-0.02	0.01	0.30***	0.18	0.70
PHP	0.70***	0.24	0.10	0.01	0.12***	0.10	0.03	0.01	0.05	-0.00	0.95
THB	0.77***	0.24	0.13**	0.03	0.07**	0.04	0.00	-0.01	0.04	-0.01	0.96
TRY	0.58***	0.53	0.04**	0.02	0.02***	0.04	0.01**	0.03	0.36***	0.31	0.64
TWD	0.59***	0.19	0.22***	0.05	0.19***	0.17	0.09**	0.03	-0.09	-0.00	1.09
ZAR	0.77***	0.75	0.07***	0.06	0.03***	0.06	0.01	0.00	0.12***	0.06	0.88