Capital Flows and the Making of Risky Currencies

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Abstract

A currency is considered risky if it depreciates during downturns. I show that currency risk is caused by foreign capital flows induced by heterogeneous responses of foreign and domestic investors to global shocks. I establish that foreign flows are "flighty": foreign investors withdraw capital in response to negative news. Empirically, currency risk appears to play a limited role at most in driving this flightiness. However, consistent with an explanation based on heterogeneous beliefs, I find that foreign forecasts react more strongly to news, and their returns are relatively lower. Motivated by these findings, I develop a model in which foreign investors update their beliefs more strongly to negative shocks, creating flighty foreign flows. In the model, the relative flightiness of a country's external liabilities and external assets determines its currency risk. That is, if foreign holdings of domestic assets respond more to global shocks than do domestic holdings of foreign assets, the country's currency is risky (and vice versa for safe currencies). Based on this, I construct a model-informed measure, "net asset flightiness"—the difference between external assets and liabilities weighted by their specific flightiness, which I show strongly correlates with currency risk.

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1 Introduction

Currencies differ in their exposure to global risk. Some currencies are risky as they depreciate during global downturns, while others act as a hedge as they appreciate. Given the central role of exchange rates in macrofinancial stability, it is crucial to understand the determinants of a currency's exposure to global factors. Policymakers and practitioners often attribute currency risk to capital flows, especially since capital flows move hand-in-hand with the global business cycle. However, the role capital flows may play in a currency's global risk exposure lacks theoretical and empirical underpinnings in the literature.

In this paper, I show that the heterogeneous responses of foreign and domestic investors to global shocks generate cross-border flows, which create currency risk. This inquiry proceeds in three stages.

First, I show that foreign investors are more sensitive to macroeconomic and financial news than are domestic investors: in response to negative news, foreign investors tend to withdraw capital more aggressively than domestic investors. I refer to the differential response to news between foreign and domestic investors as "foreign flightiness."

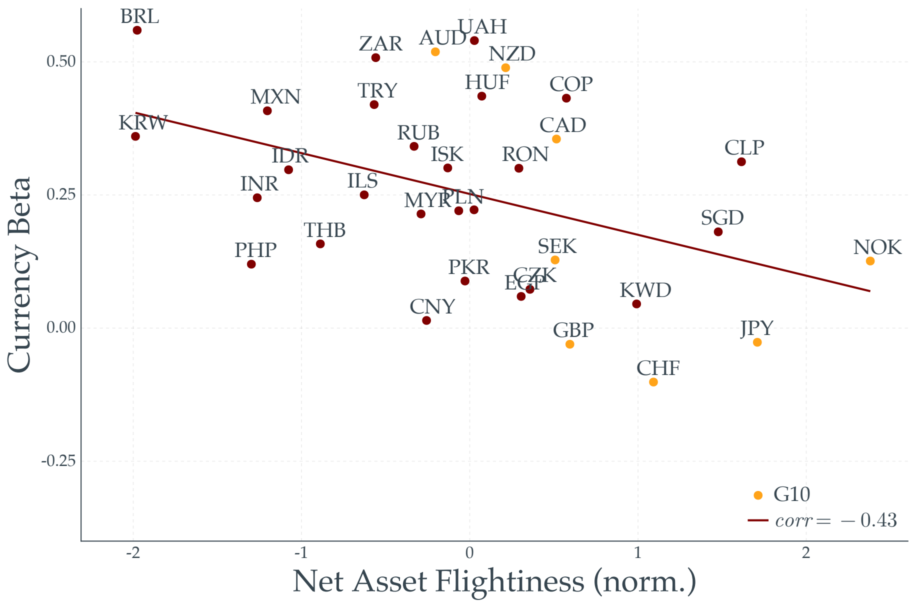
Second, I develop a model in which currency risk is determined by capital flows. In the model, a currency is risky if the country's external liabilities face flightier foreign flows than do its external assets.[1] During global downturns, if foreign investors withdraw from a country more than domestic investors retrench, the country's exchange rate must depreciate to clear the market, making its currency risky.

Third, I construct a new measure, termed *net asset flightiness*, to measure the relative flightiness of a country's external assets versus external liabilities. It is defined as the difference between a country's external assets and external liabilities, each weighted by their respective asset-specific flightiness. For example, Brazil has flightier external liabilities than external assets because its external liabilities are predominantly in equities while its external assets are largely in non-portfolio assets that are not susceptible to flighty flows. It faces net outflows upon negative news, and hence has a risky currency. Empirically, net asset flightiness has a strong negative correlation with measures of currency risk. Figure 1 displays the negative relationship in the cross-section where currency risk is measured by the beta of each currency's returns on global equity returns.

I begin with an investigation into the heterogeneous behavior of foreign and domestic investors. Using granular data on global mutual funds and ETFs, I show that foreign funds are systematically more sensitive to macroeconomic and financial news than are their domestic counterparts. In response to negative shocks, foreign funds withdraw more capital than do domestic funds, and inject more capital upon positive news. Foreign flightiness extends to risky bonds issued by advanced economies including the United States. This contrasts the conventional wis-

[1] A country's external liabilities are foreign holdings of assets issued by this country, and a country's external assets are domestic investors' holdings of assets in the rest of the world. I refer to changes in foreign holdings of domestic assets as liability flows, and changes in domestic holdings of foreign assets as asset flows. The former is also often referred to as gross inflows, and the latter is referred to as gross outflows in the international finance literature.

Figure 1: Net Asset Flightiness Strongly Correlates with Currency Beta



Notes. This figure plots currency beta against average net asset flightiness for each country. Currency beta is estimated from regressions $Re_{c,t} = \beta_c^{FX} r_t^{global} + \varepsilon_{c,t}$ between January 2000 to December 2021 at the monthly frequency, where $Re_{c,t}$ is the excess return (uncovered interest parity premium) of the currency against its reference currency, the euro for European countries and the US dollar otherwise, and r_t^{global} is the return on the MSCI world equity index. Net asset flightiness captures the relative flightiness between a country's external assets and external liabilities, constructed from countries' external balance sheet composition. Section 5 describes the methodology and robustness in detail.

dom that flighty flows are concerns mainly for emerging markets. I show that foreign flightiness is not limited to the mutual-fund sector but is also evident in aggregate flows from the Balance of Payments data, in both equity and portfolio debt flows.

I then study the origins of flighty capital flows to better understand their behavior and inform the modeling choice. One may think flighty flows are *caused by* currency risk: during downturns, foreign investors tend to avoid additional currency risk and therefore unload the assets to domestic investors. This conjecture provides an incomplete account of foreign flightiness. I find that foreign flightiness is prominent even when foreign and domestic investors are using the same currency. The most direct evidence comes from the euro area. Within the euro area where both foreign and domestic investors use the euro as the base currency, foreign funds withdraw more capital than domestic funds upon negative news. I further discuss several hypotheses for foreign flightiness in the literature, such as institutional frictions and investor types, and argue that they are not sufficient to explain foreign flightiness.

I propose an explanation of flighty foreign flows based on heterogeneous beliefs: foreign investors' beliefs are more sensitive to news than domestic investors. I provide two pieces of evidence consistent with the belief explanation. First, using cross-country forecast data, I show that foreign forecasters tend to revise their forecasts more in response to news than do domestic forecasters. Second, I show that a trading strategy following flighty capital flows underperforms relative to a buy-and-hold strategy in terms of risk-adjusted returns, indicating that flighty foreign investors are not sophisticated but instead less informed.

Based on these stylized facts on flighty capital flows, I develop a two-country general equilibrium model in which flighty capital flows induce currency risk. The model seeks to capture the following intuition: during global downturns, investors from two countries tend to withdraw capital from abroad and retrench to their home countries. The country with flightier external liabilities than external assets faces net capital outflow during downturns. Consequently, its currency depreciates to clear the market. This mechanism relies on two key model ingredients: international portfolio choice with flighty capital flows and a frictional foreign-exchange market.

To generate flighty capital flows in the model, I introduce belief heterogeneity between foreign and domestic investors. Each country is endowed with a Lucas tree that yields dividends following a mean-reverting process. Investors in both countries know the law of motion for their own domestic trees, but their perception of the long-run mean of foreign trees are influenced by recent realizations of dividends. The process for the perceived long-run mean is specified generically and can be micro-founded with several mainstream overreaction models such as learning with fading memory (Nagel & Xu, 2022) or diagnostic expectations (Bordalo, Gennaioli, La Porta, & Shleifer, 2020). More broadly, this specification captures, in a reduced-form fashion, the notion that foreign investors have more uncertain priors, and therefore update their beliefs more responsively to the news. For example, when Europe faces a negative shock, US investors lower their beliefs for the long-run mean of the European tree, and hence withdraw capital from Europe. In this way, the model generates the comovement of asset prices and foreign capital flows observed in data. If trees in two countries are subject to different degrees of foreign flightiness, then a global shock will lead to asymmetric cross-border flows, with one country receiving net portfolio inflows and the other country experiencing net portfolio outflows.

Capital flows affect the exchange rate through the balance sheet of financial intermediaries, similar to Hau and Rey (2006), Gabaix and Maggiori (2015), and Itskhoki and Mukhin (2021). In general equilibrium, net portfolio flows in trees result in net cross-border lending. For example, if US investors sell the European tree, European investors need to purchase it back, partially financed by the net borrowing from the United States. The foreign-exchange market is incomplete in this model: households can only borrow and lend in their local currencies, and cross-border lending has to be intermediated by banks with limited risk-bearing capacity. When borrowing in one currency and lending in the other, banks assume currency risk and demand a risk premium. More lending from the United States to Europe requires a higher excess return from the euro, suppressing the current exchange rate of the euro.

In summary, in the model, a country's currency is risky if the country's external liabilities face flightier flows than its external assets do. Guided by this insight from the model, I construct a new measure, *net asset flightiness,* from a country's external balance sheet to capture the relative flightiness of its external assets vs. liabilities. Net asset flightiness strongly correlates with measures of currency risk in data, as illustrated in Figure 1.

To construct net asset flightiness, I utilize cross-country variation in the external balance sheet compositions and heterogeneity in foreign flightiness across asset types. I classify assets by issuing country type (core advanced economies vs. others) and asset class (public bonds, private bonds, equities, etc.), as assets issued by countries of the same type in the same asset class face similar levels of foreign flightiness. I first estimate asset-specific foreign flightiness for each type of asset, using the Balance of Payments data pooling from all countries. I then construct net asset flightiness as the differences between external assets and external liabilities, weighted by respective asset-specific flightiness.

The methodology can be illustrated using Brazil as an example. On the external liability side, Brazil has large portfolio equities held by foreign investors. As discussed in Section 5, portfolio equities issued by emerging markets are most susceptible to flighty foreign flows. On the external asset side, although Brazil's external assets are similar in size to its external liabilities, the country holds few portfolio assets. Non-portfolio assets, such as foreign direct investment (FDI), are typically not susceptible to flighty flows. Consequently, Brazil's liability flows are flightier than its asset flows. Therefore, during downturns, foreign investors tend to withdraw from Brazil, whereas Brazilian investors tend not to retrench. This results in a net outflow pressure on the Brazilian real, which depreciates to clear the market.

I compare net asset flightiness with a range of other explanatory variables for currency risk identified in the literature. Among those explanatory variables, the net foreign asset (NFA) position is of particular interest. A country's NFA has been shown to negatively correlate with currency risk measures (Della Corte et al., 2016; Habib & Stracca, 2012). Net asset flightiness is essentially NFA weighted by asset-specific flightiness. Net asset flightiness remains robust when I control for NFA. This demonstrates the crucial role of asset-specific weighting in explaining currency risk.

Throughout the discussion above, I measure currency risk as the beta of currency on global equity. This interpretation is the closest to the spirit of the model, though the explanatory power of net asset flightiness is not limited to this choice. Currency risk can also be measured as currency loadings on risk factors constructed from currency portfolios. For example, Verdelhan (2018) shows that a large share of variation in exchange rates is explained by the carry factor and the global dollar factor. Net asset flightiness significantly explains the currency loadings on both of these factors. The literature also often uses a currency's average excess return vis-à-vis a benchmark currency as the measure of currency risk, assuming that global investors price in currency risk. I show that the risk associated with flighty capital flows is indeed priced in the currency excess return. Currencies with high net asset flightiness, on average, yield lower excess returns compared to those with low net asset flightiness.

The remainder of this paper is organized as follows. I review the related literature in the remainder of this section. In Section 2, I present stylized facts on flighty foreign capital flows. In Section 3, I propose the explanation of flighty capital flows based on heterogeneous beliefs and provide supportive evidence. In Section 4, I present my model. In Section 5, I test the model's prediction on currency risk in the data.

Literature. This paper combines several strands of the vast literature at the intersection of capital flows and currency risk.

First and foremost, this paper contributes to the literature studying currency risk determination. The mechanisms discussed in the literature generally fall into two categories, macro fundamentals and financial positions. In terms of macro fundamentals, studies have shown that factors such as country size (Hassan, 2013), commodity reserves (Ready et al., 2017a, 2017b), trade centrality (Richmond, 2019), and fiscal shocks (Jiang, 2021) are associated with low currency risk premia. Following the macro-finance tradition, the corresponding mechanisms typically rely on consumption-based stochastic discount factors. The second branch of literature seeks to explain currency risk with countries' financial positions. Empirically, studies find that overall net foreign asset (NFA) positions (Della Corte et al., 2016; Goldberg & Krogstrup, 2023; Habib & Stracca, 2012) and net dollar imbalances (Liao & Zhang, 2021; Wiriadinata, 2021) strongly correlate with currency risk; Fang (2021) develops a model linking financial intermediaries' leverage ratio to currency risk, and provides empirical evidence. The underlying mechanisms in this literature typically rely on price impacts of capital flows via financial intermediaries' balance sheets, reviewed below. Building upon this body of work, this paper introduces a novel mechanism of currency risk determination based on flighty capital flows and proposes a new explanatory variable, net asset flightiness, which demonstrates a strong correlation with currency risk.

Second, this paper contributes to the large empirical literature on the cyclical behavior of gross capital flows. Literature on capital flows traditionally focuses on net flows, which are equivalent to the current accounts, but since the Great Recession more attention has been paid to gross flows. The literature documents that gross flows are procyclical: during expansions investors invest more abroad while during contractions they retrench back home (Avdjiev et al., 2022; Broner et al., 2013; Forbes & Warnock, 2012b; Milesi-Ferretti & Tille, 2011). Recent studies show that there is a strong global factor in capital flows that closely comoves with the global factor in asset prices (Davis & van Wincoop, 2021; Davis et al., 2021; Miranda-Agrippino & Rey, 2020, 2021). This phenomenon is termed the global financial cycle. Related literature uses mutual-fund flows (to emerging markets typically) to show how fund investors and managers contribute to the global financial cycle (Converse et al., 2020; Raddatz & Schmukler, 2012). This paper contributes to the existing body of work by empirically investigating the drivers of cyclical capital flows. I show that the common conjectures—currency risk, investor type, and institutional frictions—are not sufficient in explaining foreign flow cyclicality. A strand of literature explains cyclical capital flows using heterogeneous beliefs, micro-founded either using behavioral biases or asymmetric information (Albuquerque et al., 2009; Benhima & Cordonier, 2022; Brennan & Cao, 1997). This paper aligns with this strand of literature, providing additional evidence to support this explanation. I provide a more thorough review and discussion on the origins of flow cyclicality in Section 2.

Third, this paper is connected to the large literature on the investment home bias. This literature documents a tendency among investors to disproportionately allocate assets domestically, a phenomenon at odds with standard asset-pricing models, which suggests that investors with fully mobile capital would hold a globally diversified equity portfolio (see Coeurdacier and Rey, 2013 for a thorough review). The home bias literature focuses on the level of foreign investments while my findings focus on the sensitivity of foreign investments to news. Related to the home bias literature, my findings on flighty capital flows suggest that home bias is countercyclical: during booms investors tend to invest abroad more than during busts. Several studies in the home bias literature show that part of home bias can be explained by heterogeneous beliefs between domestic and foreign investors (Bekaert & Wang, 2009; Dumas et al., 2017; Gehrig, 1993; Portes & Rey, 2005; Van Nieuwerburgh & Veldkamp, 2009). Consistent with this perspective, my paper also link heterogeneous beliefs to the observed countercyclical home bias.

Finally, this paper builds on the literature of the price impacts of international capital flows. In empirical studies, research on demand elasticities in the foreign-exchange market consistently indicates that the currency market is highly inelastic: an average of 2–10 billion USD is sufficient to move exchange rates by 1% in weekly to quarterly windows (Beltran & He, 2023; Camanho et al., 2022; Hau et al., 2010). Recent theoretical development in the literature recognizes the price impacts of capital flows (Camanho et al., 2022; Gabaix & Maggiori, 2015; Hau & Rey, 2006; Itskhoki & Mukhin, 2021), and my model follows the same vein. The closest to my model are Hau and Rey (2006) and Camanho et al. (2022), who develop an international portfolio choice model where portfolio flows are assumed to have price impacts on exchange rates. Building upon this model, I close it in the general equilibrium framework with modeling techniques taken from Gabaix and Maggiori (2015). In my model, net portfolio flows are financed by net cross-border lending via financial intermediaries. Financial intermediaries have limited risk-bearing capacity and demand higher returns for higher cross-border lending, consequently lowering the spot exchange rate. Itskhoki and Mukhin (2021) also employ a similar modeling technique, arguing that exchange-rate movements are largely caused by financial shocks, modeled as noise traders in their paper. My model offers one concrete source of those financial shocks: flighty capital flows.

2 Stylized Facts on Flighty Capital Flows

I study heterogeneous responses in foreign and domestic flows to macrofinancial news. Specifically, in this section, I study the following regression of the differences in foreign and domestic flows on macroeconomic and financial news under various specifications:

$$f_t^{foreign} - f_t^{domestic} = \underbrace{(\theta^{foreign} - \theta^{domestic})}_{\Delta\theta} \times \text{Macro\&Financial news}_t + \varepsilon_t,$$

where $\Delta\theta$ is the coefficient of interest, $f_t^{foreign}$ and $f_t^{domestic}$ are flows from the foreign and domestic investors, respectively, defined as the changes in portfolio holdings, expressed percentages as total assets under management (AUM), and I use various proxies for macroeconomic and financial news in the paper, such as the equity market returns and volatility measures.

I show that foreign flows are "flighty" ($\Delta\theta > 0$): their investment positions are more sensitive to macrofinancial news than those of domestic investors. I first demonstrate foreign flightiness within the investment-fund sector, followed by evidence that the same pattern is also salient at the aggregate level. Exploiting comprehensive data from the fund sector, I further show that these flighty foreign flows cannot be solely attributed to currency risk, and are also prevalent among retail investors. I conclude this section with a discussion of potential explanations.

2.1 Data, Notations, and Definitions

I use data on global mutual funds and exchange-listed funds (ETFs) to study the heterogeneous responses of foreign flows and domestic flows. Investment funds are a natural candidate to study foreign flightiness: first, investment funds play a significant role in global foreign portfolio investments, constituting around 50% of global foreign portfolio investment as of 2021, according to the Coordinated Portfolio Investment Survey (CPIS) by International Monetary Fund (IMF);[2] second, investment funds are commonly considered "weak-hand" investors, who are prone to quickly liquidate their investments in times of market-wide distress (Chari, 2023; Coppola, 2022; Zhou, 2023); finally, detailed micro-level information on fund holdings allows me to control for alternative hypotheses to investigate the origin of foreign flightiness. The recent literature on international finance also increasingly utilizes fund data to investigate global asset allocation.[3] It is worth noting that even though I focus on fund flows in this section, foreign flightiness is not limited to investment funds. After presenting the baseline results from funds, I demonstrate that foreign flightiness is also observed in aggregate capital flows.

The major dataset used in this section is the global mutual fund and ETFs data from Morningstar, Inc. Morningstar is one of the world's largest providers of investment research to the asset-management industry. They collect self-reported data from fund managers on detailed portfolio allocation, fund flows, and investment performance, on a monthly or at least quarterly basis. This data set is similar to data used in Maggiori et al. (2020) and Coppola et al. (2021). In the main text, I use a sample that covers all fixed-income funds and allocation funds around the world between 2005Q1 to 2020Q3 at the quarterly frequency. As shown in the literature, portfolio debt flows are more closely linked to global factors than equity flows (Forbes & Warnock, 2012a; Lilley et al., 2020). This sample allows me to observe fund positions at the security level and related security information, such as the country of security issuance and currency denomination. Appendix A.1 reports the global coverage of my sample. The sample coverage is overall extensive for funds domiciled in advanced economies, although less extensive for those in emerging mar-

[2]This is computed as the share of the "Other Financial Institutions: Others" sector in total foreign portfolio investments. This sector excludes deposit-taking institutions, insurance companies and pension funds and money-market funds, and units controlled by general governments. This sector may include open-ended funds, close-ended funds, exchange-listed funds, etc.

[3]Notable studies in this domain include Beck et al. (2023), Camanho et al. (2022), Chari (2023), Chari et al. (2022), Converse and Mallucci (2019), Converse et al. (2020), Coppola (2022), Coppola et al. (2021), Jotikasthira et al. (2012), Maggiori et al. (2020), and Raddatz and Schmukler (2012).

kets.[4] For equity-only funds, my sample does not include positions at the security level. Instead, I observe fund investor flows at the fund level and the portfolio composition at the regional level. In Appendix A.5 I show equity fund investors also exhibit foreign flightiness.

Inflow and outflow countries. The inflow country is defined as the country that incurs additional external liabilities (the recipient of capital flows), and the outflow country is defined as the country that accumulates additional external assets (the provider of capital). Consistent with this definition, for each investment in my sample—for example, fund i holding asset s—I define the domicile of the fund as the outflow country, the issuing country of the security as the inflow country. Therefore, an investment is foreign if and only if the domicile of the fund is not the same as the issuing country of the security. For instance, consider a US-domiciled fund holding a corporate bond issued by a French firm. In this example, the US is considered the outflow country, and France is the inflow country.

There are concerns about whether domiciles and the countries of issuance accurately reflect the sources and destinations of flows. Here, I provide a short discussion on how I address these issues.

For the outflow countries, I assume that domiciles represent the sources of flows. As argued by Maggiori et al. (2020), tax optimization and regulatory restrictions make it unlikely that investors invest in mutual funds domiciled in other countries. They also show that cross-border investment in mutual-fund shares between the US and the rest of the world is generally very small. Two countries, Ireland and Luxembourg, are the exceptions, as they serve as the onshore offshore financial centers (OOFCs) for the euro area (Beck et al., 2023). Both countries receive disproportionately large foreign investments in mutual-fund shares. For the baseline, I consider the investment from Luxembourg and Ireland to other countries as foreign investment. This is because unlike domestic-focused funds, few funds in these financial centers specialize in one particular country. Instead, funds domiciled in Luxembourg and Ireland typically diversify their portfolio globally. In this sense, they are more similar to global-investing funds instead of domestic funds. See Appendix A.2 for a more detailed discussion. My results are not driven by funds domiciled in onshore offshore offshore financial centers: excluding financial hubs from the analysis yields results that are consistent with the baseline.

I rely on fund managers' self-reports to identify the countries receiving inflows. In Morningstar's survey, fund managers are asked to specify the country for each security they hold to gauge the global risk exposure of the fund. Therefore, mutual-fund managers typically report the issuer's nationality instead of the country of legal registration. This human input helps to mitigate the concern of security issuance in tax-haven countries. When multiple funds report different nationalities of a single CUSIP, I use the most frequently reported non-tax-haven country as the nationality of the security. This practice and tax haven classification follows Coppola et al. (2021)

[4] The major advanced economy that is missing from the fund-level analysis is Japan. Japanese-domiciled funds are not included in my sample as they have an irregular reporting schedule to Morningstar. Japan is included in the analysis at the aggregate level.

in their study of corporate issuance in tax havens.

Flows. For every fund indexed by i, I observe the quantity of its holding in security s at the quarter end of t, denoted as $Q_{i,s,t}$ along with the associated price $P_{i,s,t}$.[5] For every security, I also observe the country of the issuer c. Therefore, the flow into country c's bond market from fund i over the quarter t can be computed as:

$$\begin{aligned} f_{i,c,t} &\equiv \frac{F_{i,c,t}}{\hat{A}_{i,c,t}} \\ F_{i,c,t} &\equiv \sum_{s\in c} \left(Q_{i,s,t} - Q_{i,s,t-1}\right) P_{s,t-1} \\ \hat{A}_{i,c,t} &\equiv \sum_{s\in c} \frac{Q_{i,s,t} + Q_{i,s,t-1}}{2} P_{s,t-1}, \end{aligned}$$

where $F_{i,c,t}$ represents the dollar flow, computed as total changes in holdings in country c weighted by the prices in the previous quarter, the notation $s \in c$ indicates that security s is issued in country c, and $\hat{A}_{i,c,t}$ is a measure of total assets under management of the fund i in this country. I use average holdings across two periods to mitigate the impact of outliers. This flow measure resembles the Davis-Haltiwanger (1992) growth rate. The findings remain robust when employing the standard growth rate coupled with winsorization.

It is worth noting that valuation effect does not enter this flow measure, since I use the same price in both the numerator and the denominator. The flow measure is non-zero only when the fund actively changes its positions in the given country ($Q_{i,s,t} \neq Q_{i,s,t-1}$).

The flow measure can also be aggregated to the country level. Inflows to country c's bond market from foreign and domestic funds in quarter t are constructed as:

$$f_{c,t}^{foreign} \equiv \frac{\sum_{i\notin c} \hat{A}_{i,c,t} f_{i,c,t}}{\sum_{i\notin c} \hat{A}_{i,c,t}} \tag{2.1}$$

$$f_{c,t}^{domestic} \equiv \frac{\sum_{i\in c} \hat{A}_{i,c,t} f_{i,c,t}}{\sum_{i\in c} \hat{A}_{i,c,t}}, \tag{2.2}$$

where the notation $i \in c$ indicates that fund i's domicile is country c.

Proxies for macrofinancial news. To study the differential responses to macrofinancial news by foreign and domestic flows, I need proxies for macrofinancial news for each country. As a baseline, I use local stock-market returns denominated in local currencies as the proxy. There are several considerations behind this choice. First, stock-market returns are timely and forward-looking, capturing investors' real-time perception. Second, they are widely available for all countries in the sample. Finally, this choice is also consistent with the model in Section 4, which predicts

[5]For every security in their portfolio, funds report the quantity of their holdings and their market values. From this information I compute the price per unit of the security.

that foreign flows are positively correlated with returns. Admittedly, stock-market returns are imperfect measures for macrofinancial news. A prevalent concern pertains to the endogeneity between equity returns and flows. I discuss this concern in detail after introducing my empirical strategy.

In addition to stock-market returns, I employ alternative measures as proxies for macrofinancial news. These alternative measures include: 1) the innovations to the realized volatility of stock-market returns; 2) text-based uncertainty measures constructed from earning calls (Hassan et al., 2021); 3) revisions to GDP growth forecasts by global forecasters. My results are robust to these alternative measures. Stock-market returns are retrieved from Global Financial Data, the text-based uncertainty measures are estimated by Hassan et al. (2021), and the forecast revisions are obtained from Consensus Economics. All series are at the quarterly frequency, and I use the periods between 2005Q1–2021Q3 whenever available.

2.2 Flighty Capital Flows at the Country Level

I show that foreign investors are more sensitive to macrofinancial news than domestic investors. I first establish this fact at the country level using the following specification. For each inflow country c, I perform the following regression:

$$f_{c,t}^{foreign} - f_{c,t}^{domestic} = \Delta\theta_c \times r_{c,t} + \beta_c + \varepsilon_{c,t}, \tag{2.3}$$

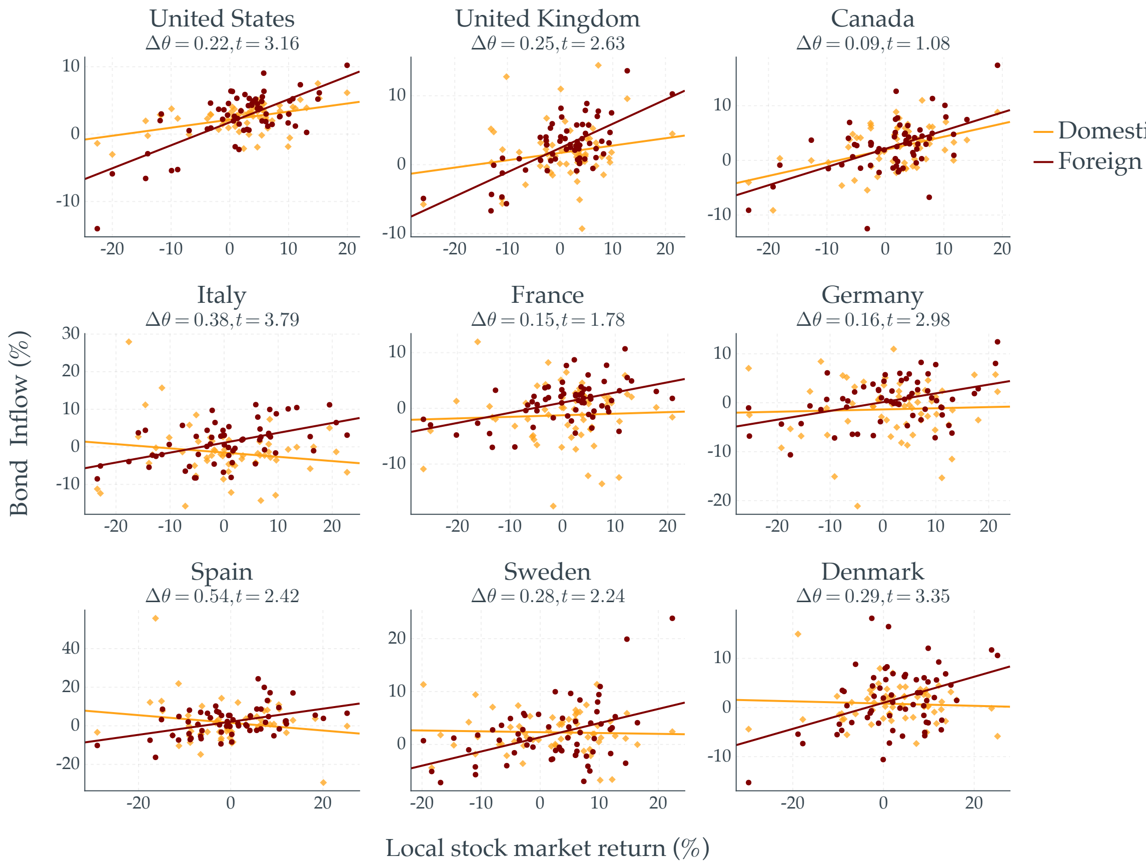
where $f_{c,t}^{foreign}$ and $f_{c,t}^{domestic}$ are flows into country c's bond market from foreign funds and domestic funds respectively, as defined in Equations (2.1) and (2.2), $r_{c,t}$ is the stock-market return in country c in the local currency, and $\Delta\theta_c$ is the coefficient of interest, capturing higher sensitivity of foreign flows relative to domestic flows.

Regression (2.3) is visualized in Figure 2. This figure plots the flows from both foreign and domestic funds against the stock-market returns, into the 9 largest countries in my sample. Take the United States (the top-left panel) as an example. Each dot represents the flow in a given quarter into the US bond market. The red dot represents $f_{c,t}^{foreign}$, flows from non-US countries to the US, while the orange dot represents $f_{c,t}^{domestic}$, inflows from domestic funds to the US bond market. Positive slopes show that during adverse conditions fund flows to the US bond market drop and even turn negative. The foreign line (red) exhibits a steeper slope than the domestic line (orange) ($\Delta\theta > 0$), indicating foreign funds are more sensitive, or "flighty," in response to macrofinancial news than are domestic funds. This pattern is observable in all countries in the figure. In most countries, these differences in sensitivities are statistically significant.[6]

One may be concerned that returns are *caused by* flows. Notice that the focus of this exercise is on heterogeneous slopes between domestic and foreign investors, $\Delta\theta$, while not taking a strong interpretation of the slope of either line. If foreign and domestic funds are homogeneous, then

[6]The standard errors here are computed from Newey and West (1994) with automatically chosen bandwidths. Results are robust to block bootstrapping with alternative block lengths.

Figure 2: Inflows from Foreign and Domestic Investors and Stock Market Returns



Notes. This figure presents domestic (orange) and foreign (red) inflows into the bond market of the 9 largest inflow countries against local stock-market returns in local currencies. Flows are defined in Equations (2.1) and (2.2). The coefficient $\Delta\theta$ under the subtitle of each panel reports the estimate from Equation (2.3) for each country. A positive $\Delta\theta$ indicates a larger slope for foreign flows. Standard errors are estimated using Newey and West (1987) HAC standard errors, with bandwidths chosen automatically following Newey and West (1994).

I should not be able to detect significant differences in slopes, regardless of the causes. Further concern may be raised that the heterogeneous slopes can be explained by the greater price impacts from foreign flows compared to domestic flows, rather than by higher foreign flightiness. This concern can be addressed with proxies unrelated to asset prices such as the GDP growth revision or text-based risk measures, reported in Table 11 in Appendix. The results are robust to these alternative measures.

2.3 Flighty Capital Flows at the Fund Level

I proceed with regressions at the fund level to allow for more flexible controls. As a baseline, I regress fund-level flows on stock-market returns, allowing for different slopes between domestic and foreign flows, as specified in Equation (2.4):

$$f_{i,c,t} = \left(\theta^{domestic} + \Delta\theta \times \mathbb{I}_{i \notin c}^{foreign}\right) \times r_{c,t} + \beta_{control} \cdot X_{i,c,t} + \delta_{d(i)} + \delta_c + \varepsilon_{i,c,t}. \tag{2.4}$$

The foreign indicator function $\mathbb{I}_{i \notin c}^{foreign}$ equals 1 if the fund i is not domiciled in country c, and 0 otherwise. I control for fund sizes, fund past returns, and lagged flows to account for the return-chasing behavior and auto-correlations in flows. I also include outflow country (domicile) fixed effects $\delta_{d(i)}$ and inflow country fixed effects δ_c in the baseline specification.

Column (1) of Table 1 reports estimates of Equation (2.4) pooling from all funds. A one percent increase in the local stock-market return is associated with a 6.4 bps increase in domestic fund inflows, but a 19.4 (13+6.4) bps increase in foreign fund inflows. The estimate of $\Delta\theta$ is statistically and economically significant. Standard errors are two-way clustered at the inflow country level and the quarter level whenever feasible.

I show that foreign flighty flows are most salient in risky assets. Columns (2) and (3) split the flows into safe bond flows and risky bond flows. Safe bonds are defined as sovereign bonds issued by core advanced economies, while all private bonds and emerging-market sovereign bonds are considered risky.[7] For instance, if a fund domiciled in the United Kingdom invests in US Treasuries as well as corporate bonds, its total flows to the US enter in Column (1), its flows to Treasuries enter Column (2), and its flows to corporate bonds are included Column (3). Column (2) shows that for safe bond flows, foreign investors are no more sensitive than domestic investors. The estimate of $\Delta\theta$ is close to 0 and statistically insignificant. Column (3) shows that foreign flightiness is driven by risky assets.

One conjecture for foreign flightiness is that foreign and domestic investors are two different types of investors with different risk preferences.[8] In Column (4) I show that foreign flightiness persists even when conditioning on the same fund. I employ the following regression specification:

$$f_{i,c,t} = \left(\theta_i^{fund} + \theta_c^{country} + \Delta\theta \times \mathbb{I}_{i \notin c}^{foreign}\right) \times r_{c,t} + \beta_{control} \cdot X_{i,c,t} + \delta_{i,c} + \varepsilon_{i,c,t}, \tag{2.5}$$

where I allow for the baseline sensitivity to be fund-specific θ_i^{fund} and inflow country-specific $\theta_c^{country}$ by including interaction terms between fund fixed effects and $r_{c,t}$, as well as country fixed effects and $r_{c,t}$. This specification utilizes the within-fund variation of funds that invest both in foreign and domestic markets. For example, consider a fund domiciled in the UK investing both in the UK as well as foreign markets such as the US. This specification studies whether the fund's positions in the US are more responsive to US stock-market returns than its domestic positions are to UK stock-market returns. The coefficient $\Delta\theta$ represents the average additional sensitivity of foreign flows compared to domestic flows, *conditional on the same fund*. The estimate for the new specification is close to that in Column (1) and statistically significant.

I report in Table 11 in the appendix the same regression with alternative proxies for macrofinancial news, including innovations to the realized volatility of stock-market returns, the consensus revisions to GDP forecasts, and text-based uncertainty measures. The results above are robust

[7] These countries are AUS, CAN, DNK, DEU, LUX, NLD, NOR, SGP, SWE, CHE, AUT, FIN, USA, NZL, FRA, KOR, BEL, GBR. These countries are also the countries whose credit ratings are AA or higher as of 2022Q4, according to Standard & Poor's.

[8] For example, Davis and van Wincoop (2021) take this modeling approach to generate cyclical capital flows as in global financial cycles.

Table 1: Flow Sensitivity to Stock-market Returns by Foreign and Domestic Investors

	$f_{i,c,t}$			
	(1)	(2)	(3)	(4)
$r_{c,t}$	0.064	0.101	0.072	
	(0.038)	(0.105)	(0.038)	
$r_{c,t} \times I_{foreign}$	0.130**	-0.007	0.132*	0.115*
	(0.047)	(0.073)	(0.049)	(0.050)
Out. Country FE	Yes	Yes	Yes	
In. Country FE	Yes	Yes	Yes	
In. country-specific θ				Yes
Fund-specific θ				Yes
Fund $\times$ In. Country FE				Yes
Sample	All	Safe	Risky	All
Controls	Yes	Yes	Yes	Yes
N	1,867,566	424,267	1,721,593	1,862,384

Notes. Columns (1)-(3) report the estimates of the regression specification in Equation (2.4). The left-hand variable is flows by fund i into country c at quarter t; the key right-hand variables are country-specific stock-market returns in local currencies, and the interaction term with the foreign indicator. Control variables include fund sizes, fund past returns, and lagged fund flows. Column (1) uses the full sample. Columns (2)-(3) split flows into safe-bond flows and risky-bond flows. Safe bonds are defined as sovereign bonds issued by core advanced economies (AUS, CAN, DNK, DEU, LUX, NLD, NOR, SGP, SWE, CHE, AUT, FIN, USA, NZL, FRA, KOR, BEL and GBR), and the rest are risky bonds. As some funds holds both safe bonds and risky bonds from the same country, those fund-country pairs enter both Columns (2) and (3). Column (4) reports the estimates of specification in Equation (2.5). The coefficient of $r_{c,t}$ is absorbed by country and fund-specific slopes. Standard errors are two-way clustered at the quarter level and the inflow country level, and are reported in parentheses. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

to these alternative measures.

Global shocks vs. local shocks. In the preceding discussions, I have not distinguished between local shocks and global shocks. Empirically, in an increasingly financially connected world, it is challenging to cleanly isolate pure local shocks from global shocks, particularly for advanced economies. Within the period of my sample, the Great Recession, the Euro Crisis, and Brexit all originated from one economy (or region) but turned into global turmoil with heightened uncertainty and a dimmed economic outlook. This empirical challenge has theoretical roots. As the model below illustrates, flighty capital flows can transmit local shocks in one country to another country's asset market, and therefore generate patterns in asset prices and capital flows just like a global financial cycle.

With these caveats, the literature on capital flows does find that foreign inflows drop during both local and global crises (e.g., Broner et al., 2013). Here, I also show that foreign flightiness is observed for both global and local shocks. I use global stock-market returns and the country return residuals that are orthogonal to the first principal component of global returns to proxy global and local shocks, respectively. Appendix Table 13 reports estimates of Equation (2.4) using global and local shocks. The results are robust to both specifications. This finding is also consistent with my model, which predicts foreign flows are flighty regardless of the source of the shock.

2.4 Flighty Capital Flows in the Aggregate Data

In the exercises above, I compare foreign fund flows against domestic fund flows and show that foreign investors are more sensitive to news than domestic investors. However, to derive implications for currency risk, it is essential that similar patterns are observed not only within the investment fund sector but also at the aggregate level. Here, I present the patterns in the aggregate capital flows, and discuss in detail how it connects to currency risk in Section 5.

Figure 3 plots foreign portfolio flows aggregated across all countries for each quarter on the y axis, with the MSCI global equity returns plotted on the x axis. Global aggregate foreign portfolio flows are defined as:

$$f_{agg,t}^{foreign} \equiv \frac{\sum_c F_{c,t}^{foreign}}{\sum_c A_{c,t-1}^{foreign}},$$

where $F_{c,t}^{foreign}$ is aggregate foreign portfolio dollar inflows into country c, including both portfolio equity flows and portfolio debt flows, and $A_{c,t}^{foreign}$ is total foreign portfolio investment in country c (the country's external portfolio liability). All variables are measured from the Balance of Payment (BOP) and the International Investment Position (IIP) from the IMF.

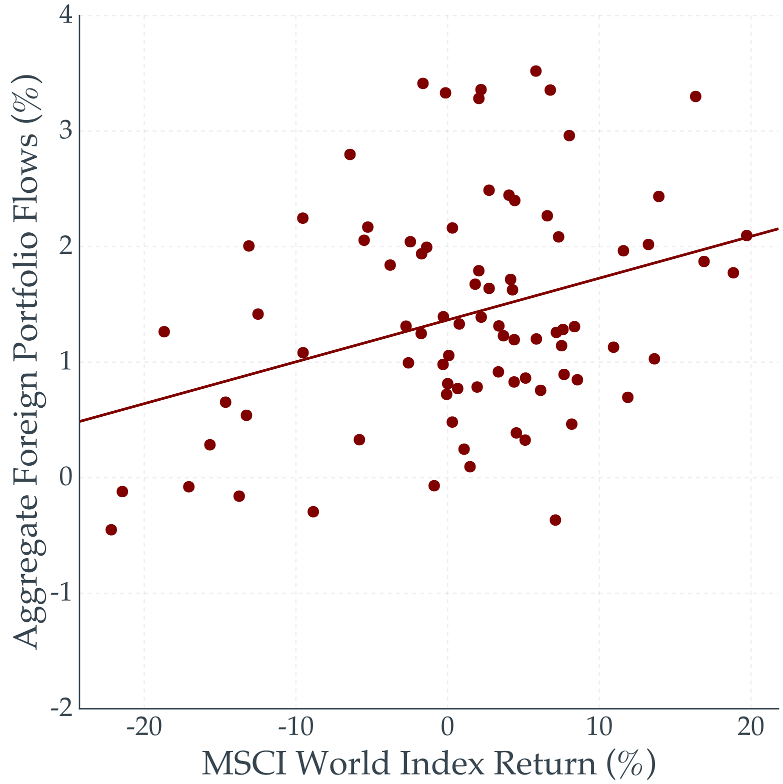
Similar to the fund results, foreign inflows are positively correlated with global stock-market returns. Different from the fund flow results, the aggregate domestic flows are typically not observed for most countries. However, assuming a constant supply in the short run, market clearing requires that positive aggregate foreign flows must be accompanied with negative domestic flows.[9] Therefore, a positive slope in aggregate foreign flows ($\theta^{foreign} > 0$) implies a negative slope in aggregate domestic flows ($\theta^{domestic} < 0$) and hence foreign flightiness ($\Delta\theta > 0$).

As further discussed in Section 5 where I estimate foreign flightiness by asset type, aggregate foreign flightiness is not driven by specific countries or asset classes, but is robustly observed across countries and asset classes.

However, there are inherent limitations with aggregate data. As these aggregate measures lump together all types of investors, they obscure the key heterogeneity between foreign and domestic investors that drives foreign flightiness. Crucially for the purpose of this paper, from aggregate observations it is unclear whether flighty foreign flows result from currency risk: as foreign investors are often exposed to currency mismatch, they tend to reduce their risk exposure during downturns by offloading assets exposed to currency risk to domestic investors. Yet, distinguishing between different explanations is important, as they suggest different underlying

[9] The assumption of fixed supply may not always hold, for example, if governments issue public debt to finance fiscal stimulus upon adverse shocks. I address this concern in Section 5 by adjusting for supply-driven debt flows.

Figure 3: Global Foreign Portfolio Flows and Global Equity Returns



Notes. This figure plots global foreign portfolio flows across the world, against the MSCI global equity return at the quarterly frequency from 2000Q1–2020Q4. Global foreign portfolio flows are computed as the $f_t^{foreign} \equiv \frac{\sum_c F_{c,t}^{foreign}}{\sum_c A_{c,t}^{foreign}}$, the total dollar inflows normalized by total foreign assets under management, summed across all countries where data are available. $F_{c,t}^{foreign}$ and $A_{c,t}^{foreign}$ are measured directly from the Balance of Payments and the International Investment Positions, both are retrieved from the IMF.

mechanisms connecting capital flows and currency risk. Therefore, in the remainder of this section, I analyze the micro-level dataset from global funds to further develop a better understanding of foreign flightiness.

2.5 Empirical Tests of Hypotheses on Flighty Capital Flows

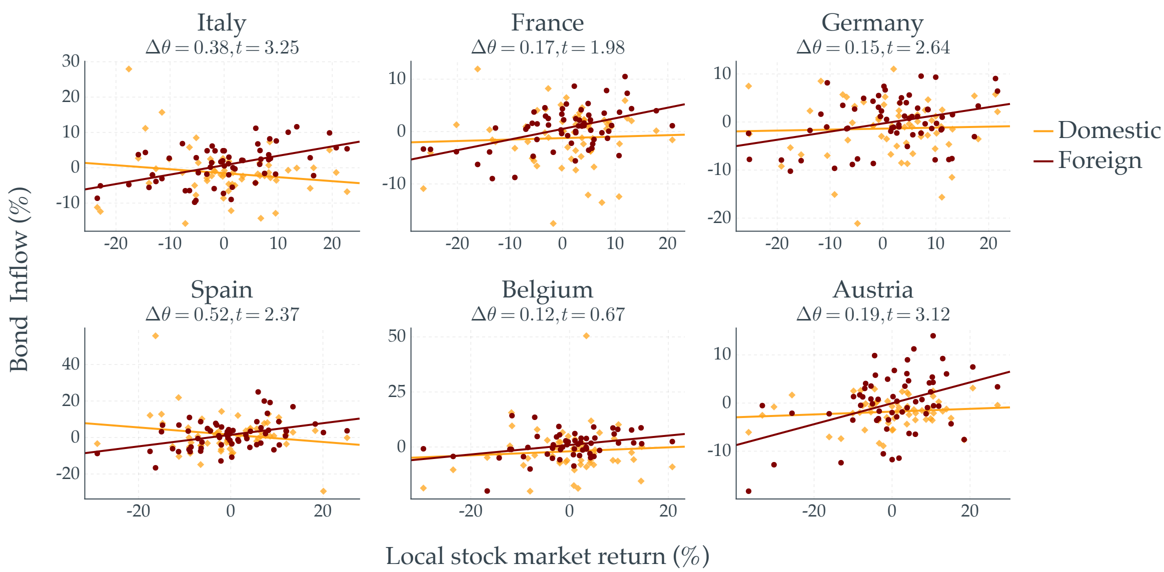
Having established the baseline findings, an immediate question arises: what are the causes of flighty capital flows? In this subsection, I first present evidence that flighty capital flows persist even in the absence of currency risk, and retail fund investors also exhibit foreign flightiness. I then evaluate different hypotheses in light of my empirical findings and argue that belief-based explanations are the most consistent with my findings. I provide direct evidence that is consistent with belief-based explanations in the next section.

2.5.1 Flighty Capital Flows in the Absence of Currency Risk

One potential source of the asymmetry between foreign and domestic investors is heterogeneous exposures to currency risk. If investors care about returns in their own currency, foreign investors are exposed to additional foreign-exchange risks relative to domestic investors, and therefore offload local-currency-denominated assets to domestic investors when uncertainty is high.

Perhaps surprisingly, currency risk has a limited role in explaining foreign flightiness observed above. The most straightforward illustration is from flows within the euro area. Figure 4 reproduces the plots in Figure 2 while restricting *both* inflow and outflow countries within the euro area.[10] In this analysis, I also only use funds that report their base currency to be the euro. The different sensitivities between domestic and foreign investors persist. This result shows that currency risk cannot fully explain foreign flightiness, and additional factors contribute to heterogeneous sensitivities.

Figure 4: Foreign flightiness within the Euro Area



Notes. This figure presents domestic (orange) and foreign (red) inflows into each country's bond market against local stock-market returns. Both the inflow and outflow countries are within the euro area, and only funds using the euro as the base currency are included. The coefficient $\Delta\theta$ under the subtitle of each panel reports the estimate from Equation (2.3) for each country. A positive $\Delta\theta$ indicates a larger slope for foreign flows. Standard errors are estimated using Newey and West (1987) HAC standard errors, with bandwidths chosen automatically following Newey and West (1994).

I perform several robustness checks in Appendix A.4. One potential concern for the evidence from the euro area is the risk of a potential euro breakup at the peak of the European debt crisis. I show that the results are robust even excluding the periods of the European debt crisis. In Appendix Table 10, I report regressions within the euro area excluding onshore offshore financial centers, Luxembourg and Ireland, and the results are robust. In Table 14, I show that fund

[10] Figure 4 include funds domiciled in onshore offshore financial centers, Luxembourg and Ireland. The results within the euro area are also robust to excluding those funds, as reported in Table 10 in Appendix A.2.

investor flows into currency-hedged share classes also exhibit higher sensitivity toward funds' foreign exposure than those to their domestic exposure.

Using full-sample regressions, I gauge the contribution of currency mismatch to foreign flightiness. I split flows into currency-matched flows and currency-mismatched flows. A flow from a fund to a security is currency-matched if the base currency of the fund is the same as the currency denomination of the security. The results are reported in Table 2. Columns (1) and (3) report estimates for currency-matched flows with Equations (2.4) and (2.5), respectively. The coefficients are close to the baseline. Foreign flows are more sensitive to macrofinancial news than domestic flows are, even if the foreign fund is not exposed to additional currency risk. Columns (2) and (4) report estimates for currency-mismatched flows. A comparison of the point estimates between columns (1) and (2), as well as (3) and (4), indicates a slight increase in foreign flightiness when the fund's base currency differs from the security's currency; however, the difference, at 0.042, is both relatively small and statistically insignificant. To conclude, currency risk plays a limited role in the observed foreign flightiness.

Table 2: Foreign Flightiness with and without Currency Mismatch

	$f_{i,c,t}$			
	(1)	(2)	(3)	(4)
$r_{c,t}$	0.064	0.058		
	(0.039)	(0.105)		
$r_{c,t} \times I_{foreign}$	0.132*	0.174	0.116*	0.183**
	(0.061)	(0.096)	(0.055)	(0.053)
In. Country FE	Yes	Yes		
Out. Country FE	Yes	Yes	Yes	Yes
In. country-specific θ			Yes	Yes
Fund-specific θ			Yes	Yes
Fund $\times$ In. Country FE			Yes	Yes
Currency mismatch	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
N	1,420,113	690,721	1,415,561	687,262

Notes. Columns (1)-(2) report the estimates of the regression specification in Equation (2.4). The left-hand variable is flows by fund i into country c at quarter t; the key right-hand variables are country-specific stock-market returns in local currencies, and its interaction with the foreign indicator. Control variables include fund sizes, fund past returns and lagged fund flows. Column (1) reports results for currency-matched flows, and Column (2) reports results for currency-mismatched flows. A flow is currency-matched if the base currency of the fund is the same as the security currency. Columns (3)-(4) report the estimates of specification in Equation (2.5). The coefficient of $r_{c,t}$ is absorbed by country and fund-specific slopes. Standard errors are two-way clustered at the quarter level and the inflow country level, and are reported in parentheses. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

2.5.2 Flighty Capital Flows without Institutional Frictions: Retail Fund Investor Flows

Mutual funds are subject to various regulations, mandates, and internal risk-management policies. It is possible that those institutional factors may have asymmetric treatments for foreign and domestic investments, triggering flighty flows during financial distresses. In this section, I study foreign flightiness under a scenario that is less influenced by those institutional factors: flows induced by fund investors. I show that fund investors, and particularly retail fund investors, are more sensitive to foreign exposures of the fund than domestic exposures. Fund investors withdraw capital from a fund when the foreign countries in its portfolio have lower stock-market returns; in contrast, they tend to be unresponsive to domestic equity returns. As fund investors redeem or purchase fund shares, fund managers often adjust their investment positions, passing through fund investor flows to the inflow countries.

Fund investors can include both retail investors as well as institutional investors, such as insurance companies and pension funds (ICPF).[11] To identify flows by retail investors, I utilize the share-class information. Mutual funds often offer multiple share classes with different fee structures, all investing in the same portfolio. Retail investors typically invest in A, B, C and R shares, whereas institutional investors typically choose institutional shares that offer low expense ratios but require higher minimum investments.[12] Unfortunately, the share-class information is only available for US funds. Therefore, in the following analysis, I first use all share classes for funds globally, and then zoom in on the United States.

I obtain net cash flows $F_{i,t}^{fund}$ into each fund over a given quarter from Morningstar Direct.[13] Flows in the following analyses are at the share-class level, but for simplicity, they are referred to as fund investor flows. The construction of fund investor flows follows a similar methodology to that of fund-country flows, using the Davis and Haltiwanger (1992) growth rate:

$$f_{i,t}^{fund} = \frac{F_{i,t}^{fund}}{(A_{i,t-1} + \hat{A}_{i,t})/2},$$

where $A_{i,t-1}$ is the net total assets of each fund (share class), and $\hat{A}_{i,t} \equiv A_{i,t-1} + F_{i,t}^{fund}$.

Fund flow flightiness can be estimated from Equation (2.4) with the right-hand side replaced with fund flows $f_{i,t}^{fund}$. However, recognizing that $f_{i,t}^{fund}$ is at the fund level, it is more meaningful to conduct the regression at the fund level. I aggregate Equation (2.4) to the fund level using

[11] According to the Flow of Funds in the US, households account for around 50% of direct holdings of mutual-fund shares while insurance companies and pension funds account for around 30% (as of 2022Q2). Almost all mutual-fund shares held by insurance companies are under separate accounts. Emiris et al. (2023) report similar numbers for the European mutual-fund sector using Securities Holdings Statistics.

[12] Institutional shares sometimes are also available to retail investors through their retirement plans.

[13] The estimate of fund flows by Morningstar is based on surveyed total net assets and total returns, accounting for reinvestment of distributions. Their detailed methodology is available in https://www.morningstar.com/content/dam/marketing/shared/research/methodology/765555_Estimated_Net_Cash_Flow_Methodology.pdf.

lagged country weights $S_{i,c,t-1}$ in each fund's portfolio:

$$f_{i,t}^{fund} = \theta^{domestic} \underbrace{\left(\sum_c S_{i,c,t-1} r_{c,t}\right)}_{r_{i,t}^{portfolio}} + \Delta\theta \underbrace{\left(\sum_c S_{i,c,t-1} \mathbb{I}_{i \notin c}^{foreign} r_{c,t}\right)}_{r_{i,t}^{foreign}} + \beta_{control} \cdot X + \delta_{d(i)} + \varepsilon_{i,t}. \quad (2.6)$$

Here, I define two new variables capturing each fund's exposure, $r_{i,t}^{portfolio} \equiv \sum_c S_{i,c,t-1} r_{c,t}$ the portfolio exposure to all countries, and $r_{i,t}^{foreign} \equiv \sum_c S_{i,c,t-1} \mathbb{I}_{i \notin c}^{foreign} r_{c,t}$ the exposure to foreign countries. The interpretation for the coefficients is the same as Equation (2.4): $\theta^{domestic}$ captures the baseline sensitivity of fund investor flows, and $\Delta\theta$ reflects the additional sensitivity to foreign exposures.

Table 3 reports the estimates of Equation (2.6). Column (1) reports the regression pooling from all funds. Fund investors are much more sensitive toward foreign exposures than domestic exposures. A one percent decrease in the domestic stock-market return is associated with 2.1 bps flows out of a fully domestic fund. For a fund exposed to foreign investments, the flow response to a one percent decrease in the foreign stock-market return is 24.8 bps larger. The difference is both economically and statistically significant.

Column (2) repeats the same exercise exclusively for US retail share classes. Foreign flightiness is highly prominent within US retail shares. A one percent decline in the US stock-market return is associated with an 10bps inflow. Presumably, this is because US bonds, and Treasuries, in particular, serves as a safe haven in downturns. In contrast, a 1% decline in stock-market returns in foreign countries leads retail investors to withdraw 32.6 basis points (-10 + 42.6) from funds exposed to these markets. While the result is pronounced in retail shares, it is not exclusively attributable to them. Column (3) reports the fund investor flows for other share classes in the US. The estimates are comparable to Column (1).

2.5.3 Discussion on the causes of flighty capital flows

The literature on global financial cycles shows that aggregate capital flows are cyclical (see Miranda-Agrippino and Rey, 2021). Several hypotheses have been proposed in the literature as to the source of this cyclicality, but due to limitations of aggregate data, these hypotheses largely remain untested. In this section, I discuss the potential drivers of flighty capital flows based on previously presented results. It is important to clarify that this paper does not seek to *rule out* certain hypotheses; instead, as I will argue below, my results suggest that certain hypotheses are *not sufficient* to explain the observed foreign flightiness.

Heterogeneous beliefs. A large literature suggests that heterogeneous beliefs between domestic and foreign investors may underlie flighty capital flows. Such explanations have a long tradition in the international portfolio choice literature. Heterogeneous beliefs are commonly cited as the reason behind investment home bias (Bekaert & Wang, 2009; Dumas et al., 2017; Gehrig, 1993;

Table 3: Fund flow sensitivity by foreign and domestic exposures

	$f_{i,t}^{fund}$		
	(1)	(2)	(3)
$r_{i,t}^{portfolio}$	0.021	-0.100*	0.059
	(0.033)	(0.040)	(0.039)
$r_{i,t}^{foreign}$	0.248***	0.426***	0.267*
	(0.032)	(0.086)	(0.105)
Out. Country FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Sample	All	US Retail	US Other
N	844,111	106,607	116,376

Notes. This table reports the estimates of regression specification in Equation (2.6). The left-hand variable is fund investor flows, and the right-hand variables are fund exposures. Portfolio exposure is defined as $r_{i,t}^{portfolio} \equiv \sum_c S_{i,c,t-1} r_{c,t}$, where $S_{i,c,t-1}$ is the share of country c in the bond portfolio of fund i, and $r_{c,t}$ is the stock-market return in country c. Foreign exposure is defined as $r_{i,t}^{foreign} \equiv \sum_c S_{i,c,t-1} \mathbb{I}_{i \notin c}^{foreign} r_{c,t}$. Control variables include fund sizes, fund past returns, and lagged fund flows. Column (1) reports the estimates for the full sample. Column (2) reports the estimates for the flows of retail share classes in the US These share classes include A, B, C, and Inv classes. Column (3) reports the estimates for other share classes in the US Standard errors are two-way clustered at the quarter level and the outflow country level, and are reported in parentheses. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

Portes & Rey, 2005; Van Nieuwerburgh & Veldkamp, 2009). In the same spirit, Brennan and Cao (1997), Albuquerque et al. (2009), Dumas et al. (2017), and Benhima and Cordonier (2022), among others, develop models with heterogeneous beliefs to explain cyclical foreign flows. These models are often micro-founded using asymmetric information or behavioral biases. That is, foreign investors either do not observe private signals that are available to domestic investors, or they fail to correctly interpret the signals, putting them at an informational disadvantage. As a result, foreign investors have larger responses to news in beliefs, and henceforth larger adjustments in portfolio allocation, than domestic investors. Using cross-country forecast data, Benhima and Bolliger (2022) provide direct evidence that foreign forecasters are indeed less informed compared to domestic forecasters. The explanation based on heterogeneous beliefs are consistent with my empirical findings, and I will provide additional empirical evidence in the next section.

Currency risk. One of the most salient heterogeneities between foreign and domestic investors is their base currencies. If investors care about returns in their home currency (e.g., due to consumption home bias), then foreign investors are exposed to additional currency risk compared to domestic investors. A substantial body of literature on general-equilibrium international portfolio choice models largely hinges on currency denomination to generate capital flows (Dou & Verdelhan, 2015; Hnatkovska, 2010; Tille & van Wincoop, 2010). However, currency risk cannot be the full picture: as shown in Section 2.5.1, flighty foreign capital flows are still salient even when investors use the same currency.

Heterogeneous investor types. Another common hypothesis in the literature is that domestic-focused investors and foreign-oriented investors constitute two different types of investors. For instance, foreign investors tend to be mutual funds with flighty funding sources, while domestic investors tend to be pension funds or insurance companies with more stable funding (Coppola, 2022; Zhou, 2023); foreign-oriented investors and domestic-focused investors may also differ in risk aversion, leading to heterogeneous response to global risk aversion shocks (Davis & van Wincoop, 2021). My results indicate that the heterogeneous-type hypothesis cannot be the full story as well. Even conditional on the same fund, its foreign positions are more sensitive to macrofinancial news than its domestic positions to domestic news.

Institutional factors. Internal mandates of mutual funds may bias investment toward assets in their home countries. Governments may use either "strong-arm tactics" or other soft approaches to persuade institutions to hold domestic assets (Reinhart, 2012; Uhlig, 2014). In Section 2.5.2, I highlight the foreign flightiness observed among retail investors, who are relatively insulated from these institutional factors.

Political risk. During financial distress, foreign investors may perceive themselves to be under weaker property-rights protection compared to domestic investors, potentially even facing expropriation risk (Gourio et al., 2014). The fear of such political risks could conveivably underlie foreign flightiness. However, while the current study does not directly test this hypothesis, several pieces of evidence suggest that political risk is unlikely to be the whole story. Concerns for political risks typically apply to investment in emerging markets. However, Figure 2 shows that foreign investors are flighty for major advanced economies as well, such as the US, where property-rights protection for foreign investors has traditionally been secure. Furthermore, political risk concerns are also most pronounced during significant recessions. Yet, Column (5) of Appendix Table 12 reports that even under normal economic conditions, foreign investors tend to be more sensitive to news than domestic investors.

The explanation based on heterogeneous beliefs aligns most closely with the stylized facts presented earlier. In the next section, I provide supportive evidence for belief-based explanations, drawing from investment performance and survey data from global forecasters.

3 An Origin of Flighty Capital Flows: Belief Heterogeneity

In this section, I propose one explanation behind flighty capital flows: foreign investors' beliefs are more responsive to news than domestic investors', possibly due to behavioral biases or asymmetric information. I provide evidence from the investment performance as well as surveys of foreign forecasters that are consistent with this explanation.

3.1 Flighty Capital Flows Underperform

If foreign investors are subject to greater behavioral biases or asymmetric information, they will have lower performance compared to domestic investors, owing to their tendency to buy assets at high prices and sell at low prices. I test this hypothesis by comparing the performance of two counterfactual trading strategies of fund shares, described in Equation (2.6).

For every foreign-investing fund in the sample,[14] consider two strategies of trading the fund share, the foreign flighty flow strategy and the domestic strategy, defined below. I initialize both strategies with initial wealth $n_0 = 1$ all invested in the fund at its inception (or the earliest observation in the sample), and trace the realized returns of both strategies from the fund until the end of the sample. I then compare the risk-adjusted returns of two strategies for every fund.

The two trading strategies trade fund shares according to the predicted flows from Equation (2.6). Specifically, at the end of each quarter, investors receive returns from the fund, and then adjust their positions in the fund following respective strategies. The domestic strategy adjusts the positions in response to the portfolio exposure: $\hat{f}_{i,t}^{domestic} \equiv \hat{\theta}^{domestic} r_{i,t}^{portfolio}$. With the foreign strategy, investors adjust the positions in response to two components: the adjustment dictated by the domestic flow strategy, and an additional response to the foreign exposure: $\hat{f}_{i,t}^{foreign} \equiv \hat{\theta}^{domestic} r_{i,t}^{portfolio} + \Delta\hat{\theta} r_{i,t}^{foreign}$. Coefficients $\hat{\theta}^{domestic}$ and $\Delta\hat{\theta}$ are set to the empirical estimates in Column (1) of Table 3. As $\hat{\theta}^{domestic}$ is estimated to be close to zero, the domestic strategy is similar to a buy-and-hold strategy; $\Delta\hat{\theta}$ is positive, so the foreign strategy withdraws from the fund when the foreign countries to which the fund is exposed experienced negative stock-market returns *in the past quarter*. Flows are financed by borrowing—or saving, if the flows are negative—at the risk-free rate of $r_{f,t}$.

At the inception of the fund i, the investor following strategy $x \in \{foreign, domestic\}$ invests her entire wealth $n_{i,0}^x = 1$ in the fund $a_{i,0}^x = 1$. At the end of each quarter, the investor receives fund returns $\left(1 + r_{i,t}^{fund}\right)$ first, and then adjusts her positions in the fund by a factor of $1 + \hat{f}_{i,t}^x$:

$$a_{i,t}^x = a_{i,t-1}^x \left(1 + r_{i,t}^{fund}\right) \left(1 + \hat{f_{i,t}^x}\right),$$

Flows are financed or saved at the risk-free rate. The total wealth of the investor following each strategy evolves according to the law of motion:

$$\begin{aligned} n_{i,t}^x &= n_{i,t-1}^x \left(r_{f,t} + re_{i,t}^x\right) \\ re_{i,t}^x &= \frac{a_{i,t-1}^x}{n_{i,t-1}^x} \left(r_{i,t}^{fund} - r_{f,t}\right). \end{aligned}$$

The relative performance of foreign and domestic strategies is captured by return differentials, $\Delta re_{i,t} \equiv re_{i,t}^{foreign} - re_{i,t}^{domestic}$, which takes a long position in the foreign strategy and a short

[14]Specifically, the subsample comprises funds with at least 25% of their portfolios invested in foreign countries in at least one quarter in the sample period.

position in the domestic strategy. I perform factor regressions on return differentials:

$$\Delta re_{i,t} = \alpha_i^{foreign} + \Lambda_i' \eta_t + u_{i,t}, \tag{3.1}$$

where η_t is a vector of common factors in fund returns and Λ_i is the corresponding loading vector. One potential benefit of being flighty is that it may reduce risk exposures during downturns. Therefore, to compare the risk-adjusted performance, I control for common factors in the regression. The common factors η_t are extracted using principal component analysis (PCA) on fund returns for each fund domicile in the sample separately.[15] I include three factors in the baseline regression. The results are not sensitive to the number of factors. The coefficient $\alpha_i^{foreign}$ gives the average excess return of the foreign strategy versus the domestic strategy for fund i.

Figure 5 reports the distribution of the information ratio of the foreign strategy against the domestic strategy, defined as the average foreign excess return $\alpha_i^{foreign}$ divided by the standard deviation of tracking errors $u_{i,t}$. For 74% of funds in the sample, the foreign strategy yields negative average excess returns, with a median information ratio around -0.56 (annualized). In Appendix Table 15, I report factor regressions pooling from all funds to estimate the average foreign excess return of $\alpha_i^{foreign}$ across funds. The average foreign excess returns significantly negative across specifications with different numbers of common factors. In summary, foreign investors tend to incur losses when exhibiting foreign flightiness.

3.2 Evidence from Cross-country Forecasts

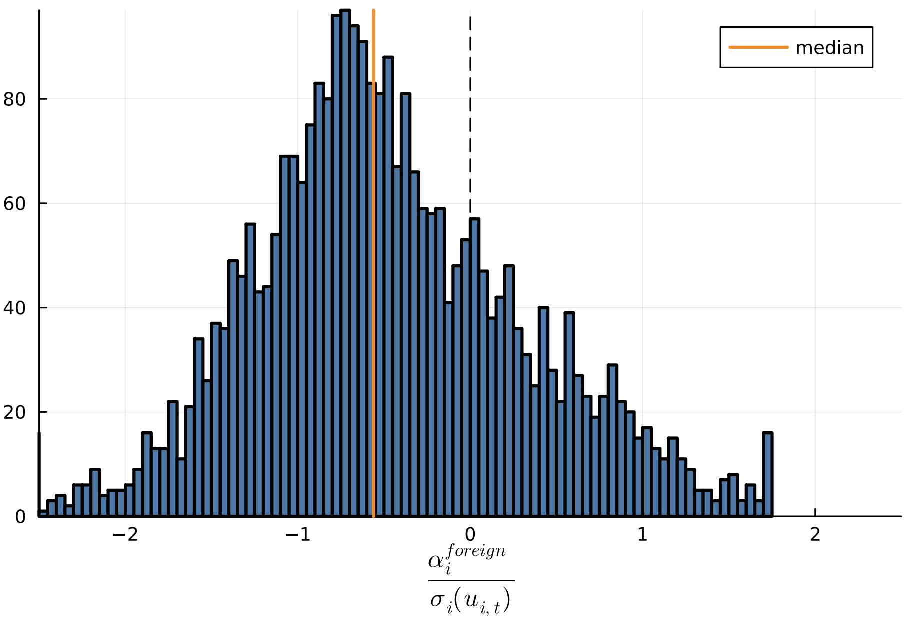
I utilize a dataset of cross-country GDP forecasts to provide direct evidence on heterogenous beliefs between foreigners and locals. Following the methodology of Coibion and Gorodnichenko (2015) regression, I show that foreign forecasters tend to revise more in response to news than domestic forecasters do.

Data. The GDP growth forecast data are obtained from Consensus Economics, a global macroeconomic survey firm. It polls economic-forecasting institutions around the world for their forecasts for macroeconomic indicators in different countries. In recent years, researchers have increasingly used this dataset in the international finance literature to understand how beliefs affect global portfolio allocation as well as asset prices (Benhima & Bolliger, 2022; Stavrakeva & Tang, 2020a, 2020b).

The forecasting institutions in the dataset include investment banks, think tanks, and other macroeconomic research institutions. Crucial to my analysis, the pool of forecasters in the dataset includes not only local specialized firms, such as the economist team at Toyota Motor, which only forecasts for Japan, but also international forecasters, such as Goldman Sachs, which forecasts for

[15] As the fund samples are highly unbalanced, the standard PCA is not suitable as it does not allow for missing values. Here I use Alternating Least Square (ALS), which gives the same results as PCA when the panel is balanced but is able to handle unbalanced panels.

Figure 5: Information Ratio of the Foreign Strategy's Excess Return



Notes. This figure reports the distribution of the (annualized) information ratio of the foreign strategy against the domestic strategy for each fund under the three-factor model in Equation (3.1). The information ratio is computed as the average foreign excess return $\alpha_i^{foreign}$ divided by the standard deviation of tracking errors $u_{i,t}$. The distribution is winsorized at 0.5% at both tails. The orange vertical line indicates the median of the distribution, -0.56. The foreign strategy underperforms relative to the domestic strategy for 74% of funds.

multiple countries. The cross-country forecast structure provides variation in the nationality of forecasters to study the heterogeneity between foreigners and domestic forecasters.

Consensus Economics does not report the identity of individual forecasters but only the names of the affiliating institutions. I classify the nationality of institutions based on their headquarters. Therefore, Goldman Sachs is considered a US forecaster, while Toyota Motor is a Japanese forecaster. This classification can be inevitably fuzzy, and there are several cases where the nationality of firms is ambiguous. One such case is that forecasts are made by local subsidiaries. For example, Consensus Economics record "Citigroup Japan" as a forecaster for Japan in the dataset. Another case is when a local forecaster is acquired by international institutions. For example, First Boston, a New York-based investment bank, was acquired by Credit Suisse in 1988, and continued to operate independently until 2006. In the baseline, I consider forecasters in these cases to be domestic, as they carry local knowledge. Alternatively, I can also drop those ambiguous cases. The results are robust, and if anything slightly stronger.[16]

I use forecasts of the real GDP growth for the following analysis as it captures forecasters' be-

[16]Unfortunately, Consensus Economics does not always report as detailed as the branches for the forecasting institution. For example, Goldman Sachs' forecasts for the UK are made by local teams based in London, but in the dataset it is simply registered as "Goldman Sachs." Without knowing the corporate structure of each forecasting institution in the sample, it is impossible to classify forecasters perfectly. However, as my goal is to detect the differences between foreign and domestic forecasters, failure to separate foreign forecasters from domestic ones will lead to attenuation biases. Therefore, to the extent that I detect the significant differences between foreign and domestic forecasters, my results serve as a lower bound.

liefs for macro fundamentals. It is also the most widely reported forecast across countries. The sample spans from as early as February 1990 and ends in December 2022, and covers countries in the G7, West Europe, and Africa/Middle East.[17] Each month, Consensus Economics polls around 10-30 forecasters for a given country's annual GDP growth over the surveyed year and the next. The forecast targets are always year-end GDP growth rates and hence fixed within a given calendar year. For example, in August 2020, Consensus Economics surveyed 23 institutions for Japan's annual GDP growth in 2020 and 2021. The panel of forecasters is highly unbalanced. The composition of forecasters differ across countries, and may also vary across months for a given country. To reduce gaps in data, forecast revisions are calculated on a quarterly basis.

Empirical specifications and results. I denote $y_{c,T}$ as the realized real GDP growth for country c in year T, and $F_{i,t}y_{c,T}$ as the forecast for $y_{c,T}$ made by institution i in the quarter t. The one-quarter revision is defined as:

$$rev_{i,c,t}^{T} \equiv F_{i,t}y_{c,T} - F_{i,t-1}y_{c,T}.$$

The forecast error is defined as the difference between the realized value at time T and the forecast made at t:

$$err_{i,c,t}^{T} \equiv y_{c,T} - F_{i,t}y_{c,T}.$$

The realized real GDP growth for each country is obtained from the World Economic Outlook database by the IMF.

Coibion and Gorodnichenko (2015) suggest running the error-revision regression to study the deviations of forecasters from full-information rational expectations (FIRE):

$$err_t^T = \beta_{CG} rev_t^T + \varepsilon_t^T. \tag{3.2}$$

To understand this specification, consider an investor with rational expectations. Forecasts under rational expectations are conditional expectations. By the definition of conditional expectations, forecast errors are unpredictable by any variables X_t in the information set when forecasts are made, and revisions $rev_{i,c,t}^T$ are in forecasters' information set at time t. Therefore,

$$\mathbb{E}_t\left[err_t^T rev_t^T\right] = \mathbb{E}_t\left[\left(y_{c,T} - \mathbb{E}_t y_{c,T}\right) rev_t^T\right] = 0.$$

If an econometrician estimates Equation (3.2) from a stationary process of forecasts under rational expectations, they will recover $\beta_{CG} = 0$.

A negative β_{CG} suggests that the forecaster overshoots when making revisions and hence their positive revisions correspond to more negative forecast errors. There are several potential explanations for negative coefficients. One common interpretation is that forecasters overreact to news received during the revision periods. This overreaction could be attributed to behavioral

[17] These countries are: the United States, Japan, Germany, France, UK, Italy, Canada, Netherlands, Norway, Spain, Sweden, Switzerland, Austria, Belgium, Denmark, Egypt, Finland, Greece, Ireland, Israel, Nigeria, Portugal, Saudi Arabia, and South Africa. The coverage of time periods varies across countries.

biases such as diagnostic expectations, learning with fading memory, memory retrieval costs, etc. (Afrouzi et al., 2020; Bordalo, Gennaioli, La Porta, & Shleifer, 2020; Nagel & Xu, 2022). Alternatively, if the forecast process is not stationary, the estimated CG coefficient can also deviate from zero. For example, if the forecaster is equipped with a loose prior and observes a short history of data, their forecasts are formed along the transition path converging toward the stationary distribution, and the CG coefficient estimated from their forecasts can also be negative. In this paper, I do not take a structural interpretation of the coefficient. Instead, I refer to the CG coefficient as "revision strength," as it quantifies deviations from the true target associated with revisions.

The focus of this paper is to test whether foreign forecasters revise their beliefs in response to news more strongly than domestic forecasters do. For this purpose, I use the following specification:

$$err^T_{i,c,t} = \left(\beta^{domestic} + \Delta\beta_F \times \mathbb{I}^{foreign}_{i \notin c}\right) rev^T_{i,c,t} + \beta_0 \mathbb{I}^{foreign}_{i \notin c} + \alpha_{i,c} + \varepsilon^T_{i,c,t}. \tag{3.3}$$

The coefficient of interest is $\Delta\beta_F$. It represents the additional deviation from the true values foreign forecaster make compared to domestic forecasters for each one-percent increase in their revision of GDP growth.

The revision strength may vary across target countries, for example, due to the persistence of the GDP growth series (Bordalo, Gennaioli, Ma, & Shleifer, 2020). To control for the heterogeneity due to target countries, I control for country-specific slopes β_c in the following specification:

$$err^T_{i,c,t} = \left(\beta_c + \beta_{n(i)} + \Delta\beta_F \times \mathbb{I}^{foreign}_{i \notin c}\right) rev^T_{i,c,t} + \beta_0 \mathbb{I}^{foreign}_{i \notin c} + \alpha_{i,c} + \varepsilon^T_{i,c,t}. \tag{3.4}$$

Under this specification, the coefficient $\Delta\beta_F$ captures how, on average, foreign forecasters differ from domestic forecasters in terms of revision strength, *conditional on* the same country. Similarly, I also control for nationality-specific slopes $\beta_{n(i)}$ to control for common tendencies of revision strength by forecasters' origins.

Table 4 reports the estimates of Equations (3.3) and (3.4). In Column (1) I do not control country-specific slopes. The estimated revision strength for domestic forecasters, reported in the first row, is close to zero and insignificant. This result is similar to Bordalo, Gennaioli, Ma, and Shleifer (2020), who also do not detect significant under/overreactions in real GDP growth forecasting in both Survey of Professional Forecasters and Blue Chip. My focus is on the coefficient of the interaction term, $\Delta\beta_F$, reported in the second row. The coefficient is significantly negative. The coefficient suggests that for a one percent upward revision in the GDP growth, foreign investors on average overshoot by 7.5 (9.8-2.3) basis points relative to true realizations.

In Column (2) I control for country-specific and nationality-specific slopes, which absorb the coefficient for domestic baseline (first row). The coefficient of interest, $\Delta\beta_F$, becomes stronger after controlling for heterogeneous slopes. In Column (3) I exclude the ambiguous cases (local firms acquired by foreign companies, or forecasts made by local branches of global firms). The coefficient is robust, and if anything, marginally stronger.

One potential concern for the CG regression is that, as the forecast $F_{i,t}y_{c,T}$ appears on both sides of the regression with different signs, if there are measurement errors in forecasts, it will

Table 4: CG Regressions: Foreign Forecasters Revise More Strongly

	Forecast Err.		
	(1)	(2)	(3)
revision	0.023		
	(0.123)		
revision $\times I_{foreign}$	-0.098**	-0.144***	-0.158***
	(0.031)	(0.034)	(0.034)
Firm $\times$ Country FE	Yes	Yes	Yes
Nationality FE		Yes	Yes
$\beta_{country}$		Yes	Yes
$\beta_{\text{inst. nationality}}$		Yes	Yes
Estimator	OLS	OLS	OLS
Sample	All	All	Unambiguous
N	56,179	56,179	51,557

Notes. This table reports the estimates of regression specification in Equations (3.3) and (3.4). Column (1) pools from all forecasters and all countries and assumes a homogeneous revision strength for domestic forecasters. Column (2) allows for country-specific revision strength β_c and forecaster-nationality-specific revision strength $\beta_{n(i)}$, which absorb the domestic coefficient. Column (3) drops cases that are ambiguous in the domestic/foreign classification. These cases include forecasts made by local branches of global companies, or by local firms acquired by foreign companies. Standard errors are reported in parentheses. Standard errors are two-way clustered at the quarter level and the forecasted country level. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

create a mechanical negative correlation between revisions and errors. I address this concern in Appendix B by performing the CG regression using staggered forecast errors and revisions to avoid the mechanical correlation. The results are robust to the staggered specification, indicating the results are not driven by heterogeneous measurement errors between foreign and domestic forecasters.

4 A Model of Flighty Capital Flows

Based on empirical results in the previous sections, I develop a qualitative two-country model of flighty capital flows. The objective of the model is two-fold: first, to generate flighty capital flows as observed in the empirical section, and second, to investigate the mechanisms linking flighty capital flows to currency risk. To achieve those objectives, the model relies on two critical components: foreign belief updating in response to shocks, and a frictional foreign-exchange market. Regarding the first objective, the interaction of these two ingredients generates the movements of capital flows and asset prices as in the global financial cycle: global asset prices drop accompanied by reductions in inflows to both countries. For the second objective, the model shows that countries have risky currencies if their external liabilities face flightier flows than their external assets. This insight is captured by a new empirical measure, *net asset flightiness*, which will be tested in the next section.

4.1 Setup

Time is continuous. Figure 6 presents the structure of the model. There are two countries in the model, the United States and Europe. To illustrate, I introduce the model from the perspective of the US. The European counterparts are symmetric, denoted with an asterisk.

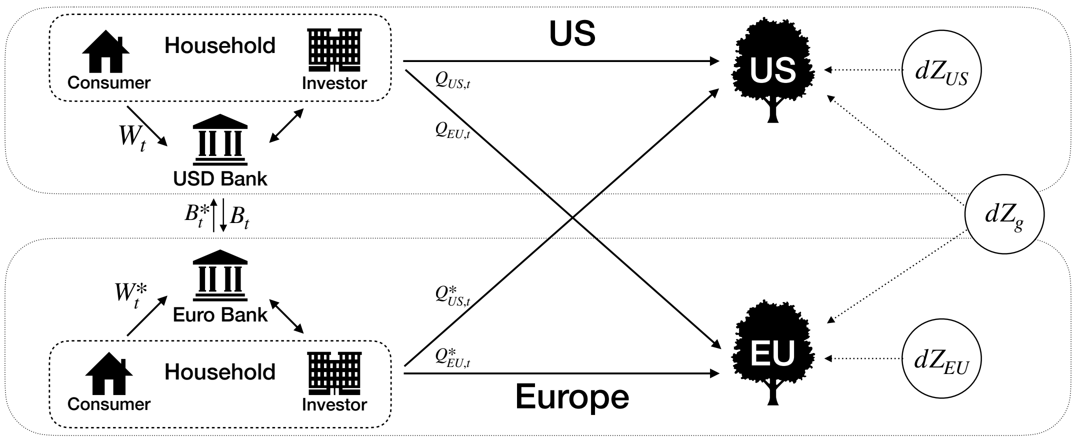


Figure 6: Model Structure

It is worth noting that the objective of this model is to provide a *qualitative* characterization of capital flows and exchange rates instead of a quantification. To this end, I make several assumptions deviating from the standard consumption-based international finance model. These assumptions allow me to solve the model analytically and highlight the key mechanisms.

Dividend processes and foreign beliefs. Both countries are endowed with a tree that yields a dividend flow $D_{c,t}dt, c \in \{US, EU\}$. Dividends evolve following Ornstein–Uhlenbeck processes. For the US tree, [18]

$$dD_{US,t} = -\alpha(D_{US,t} - \bar{D}_{US})dt + \sigma_{US}dZ_{US,t} + \sigma_g dZ_{g,t}, \tag{4.1}$$

where $dZ_{US,t}$ denotes the US-specific shock and $dZ_{g,t}$ denotes the global shock shared by both countries. Following shocks, dividends mean-revert to the steady state level $\bar{D}_{US}$ at a rate of α.

[18] It is common to assume outputs to be mean-reverting in the international portfolio choice literature, particularly for models solved around a steady state. Without mean reversion, the output for two countries can deviate arbitrarily and hence alternative assumptions are required to maintain the stationarity. See discussions in Tille and van Wincoop (2010).

Standard models without additional frictions often have difficulties in inducing cyclical capital flows.[19] To generate flighty capital flows in the model, I introduce a belief process for foreign investors. US investors understand the law of motion for their domestic tree as in Equation (4.1), while European investors perceive the law of motion for the US tree differently, and similarly for US investors' perception of the European tree. I first introduce the general specification and then discuss the microfoundations.

From the perspective of European investors, dividends from the US tree follows:

$$dD_{US,t} = -\alpha(D_{US,t} - \tilde{D}_{US,t})dt + \sigma_{US} d\tilde{Z}_{US,t} + \sigma_g d\tilde{Z}_{g,t}, \tag{4.2}$$

where the true long-run mean $\bar{D}_{US}$ is replaced by $\tilde{D}_{US,t}$, the perceived long-run mean of US dividends by European investors. The perceived long-run mean itself follows a mean-reverting process around the true long-run mean $\bar{D}_{US}$, but responds to the latest shocks to the US tree:

$$d\tilde{D}_{US,t} = -\kappa_{US}\left(\tilde{D}_{US,t} - \bar{D}_{US}\right)dt + \theta_{US}\left(\sigma_{US} dZ_{US,t} + \sigma_g dZ_{g,t}\right). \tag{4.3}$$

I refer to the parameter θ_{US} as the foreign flightiness toward the US tree. This parameter captures the sensitivity of European investors' perceived long-run mean $\tilde{D}_{US,t}$ to the latest news. As I demonstrate later, it governs the flightiness of flows to the US tree in equilibrium. Similarly, US investors' beliefs also respond to shocks to the European tree, with foreign flightiness parameter θ_{EU}. In the general model, I allow for θ_{EU} to be different from θ_{US}. The asymmetry in foreign flightiness generates the net portfolio flows in response to global shocks, and the exchange-rate movements.

Interpretations of the perceived law of motions. Equation (4.3) can be microfounded in multiple ways, including learning with fading memory (Nagel & Xu, 2022) and diagnostic expectations (Bordalo, Gennaioli, La Porta, & Shleifer, 2020), as discussed in Appendix C.1. These models differ in the microfoundation, and hence the interpretation of the coefficients, κ_{US} and θ_{US}, but they generate similar results for the purpose of this paper. For instance, under the fading-memory interpretation, investors learn long-run means from past realizations $D_{US,t}$. They form beliefs using Bayes' rule, but underweight foreign information in the past with exponentially decaying weights at a rate of ν_{US}. The memory-fading rate ν_{US} coincides with the mean-reverting rate of the perceived long-run mean , $\kappa_{US} = \nu_{US}$, and proportional to the flightiness coefficient, $\theta_{US} = \frac{\nu_{US}}{\alpha}$. This is because the faster the memory fades, the larger the posterior uncertainty at the stationary distribution, and therefore the more weights investors put on the new signals.

Equation (4.3) can also be deemed as a reduced-form approach to parsimoniously capture the core idea that foreign investors' beliefs are more responsive to news, a feature that is often microfounded with rich information heterogeneities between domestic and foreign investors in the

[19] For example, Tille and van Wincoop (2010) and Camanho et al. (2022) both generate negative inflows upon positive shocks.

literature of international portfolio choice. For example, domestic investors may observe a private signal in addition to the public signal (Benhima & Cordonier, 2022), or they simply understand the correlation between signals and fundamentals better (Dumas et al., 2017). Another potential source of heterogeneous response in beliefs is heterogeneous priors: foreign investors have a looser prior for the long-run mean of the dividend process, and therefore, given the same public signal, they update their beliefs more than domestic investors do. The looser prior can further be microfounded as accumulated information disadvantage over time, which could be due to a shorter history or less precise signals, as modeled in Brennan and Cao (1997). Given the primary aim of this model is to study how capital flows affect currency risk, incorporating various information frameworks to induce capital flows does not significantly alter the primary mechanism. However, integrating them into the general equilibrium model will make the model less tractable. As such, Equation (4.3) can be seen as a reduced-form approach to induce a larger belief update from the foreign investors in a tractable way.

Households. Each household has two members, a consumer and an investor. Two members share the same budget constraint:

$$dW_t = r_t W_t dt - C_t dt + d\Pi_t. \tag{4.4}$$

where W_t is the total wealth of households, and $d\Pi_t$ is the excess returns from risky investments. C_t is the consumption of dividends.

The consumer chooses consumption flows C_t to maximize their lifetime utility $V_0 = \mathbb{E}_0 \int e^{-\rho t} C_t dt$, taking excess payoffs $d\Pi_t$ as given. As their utility function is linear in consumption, their optimization pins down the risk-free rate with their discount rate, $r_t = \rho$. This assumption neutralizes the fluctuations in the risk-free rate, which is beyond the scope of the current paper.

The investor determines the asset allocation W_t between bank deposits B_t (or loans if B_t is negative) and holdings of trees $\mathbf{Q}_t'\mathbf{P}_t$, where $\mathbf{Q}_t \equiv (Q_{US,t}, Q_{EU,t})'$ is the vector of quantities of two trees held by US investors, with $\mathbf{P}_t$ being the corresponding price vector.

$$W_t = B_t + \mathbf{P}_t'\mathbf{Q}_t. \tag{4.5}$$

The investor chooses the allocation to maximize mean-variance utility over the instantaneous payoffs, denominated in her own currencies:

$$\begin{aligned}
\max_{Q_{h,t}, Q_{f,t}} \mathbb{E}\left[d\Pi_t\right] - \frac{\gamma}{2} Var\left(d\Pi_t\right) \\
d\Pi_t &= \mathbf{Q}_t' d\mathbf{R_t} \\
dR_{c,t} &= dP_{c,t} - rP_{c,t}dt + D_{c,t}dt \text{ for } c \in \{US, EU\}.
\end{aligned}$$

The problem faced by the European investor is symmetric. I denote $P^*_{c,t}$ as the price of trees denominated in euros, and E_t is the price of one euro in the USD. That is, an increase in E_t corresponds to the euro appreciation. As investors can freely trade the share of trees, the law of one price holds so that

$$P_{c,t} = P^*_{c,t} E_t \text{ for } c \in \{US, EU\}. \tag{4.6}$$

Cross-border lending. The household's intertemporal budget constraint can be written in terms of bank deposits:

$$dB_t = rB_t dt - \mathbf{P}'_{\mathbf{t}} d\mathbf{Q}_t + \left(\mathbf{Q}'_t \mathbf{D}_{\mathbf{t}} - C_t\right) dt. \tag{4.7}$$

Equation (4.7) can be deemed as the supply of bank deposits. It has three components: accrued interest $rB_t dt$, withdrawal for risky investment $-\mathbf{P}'_{\mathbf{t}}\mathbf{dQ}_{\mathbf{t}}$, and current account $CA_t dt \equiv \left(\mathbf{Q}'_t \mathbf{D}_{\mathbf{t}} - C_t\right) dt$. Similarly, for European households, we have a symmetrical law of motion for B^*_t. In the global economy, the net supply of risk-free assets is zero; therefore, in equilibrium, we have:

$$B_t + B^*_t E_t = 0. \tag{4.8}$$

Households cannot save or borrow directly in the other currency. Cross-border lending has to be intermediated by banks. For concreteness, let us consider the case where the US bank lends to Europe, $B_t > 0 > B^*_t$. By performing cross-border lending, the US bank is exposed to exchange-rate volatility. The bank is also risk-averse. It chooses its exchange-rate exposure by maximizing a mean-variance utility function:

$$\max_{B^*} \mathbb{E}\left[-B^* dE_t\right] - \frac{\gamma^b}{2} Var(-B^* dE_t).$$

Their optimization leads to the first-order condition:

$$-B^*_t = \underbrace{(\gamma^b \sigma^2_{E,t})^{-1}}_{\zeta_t} \times \mu_{E,t}, \tag{4.9}$$

where $\mu_{E,t}$ and $\sigma^2_{E,t}$ are the instantaneous drift and volatility of the exchange-rate process. Equation (4.9) provides a downward-sloping demand curve for cross-border lending: to incentivize banks to take more exposure to exchange-rate movements, the foreign currency has to offer higher expected returns, and therefore its spot price has to be lower. Alternatively, the downward-sloping demand curve can be microfounded with a limited commitment constraint as in Gabaix and Maggiori (2015); similar formulations are also used in Hau and Rey (2006) and Itskhoki and Mukhin (2021).

In equilibrium, the exchange rate has a constant volatility, so I can define the parameter $\zeta \equiv \frac{1}{\gamma^b \sigma^2_E}$ to represent the bank's capacity in the foreign-exchange market. When $\zeta \to \infty$, banks have an infinite intermediation capacity, so unlimited cross-border lending can be channeled without moving the exchange rate; when $\zeta = 0$, banks have zero intermediation capacity, so no cross-border lending is allowed.

Current account and trade. The exchange-rate disconnect literature shows that trade has little to no correlation with exchange rates in the short run (Fukui et al., 2023; Itskhoki & Mukhin, 2021; Meese & Rogoff, 1983). Instead, the literature now focuses on financial flows driving exchange-rate fluctuations (Camanho et al., 2022; Gabaix & Maggiori, 2015; Itskhoki & Mukhin, 2021). My model is in the same spirit. However, the long-run exchange rate is eventually determined by trade in a general equilibrium model. To close the model, I assume a stylized model of international trade with frictions between two countries, in the similar spirit of Ready et al. (2017b).

I assume dividends are distributed to each investor proportional to their shares without costs. For example, if US investors hold half of the European tree, they can consume half of the European dividends frictionlessly. In addition to the dividend distribution, an exporter can ship goods between two countries at a quadratic cost. Therefore, when the exchange rate deviates from 1, the exporter can arbitrage by buying goods from the low exchange-rate country and selling them to the other. She determines the current account by maximizing the profit net of the trade cost:

$$\max_{CA_t} CA_t \left(E_t - 1\right) - \frac{\chi}{2} CA_t^2,$$

where $\frac{\chi}{2}CA^2$ is the trade cost, which is considered a deadweight loss. The quadratic form assumes the marginal cost of trade to be increasing with the amount of exports. This assumption is consistent with empirical evidence on the trade cost (see discussions in Ready et al., 2017b). The first-order condition results in CA_t as a linear function of price gaps:

$$CA_t = \frac{1}{\chi}\left(E_t - 1\right). \tag{4.10}$$

When χ is close to zero, the arbitrage cost is very low, and therefore, a small deviation in exchange rates will result in large current-account flows; when $\chi \to \infty$, the arbitrage is infeasible, and the exchange-rate dynamics are solely determined by capital flows.

Equilibrium. The equilibrium is defined as a tuple of variables $\mathbf{X_t} \equiv \left(P^{(*)}_{US,t}, P^{(*)}_{EU,t}, E_t, Q^{(*)}_{h,t}, Q^{(*)}_{f,t}, ...\right)'$ as functions over the state space $\mathbf{S_t} \equiv \left(D_{US,t}, D_{EU,t}, \tilde{D}_{US,t}, \tilde{D}_{EU,t}, W_t - W_t^*\right)'$, such that: 1) given prices, investors, households, and banks and the exporter optimize; 2) the law of one price holds for risky assets, and 3) markets clear. The market clearing of risky assets requires the sum of the holdings of both trees from the two countries to be equal to 1:

$$Q_i + Q_i^* = 1 \; for \; i \in \{US, EU\}. \tag{4.11}$$

The risk-free asset market clears so that one country's lending equals the other country's borrowing:

$$B_t + B_t^* E_t = 0.$$

The goods-market clearing follows automatically by Walras' law:

$$C_t + C_t^* = D_t + D_t^* - \frac{\chi}{2} CA_t^2 \tag{4.12}$$

To obtain an analytical characterization of the equilibrium, I linearize the equilibrium conditions around the risky steady state $\bar{\mathbf{S}} \equiv \left(\bar{D}_h, \bar{D}_f, \bar{D}_h, \bar{D}_f, 0\right)'$. Following linearization, the equilibrium can be represented as affine functions of the state:[20]

$$\mathbf{X_t} = \bar{\mathbf{X}} + \beta_X' \left(\mathbf{S_t} - \bar{\mathbf{S}}\right).$$

$\bar{X}$ and $\beta_{\mathbf{X}}$ are the solution to a system of nonlinear equations, formally derived in Appendix C.2. The nonlinear equations do not yield closed-form solutions for general cases. Fortunately, the symmetric case of the two countries offers an analytical characterization of the coefficients. Therefore, I first characterize the equilibrium under the symmetric case to provide intuitions of the key mechanism, and then I perturb around the symmetric case to understand the interaction of capital flows and currency risks. I also use numerical solutions to verify that the analytical results hold more generally.

4.2 Flighty Capital Flows in the Model

I first analytically characterize capital flows in the equilibrium under the symmetric case. Portfolio flows in the model are defined as:

$$\begin{aligned} dF_{L,t} &= dF_{A,t}^* \equiv \bar{P}_{US} dQ_{US,t}^* \\ dF_{L,t}^* &= dF_{A,t} \equiv \bar{P}_{EU} dQ_{EU,t}. \end{aligned}$$

I define the *liability flow* into the US $dF_{L,t}$ as the change in European investors' holdings of the US tree $\bar{P}_{US} dQ_{US,t}^*$. It is also the *asset flow* of Europe $dF_{A,t}^*$ in this two-country economy. Similarly, the liability flow into Europe $dF_{L,t}^*$ is the change in US investors' holdings of the European tree. Following the terminology in the Balance of Payment Manual, liability flows are also referred to as gross inflows, and asset flows are referred to as gross outflows. Here, I use liability flows and asset flows for clarity.

To capture the responses of flows to news, I focus on the responses of flows to shocks dZ_t. Proposition 1 characterizes loadings of flows on shocks:

Proposition 1. *Under the symmetric case, $\theta_{US} = \theta_{EU} = \theta > 0$, we have:*

$$\begin{aligned} dF_{L,t} &= dF_{A,t}^* = \mu_{F_L,t} dt + \theta \bar{f} \left(\psi \sigma dZ_{US,t} + (1-\psi) \sigma dZ_{EU,t} + \sigma_g dZ_{g,t}\right) \\ dF_{A,t} &= dF_{L,t}^* = \mu_{F_A,t} dt + \theta \bar{f} \left((1-\psi) \sigma dZ_{US,t} + \psi \sigma dZ_{EU,t} + \sigma_g dZ_{g,t}\right) \end{aligned}$$

[20] Linearization is necessary because of the exchange-rate movements, which introduces quadratic terms (e.g. $E_t P_{EU,t}^*$) into the system. In the case where banks have infinite capacity ($\zeta = \infty$), the exchange rate is constant, $E_t = \bar{E}$, and thus the solution is exact rather than approximate.

where $\bar{f} > 0$. $\psi = \frac{\sigma_g^2+\sigma^2}{2\sigma_g^2+\sigma^2}$ when $\zeta = \infty$ (banks with infinite capacity), and $\psi = \frac{1}{2}$ when $\zeta = 0$ (banks with zero capacity).

Proof. See Appendix C.2. □

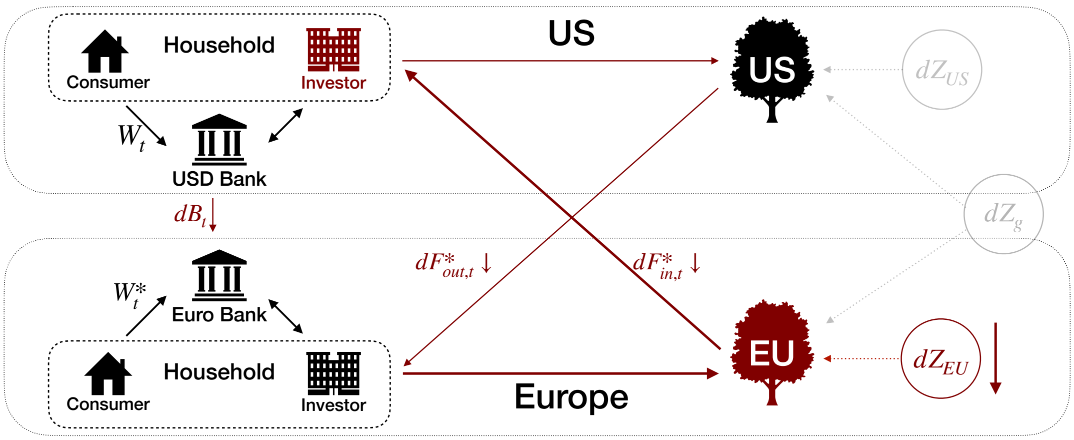


Figure 7: Capital Flows under a shock to the European tree

To understand the underlying rationale of this proposition, let us consider a negative shock to the European tree $dZ_{EU,t}$. Figure 7 illustrates the capital flows upon a local shock to Europe. Following the shock, US investors update their belief about the European long-run mean—they are uncertain whether the lower dividend of the European tree is due to a temporary shock or a long-run mean that is lower than previously believed. Therefore, US investors lower their belief for the future dividend growth more than European investors do. As a result, US investors sell their holdings of European trees to European investors. The magnitude of flows is proportional to the foreign flightiness parameter θ.

In this model, A local shock to one country generates global retrenchment in both countries. To finance the purchase of shares sold by US investors, European investors can either rebalance from their holdings of the US tree or borrow from the US investors.[21] The former results in a retrenchment of European investors (a reduction in European external asset flows), and the latter leads to a net banking inflow. The relative weights of the two sources of financing depend on the friction on the foreign-exchange market. In one extreme, when banks have infinite capacity ($\zeta = \infty$), they can intermediate infinite cross-border lending without moving the exchange rate. Therefore, European investors rely mostly on interbank borrowing to finance their purchase of the European tree. They will still reduce their investment in the US tree, given two trees are substitutes in terms of exposures to global shocks. In the other extreme, when banks have zero capacity ($\zeta = 0$), cross-border lending is prohibited. To finance their purchase, European investors

[21]In principle, European investors can also finance their portfolio flows by net exports. However, this is ruled out in the this model as capital flows respond to shocks at dZ terms while the current account operates at the dt term reflecting the trade friction. This technicality has an intuitive interpretation: as in the real world, financial flows respond to the news at a much higher frequency than trade flows.

have to sell an equivalent value of US trees. In this world, a one-dollar portfolio inflow is matched exactly by a one-dollar portfolio outflow.

Propagation of local shocks in the global asset markets. In this model, flighty capital flows propagate local shocks to asset prices in the other country. To illustrate this, consider the zero-capacity and zero-trade limit ($\zeta \to 0, \chi \to \infty$) where price dynamics can be solved in closed-form:

$$
\begin{aligned}
dP^*_{EU,t} &= \mu_p dt + \frac{1}{r+\alpha} dD_{EU,t} + p_{\tilde{D}} \left(\sigma dZ_{US,t} + \sigma dZ_{EU,t} + \sigma_g dZ_{g,t} \right), \\
dP_{US,t} &= \mu_p dt + \frac{1}{r+\alpha} dD_{US,t} + p_{\tilde{D}} \left(\sigma dZ_{US,t} + \sigma dZ_{EU,t} + \sigma_g dZ_{g,t} \right)
\end{aligned}
$$

where $p_{\tilde{D}} \equiv \frac{\alpha\theta}{2(r+\alpha)(2(r+\kappa)+\theta)}$. The expression is derived in Appendix C.2.

A negative European shock $dZ_{EU,t}$ affects the price of the European tree in two ways. First, it directly lowers the dividend level of the European tree in the short run. The shock to dividend $dD_{EU,t}$ is passed to the asset price at the discount rate of $(r+\alpha)$, the sum of the risk-free rate and the mean-reverting rate. Second, the drop in asset prices is further amplified by flighty capital flows. The negative shock reduces US investors' perceived long-run mean $\tilde{D}_{EU,t}$, resulting in negative European liability flows. European investors acquire the shares sold by US investors, demanding a higher risk premium for a higher risk-taking. This further lowers the price of the European tree, captured by the term $p_{\tilde{D}} \sigma dZ_{EU,t}$.

The response of US investors' belief to the European shock also results in a decrease in the price of the US tree in equilibrium: the same term $p_{\tilde{D}} \sigma dZ_{EU,t}$ also enters the price dynamics of the US tree. This is because European investors finance their purchase of the European tree by selling the US tree, as cross-border lending is prohibited ($\zeta = 0$), and the price of the US tree has to drop to incentivize US investors to purchase them.

Thus, a local shock to one economy can give rise to patterns characteristic of the global financial cycle, wherein cross-border capital flows are positively correlated with asset prices, leading to synchronized asset-price movements across the two countries.

4.3 Currency Risk in the Model

Now I discuss how capital flows affect currency risk in this model. A currency is risky if it depreciates during global downturns. In this model, it is captured by the exchange rate's loading on the global shock $dW_{g,t}$.

I start with the impact of a global shock in a symmetric model. Figure 8 illustrates the global capital flows following the shock. Investors in both countries adjust their beliefs downward for trees in the other country. This results in *global retrenchment*: both country investors reduce their outbound investment and retrench towards their own assets. By symmetry, the two countries are equally exposed to the global shock, so investors in the two countries simply swap their holdings without net borrowing from each other. The exchange rate as the relative price between the two countries' currencies remains unchanged.

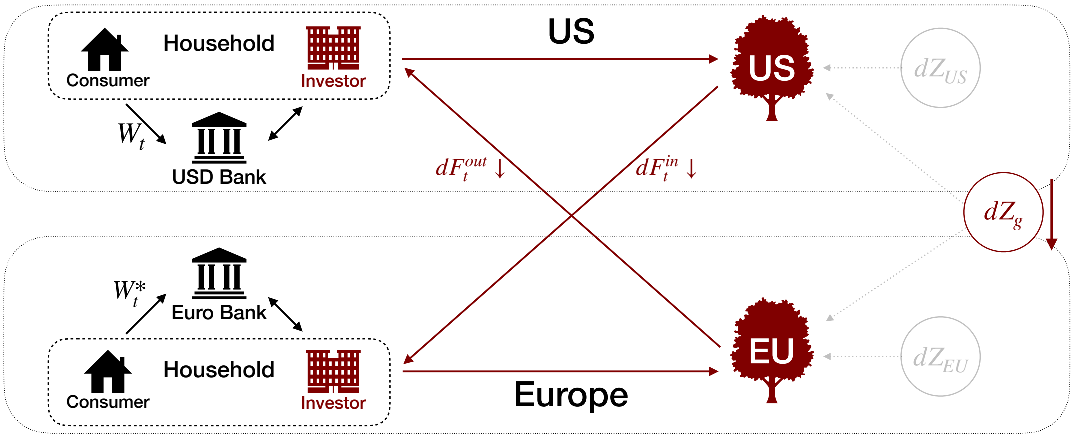


Figure 8: Capital Flows under a Global Shock

Therefore, in order to study the exchange rate's loadings on the global shock, we need to deviate from the symmetric case. Here, I allow for heterogeneity in foreign flightiness parameters θ_c between two countries, to examine its impact on capital flows and currency risk.

As a first step, I link foreign flightiness parameters θ_c to responses in flows. Lemma 1 below shows that in equilibrium, Europe's liability flows are flightier than its asset flows if foreign investors' belief for the European tree responds more than those do for the US tree ($\theta_{EU} > \theta_{US}$):

Lemma 1. *Let Δf_g^* be the loading of Europe's net outflow $dF^*_{A,t} - dF^*_{L,t}$ on the global shock $dW_{g,t}$. There exists a $\bar{\theta}$ such that for $\theta_{EU} < \bar{\theta}$ and $\theta_{US} = \theta_{EU} + \Delta\theta$, Δf_g^* is locally increasing in $\Delta\theta$ around the symmetric equilibrium $\Delta\theta = 0$, i.e.,*

$$\frac{\partial \Delta f_g^*}{\partial \Delta\theta} |_{\Delta\theta=0} > 0.$$

Proof. See Appendix C.2. □

Figure 9 illustrates capital flows under an asymmetric world where $\theta_{EU} > \theta_{US}$. Upon a negative global shock, the US investor seeks to withdraw more capital from Europe than European investors retrench. Therefore, Europe faces a net portfolio outflow, and European investors borrow from the interbank market to finance their positions. As US banks take larger positions in the euro ($dB_t > 0$), they demand higher excess returns to hold euros. Consequently, the euro must depreciate to clear the market. The currency's exposure to global shocks is formally characterized in Proposition 2:

Proposition 2. *Let e_g be the loading of dE_t on the global shock $dW_{g,t}$. There exists $\bar{\theta}$ such that for $\theta_{EU} < \bar{\theta}$ and $\theta_{US} = \theta_{EU} + \Delta\theta$, e_g is locally decreasing in $\Delta\theta$ around the symmetric equilibrium $\Delta\theta = 0$, i.e.,*

$$\frac{\partial e_g}{\partial \Delta\theta} |_{\Delta\theta=0} < 0.$$

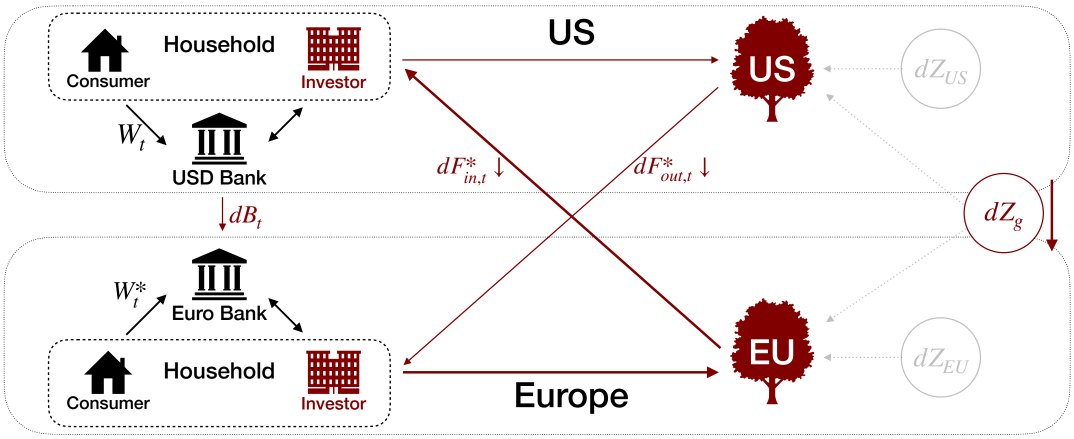


Figure 9: Asymmetric Capital Flows under a Global Shock

Proof. See Appendix C.2. □

In other words, Proposition 2 shows that the euro is riskier ($e_g > 0$) if Europe's external liabilities are more prone to flighty flows than its assets are ($\theta_{EU} > \theta_{US}$). This proposition offers a testable hypothesis.[22] In the next section, I empirically construct net asset flightiness to measure the relative flightiness of assets vs. liabilities in each country, and demonstrate its negative correlation with currency risk in data.

5 Empirical Tests of Model Prediction on Currency Risk

I test model implications on flow flightiness and currency risk. I construct an empirical measure of net asset flightiness based on countries' external balance sheet composition. It assigns positive values for countries with flightier assets relative to liabilities. I demonstrate that net asset flightiness strongly correlates with currency risk.

5.1 Construction of Net Asset Flightiness

Net asset flightiness is constructed using the external balance sheet of each country and international capital flows. The datasets used here are the International Investment Position (IIP) and the Coordinated Portfolio Investment Survey (CPIS) for balance sheet compositions, and the Balance of Payment (BOP) for aggregate flows. These datasets are all publicly accessible through the International Monetary Fund (IMF). Details of data sources are reported in Appendix D.1.

Net asset flightiness is defined as a country's external assets minus liabilities, weighted by the corresponding asset-specific flightiness coefficient $\Delta\theta_s$:

[22] Lemma (1) and Proposition (2) are stated in model parameters, which are not directly observable in data. In Appendix C.2.5, I use numerical solutions to show the hypothesis holds when expressed in terms of moments of observable variables and in a broad range of parameters.

$$NAF_{c,t} = \frac{(\sum_s A_{c,s,t-1}\Delta\theta_s - \sum_s L_{c,s,t-1}\Delta\theta_s)}{(A_{c,t-1} + L_{c,t-1})/2}, \tag{5.1}$$

I use s to denote different types of assets. Assets are classified by type of issuing country (core advanced economies and others) and asset class (public debt, private debt, equities, etc.), based on their different degrees of foreign flightiness $\Delta\theta_s$. The empirical literature on capital flows, as well Table 1 in Section 2, has documented that foreign-flow sensitivities vary across issuing country types and asset classes. For instance, foreign flows to sovereign debt issued by core advanced economies are not flighty, while private bond flows are almost universally sensitive to the financial news. To test the assumption on the asset type classification, Figure 18 in the appendix reports the estimates of foreign flightiness by country and asset class. It shows that within each asset class, countries in each group (AE vs. others) indeed tend to face similar levels of foreign flightiness.

Conceptually, asset-specific flightiness can be estimated for each asset type s by regressing the differences between foreign and domestic flows on global shocks, pooling from all countries:

$$f^{foreign}_{c,s,t} - f^{domestic}_{c,s,t} = \Delta\theta_s \times r^{global}_t + \beta_{0,s} + \epsilon_{c,s,t} \quad \text{for each } s, \tag{5.2}$$

where $f^{foreign}_{c,s,t} \equiv \frac{F^{foreign}_{c,s,t}}{A^{foreign}_{c,s,t-1}}$ is the aggregate foreign flows into the country c's asset market s at time t, and $f^{domestic}_{c,s,t}$ is the domestic counterpart. I use the global stock-market return to proxy the global shocks.[23] Equation (5.2) is the aggregate counterpart of the specification in Equation (2.3) for fund flows.

In practice, the domestic flows are often not observed for most of countries, rendering direct estimation of the specification in Equation (5.2) infeasible. Fortunately, at the aggregate level, the market-clearing condition must hold. Assuming a fixed supply of assets in the short run, the market-clearing condition requires:[24]

$$A^{foreign}_{c,s,t-1} f^{foreign}_{c,s,t} + A^{domestic}_{c,s,t-1} f^{domestic}_{c,s,t} = 0.$$

The market-clearing condition suggests that when aggregate foreign flows are positive, the domestic flows are necessarily negative. Therefore, to gauge the heterogeneous sensitivities by foreign and domestic flows, I can use the following specification:

$$f^{foreign}_{c,s,t} = \Delta\tilde{\theta}_s \times r^{global}_t + \epsilon_{c,s,t}, \tag{5.3}$$

where $\Delta\tilde{\theta}_s$ naturally captures the heterogeneity between foreign vs. domestic flows by market clearing.

[23] The results remain robust when using innovations to VIX, or innovations to the global financial cycle factor estimated by Miranda-Agrippino and Rey (2020).

[24] For certain asset classes, e.g., public debt, I can observe changes in aggregate supply for a subsample of countries from other datasets such as Quarterly Public Sector Debt (QPSD) by the World Bank. I adjust for supply changes in the foreign flows whenever feasible, as discussed in Appendix D.1.

Table 5 reports flow flightiness $\tilde{\theta}_s$ estimated using the Balance of Payments (BOP) data from 2000Q1–2021Q4. Appendix D.1 provides a detailed description of the estimation methodology. Each cell represents the asset-specific flightiness coefficient for a given asset type. To interpret the coefficients, consider the example of private debt in advanced economies. An estimate 0.04 implies that a one-percent increase in the global stock-market return is associated with an increase of 4 basis points in global flows into foreign private debt issued by core advanced economies. Consistent with results in Section 2, foreign flows to public debt issued by advanced economies are not flighty, whereas other asset types exhibit varying degrees of susceptibility to foreign flightiness.[25]

Table 5: Asset-specific flightiness

	Public Debt	Private Debt	Equity
Core Advanced Economies	-0.00	0.04*	0.03**
	(0.053)	(0.021)	(0.010)
Others	0.05	0.07**	0.09***
	(0.033)	(0.026)	(0.012)

Note. This table reports asset-specific flightiness coefficients, estimated from regressions $f^{foreign}_{c,s,t} = \Delta\tilde{\theta}_s \times r^{global}_t + \epsilon_{c,s,t}$, pooling across all countries for the same type of flows between 2000Q1-2021Q4. Asset types are defined by issuance country type and asset class. Flows are computed using the Balance of Payment and the International Investment Positions by the IMF. Core advancecd economies here refer to Australia, Austria, Belgium, Canada, Denmark, France, Germany, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, United Kingdom, and United States. Standard errors are reported in parentheses, clustered at the quarter level. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

Net asset flightiness can be computed as external assets minus liabilities, weighted by asset-specific flightiness $\Delta\tilde{\theta}_s$ from Table 5. The composition of external assets and liabilities across different asset types can be directly observed from datasets by the IMF.

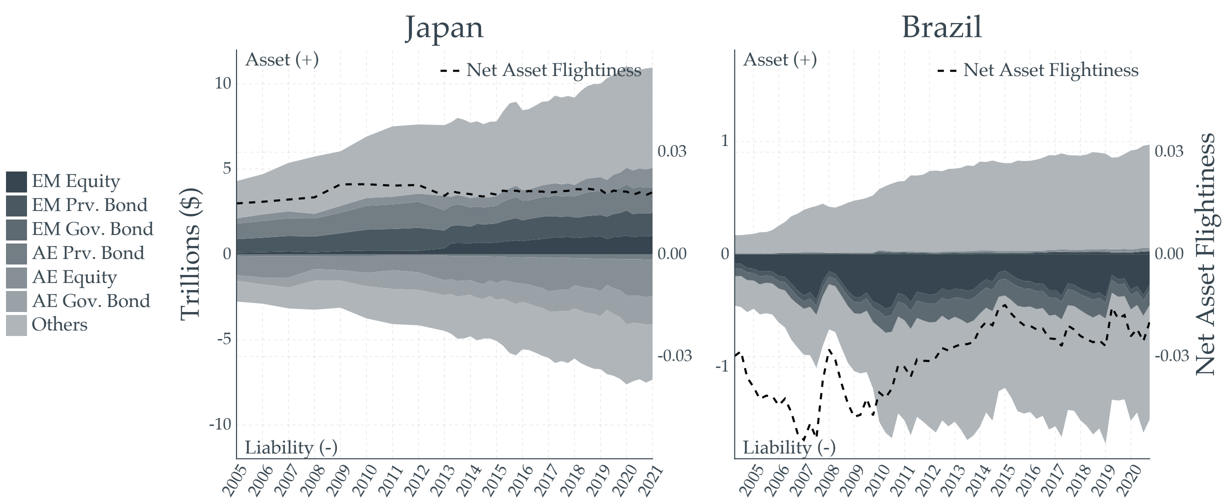
If all assets were equally flighty, $\Delta\theta_s = \Delta\bar{\theta}$, net asset flightiness would be equivalent to net foreign asset (NFA) position, an explanatory variable of currency risk explored in the literature (Della Corte et al., 2016; Habib & Stracca, 2012). However, not all investments are made equal. With the same size of external liabilities, a country with a greater proportion of external liabilities in private bonds experiences significantly larger withdrawals during economic downturns than a country with a greater proportion of external liabilities in sovereign bonds. In the subsequent empirical tests below, I control for net foreign assets to show the asset-flightiness weighting provides added value in understanding currency risk.

Figure 10 provides two concrete examples, Japan and Brazil. In each panel, I plot external assets on the positive y-axis and external liabilities on the negative y-axis. For both external assets and liabilities, I decompose them into different asset types. The color corresponds to the asset-specific flightiness report in Table 5. The darker the color, the flightier investors are for the asset type. The net asset flightiness, reported on the right axes, is the average of external assets and

[25]Here, I only report coefficients for portfolio flows, which are the focus of this paper. This choice effectively puts zero weight on other types of investments such as bank loans and FDIs. In fact, bank loan flows and FDIs have close to zero coefficients when regressed on global stock-market returns, as reported in Table 17 in the appendix. Hence, including other types of flows does not change the results at all.

liabilities weighted by the asset-specific flightiness. Japan's external assets are "flightier" than its external liabilities: its external liabilities are largely in government bonds and equity, both of which are less susceptible to flighty capital flows since Japan is an advanced economy, while its external assets consist of large investments in emerging markets.[26] This composition results in a large positive net asset flightiness for Japan. Conversely, Brazil has large external liabilities in bonds and equities but few portfolio assets. Being an emerging market, Brazil's bonds and equities are susceptible to flighty foreign flows. Therefore, Brazil has a large negative net asset flightiness. As I show below, the Japanese yen and the Brazilian real are indeed among the safest and riskiest currencies, respectively.

Figure 10: Net Asset Flightiness: Japan and Brazil



Note. This figure presents the external balance sheet composition of Japan and Brazil. The figure plots external assets in the positive y-axis and external liabilities in the negative y-axis. The darkness of color indicates the asset-specific foreign flightiness, estimated in Table 5. The black dotted line (right axes) reports net asset flightiness, computed following Equation (5.1).

By construction, the variation of net asset flightiness originates from the balance sheet composition of each country. The asset-specific flightiness is estimated across countries and therefore is not country-specific but asset-specific. In this way, I circumvent the reverse causality concern that the inflow to a country is flighty *because* its currency is risky, since I do not directly estimate the flightiness of the country's inflow.

An alternative way of constructing the net asset flightiness would be to directly estimate the flow flightiness *country-by-country*. This alternative approach has two major drawbacks. First, the reverse causality concern discussed above applies, as the flows can be driven by currency movements. Second, the panel of external balance sheet composition is relatively short, making country-by-country estimates much noisier. For example, the US only started to report external

[26]Japan, as well as many other countries, does not break down external bond holdings into government bonds and private bonds. Here I impute the share of public and private bonds in total bond holdings using global averages. Alternatively, I construct the net asset flightiness by lumping outflows in private bonds and public bonds together and estimate the beta asset for general portfolio bonds by country type. Both methods yield very similar results.

balance sheet composition to IMF in 2005, and for many emerging markets the reporting started even later. In Appendix D.1 I directly estimate the net portfolio flow flightiness for each country and compare it with net asset flightiness. The direct estimates of net portfolio flow flightiness strongly correlate with net asset flightiness constructed from the balance sheet composition above, and weakly correlate with currency risk as well.

5.2 Empirical Tests of Net Asset Flightiness and Currency Risk

As a benchmark, I use the currency beta on global stock-market returns as the measure of currency risk. This measure captures the cyclical behavior of each exchange rate throughout the global business cycle, and is directly motivated by the implication of my model. I estimate currency beta by regressing currency excess returns on global equity returns for each country at the monthly frequency, as in Equation (5.4):

$$Re_{c,t} = \beta_c^{FX} \times r_t^{global} + \beta_{0,c} + \varepsilon_{i,t}. \tag{5.4}$$

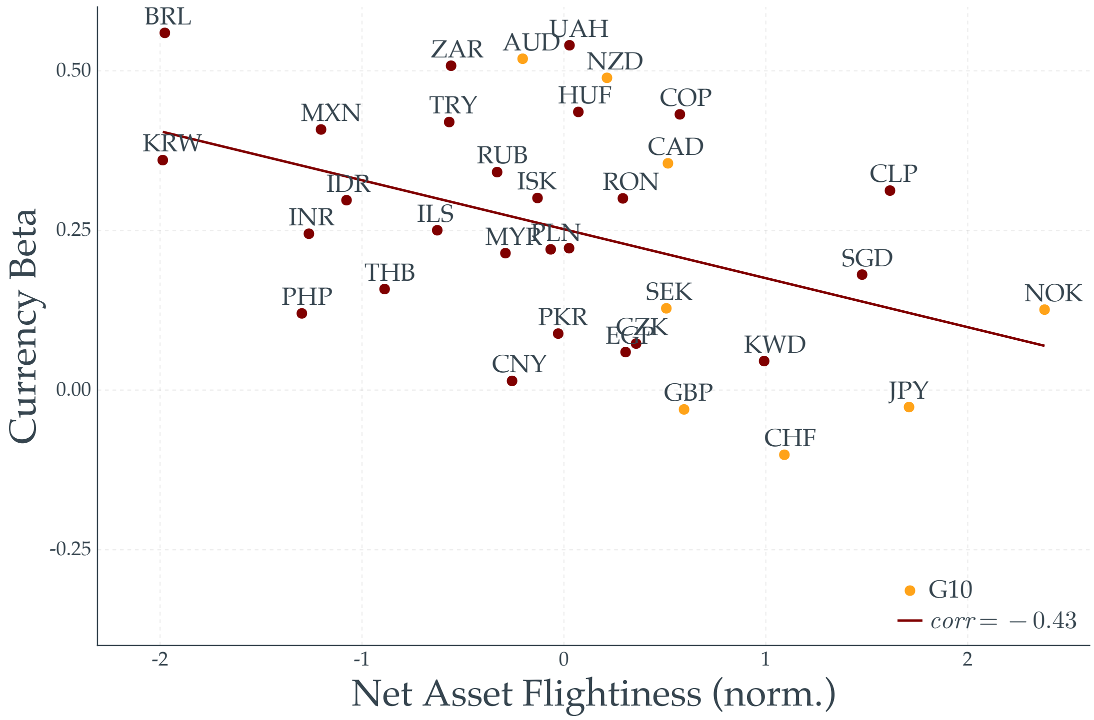
The currency excess returns $Re_{c,t}$ are excess returns from borrowing in a reference currency and lending in currency c, defined as $Re_{c,t+1} \equiv \frac{E_{c,t+1}}{E_{c,t}} \frac{R^f_{c,t}}{R^f_{ref,t}} - 1$. In the baseline, the reference currency is set to the euro for European currencies outside of the euro area, and the USD for all other countries. My results are robust to different choices of the reference currency such as the basket of G10 currencies or the USD for all countries. The baseline choice is based on two considerations. First, the model's prediction on the currency risk is relative to the counterparty with whom the country is trading assets. For European countries outside of the euro area, the largest counterparty is typically the eurozone. Additionally, the euro holds the most substantial weight in the Bank for International Settlements' effective exchange-rate indices for these currencies. Second, according to Fratzscher et al. (2019), European countries outside of the euro area manage their currencies against the euro to different extents, ranging from a hard peg to broad crawling bands. Computing excess return against the reference currency for intervention neutralizes the benchmarking effect caused by the movement of the reference currency (the euro) itself.

As a start, I show in the cross-section that the currency beta is negatively correlated with net asset flightiness. Figure 11 reproduces Figure 1 in the introduction for convenience. It plots the currency beta against the average net asset flightiness for each country. They exhibit a strong negative correlation: countries with high net asset flightiness have low currency beta. The correlation coefficient is 0.43 and highly significant.[27] As predicted by their net asset flightiness, the Japanese yen and the Brazil real are indeed among the safest and riskiest currencies, respectively. Another well-known safe-haven currency, the Swiss franc, also has a high net asset flightiness.[28]

[27] The standard error is calculated using block bootstrapping across periods. The results are robust with different block sizes.

[28] The US dollar is a relative outlier of this relationship. The US has a modestly negative net asset flightiness (~ -1 s.t.d.) but it is the safest currency measured against the basket of G10 currencies. This is also shown in Figure 11, as most currencies have positive betas against the USD as the reference currency. It suggests that the USD does enjoy a

Figure 11: Net Asset Flightiness Correlates with Currency Beta



Notes. This figure reproduces Figure 1 for convenience. It plots currency beta against the average net asset flightiness for each country. Currency beta is estimated from regressions $Re^e_{c,t} = \beta^{FX} r^{global}_t + \varepsilon_{c,t}$ between 2000Q1–2021Q4, where $Re_{c,t}$ is the excess return (uncovered interest parity premium) of the currency against its reference currency, the euro for European countries and the US dollar otherwise, and r^{global}_t is the return on the MSCI world equity index. Net asset flightiness is constructed following Equations (5.1). It aggregates a country's external balance sheet based on asset-specific flightiness estimated in Table 5.

I then turn to panel regressions to study the relationship between currency betas and net asset flightiness, controlling for other explanatory variables identified in the literature:

$$Re_{c,t} = \left(\gamma_0 + \gamma \times NAF_{c,t-1} + \gamma_{AE} I_{AE} + \gamma'_x x_{c,t}\right) \times r^{global}_t + \delta_c + \psi'_x x_{c,t} + \delta_{AE} + \varepsilon_{c,t}. \tag{5.5}$$

The left-hand side of Equation (5.5) is currencies' excess returns. The terms in parentheses are the currency beta. The coefficient γ is the coefficient of interest: it captures the differences in currency beta associated with different levels of net asset flightiness $NAF_{c,t-1}$. I also allow for different currency betas between advanced economies and emerging markets to study the within-group variations.

In $x_{c,t}$, I control for explanatory variables of currency risk documented in the literature. Habib and Stracca (2012) and Della Corte et al. (2016) empirically show that net foreign asset (NFA) positions negatively correlate with currency risk. Brunnermeier et al. (2008) suggest that the unwinding of carry trade during market turmoil may lead to risky currency crashes, and Menkhoff et al. (2012) shows that high-interest-rate currencies are negatively related to the innovations in global

special status.

volatility. This mechanism is captured with the interest-rate differential (Δr). Hassan (2013) proposes that currencies of large economies are safer as they naturally offer better hedges against consumption risks. Country sizes are proxied with log(GDP) in the regressions. I include indicator functions for advanced economies and commodity currencies as well.[29] Finally, I also control the financial openness index by Chinn and Ito (2006) as countries with different levels of financial openness are exposed to global risks differently.

Table 6 reports the estimation results. Columns (1)-(2) use excess returns against their reference currencies, the US dollar or the euro. Column (1) reports the baseline regression without controls. The estimate of γ is negative and highly significant. I scale net asset flightiness by its standard deviation to simplify the interpretation of the coefficient. The point estimate of γ indicates that a one-standard-deviation increase in net asset flightiness is correlated with a 0.082 decrease in currency beta. To put it into perspective, the coefficient of r_t^{global} reports the currency beta of a flightiness-neutral currency ($NAF = 0$) against the reference currency (typically the USD) to be 0.229, suggesting that approximately three standard deviations of net asset flightiness are required for a currency to achieve neutrality with the USD. In Column (3) I report the same exercise but use excess returns against G10 currencies instead. The estimate of the key coefficient γ is similar, though slightly smaller. Notably, the coefficient associated with r_t^{global} is close to zero. That is, a country whose net inflow is acyclical also has an acyclical currency against a basket of major currencies.

Column (2) compares net asset flightiness with other explanatory variables for currency risk, particularly the net foreign assets (NFA). Coefficients for stand-alone controls without interactions (ψ_x) are not reported in the table to save space. The coefficient for net asset flightiness remains stable and significant after controlling for other variables. As previously discussed, net asset flightiness can be considered as net foreign assets (NFA) weighted by asset-specific flightiness. The significance of net asset flightiness indicates that the weighting by flightiness captures critical information pertinent to currency risk.

[29] Commodity currencies here are the New Zealand dollar, Norwegian krone, South African rand, Brazilian real, Russian ruble and the Chilean peso.

Table 6: Currency Beta explained by Net Asset Flightiness

	R^e			
	(1)	(2)	(3)	(4)
r_t^{global}	0.229***	0.211	-0.002	0.565**
	(0.016)	(0.249)	(0.013)	(0.197)
$r_t^{global} \times NAF_{(norm.)}$	-0.082***	-0.070***	-0.036***	-0.041***
	(0.011)	(0.013)	(0.008)	(0.010)
$r_t^{global} \times NFA_{(norm.)}$		-0.054***		-0.052***
		(0.010)		(0.012)
$r_t^{global} \times$ AE		-0.077*		-0.023
		(0.033)		(0.034)
$r_t^{global} \times \Delta r$		0.040		0.052
		(0.039)		(0.046)
$r_t^{global} \times log(GDP)$		-0.003		-0.025**
		(0.009)		(0.008)
$r_t^{global} \times$ Open		0.030***		0.043***
		(0.008)		(0.008)
$r_t^{global} \times$ Commodity		0.254***		0.238***
		(0.027)		(0.028)
Country FE	Yes	Yes	Yes	Yes
vis-à-vis	Benchmark	Benchmark	G10	G10
N	8,248	7,712	8,598	8,062
R^2	0.158	0.209	0.008	0.065

Note. This table reports the estimates of Equation (5.5). The left-hand variable is the currency excess returns. The key right-hand variable is the interaction term between global equity return and net asset flightiness. Net asset flightiness is scaled by its standard deviation. Columns (1)-(2) use the USD or the euro as the reference currencies, following Fratzscher et al. (2019), and Columns (3)-(4) use the basket of G10 currency (excluding the test currency itself). Control variables are: net foreign asset positions (NFA), indicators for advanced economy and commodity currency, interest-rate differentials, log of GDP, and financial openness index by Chinn and Ito (2006). Standalone controls (noninteractive terms) are omitted from the table for readability. Standard errors are reported in parentheses, clustered at the monthly level. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

5.3 Alternative Measures of Currency Risk

In the discussion above, currency risk is measured as the currency beta on global equity returns. This definition directly measures the risk exposure of a currency for a representative global investor. It is also closely linked to the model implication. Nevertheless, the explanatory power of net asset flightiness is not limited to this particular measure. In this subsection, I show that net asset flightiness is also correlated with alternative measures of currency risk.

Instead of the global equity return, the asset pricing literature on exchange rates identifies several risk factors specific to the foreign-exchange market (Lustig et al., 2011, 2014; Verdelhan, 2018). In particular, Verdelhan (2018) identifies two global factors, the dollar factor and the carry factor that account for a large share of variation in bilateral exchange rates. Net asset flightiness explains currency loadings on both factors. Table 7 reports the estimates of Equation (5.5) but with the global equity return replaced by risk factors estimated by Verdelhan (2018). The sign of risk factors is chosen to be consistent with equity returns. The coefficients in front of net asset flightiness are negative and significant for both factors.

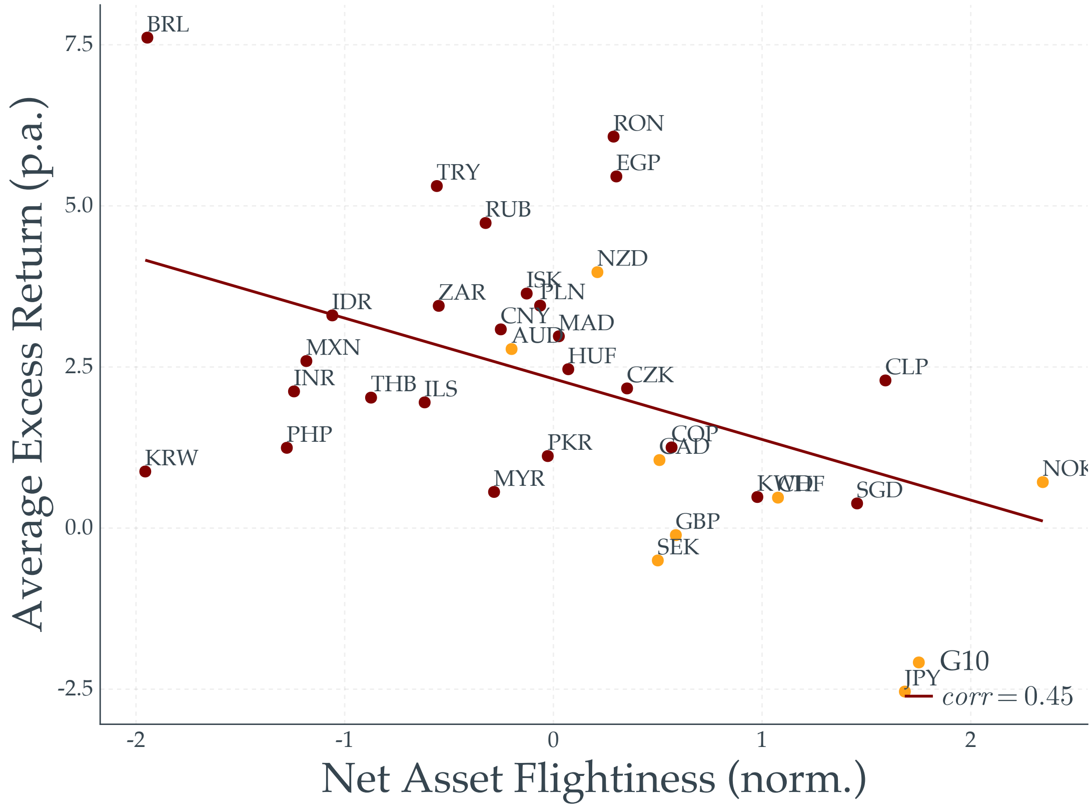
Table 7: Currency Loadings on Risk Factors Explained by Net Asset Flightiness

	Carry		Dollar	
	R^e			
	(1)	(2)	(3)	(4)
f_t	31.780***	-57.454	41.372***	84.209**
	(4.626)	(59.857)	(1.967)	(30.331)
$f_t \times NAF_{(norm.)}$	16.682***	9.809**	8.881***	7.159***
	(2.460)	(3.468)	(1.636)	(1.874)
$f_t \times NFA_{(norm.)}$		-5.676*		-9.278***
		(2.287)		(1.280)
$f_t\times$ AE		-13.649		-20.318***
		(7.211)		(4.720)
$f_t \times \Delta r$		33.408***		-6.589
		(6.873)		(5.690)
$f_t \times log(GDP)$		2.706		-2.049
		(2.261)		(1.165)
$f_t\times$ Open		1.511		4.366***
		(1.653)		(1.121)
$f_t\times$ Commodity		38.622***		44.224***
		(5.258)		(3.880)
Country FE	Yes	Yes	Yes	Yes
N	7,481	6,995	7,481	6,995
R^2	0.100	0.149	0.215	0.251

Note. This table reports the estimates of Equation (5.5), with the global equity return replaced by risk factors from Verdelhan (2018). The left-hand variable is the currency excess returns. The key right-hand variable is the interaction term between global equity return and net asset flightiness. Net asset flightiness is scaled by its standard deviation. Columns (1)-(2) use the carry factor as the cyclical variable while Column (3)-(4) use the global dollar factor. Control variables are: net foreign asset positions (NFA), advanced economy indicator, interest rate differentials, log of GDP, and financial openness index by Chinn and Ito (2006). Standalone controls (noninteractive terms) are omitted from the table for readability. Standard errors are reported in parentheses, clustered at the monthly level. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

With higher exposure to risk factors, investors demand risk premia as compensation. Therefore, in equilibrium, risky currencies offer excess returns on average. Indeed, currencies with high net asset flightiness provide high average excess returns vis-à-vis the benchmark currency, as illustrated in Figure 12.

Figure 12: Net Asset Flightiness Correlates with Currency Returns



Notes. This figure plots currency average excess returns against average net asset flightiness for each country. Net asset flightiness is constructed following Equations (5.1). It aggregates a country's external balance sheet based on asset-specific flow flightiness estimated in Table 5.

Table 8 reports the predictive regression of currency excess returns on net asset flightiness to test whether net asset flightiness negatively predicts the average excess returns:

$$R^e_{c,t} = \beta \times NAF_{c,t-1} + \beta'_X X_{c,t} + \varepsilon_{c,t}. \tag{5.6}$$

In Column (1) I report the univariate regression. A one-standard-deviation increase in net asset flightiness is associated with -1.25 percent of average excess return per year. In Column (2) I control for the same set of control variables as before except the interest rate differential, since it enters the left-hand side. The point estimate is stable, though the statistical significance is slightly reduced. Columns (3)-(4) repeat the same exercise but with the average of the basket of G10 currencies as the reference currency. The results are similar to Columns (1)-(2) and statistically significant.

Table 8: Net Asset Flightiness Predicts Excess Returns

	$R^e(p.a.)$			
	(1)	(2)	(3)	(4)
$NAF_{(norm.)}$	-1.250**	-0.930†	-1.323**	-1.050*
	(0.411)	(0.524)	(0.403)	(0.481)
$NFA_{(norm.)}$		-0.843*		-0.779†
		(0.420)		(0.410)
Core AE		-0.481		-0.080
		(1.357)		(1.459)
$log(GDP)$		-0.268		-0.265
		(0.359)		(0.367)
Open		-0.084		-0.134
		(0.325)		(0.365)
Commodity		2.350		2.090
		(1.517)		(1.488)
Month FE	Yes	Yes	Yes	Yes
vis-à-vis	Benchmark	Benchmark	G10	G10
N	8,254	7,718	8,627	8,089
R^2	0.278	0.271	0.091	0.093

Note. This table reports the estimates of Equation (5.6). The left-hand variable is the currency excess return. The key right-hand variable is net asset flightiness. Net asset flightiness is scaled by its standard deviation. Columns (1)-(2) use the USD or the euro as the reference currencies, following Fratzscher et al. (2019), and Columns (3)-(4) use the basket of G10 currencies (excluding the test currency itself). Control variables are: net foreign asset positions (NFA), indicators for advanced economy and commodity currency, interest-rate differentials, log of GDP, and financial openness index by Chinn and Ito (2006). Standard errors are reported in parentheses, clustered at the monthly level. †, *, **, and *** denote significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

6 Conclusion

In this paper, I show how capital flows contribute to currency risk. I first show foreign capital flows are flighty: foreign flows are more sensitive than domestic flows to financial news, and the flightiness cannot be fully explained by currency risk, investor type, and institutional factors. I propose heterogeneous beliefs between domestic and foreign investors as an explanation for flighty capital flows, and provide supportive evidence. Motivated by empirical evidence, I develop a model of international portfolio choice. The model generates comovements of capital flows and asset prices characteristic of the global financial cycle, wherein a drop in global asset prices is accompanied by reduced capital inflows to both countries. The model further illustrates the mechanism linking capital flows to currency risk. Through the lens of the model, a currency is risky if the country's external liabilities face flightier flows than its external assets. Based on this insight, I construct a novel measure termed net asset flightiness, which exhibits a strong correlation with currency risk measures in data.

There are several avenues worth exploring in future research. First, this paper focuses on the general patterns across countries, while one natural future path is to better understand the USD specialness from the perspective of capital flows. The results in this paper depict a more subtle picture than what is previously understood in the literature. I show that the United States is also subject to foreign flightiness: during downturns, foreigners tend to withdraw capital from the U.S., while domestic investors are the net buyers of US assets. Therefore, if there is a special demand for the USD assets during downturns, it is stronger for US domestic investors than foreign investors. On the other hand, the US is still special in that it only has moderately positive net asset flightiness, but its currency is one of the safest in the world. It is an outlier of the relationship. To better understand factors behind the USD specialness, it is informative to study the patterns of capital flows for the US specifically. Taking a demand-system approach, Jiang et al. (2022) advance the literature in this direction.

Second, as I show in Section 2, a portion of foreign flightiness is driven by fund investors. When one country in the portfolio of a global-investing fund receives a negative shock, fund investors redeem shares from the fund, leading fund managers to reduce their positions in their portfolio. As foreign-investing funds are also highly diversified across countries, outflows induced by fund investors also affect other countries in the same portfolio, not just the country experiencing the negative shock. This spillover effect can result in global contagion due to fund co-ownership. Jotikasthira et al. (2012) explore a similar contagion mechanism in the equity market of emerging markets. The macrofinancial implication of such contagion effect on the global economy warrants further exploration in a multi-country version of the model in Section 4.

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A Appendix to Facts on Flighty Capital Flows

A.1 Morningstar Dataset Construction and Description

The data for investment funds are provided by Morningstar. I use fund information at two levels: fund-level variables and holdings at the security level. The fund-level information, such as fund sizes, investor flows, fund returns, etc., is retrieved from Morningstar Direct, and is available for all funds in the database. For fixed-income and allocation funds in the Morningstar universe, I also access the detailed holdings at the security level. I restrict the sample to open-end funds and exchange-traded funds (ETFs). Some funds update the information at a monthly frequency, while most of the funds update quarterly. Therefore, I conduct the analysis at a quarterly frequency to use as much information as possible.[30]

Table 9 provides a snapshot of the coverage of Morningstar data in each domicile country in my sample as of 2019Q4. All numbers are presented in billions of US dollars. The second column ICI Total reports total net assets (TNA) of all regulated open-end funds (including mutual funds, exchange-traded funds, and institutional funds) registered in each country, retrieved from Investment Company Institute's (ICI) Fact Book 2020 Table 65. The third column presents the total net assets of *all* open-end funds and ETFs in the Morningstar universe in each country. The numbers in this column are aggregated from each fund's total net assets, retrieved from Morningstar Direct. The coverage of the Morningstar universe relative to the ICI estimates varies across domiciles, but overall, it captures significant, if not major, shares of fund AUM outstanding.

The third column reports the total market values of bonds in the fixed income and asset allocation funds in my sample, computed from the security-level dataset.[31] The security-level dataset is less complete and accurate compared to the fund-level variables. I follow the procedures below to clean the data and filter the sample:

1. Drop holdings with missing identifiers (CUSIP or ISIN) as they cannot be matched across periods; drop holdings with missing issuance countries and currencies;

2. Keep funds whose portfolio has more than 50% of bonds at least at one point in the sample;

3. Drop funds whose security information is relatively incomplete (more than 10% of their bond portfolio has missing identifiers or countries for more than 20% of the periods. The results are not sensitive to the threshold);

4. Drop fund-periods when their assets under management have irregular changes (10x changes of total AUM in a single quarter);

[30] Japanese funds in the Morningstar universe do not report their holdings at the quarter end and hence are excluded from my analysis.

[31] Bonds are defined as the securities with security types being one of the following in the holdings data: Bond - Gov't Inflation Protected, Muni Bond - Cash, Bond - Covered Bond, Bond - Commercial MBS, Bond - Supranational, Bond - Gov't Agency CMO, Muni Bond - Revenue, Muni Bond - General Obligation, Bond - Non-Agency Residential MBS, Bond - Gov't/Treasury, Bond - Asset Backed, Bond - Gov't Agency Pass-Thru, Bond - Corporate Bond, Bond - Undefined, Bond - Gov't Agency ARM, Bond - Convertible, Muni Bond - Unspecified, Bond - Units, Bond - Corp Inflation Protected.

5. Keep funds with at least 10 million USD under management at any point in time, or funds with 100 million USD at least at one point;

The last column of Table A.1 reports the bond AUM in the final sample used for analyses. For advanced economy, the security information is relatively complete and therefore most of the funds are kept in the final sample. The coverage is less comprehensive for funds in emerging economies. Typically they have less complete security information such as identifiers.

Table 9: Coverage of Morningstar Holdings Data in 2019Q4 ($ billions)

Domicile	ICI Total	Morningstar Total	Bond	Final Sample
United States	25687.7	22880.7	5346.9	3911.3
Luxembourg	5301.2	4530.5	1436.1	1001.9
Ireland	3424.6	2634.7	760.4	535.2
Brazil	1333.6	1863.5	819.3	403.4
Canada	1413.0	1644.0	403.4	248.4
United Kingdom	1889.3	1887.8	276.5	210.1
Switzerland	653.3	594.9	159.1	123.1
France	2197.5	1118.6	121.7	69.3
Italy	239.5	285.9	86.9	66.1
Spain	340.9	348.8	107.9	65.6
Denmark	151.3	183.4	75.0	63.3
Germany	2488.7	607.3	87.2	62.5
Sweden	412.6	500.0	78.1	46.7
Mexico	123.3	123.0	48.8	40.1
Australia	2201.1	584.6	77.1	36.5
Norway	151.2	152.7	54.3	31.4
Austria	182.1	111.6	34.6	29.3
Finland	110.2	132.1	37.9	27.6
Republic of Korea	538.2	425.8	33.7	25.9
India	345.6	350.7	77.6	14.0
Netherlands	960.2	156.3	16.5	14.0
Taiwan	128.5	134.8	52.7	10.1
Belgium	108.4	179.7	10.9	5.7
Liechtenstein	60.1	51.8	5.5	4.5
Hong Kong	-	115.5	24.1	4.2
Portugal	14.8	17.0	5.7	4.2
Israel	-	74.9	44.8	3.6
New Zealand	78.4	33.2	8.2	3.3
South Africa	177.4	199.7	39.3	2.6
Singapore	-	45.6	11.3	0.6
Monaco	-	1.9	1.3	0.5
Greece	6.3	4.5	1.1	0.5
Malta	3.7	3.5	0.2	0.1
Chile	59.1	58.7	13.7	0.1
Thailand	-	144.0	36.5	0.1
United Arab Emirates	-	0.6	0.1	0.1

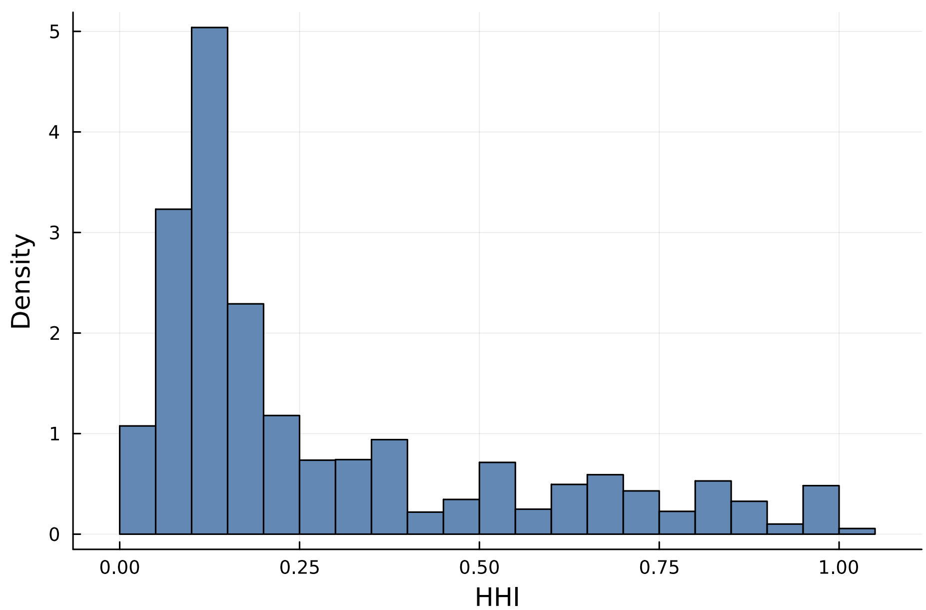
Notes. This table reports assets under management of mutual funds for each domicile country in my sample as of 2019Q4. All numbers are in billions of US dollars. The second column ICI Total presents reports of total net assets (TNA) of all regulated open-end funds (including mutual funds, exchange-traded funds, and institutional funds) registered in each country, retrieved from ICI Fact Book 2020 Table 65. The third column presents the total net assets of all open-end funds and ETFs reported to Morningstar in each country. Numbers are retrieved from Morningstar Direct. The fourth column (Bond) reports the total market values of bonds held by fixed-income and allocations funds domiciled in each country. Numbers are computed from holdings. The last column (Final Sample) reports market values of bonds in the final sample. The sample selection procedures are detailed in A.1.

A.2 Onshore-Offshore Financial Centers

As reported in Table A.1, Luxembourg and Ireland, as two major onshore-offshore financial centers (OOFCs) in Europe, harbor a large sector of investment funds. The funding of these funds is typically sourced across Europe if not globally. Beck et al. (2023) studies the role of onshore offshore financial centers for the financial integration of the euro area.

In the main text, I treat the flows from funds domiciled in these financial centers to the rest of the world as foreign flows. This is because funds domiciled in financial centers are typically well-diversified across countries instead of specialized for one particular country. Therefore, even though they may receive funding predominantly from one country, their investment in other countries should be considered foreign. Figure 13 plots the Herfindahl-Hirschman Index (HHI) for funds domiciled in offshore centers, computed as $h_{i,t} = \sum_c w_{i,c,t}^2$, where $w_{i,c,t}$ is the weight of country c in fund i's portfolio. The majority of funds domiciled in OOFCs have very low concentration: they are largely diversified across countries.

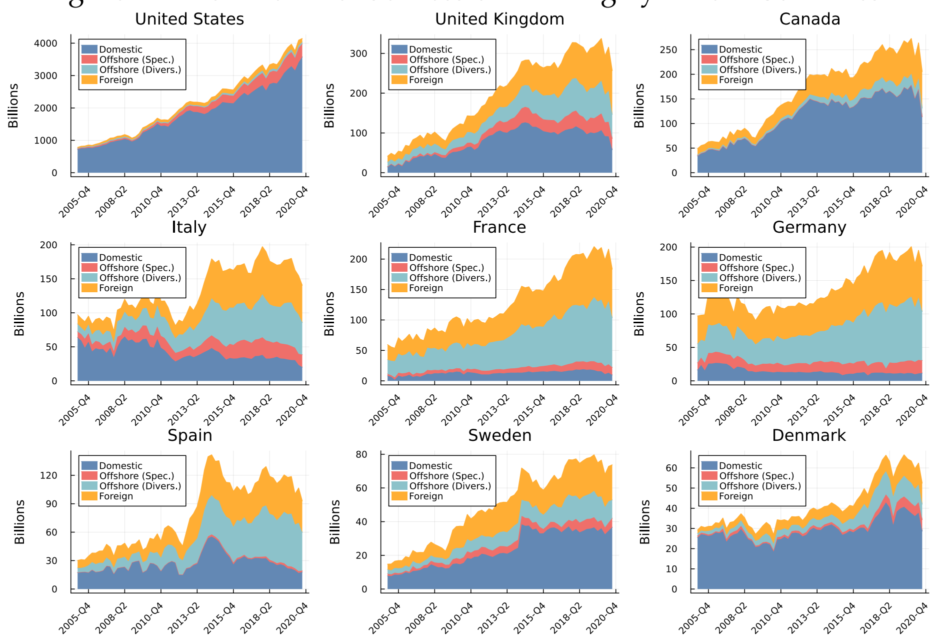
Figure 13: Portfolio Herfindahl-Hirschman Index of Funds Domiciled in OOFCs



Notes. This figure plots the portfolio Herfindahl-Hirschman Index (HHI) for funds domiciled in onshore-offshore financial centers: Ireland and Luxembourg. HHI is computed as $h_{i,t} = \sum_c w_{i,c,t}^2$, where $w_{i,c,t}$ is the weight of country c in fund i's portfolio. The histogram is weighted by the AUM of the fund.

Figure 14 shows the similar features from the perspective of inflow countries. Each panel shows an inflow country and sources of funding. In particular, I break down the investment from OOFCs by funds whose more than 50% of portfolio are invested in this inflow country (specialized), and funds who diversify across countries. For European countries, a large proportion of foreign investments are from these OOFCs, but among these investment, few are from funds that specialized in the given countries. Most are from funds who include the given country in a diversified portfolio. In this sense, Therefore, these flows are better to be treated as foreign flows instead of domestic flows.

Figure 14: Breakdown of Sources of Funding by Inflow Countries



Notes. This figure plots the decomposition of funding sources for the 9 largest inflow countries in my sample. Offshore refers to investment by funds domiciled in Luxembourg or Ireland. Specialized funds are funds who have more than 50% portfolio invested in the given country, and others are diversified investment.

The results on flighty capital flows are not driven by funds domiciled in the OOFCs. Columns (1)-(2) in Table 10 presents estimates of regressions in Equations (2.4) and (2.5), with funds outside of the OOFCs. The results largely remain the same as those in Table 1. Foreign investors are still significantly more sensitive than domestic investors within this sample. Columns (3)-(4) repeat the same exercise within the euro area, and the results are also robust.

Table 10: Foreign Flightiness Excluding Funds in the Onshore Offshore Financial Centers

	$f_{i,c,t}$			
	(1)	(2)	(3)	(4)
$r_{c,t}$	0.065		-0.026	
	(0.038)		(0.046)	
$r_{c,t} \times I_{foreign}$	0.104*	0.127*	0.271**	0.215***
	(0.048)	(0.051)	(0.079)	(0.061)
Out. Country FE	Yes		Yes	
In. Country FE	Yes		Yes	
In. country-specific θ		Yes		Yes
Fund-specific θ		Yes		Yes
Fund $\times$ In. Country FE		Yes		Yes
Sample	All	All	Euro Area	Euro Area
Controls	Yes	Yes	Yes	Yes
N	1,200,943	1,197,717	219,927	219,428

Notes. This table tests the foreign flightiness excluding funds domiciled in onshore offshore financial centers. The left-hand variable is flows by fund i into country c at quarter t, the key right-hand variables are country-specific stock-market returns in local currencies, and its interaction with the foreign indicator. Control variables include fund sizes, fund past returns and lagged fund flows. Columns (1) and (3) report the estimates of the specification in Equation (2.4) and Columns (2)-(4) report the estimates of the specification in (2.5). Columns (1)-(2) report the estimates in the full sample, while Columns (3)-(4) report estimates within the euro area. Standard errors are reported in parentheses, two-way clustered at the quarterly level and the inflow country level. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

A.3 Robustness of Baseline Specifications

Alternative measures for macrofinancial news. One potential concern of regressing flows on stock-market returns is that the correlation may be driven by flows' price impact. Even though I focus on the heterogeneous sensitivities between domestic and foreign investors, one may still be concerned that foreign flows may have larger price impacts than domestic flows do. To address such concerns, here I repeat the estimation of Equation (2.5) but with alternative measures of financial news in Table 11.

The first alternative measure I consider is the median GDP forecast revision for the given country made by global forecasters. The data are obtained from Consensus Economics, and is the same dataset used in Section 3. In Column (2), I use innovations to the realized volatility on the stock market in the given quarter as the proxy for macrofinancial news. I flip the sign so a positive number means lower volatility, to be consistent with other measures. In Column (3) I use perceived country risk measure constructed by Hassan et al. (2021) using textual analysis of earnings calls. The results are significant and consistent across three different specifications, all suggesting investors are more sensitive to foreign news than to domestic news.

Table 11: Alternative Proxies for Financial News in the Baseline Specification

	$f_{i,c,t}$		
	(1)	(2)	(3)
$r_{c,t} \times I_{foreign}$	1.877*	0.153*	0.079**
	(0.856)	(0.059)	(0.024)
In. country-specific θ	Yes	Yes	Yes
Fund-specific θ	Yes	Yes	Yes
Fund $\times$ In. Country FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Variable	CF revision	Vol. Innov.	Hassan et al.
N	1,488,475	1,766,270	1,553,192

Notes. This table tests foreign flightiness using alternative measures for macroeconomic and financial news under the specification in Equation (2.5):

$$f_{i,c,t} = \left(\theta_i^{fund} + \theta_c^{country} + \Delta\theta \times \mathbb{I}_{i \notin c}^{foreign}\right) \times r_{c,t} + \beta_{control} \cdot X_{i,c,t} + \delta_{i,c} + \varepsilon_{i,c,t}.$$

The left-hand variable is flows by fund i into country c at quarter t, and $r_{c,t}$ represents different measures for macroeconomic and financial news. In Column (1), $r_{c,t}$ is the GDP forecast revision by median forecasters surveyed by Consensus Economics; Column (2) uses (inverse) innovations to realized volatility on the local stock market; Column (3) uses perceived country risk measures constructed by Hassan et al. (2021) using textual analysis of earning calls. Control variables include fund sizes, fund past returns and lagged fund flows. Standard errors are reported in parentheses, two-way clustered at the quarterly level and the inflow country level. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

Symmetry and nonlinearity of foreign flightiness. I use different sample periods to study whether foreign flightiness exhibits asymmetry between positive and negative shocks or nonlinearity across the size of shocks. Table 12 reports the estimates of Equation (2.5) under different subsamples. Columns (1)-(2) split the samples between small and large shocks. The periods with small shocks are defined as the country-periods where stock-market returns are within the 10–90th percentiles of the given country, and the periods with large shocks are defined as the tails. The point estimates are close across these two columns, though for large shocks the coefficient is not statistically significant at the 5% level, possibly due to the smaller sample. Columns (3)-(4) split the sample between negative and positive shocks, defined as lower or higher than median stock-market returns. Foreign flightiness seems to be stronger in response to negative shocks than to positive shocks, as suggested by the point estimates and significance, though the difference is also not statistically significant. The point estimate for positive shocks is also positive. In the last column, I study foreign flightiness during "normal times" by dropping the periods of recessions in each country. Recessions are defined as periods from the peaks of the OECD Composite leading indicator for each country to the troughs, retrieved via FRED. The estimate in this column shows that foreign flightiness is not only a phenomenon triggered by extreme events such as recessions, but also observed during normal times.

Table 12: Foreign Flightiness under Different Shocks

	$f_{i,c,t}$				
	(1)	(2)	(3)	(4)	(5)
$r_{c,t} \times I_{foreign}$	0.111*	0.090	0.158*	0.089	0.146*
	(0.041)	(0.056)	(0.065)	(0.060)	(0.071)
In. country-specific θ	Yes	Yes	Yes	Yes	Yes
Fund-specific θ	Yes	Yes	Yes	Yes	Yes
Fund $\times$ In. Country FE	Yes	Yes	Yes	Yes	Yes
Sample	Small	Large	Neg.	Pos.	No Recess.
Controls	Yes	Yes	Yes	Yes	Yes
N	1,593,714	242,416	895,604	952,916	976,095

Notes. This table tests foreign flightiness in different sample periods under the specification in Equation (2.5):

$$f_{i,c,t} = \left(\theta_i^{fund} + \theta_c^{country} + \Delta\theta \times \mathbb{I}_{i \notin c}^{foreign}\right) \times r_{c,t} + \beta_{control} \cdot X_{i,c,t} + \delta_{i,c} + \varepsilon_{i,c,t}.$$

The left-hand variable is flows by fund i into country c at quarter t; the key right-hand variables are country-specific stock-market returns in local currencies, and its interaction with the foreign indicator. Control variables include fund sizes, fund past returns and lagged fund flows. Columns (1)-(2) split the samples between small and large shocks. The periods with small shocks are defined as the country-periods where stock-market returns are within the 10–90th percentiles of the given country, and the periods with large shocks are defined as the tails. Columns (3)-(4) split the sample between negative and positive shocks, defined as lower or higher than median stock-market returns. Column (5) exclude the periods of recessions for each country from the sample. Recessions are defined as periods from the peaks of the OECD Composite leading indicator for each country to the troughs, retrieved via FRED. Standard errors are reported in parentheses, two-way clustered at the quarterly level and the inflow country level. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

Global vs. local shocks. In the main text, I do not distinguish between the global and local components of financial news. This is because, in the increasingly financially connected world, it is challenging to isolate local shocks to large advanced economies. Theoretically, my model predicts foreign flightiness in response to both global and local shocks. Here, I show empirically that foreign flightiness indeed is observed for both global and local shocks. Table 13 reports the estimates of my baseline specification in Equation (2.4) with global and local shocks, respectively. Column (1) uses global stock-market return to proxy the global shocks (here, $r_{c,t}$ is constant across country $c$within a quarter). The results are highly significant. Column (2) uses local stock-market returns but controls for the quarter fixed effects to control for the aggregate market movements and exploit the cross-sectional variations. Column (3) uses local stock-market returns residualized against the first principal component of cross-country stock-market returns to control for heterogeneous loadings. The point estimates are close across three columns and all statistically significant at the 5% level.

Table 13: Foreign Flows in Response to Global vs. Local Shocks

	$f_{i,c,t}$		
	(1)	(2)	(3)
$r_{c,t}$	0.070	-0.031	0.015
	(0.035)	(0.040)	(0.042)
$r_{c,t} \times I_{foreign}$	0.156***	0.135**	0.131*
	(0.042)	(0.048)	(0.059)
Out. Country FE	Yes	Yes	Yes
In. Country FE	Yes	Yes	Yes
Quarter FE		Yes	
Controls	Yes	Yes	Yes
Variable	r_t^{world}	$r_{c,t}$	$r_{c,t}^{idio.}$
N	1,881,371	1,867,566	1,668,105

Notes. This table tests foreign flightiness against global and local shocks under the specification in Equation (2.4). The left-hand variable is flows by fund i into country c at quarter t. In Column (1), $r_{c,t}$ is the return on the MSCI World Equity Index (constant across countries); Column (2) uses local stock-market returns and controls for quarter fixed effects; Column (3) uses local stock-market return residualized against the first principal component in cross-country stock-market returns. Control variables include fund sizes, fund past returns and lagged fund flows. Standard errors are reported in parentheses, two-way clustered at the quarterly level and the inflow country level. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

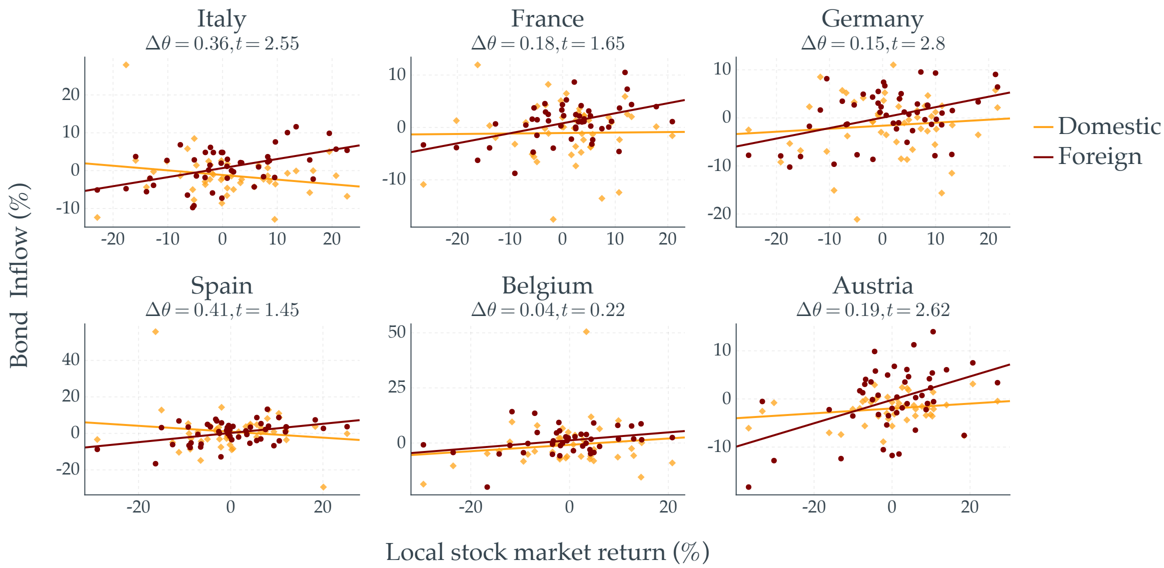
A.4 Robustness of Foreign Flightiness in the Absence of Currency Risk

The risk of a euro breakup. At the peak of the European debt crisis in 2012, concerns over a potential euro breakup is widely discussed among policymakers and financial market participants.[32] A euro breakup may result in currency redenomination, which incurs asymmetric currency risk for domestic and foreign investors. Such redenomination risk is most acutely borne by Spain, followed by Italy. Though redenomination risk is negligible for countries with strong fiscal fundamentals such as Germany, the potential fallout of a euro breakup is unfathomable, and therefore, investors within the euro area may choose to retrench to reduce their risk exposure. The risk of a euro breakup was dramatically reduced after the famous "whatever-it-takes" speech by Draghi on July 26, 2012, in which he pledged to protect the euro area from collapse (De Santis, 2019).

In Figure 15 I plot the flows within the euro area but exclude periods of the European debt crisis between 2009Q4-2012Q4 to avoid concerns for euro breakup. The patterns are largely consistent with those in Figure 4 in the main text.

[32] For example, Wall Street Journal reported on May 16, 2012 that the Bank of England was making contingency plans for the breakup of the euro zone (Douglas & Hannon, 2012).

Figure 15: Foreign Flightiness within the Euro Area Excluding 2009Q4–2012Q4



Notes. This figure presents domestic (orange) and foreign (red) inflows into each country's bond market against local stock-market returns, excluding the periods of the European debt crisis between 2009Q4 to 2012Q4. Both the inflow and outflow countries are within the euro area, and only funds using the euro as the base currency are included. The coefficient $\Delta\theta$ under the subtitle of each panel reports the estimate from (2.3) for each country. A positive $\Delta\theta$ indicates a larger slope for foreign flows. Standard errors are estimated using Newey and West (1987) HAC standard errors, with bandwidths chosen automatically following Newey and West (1994).

Flows into currency-hedged share classes. Mutual funds may offer share classes that use financial derivatives to hedge currency risk. This provides an additional environment to study flighty foreign flows unaffected by currency risk. For each share class, Morningstar Direct reports its hedging status. In addition to self-reported hedging status, I also identify additional hedged share classes if their tracking benchmarks are currency-hedged, for example, "U.S. Corporate Bond EUR Hedged".

I show that fund investor flows to the currency-hedged share classes are also more sensitive to foreign exposures than to domestic exposures, using the specification in Equation (2.6), restated below for convenience. See Section 2.5.2 for the motivation of this specification.

$$f_{i,t}^{fund} = \theta^{domestic} \underbrace{\left(\sum_{c} S_{i,c,t-1} r_{c,t} \right)}_{r_{i,t}^{portfolio}} + \Delta\theta \underbrace{\left(\sum_{c} S_{i,c,t-1} \mathbb{I}_{i \notin c}^{foreign} r_{c,t} \right)}_{r_{i,t}^{foreign}} + \beta_{control} \cdot X + \delta_{d(i)} + \varepsilon_{i,t}. \quad \text{(A.1)}$$

Table 14 reports the estimates of Equation (A.1) by the hedging status of share classes. In the first column I report the estimates from the full sample. The estimate of $\Delta\theta$ is positive and significant, indicating investors are more sensitive to foreign exposures than to domestic exposures.

Column (2) reports the estimates in the subset of share classes that report to hedge currency risk. The estimate of $\Delta\theta$ is still positive and statistically significant. The point estimate of $\Delta\theta$ is smaller; however, this is attributed to the heightened sensitivity to the overall portfolio exposure : $\theta^{domestic}$ is estimated to be 0.217 in this subset, higher than 0.062 from the full sample. The sensitivity to foreign exposure, which is the sum of $\theta^{domestic}$ and $\Delta\theta$, are actually not particularly different across columns. The heterogeneity in $\theta^{domestic}$ by hedging status may reflect the clientele effect: investors of the hedged share classes are less willing to take risks, and therefore, more sensitive to macrofinancial news generally.

Table 14: Fund Flow Flightiness by the Hedging Status

	$f_{i,t}^{fund}$		
	(1)	(2)	(3)
$r_{i,t}^{portfolio}$	0.062	0.217***	0.059
	(0.033)	(0.012)	(0.031)
$r_{i,t}^{foreign}$	0.274***	0.097***	0.263***
	(0.042)	(0.020)	(0.047)
Out. Country FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Sample	All	Currency Hedged	Others
N	865,134	157,960	707,174

Notes. This table reports the estimates of regression specification in Equation (2.6) by hedging status of share classes. The left-hand variable is flows for each share class, and the key right-hand variables are fund exposures. Portfolio exposure is defined as $r_{i,t}^{portfolio} \equiv \sum_c S_{i,c,t-1} r_{c,t}$, where $S_{i,c,t-1}$ is the share of country c in the bond portfolio of fund i, and $r_{c,t}$ is the stock-market return in country c. Foreign exposure is defined as $r_{i,t}^{foreign} \equiv \sum_c S_{i,c,t-1} \mathbb{I}_{i \notin c}^{foreign} r_{c,t}$. Control variables include fund sizes, fund past returns and lagged fund flows. Column (1) reports the estimates for the full sample. Column (2) reports the estimates for share classes that hedge currency risk. Column (3) reports the etimates for other share classes. Standard errors are two-way clustered at the quarter level and the outflow country level, and are reported in parentheses. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

A.5 Foreign Flightiness in Equity Flows

For equity funds in my sample, I do not observe the security-level holdings and therefore cannot compute the fund-country flows as in Section 2. I do observe fund level information for equity funds, including fund investor flows, and coarse portfolio allocation in global geographic regions. In this section, I show foreign flightiness is also evident for equity fund investor flows at the regional level.

With slight abuse of notations, I continue to use c to denote country/geographic regions. Denote $S_{i,c,t}$ as the portfolio share of region c in fund i at the end of quarter t, $F_{i,t}$ the dollar flows in and out of fund i, and $A_{i,t}$ the total net assets of fund i. All variables are directly observed from

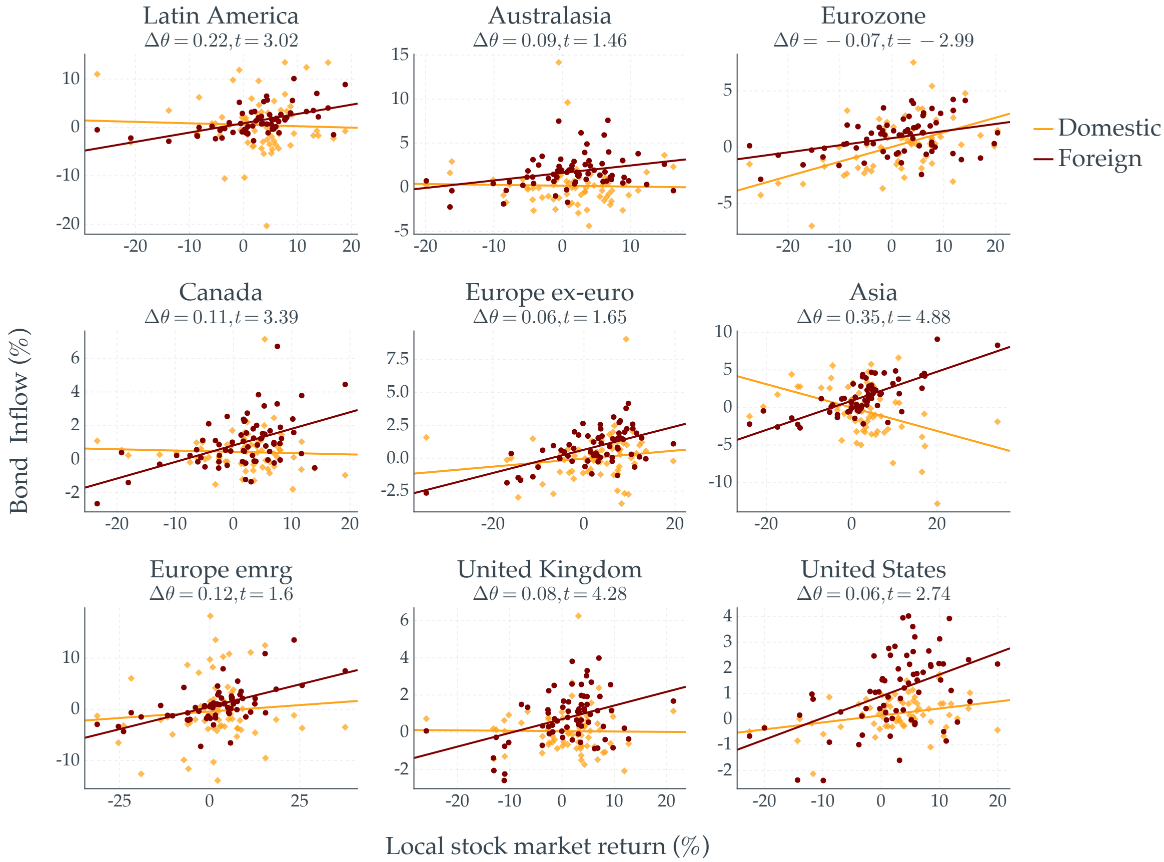
Morningstar Direct. Aggregate flows into each region is defined as:

$$f_{c,t}^{foreign} = \frac{\sum_i \mathbb{I}_{i \notin c} S_{i,c,t-1} F_{i,t}}{\sum_i \mathbb{I}_{i \notin c} S_{i,c,t-1} A_{i,t-1}}$$
$$f_{c,t}^{domestic} = \frac{\sum_i \mathbb{I}_{i \in c} S_{i,c,t-1} F_{i,t}}{\sum_i \mathbb{I}_{i \in c} S_{i,c,t-1} A_{i,t-1}},$$

where the indicator $\mathbb{I}_{i \in c}$ equals 1 if the fund i is not domiciled in the country/region c and 0 otherwise. Notice that flows here capture the "passive" flows driven by end investors of each fund. The underlying assumption is that fund manager will adjust their positions in the recipient regions proportional to their existing portfolio shares. In this sense, the exercise here captures the foreign flightiness of end investors similar to those in Section 2.5.2.

Figure 16 reports the domestic and foreign equity inflows into each region driven by end investors. Similar patterns as in Figure 2 are also observed in equity flows, even with a coarser definition of regions: Foreign investors are more sensitive to financial news than domestic investors.

Figure 16: Foreign Flightiness in Equity Fund Investor Flows



Notes. This figure presents domestic (orange) and foreign (red) inflows into each country/region's equity market against local stock-market returns. The coefficient $\Delta\theta$ under the subtitle of each panel reports the estimate from the following regression for each region:

$$f_c^{foreign} - f_c^{domestic} = \Delta\theta \times r_{c,t} + \varepsilon_{c,t},$$

Here, foreign flows are defined as flows by funds domiciled outside of the region. Flows are constructed as fund investor flows allocated to each destination region proportional to respective portfolio shares. A positive $\Delta\theta$ indicates a larger slope for foreign flows. Standard errors are estimated using Newey and West (1987) HAC standard errors, with bandwidths chosen automatically following Newey and West (1994).

A.6 Additional Results for Foreign Flow Underperformance

A.6.1 Average excess return of the foreign strategy

I perform the following regression to estimate the average excess return $\alpha^{foreign}$ of the foreign strategy relative to the domestic strategy:

$$\Delta re_{i,t} = \alpha^{foreign} + \Lambda_i' \eta_t + u_{i,t}. \tag{A.2}$$

Table 15 reports the estimates of Equation (A.2). From Column (1) to Column (3), I successively add the number of common factors. Across specifications, the foreign trading strategy consistently delivers lower returns. Column (1) reports the excess return without controlling for common factors. The foreign trading strategy delivers 25 bps (p.a.) lower excess returns on average. As more common factors are controlled for, the negative excess returns shrink. Nevertheless, even controlling for three factors that absorb nearly 75% of variation in the total returns, the average excess return remains significantly negative, at around 12 bps (p.a.).

Table 15: Average Excess Returns of the Foreign Strategy vs. the Domestic Strategy

	R^e		
	(1)	(2)	(3)
foreign	-0.257***	-0.169***	-0.117***
	(0.066)	(0.031)	(0.026)
Factors	No	1st PC	3 PCs
N	212,860	212,860	212,860
R^2	0.046	0.331	0.759

Notes. This table reports the estimates of the factor regression (A.2). The left-hand variable is the excess return differential of the foreign strategy vs. the domestic strategy for each fund. On the right-hand side, I control for common factors, allowing for fund-specific factor loadings. Common factors are extracted from fund returns for each outflow country in the sample using principal component analysis (PCA). The table reports the average excess return of the foreign strategy versus the domestic strategy, across all funds. Standard errors are two-way clustered at the quarter level and the outflow country level, and are reported in parentheses. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

B Appendix to Over-reaction in Beliefs

B.1 Measurement Error

One potential concern for the CG regression is that, as the forecast $F_{i,t}y_{c,T}$ appears on both sides of the regression with different signs, if there are measurement errors in forecasts, it will create a mechanical negative correlation between revisions and errors. To address this concern, I perform the CG regression in a staggered fashion: instead of using the error of the time t forecast on the right-hand side, I use the error of the time $t+1$ forecast. In this specification, there is no mechanical correlation between the revision at time t and the forecast error at time $t+1$. To the extent that the next period revision does not completely undo overshooting, the coefficient should be still negative. Table 16 reports the estimates from the staggered CG regression. The coefficient $\Delta\beta_F$ is smaller than those in Table 4 but still significant.

Table 16: Staggered CG Regression: Foreign Revise More Strongly

	Forecast Err. (t+1)		
	(1)	(2)	(3)
revision	-0.084		
	(0.061)		
revision $\times I_{foreign}$	-0.051*	-0.066*	-0.072*
	(0.019)	(0.029)	(0.031)
Firm $\times$ Country FE	Yes	Yes	Yes
$\beta_{country}$		Yes	Yes
$\beta_{\text{inst. nationality}}$		Yes	Yes
Estimator	OLS	OLS	OLS
Sample	All	All	Unambiguous
N	45,518	45,518	41,812

Notes. This table reports the estimates of Equations (3.3) and (3.4), but with one-quarter staggered forecast errors on the left hand side instead. Column (1) pools from all forecasters and all countries and assumes a homogeneous revision strength for domestic forecasters. Column (2) allows for country-specific revision strength β_c and forecaster-nationality-specific revision strength $\beta_{n(i)}$, which absorb the domestic coefficient. Column (3) drops cases that are ambiguous in the domestic/foreign classification. These cases include forecasts made by local branches of global companies, or by local firms acquired by foreign companies. Standard errors are reported in parentheses. Standard errors are two-way clustered at the quarter level and the forecasted country level. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

C Model Appendix

C.1 Microfoundations of Foreign Beliefs

Below I present different approaches to micro-found the belief process in Equation (4.2). These approaches yield the same law of motion of subjective beliefs, only differing in the interpretations of parameters.

C.1.1 Learning with Fading Memory (Constant-gain Learning)

Fading memory is one of the common approaches to induce overreaction (Malmendier & Nagel, 2011, 2016; Nagel & Xu, 2022). It is originally formulated in the discrete time. Here, I cast it in the continuous time to be compatible with the model. I first introduce the scalar case to illustrate the intuition, and then turn to the two-tree case as in the model.

With fading memory, investors put lower weights on information in the past, as the memory fades. Specifically, Given the history $\mathcal{H}_t$ that contains the past realizations D_t and a normal prior

$p_0 \sim N(\bar{D}_0, \sigma_0^2)$, investors learn the true long run mean using a modified Bayes' rule:[33]

$$p(D \mid \mathcal{H}_t) = \frac{\mathcal{L}(\mathcal{H}_t \mid D) p_0(D)}{\int_{-\infty}^{\infty} \mathcal{L}(\mathcal{H}_t \mid D) p_0(D) d\mu}, \tag{C.1}$$

with the log likelihood function given as:

$$\mathcal{L}(\mathcal{H}_t \mid D) \propto \exp\left\{ -\frac{1}{2} \frac{\left(\int_{t_0}^{t} e^{-\nu(t-\tau)} \left(dD_\tau - \mu_{D\tau}(D)\, d\tau \right) \right)^2}{Var\left(\int_{t_0}^{t} e^{-\nu(t-\tau)} dD_\tau \right)} \right\}, \tag{C.2}$$

where $\mu_{Dt}(D)$ is the drift of D_t under the belief that long-run mean is D. This likelihood function assigns exponentially decaying weights $e^{-\nu(t-\tau)}$ to information in the past.

The classic Bayesian is nested in this specification by setting $\nu = 0$, so all past information is fully utilized. In this case, with a sufficiently long history, the posterior uncertainty about $\bar{D}$ converges to zero, so the Bayesian agent learns the true value of $\bar{D}$ asymptotically.

With a positive ν, agents never learn the true $\bar{D}$ even with an infinitely long history, as they keep forgetting information in the distant past. Instead, their belief will fluctuate around the true parameter $\bar{D}$ with a constant posterior variance. This is characterized in the following proposition:

Proposition 3. *Let D_t follow the law of motion in equation (4.1), where $\bar{D}$ is unknown to agents. With a sufficiently long history ($t_0 \to -\infty$) and an uninformed prior ($\sigma_0 \to \infty$), the posterior of $\bar{D}$ is given as:*

$$\bar{D} \sim \mathcal{N}\left(\tilde{D}_t, \frac{\nu}{2\alpha^2}\left(\sigma^2 + \sigma_g^2\right) \right),$$

where the posterior mean $\tilde{D}_t$ follows the law of motion:

$$d\tilde{D}_t = -\nu\left(\tilde{D}_t - \bar{D} \right) dt + \frac{\nu}{\alpha} \sigma dZ_t + \frac{\nu}{\alpha} \sigma_g dZ_{g,t}. \tag{C.3}$$

Proof. See the multi-dimensional case below. □

As shown in the law of motion above, fading memory induces constant-gain learning—the posterior mean has constant loadings on shocks.

In the full model, investors observe the realizations of two trees, and therefore can use the information from both trees jointly. Below I derive the case of learning from two trees, and show that it essentially gives the same law of motion as in Proposition 3.

To simplify the notations, I use subscript d to denote X_d as domestic variables and X_f as foreign variables. Denote $\mathbf{D}_t \equiv (D_{d,t}, D_{f,t})^\intercal$ as the vector of dividend realizations of two trees, and $\nu \equiv (\nu_d, \nu_f)^\intercal$ as the vector of memory fading rates for domestic and foreign news, respectively. I allow the memory fading rates to differ across domestic and foreign cases. In particular, investors

[33] I assume investors only learn from the dividend realizations but not from prices. One interpretation is that investors are unaware their own bias and do not think investors in the other countries have superior information. This assumption is commonly made in the literature (e.g., Benhima and Cordonier, 2022) to keep the model more tractable.

forget foreign information faster ($\nu_f > \nu_d$), presumably because they have fewer day-to-day interactions with foreign countries. Proposition 4 characterizes posteriors after learning from two trees:

Proposition 4. *Let $D_{c,t}$ be the dividend produced by tree $c \in \{d, f\}$, following the law of motion*

$$dD_{c,t} = -\alpha\left(D_{c,t} - \bar{D}_c\right)dt + \sigma dZ_{c,t} + \sigma_g dZ_{g,t}, \quad for\ c \in \{d, f\},$$

where both $\bar{D}_d$ and $\bar{D}_f$ are to be learned from realizations, and ν_c be the agent' memory fading rate towards tree c. With a sufficiently long history ($t_0 \to -\infty$) and an uninformed prior ($\Sigma_0 \to \infty$), the posterior is given as:

$$\begin{bmatrix} \bar{D}_d \\ \bar{D}_f \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \tilde{D}_{d,t} \\ \tilde{D}_{f,t} \end{bmatrix}, \begin{bmatrix} \frac{\nu_d\left(\sigma^2+\sigma_g^2\right)}{2\alpha^2} & \frac{\nu_f\nu_d\sigma_g^2}{\alpha^2\left(\nu_f+\nu_d\right)} \\ \frac{\nu_f\nu_d\sigma_g^2}{\alpha^2\left(\nu_f+\nu_d\right)} & \frac{\nu_f\left(\sigma^2+\sigma_g^2\right)}{2\alpha^2} \end{bmatrix}\right),$$

where the posterior mean $\tilde{D}_{c,t}$ follows the law of motion

$$d\tilde{D}_{c,t} = -\nu_c\left(\tilde{D}_{c,t} - \bar{D}_c\right)dt + \frac{\nu_c}{\alpha}\sigma dZ_{c,t} + \frac{\nu_c}{\alpha}\sigma_g dZ_{g,t},\ for\ c \in \{d, f\}. \tag{C.4}$$

Proof. I first prove a more general case. Consider a linear system:

$$d\mathbf{s}_t = \left[\mathbf{a}_{s0} + \mathbf{a}_{sz}\mathbf{z} + \mathbf{a}_{ss}\mathbf{s}_t\right]dt + \mathbf{b}_s d\mathbf{Z}_t \quad ,$$

where $\mathbf{s}_t$ is an $n \times 1$ vector of signals observable to agents, and $\mathbf{z}$ is an $m \times 1$ vector of unobserved parameters to be learned, and $\mathbf{a}_{s0}$, $\mathbf{a}_{sz}$, $\mathbf{a}_{ss}$, and $\mathbf{b}_s$ are matrices with compatible dimension that are known to agents. Denote θ as the $n \times 1$ vector of memory fading rate for each signal. Also define $\Theta \equiv diag(\theta)$ as the $n \times n$ diagonal matrix formed from θ.

Agents learn $\mathbf{z}$ from the past realizations of $\mathbf{s}_t$ with Bayes' rule. Their posterior of $\mathbf{z}$ is given as:

$$p(\hat{\mathbf{z}} \mid \mathcal{H}_t) = \frac{\mathcal{L}(\mathcal{H}_t \mid \hat{\mathbf{z}})p_0(\hat{\mathbf{z}})}{\int_{-\infty}^{\infty}\mathcal{L}(\mathcal{H}_t \mid \hat{\mathbf{z}})p_0(\hat{\mathbf{z}})d\mu}, \tag{C.5}$$

where the prior is normally distributed with mean μ_0 and variance Σ_0, and the likelihood function is given as:

$$
\begin{aligned}
\mathcal{L}\left(\mathcal{H}_t \mid \hat{\mathbf{z}}\right) &\propto \exp\left\{-\frac{1}{2}\mu_t'\mathbf{\Sigma}_t^{-1}\mu_t\right\} \\
\mu_t &\equiv \int_{t_0}^{t} e^{-\Theta(t-\tau)} d\mathbf{s}_\tau - \int_{t_0}^{t} e^{-\Theta(t-\tau)}\left(\mathbf{a}_{s0} + \mathbf{a}_{sz}\hat{\mathbf{z}} + \mathbf{a}_{ss}\mathbf{s}_t\right) d\tau \\
&= \int_{t_0}^{t} e^{-\Theta(t-\tau)}\mathbf{a_{sz}}\left(\mathbf{z} - \tilde{\mathbf{z}}\right) d\tau + \underbrace{\int_{t_0}^{t} e^{-\Theta(t-\tau)}\mathbf{b_s} d\mathbf{Z}_\tau}_{\mathbf{I}_t} \\
\mathbf{\Sigma}_t &\equiv Cov\left(\int_{t_0}^{t} e^{-\Theta(t-\tau)}\mathbf{b}_s d\mathbf{Z}_\tau\right).
\end{aligned}
$$

With an infinite history ($t_0 \to -\infty$), we can show that:

$$
\begin{aligned}
\mu_{\mathbf{t}} &= \Theta^{-1}\mathbf{a}_{sz}\left(\mathbf{z} - \hat{\mathbf{z}}\right) + \mathbf{I}_t \\
\left(\mathbf{\Sigma}_t\right)_{(i,j)} &= \left(\mathbf{\Sigma}_\infty\right)_{(i,j)} = \frac{1}{\theta_i + \theta_j}\left(\mathbf{b}_s\mathbf{b}_s'\right)_{ij}.
\end{aligned}
$$

Plug the likelihood function into Equation (C.5), and assuming diffusion prior ($\Sigma_0 \to \infty$), we have:

$$
\begin{aligned}
p(\hat{\mathbf{z}} \mid \mathcal{H}_t) &\propto \exp\left\{-\frac{1}{2}\left(\Theta^{\mathbf{-1}}\mathbf{a}_{sz}\left(\mathbf{z} - \hat{\mathbf{z}}\right) + \mathbf{I_t}\right)' \mathbf{\Sigma}_\infty{}^{-1}\left(\mathbf{\Theta^{-1}}\mathbf{a_{sz}}\left(\mathbf{z} - \hat{\mathbf{z}}\right) + \mathbf{I_t}\right)\right\} \\
&\propto \exp\left\{-\frac{1}{2}\left(\mathbf{a}_{sz}\hat{\mathbf{z}} - \left(\mathbf{a}_{sz}\mathbf{z} + \mathbf{\Theta I_t}\right)\right)'\left(\Theta\mathbf{\Sigma}_\infty\Theta\right)^{-1}\left(\mathbf{a_{sz}}\hat{\mathbf{z}} - \left(\mathbf{a_{sz}}\mathbf{z} + \mathbf{\Theta I_t}\right)\right)\right\}.
\end{aligned}
$$

Rearrange, it can be written in the quadratic form of $\hat{\mathbf{z}}$ up to a scaling constant:[34]

$$
\begin{aligned}
p(\hat{\mathbf{z}} \mid \mathcal{H}_t) &\propto \exp\left\{-\frac{1}{2}(\hat{\mathbf{z}} - \tilde{\mathbf{z}}_t)'\mathbf{\Sigma}_{\mathbf{z}}^{-1}(\tilde{\mathbf{z}} - \tilde{\mathbf{z}}_t)\right\} \\
\mathbf{\Sigma}_z &\equiv \left(\mathbf{a}_{sz}'\left(\Theta\mathbf{\Sigma}_\infty\Theta\right)^{-1}\mathbf{a}_{sz}\right)^{-1} \\
\tilde{\mathbf{z}}_t &\equiv \mathbf{z} + \Sigma_{\mathbf{z}}\mathbf{a}_{sz}'\left(\Theta\mathbf{\Sigma}_\infty\Theta\right)^{-1}\Theta\mathbf{I_t}.
\end{aligned}
$$

That is, the posterior of $\mathbf{z}$ is normally distributed with mean $\tilde{\mathbf{z}}_t$ and the covariance matrix $\mathbf{\Sigma}_z$. The posterior mean follows a mean-reverting process around the true $\mathbf{z}$:

$$
d\tilde{\mathbf{z}}_t = -\Theta\left(\tilde{\mathbf{z}}_t - \mathbf{z}\right) dt + \mathbf{\Sigma}_z\mathbf{a}_{sz}'\left(\Theta\mathbf{\Sigma}_\infty\Theta\right)^{-1}\Theta\mathbf{b_s}d\mathbf{Z_t}. \tag{C.6}
$$

Plug in $\mathbf{z} = \left(\bar{D}_d, \bar{D}_f\right)^\intercal$, $\mathbf{a}_{sz} = \begin{bmatrix} \alpha & \\ & \alpha \end{bmatrix}$, $\Theta = \begin{bmatrix} \nu_d & \\ & \nu_f \end{bmatrix}$, and $\mathbf{b}_s = \begin{bmatrix} \sigma & & \sigma_g \\ & \sigma & \sigma_g \end{bmatrix}$, we recover

[34] Here I use the following formula to complete the square in the matrix form:

$$
\mathbf{x}^\top M\mathbf{x} - 2\mathbf{b}^\top\mathbf{x} = \left(\mathbf{x} - M^{-1}\mathbf{b}\right)^\top M\left(\mathbf{x} - M^{-1}\mathbf{b}\right) - \mathbf{b}^\top M^{-1}\mathbf{b}.
$$

the posterior in the proposition. □

Finally, take the limit of ν_d to 0 so agents almost have perfect memory for domestic news, the posterior uncertainty for the domestic tree goes to zero. That is, agents eventually learn the true long-run mean for the domestic tree. The posterior for the foreign tree is the same as those in Proposition 3, as if investors only use information from the foreign tree to infer its long-run mean.

C.1.2 Diagnostic Expectations

The perceived law of motion in Equation (4.2) can also be micro-founded using diagnostic expectations (Bordalo, Gennaioli, Ma, & Shleifer, 2020; Bordalo et al., 2018). Here I follow Maxted's (2022) adaption of diagnostic expectations in the continuous time. To simplify the model structure, I assume investors in both countries in my model are only diagnostic towards news in the other country, but not their own domestic news, so the discussion below applies to investors forming beliefs for the trees in the other countries. This assumption is mostly for analytical tractability of the model; To generate flighty foreign flows, we only require the behavioral biases are stronger for foreign news than domestic news.

Under the interpretation of diagnostic expectations, agents have full information of the true law of motion of D_t, but their expectations for the future path is distorted by behavioral biases according to the "representativeness" of future states relative to the "background context".

Formally, given the true law of motion of D_t :

$$dD_t = -\alpha\left(D_t - \bar{D}\right)dt + \sigma dZ_t + \sigma_g dZ_{g,t},$$

I define $\mathcal{I}_t \equiv \int_0^t e^{-\kappa(t-s)}\frac{\sigma}{\alpha}dZ_s + \int_0^t e^{-\kappa(t-s)}\frac{\sigma}{\alpha}dZ_{g,s}$ as a measure of recent information. It evolves according to the law of motion:

$$d\mathcal{I}_t = -\kappa\mathcal{I}_t dt + \frac{\sigma}{\alpha}dZ_t + \frac{\sigma}{a}dZ_{g,t}$$

The "background context" can be defined as follows:

$$G_t^- = D_t - \mathcal{I}_t.$$

The "representativeness" of future state $D_{t+\tau}$ is given by the following likelihood ratio:

$$\frac{h\left(D_{t+\tau} \mid D_t\right)}{h\left(D_{t+\tau} \mid G_t^-\right)}.$$

Diagnostic expectations overweight the states that are more representative of recent news. That is, agents evaluate the future levels of dividends "as if" the dividend process follows the distorted density:

$$h_t^{\theta}\left(D_{t+\tau} \mid D_t\right) = h\left(D_{t+\tau} \mid D_t\right)\left(\frac{h\left(D_{t+\tau} \mid D_t\right)}{h\left(D_{t+\tau} \mid G_t^{-}\right)}\right)^{\theta\tau}\frac{1}{Z}, \tag{C.7}$$

where Z is the scaling factor to normalize the density function.

In Equation (C.7), true conditional probability $h\left(D_{t+\tau} \mid D_t, \mathcal{I}_t\right)$ is distorted by the representativeness of the future states in the bracket. The parameter θ controls the strength of the distortion.

Proposition below shows that the diagnostic expectations also induces the same laws of motion as in Equation (4.3).

Proposition 5. *A diagnostic agent perceives that the dividend process evolves according to:*

$$dD_t = -\alpha\left(D_t - \tilde{D}_t\right)dt + \sigma dZ_t + \sigma dZ_{g,t},$$

where $\tilde{D}_t \equiv \bar{D} + \theta\mathcal{I}_t$ *follows the law of motion:*

$$d\tilde{D}_t = -\kappa\left(\tilde{D}_t - \bar{D}\right)dt + \frac{\theta}{\alpha}\sigma dZ_t + \frac{\theta}{\alpha}\sigma_g dZ_{g,t}. \tag{C.8}$$

Proof. As D_t follows an Ornstein–Uhlenbeck process, the distribution of $D_{t+\tau}$ conditional on the history $\mathcal{H}_t$ is normally distributed. The density function can be expressed as:

$$h(D_{t+\tau} \mid \mathcal{H}_t) \propto \exp\left(-\frac{1}{2}\frac{\left(D_{t+\tau} - \mathbb{E}\left[D_{t+\tau} \mid \mathcal{H}_t\right]\right)^2}{\frac{1}{2\alpha}\left(1 - e^{-2\alpha\tau}\right)\left(\sigma^2 + \sigma_g^2\right)}\right),$$

where $\mathbb{E}\left[D_{t+t} \mid \mathcal{H}_t\right]$ is the expectation under the rational expectations. Plug it in (C.7), we can show the the distorted density is proportional to:

$$h_t^{\theta}\left(D_{t+\tau} \mid D_t, \mathcal{I}_t\right) \propto \exp\left\{-\frac{1}{2}\frac{\left(D_{t+\tau} - \left[\mathbb{E}\left[D_{t+\tau} \mid D_t\right] + \theta\tau\left(\mathbb{E}\left[D_{t+\tau} \mid \mathcal{D}_t\right] - \mathbb{E}\left[D_{t+\tau} \mid G_t^{-}\right]\right)\right]\right)^2}{\frac{1}{2\alpha}\left(1 - e^{-2\alpha\tau}\right)\left(\sigma^2 + \sigma_g^2\right)}\right\}.$$

Therefore, in a diagnostic agent's perception, the future dividend $D_{t+\tau}$ follows:

$$D_{t+\tau} \sim \mathcal{N}\left(\mathbb{E}\left[D_{t+\tau} \mid D_t\right] + \theta\tau\left(\mathbb{E}\left[D_{t+\tau} \mid \mathcal{D}_t\right] - \mathbb{E}\left[D_{t+\tau} \mid G_t^{-}\right]\right), \frac{1}{2\alpha}\left(1 - e^{-2\alpha\tau}\right)\left(\sigma^2 + \sigma_g^2\right)\right).$$

In the limit as $\tau \to dt$, we have:

$$dD_t = -\alpha\left(D_t - \bar{D}\right)dt + \theta\mathcal{I}_t dt + \sigma dZ_t + \sigma dZ_{g,t}.$$

Define $\tilde{D}_t \equiv \bar{D} + \theta\mathcal{I}_t$, we recover the law of motion as in the proposition. $\square$

C.2 Equilibrium Solution

C.2.1 General Solution to the Model

The model is solved with first-order linearization around the risky steady state. Thanks to the continuous time, the model is still able to generate time-varying risk premia with the first-order linearization.

The state variables $\mathbf{S}_t$ in the model are the dividend levels $D_{h,t}$ and $D_{f,t}$ (for the ease of notation, in this section I denote the US as h and Europe as f), the perceived long run means $\tilde{D}_{h,t}$ and $\tilde{D}_{f,t}$, and wealth differentials $W_t - W_t^*$. All other variables can be expressed as affine functions of the state variables:

$$\mathbf{X_t} = \bar{\mathbf{X}} + \beta_X^\intercal \left(\mathbf{S_t} - \bar{\mathbf{S}}\right), \tag{C.9}$$

where $\bar{\mathbf{X}}$ and β_X are coefficients to be determined by equilibrium conditions. For ease of notation, I denote variables with hats as deviations from the steady state levels, so the equation above can be formulated as:

$$\hat{\mathbf{X}}_t = \beta_X^\intercal \hat{\mathbf{S}}_t.$$

To solve the coefficients, I recast the model in an alternative state space $\tilde{\mathbf{S}}_t$ where the wealth differentials $W_t - W_t^*$ are replaced by the exchange rate E_t. This greatly simplifies the algebra in the derivation. Technically speaking, the exchange rate is an forward looking endogenous variable instead of a backward looking state variable. However, up to first order linearization two formulations are equivalent as it is simply a change of basis. With slight abuse of notations, I keep use $\mathbf{S}_t$ to denote the state space with E_t whenever it is unambiguous.

Conjecture that $\hat{\mathbf{S}}_t$ evolves according to a multi-dimensional Ornstein–Uhlenbeck process under the objective measure:

$$d\begin{bmatrix} \hat{D}_{h,t} \\ \hat{D}_{f,t} \\ \hat{\mathcal{I}}_{h,t} \\ \hat{\mathcal{I}}_{f,t} \\ \hat{E}_t \end{bmatrix} = \underbrace{\begin{bmatrix} -\alpha & & & & \\ & -\alpha & & & \\ & & -\kappa_h & & \\ & & & -\kappa_f & \\ & & e_{Ih} & -e_{If} & -\alpha_e \end{bmatrix}}_{\bar{\mathbf{A}}_\mathbf{S}} \begin{bmatrix} \hat{D}_{h,t} \\ \hat{D}_{f,t} \\ \hat{\mathcal{I}}_{h,t} \\ \hat{\mathcal{I}}_{f,t} \\ \hat{E}_t \end{bmatrix} dt + \underbrace{\begin{bmatrix} \sigma & & \sigma_g \\ & \sigma & \sigma_g \\ & & \sigma_g \\ & \frac{\sigma}{\alpha} & \frac{\sigma_g}{\alpha} \\ \sigma_{eh} & -\sigma_{ef} & \sigma_{eg} \end{bmatrix}}_{\mathbf{B}_\mathbf{S}} \underbrace{\begin{bmatrix} dZ_{h,t} \\ dZ_{f,t} \\ dZ_{g,t} \end{bmatrix}}_{d\mathbf{Z}_t}, \tag{C.10}$$

where I use $\hat{\mathcal{I}}_{i,t} \equiv \frac{1}{\theta_i}\left(\tilde{D}_{i,t} - \bar{D}\right)$ to simplify the notation. The coefficients related to E_t are unknown and to be solved.

The perceived laws of motion of $\hat{\mathbf{S}}_t$ by investors are different from the objective law of motion. From the perspective of the US investors, $d\hat{D}_{f,t}$ also loads on $\hat{\mathcal{I}}_{f,t}$ with an coefficient of $\alpha\theta_f$, and for European investors, $d\hat{D}_{h,t}$ loads on $\hat{\mathcal{I}}_{h,t}$ with an coefficient of $\alpha\theta_h$. Other entries of matrix $\bar{\mathbf{A}}_S$ and $\mathbf{B}_s$ are identical to those under the objective measure. I denote $\mathbf{A}_{Sh}$ and $\mathbf{A}_{Sf}$ as the coefficient matrices under the perception of the US investors and European investors, respectively.

Given the law of motion of $\hat{\mathbf{S}}_t$, we can express the laws of motion of all other variables in terms of matrices $\mathbf{A}_S$, and $\mathbf{B}_S$. Denote β_X as the coefficients of variable X on state variables. For example, $\beta_{Dh} = [1,0,0,0,0]^\intercal$ is the loading of $\hat{D}_{h,t}$ on $\hat{\mathbf{S}}_t$, so that $\hat{D}_{h,t} = \beta_{Dh}^\intercal \hat{\mathbf{S}}_t$. We can express $dD_{h,t}$ as:

$$dD_{h,t} = d\hat{D}_{h,t} = \beta_{Dh}^\intercal \mathbf{A}_S \hat{\mathbf{S}}_t dt + \beta_{Dh}^\intercal \mathbf{B}_S d\mathbf{Z}_t,$$

where $\mathbf{A}_S$ can be the different coefficient matrices used by different investors.

Portfolio allocation. The vector of instantaneous excess payoffs of the two trees denominated in the USD is given as:

$$d\mathbf{R}_t = \begin{bmatrix} dR_{h,t} \\ dR_{f,t} \end{bmatrix} = \begin{bmatrix} dP_{h,t} - rP_{h,t}dt + D_{h,t}dt \\ dP_{f,t} - rP_{f,t}dt + D_{f,t}dt \end{bmatrix}. \tag{C.11}$$

Uses the law of one price $P_{f,t} = P^*_{f,t}E_t$, and linearize it around the steady state, I can express the instantaneous payoff of the European tree in the USD as:

$$dR_{f,t} = P^*_{f,t}dE_t + E_t dP^*_{f,t} + dP^*_{f,t}dE_t - rP^*_{f,t}E_t dt + D_{f,t}dt \tag{C.12}$$

$$\approx \bar{P}_f dE_t + dP^*_{f,t} + dP^*_{f,t}dE_t - r\left(\bar{P}_f + \bar{P}_f\hat{E}_t + \hat{P}^*_{f,t}\right)dt + D_{f,t}dt. \tag{C.13}$$

In the second equality I use the equilibrium condition that the steady state exchange rate $\bar{E} = 1$ and $\bar{P}_f = \bar{P}^*_f$ to simplify the expression.[35]

Expressing $d\mathbf{R}_t$ using loadings on state variables $\hat{S}_t$, we have:

$$d\mathbf{R}_t = \left(\bar{\mu}_{\mathbf{R}} + \beta_{\mathbf{R}}{}^\intercal \hat{S}_t\right)dt + \sigma_{\mathbf{R}} \mathbf{dZ}_t \tag{C.14}$$

$$\bar{\mu}_{\mathbf{R}} = \begin{bmatrix} \bar{D}_h - r\bar{P}_h \\ \beta_E^\intercal \mathbf{B}_S \mathbf{B}_S^\intercal \beta^*_{Pf} + \bar{D}_f - r\bar{P}_f \end{bmatrix} \tag{C.15}$$

$$\beta_{\mathbf{R}}{}^\intercal = \begin{bmatrix} \beta_{Ph}^\intercal \mathbf{A}_{Sh} - r\beta_{Ph}^\intercal + \beta_{Dh} \\ \bar{P}_f \beta_E^\intercal \mathbf{A}_{Sh} + \beta^{*\intercal}_{Pf}\mathbf{A}_{Sh} - r\bar{P}_f\beta_E^\intercal - r\beta^{*\intercal}_{Pf} + \beta_{Df}^\intercal \end{bmatrix} \tag{C.16}$$

$$\sigma_{\mathbf{R}} = \begin{bmatrix} \beta_{Ph}^\intercal \\ \left(\bar{P}_f\beta_E^\intercal + \beta^{*\intercal}_{Pf}\right) \end{bmatrix} \mathbf{B}_S. \tag{C.17}$$

The first order condition of the US investors gives:

$$\mathbf{Q}_t = \underbrace{\frac{1}{\gamma}(\sigma_{\mathbf{R}}\sigma_{\mathbf{R}}^\intercal)^{-1}\bar{\mu}_{\mathbf{R}}}_{\bar{\mathbf{Q}}} + \underbrace{\frac{1}{\gamma}(\sigma_{\mathbf{R}}\sigma_{\mathbf{R}}^\intercal)^{-1}\beta_{\mathbf{R}}^\intercal \hat{\mathbf{S}}_t}_{\hat{\mathbf{Q}}_t}. \tag{C.18}$$

[35] To see that, notice that the definition of risky steady state requires that when the shock realizations are zero, the state variables remain constant. This requires $\bar{B} = 0$—otherwise, (4.9) implies a nonzero drift of the exchange rate at the steady state. The law of motion of B_t further requires the current account to be zero at the steady state as well so $\bar{B}$ stays constant. Finally, Equation (4.10) implies the steady state exchange rate to be the no-arbitrage price $\bar{E} = 1$. Note that this argument does not rely on the symmetry between two countries.

European investors solve the symmetrical problem with payoffs denominated in the euro. Their first-order condition gives:

$$\mathbf{Q}_t^* = \underbrace{\frac{1}{\gamma}(\sigma_{\mathbf{R}}^* \sigma_{\mathbf{R}}^{*\intercal})^{-1}\bar{\mu}_{\mathbf{R}}^*}_{\bar{\mathbf{Q}}^*} + \underbrace{\frac{1}{\gamma}(\sigma_{\mathbf{R}}^* \sigma_{\mathbf{R}}^{*\intercal})^{-1}\beta_{\mathbf{R}}^{*\intercal}\hat{\mathbf{S}}_t}_{\hat{\mathbf{Q}}_t^*}, \tag{C.19}$$

where

$$\begin{aligned} \bar{\mu}_{\mathbf{R}}^* &= \begin{bmatrix} \bar{D}_h - r\bar{P}_h - \beta_E^\intercal \mathbf{B}_S \mathbf{B}_S^\intercal \beta_{Ph} \\ \bar{D}_f - r\bar{P}_f \end{bmatrix} \\ \beta_{\mathbf{R}}{}^{*\intercal} &= \begin{bmatrix} -\bar{P}_h \beta_E^\intercal \mathbf{A}_{Sf} + r\bar{P}_h \beta_E^\intercal + \beta_{Ph}^\intercal \mathbf{A}_{Sf} - r\beta_{Ph}^\intercal + \beta_{Dh}^\intercal \\ \beta_{Pf}^{*\intercal}\mathbf{A}_{Sf} - r\beta_{Pf}^{*\intercal} + \beta_{Df}^\intercal \end{bmatrix} \\ \sigma_{\mathbf{R}}{}^* &= \begin{bmatrix} \beta_{Ph}^\intercal - \bar{P}_h \beta_E^\intercal \\ \beta_{Pf}^{*\intercal} \end{bmatrix} \mathbf{B}_S. \end{aligned} \tag{C.20}$$

Market clearing conditions in the risky asset market requires:

$$\mathbf{Q}_t + \mathbf{Q}_t^* = \mathbf{1} \implies \begin{cases} (\sigma_{\mathbf{R}}\sigma_{\mathbf{R}}^\intercal)^{-1}\bar{\mu}_{\mathbf{R}} + (\sigma_{\mathbf{R}}^*\sigma_{\mathbf{R}}^{*\intercal})^{-1}\bar{\mu}_{\mathbf{R}}^* & = \gamma\iota \\ (\sigma_{\mathbf{R}}\sigma_{\mathbf{R}}^\intercal)^{-1}\beta_{\mathbf{R}}^\intercal + (\sigma_{\mathbf{R}}^*\sigma_{\mathbf{R}}^{*\intercal})^{-1}\beta_{\mathbf{R}}^{*\intercal} & = \mathbf{0} \end{cases}. \tag{C.21}$$

The foreign-exchange market. The first order condition of bankers links the cross-border lending B_t^* to the law of motion of E_t:

$$B_t^* = -\frac{B_t}{E_t} = \zeta\mu_{E,t} = -\zeta\beta_E^\intercal \mathbf{A}_S \hat{\mathbf{S}}_t. \tag{C.22}$$

Hence, the law of motion of B_t^* can be expressed as:

$$dB_t^* = -\zeta\beta_E^\intercal \mathbf{A}_S^2 \hat{\mathbf{S}}_t dt - \zeta\beta_E^\intercal \mathbf{A}_S \mathbf{B}_S d\mathbf{Z}_t. \tag{C.23}$$

From the budget constraint of European households, we have the law of motion of B_t^*:

$$\begin{aligned} dB_t^* &= rB_t^* dt - \mathbf{P}_\mathbf{t}^{*\intercal}\mathbf{dQ}_\mathbf{t}^* + \left(\mathbf{Q}_t^{*\intercal}\mathbf{D}_\mathbf{t} - C_t^*\right) dt && \text{(C.24)} \\ &= rB_t^* dt - \mathbf{P}_\mathbf{t}^{*\intercal}\mathbf{dQ}_\mathbf{t}^* - \frac{1}{\chi}\hat{E}_t dt, && \text{(C.25)} \end{aligned}$$

where the second equality comes from the first order condition (4.10) of the exporter.

Linearize Equation (C.25) and plug in (C.19) and (C.22), we have:

$$dB_t^* \approx \left(-\zeta\beta_E^\intercal \mathbf{A}_S - \bar{\mathbf{P}}^\intercal \frac{1}{\gamma}(\sigma_{\mathbf{R}}^*\sigma_{\mathbf{R}}^{*\intercal})^{-1}\beta_{\mathbf{R}}^{*\intercal}\mathbf{A}_S - \frac{1}{\chi}\beta_E^\intercal\right)\hat{\mathbf{S}}_t dt - \frac{1}{\gamma}\bar{\mathbf{P}}^\intercal(\sigma_{\mathbf{R}}^*\sigma_{\mathbf{R}}^{*\intercal})^{-1}\beta_{\mathbf{R}}^{*\intercal}\mathbf{B}_S d\mathbf{Z}_t. \tag{C.26}$$

Equating the coefficients in (C.23) and (C.25), we have equations to pin down the last rows of $\mathbf{A_S}$

and $\mathbf{B_S}$ that govern the evolution of the exchange rate:

$$\zeta\beta_E^\intercal \mathbf{A}_S + \bar{\mathbf{P}}^\intercal \frac{1}{\gamma}(\sigma_{\mathbf{R}}^* \sigma_{\mathbf{R}}^{*\intercal})^{-1}\beta_{\mathbf{R}}^{*\intercal}\mathbf{A}_S + \frac{1}{\chi}\beta_E^\intercal = \zeta\beta_E^\intercal \mathbf{A}_S^2 \hat{\mathbf{S}}_t \tag{C.27}$$

$$\frac{1}{\gamma}\bar{\mathbf{P}}^\intercal (\sigma_{\mathbf{R}}^* \sigma_{\mathbf{R}}^{*\intercal})^{-1}\beta_{\mathbf{R}}^{*\intercal} = \zeta\beta_E^\intercal \mathbf{A}_S. \tag{C.28}$$

C.2.2 Solutions under the Symmetric Case

Under the symmetric case, the solution of the model can be further characterized in simpler expressions. Under symmetry, parameters for two countries are identical, so $\kappa_h = \kappa_f = \kappa, \theta_h = \theta_f = \theta$. Conjecture that the prices of trees also exhibit symmetry:

$$\begin{aligned}
\beta_{Ph} &= [p_d, p_{Id}, p_{Ir}, p_e] \\
\beta_{Pf}^* &= [p_d, p_{Ir}, p_{Id}, -p_e] \\
\bar{P} &= \bar{P}_h = \bar{P}_f, \\
e_I &= e_{Ih} = e_{If} \\
\sigma_e &= \sigma_{eh} = \sigma_{ef}.
\end{aligned}$$

The solution to the equilibrium is the tuple of coefficients $(p_d, p_{Id}, p_{Ir}, p_e, \bar{P}, e_I, \sigma_e, \alpha_e)$. Plug in the conjecture in Equation (C.20), the return dynamics in USD can be expressed as:

$$\beta_{\mathbf{R}}{}^\intercal = \begin{bmatrix} 1 - p_d(r+\alpha) & 0 & e_I p_e - p_{Id}(r+\kappa) & -e_I p_e - p_{Ir}(r+\kappa) & -p_e(r+\alpha_e) \\ 0 & 1 - p_d(r+\alpha) & -e_I p_e - p_{Ir}(r+\kappa) + e_I\bar{P} & e_I p_e + p_d\alpha\theta - p_{Id}(r+\kappa) - e_I\bar{P} & (r+\alpha_e)(p_e - \bar{P}) \end{bmatrix}$$

$$\sigma_{\mathbf{R}} = \left[\begin{pmatrix} \sigma p_d + p_e\sigma_e + \frac{\sigma p_{Id}}{\alpha} & \frac{\sigma p_{Ir}}{\alpha} - p_e\sigma_e & \frac{\sigma_g(\alpha p_d + p_{Id} + p_{Ir})}{\alpha} \\ \bar{P}\sigma_e - p_e\sigma_e + \frac{\sigma p_{Ir}}{\alpha} & \sigma p_d + p_e\sigma_e + \frac{\sigma p_{Id}}{\alpha} - \sigma_e\bar{P} & \frac{\sigma_g(\alpha p_d + p_{Id} + p_{Ir})}{\alpha} \end{pmatrix}\right].$$

Define $\Sigma_{\mathbf{R}} \equiv \sigma_{\mathbf{R}}\sigma_{\mathbf{R}}^\intercal$, and using $\Sigma_d, \Sigma_r, \Sigma_c$ to denote its entries:

$$\Sigma_{\mathbf{R}} = \begin{bmatrix} \Sigma_d & \Sigma_c \\ \Sigma_c & \Sigma_r \end{bmatrix}.$$

They are given as:

$$\Sigma_d = \frac{(\alpha\sigma p_d + \alpha p_e\sigma_e + \sigma p_{\mathrm{Id}})^2 + \sigma_g^2(\alpha p_d + p_{Id} + p_{Ir})^2 + (\sigma p_{Ir} - \alpha p_e\sigma_e)^2}{\alpha^2} \tag{C.29}$$

$$\Sigma_r = \frac{\left(-\alpha\bar{P}\sigma_e + \alpha\sigma p_d + \alpha p_e\sigma_e + \sigma p_{Id}\right)^2 + \left(\alpha\bar{P}\sigma_e - \alpha p_e\sigma_e + \sigma p_{\mathrm{Ir}}\right)^2 + \sigma_g^2(\alpha p_d + p_{Id} + p_{Ir})^2}{\alpha^2} \tag{C.30}$$

$$\Sigma_c = \frac{\alpha\bar{P}\sigma_e\left(\sigma(\alpha p_d + p_{Id} - p_{Ir}) + 2\alpha p_e\sigma_e\right) + 2\left(\sigma p_{\mathrm{Ir}} - \alpha p_e\sigma_e\right)\left(\alpha\sigma p_d + \alpha p_e\sigma_e + \sigma p_{\mathrm{Id}}\right) + \sigma_g^2(\alpha p_d + p_{Id} + p_{Ir})^2}{\alpha^2}. \tag{C.31}$$

By symmetry, the covariance matrix faced by European investors are given as:

$$\Sigma^*_{\mathbf{R}} = \begin{bmatrix} \Sigma_r & \Sigma_c \\ \Sigma_c & \Sigma_d \end{bmatrix}.$$

The following inequalities of Σ_d, Σ_r, and Σ_c are handy for signing coefficients later:

$$\begin{aligned}
\Sigma_d &> 0 \\
\Sigma_r &> 0 \\
\Sigma_r + \Sigma_d - 2\Sigma_c &= \frac{2\left(-\alpha\bar{P}\sigma_e + \sigma\left(\alpha p_d + p_{\mathrm{Id}} - p_{\mathrm{Ir}}\right) + 2\alpha p_e\sigma_e\right)^2}{\alpha^2} > 0 \\
\Sigma_r + \Sigma_d + 2\Sigma_c &= 2\bar{P}^2\sigma_e^2 + \frac{2\left(2\sigma_g^2 + \sigma^2\right)\left(\alpha p_d + p_{\mathrm{Id}} + p_{\mathrm{Ir}}\right)^2}{\alpha^2} > 0.
\end{aligned}$$

Solve the market clearing condition, we have coefficients of β_{Ph} as functions of exchange-rate dynamics and covariances:

$$p_d = \frac{1}{\alpha + r} \tag{C.32}$$

$$p_{Id} = \frac{\alpha\theta\left(2\Sigma_c^2 - \Sigma_d\left(\Sigma_d + \Sigma_r\right)\right)}{(r+\alpha)(r+\kappa)\left(4\Sigma_c^2 - \left(\Sigma_d + \Sigma_r\right)^2\right)} \tag{C.33}$$

$$p_{Ir} = \frac{\alpha\theta\Sigma_c\left(-\Sigma_d + \Sigma_r\right)}{(r+\alpha)\left(r+\kappa\right)\left(4\Sigma_c^2 - \left(\Sigma_d + \Sigma_r\right)^2\right)} \tag{C.34}$$

$$p_e = \frac{\left(\Sigma_c + \Sigma_d\right)\bar{P}}{2\Sigma_c + \Sigma_d + \Sigma_r}. \tag{C.35}$$

Plug them into Equations (C.27) and (C.28), we solve the coefficients governing dynamics of the exchange rate:

$$e_I = \frac{\alpha\theta\kappa\bar{P}}{\left(\alpha + r\right)\left(\alpha_e + \kappa + r\right)\left(2\bar{P}^2 + \gamma\zeta\left(2\Sigma_c + \Sigma_d + \Sigma_r\right)\right)} \tag{C.36}$$

$$\alpha_e = \frac{2}{\chi\left(\sqrt{\frac{4\left(\frac{2\bar{P}^2}{\gamma(2\Sigma_c+\Sigma_d+\Sigma_r)}+\zeta\right)}{\chi} + \left(\frac{2r\bar{P}^2}{\gamma(2\Sigma_c+\Sigma_d+\Sigma_r)} + \zeta r\right)^2} + \frac{2r\bar{P}^2}{\gamma(2\Sigma_c+\Sigma_d+\Sigma_r)} + \zeta r\right)} \tag{C.37}$$

$$\sigma_e = -\frac{\theta\sigma\bar{P}\left(\alpha_e + r\right)}{\left(\alpha + r\right)\left(\alpha_e + \kappa + r\right)\left(2\bar{P}^2\left(\alpha_e + r\right) + \gamma\zeta\alpha_e\left(2\Sigma_c + \Sigma_d + \Sigma_r\right)\right)}. \tag{C.38}$$

The equation involving α_e has two roots, a negative one and a positive one. I pick the positive one so the exchange rate is mean-revering to its steady state level; otherwise the system is not stable.

Equations (C.29)-(C.38) constitute a nonlinear system of the unknown coefficients. Generally speaking, the system of equations do not yield close-form solutions. However, we are still able to characterize the model behaviors with equations above.

C.2.3 Proof of Proposition 1

Proof. Portfolio flows in the model is defined as follows:

$$\begin{aligned} dF_{L,t} &= dF^*_{A,t} \equiv \bar{P}_{US} dQ^*_{US,t} \\ dF^*_{L,t} &= dF_{A,t} \equiv \bar{P}_{EU} dQ_{EU,t}, \end{aligned}$$

where $Q^*_{US,t}$ is European investors' holdings of the US tree, and $Q_{EU,t}$ is the US investors' holdings of the European tree. Using Equations (C.18) and (C.19), and plugging in Equations (C.36) and (C.38), we can express flows as:

$$dF_{L,t} = dF^*_{A,t} = \mu_{F_L,t} dt + \theta \bar{f} \left(\psi \sigma dZ_{US,t} + (1-\psi) \sigma dZ_{EU,t} + \sigma_g dZ_{g,t} \right) \tag{C.39}$$

$$dF_{A,t} = dF^*_{L,t} = \mu_{F_A,t} dt + \theta \bar{f} \left((1-\psi) \sigma dZ_{US,t} + \psi \sigma dZ_{EU,t} + \sigma_g dZ_{g,t} \right), \tag{C.40}$$

where

$$\bar{f} = \bar{P} \frac{\theta}{\gamma(\alpha + r)\left(-2\Sigma_c + \Sigma_d + \Sigma_r\right)} \geq 0,$$

$$\psi = \frac{(-2\Sigma_c + \Sigma_d + \Sigma_r)\left(- \frac{\kappa \bar{P}^2}{(\alpha_e + \kappa + r)\left(2\bar{P}^2 + \gamma\zeta(2\Sigma_c + \Sigma_d + \Sigma_r)\right)} - \frac{\bar{P}^2 (\alpha_e + r)^2}{(\alpha_e + \kappa + r)\left(2\bar{P}^2(\alpha_e + r) + \gamma\zeta\alpha_e(2\Sigma_c + \Sigma_d + \Sigma_r)\right)} + \frac{\Sigma_d + \Sigma_r}{-2\Sigma_c + \Sigma_d + \Sigma_r} \right)}{(2\Sigma_c + \Sigma_d + \Sigma_r)},$$

and $\mu_{F_L,t}$ and $\mu_{F_A,t}$ are time-varying drifts that depends on the loading of $\hat{\mathbf{Q}}_t$ on state variables. Their exact expressions are not relevant for the purpose of this proposition.

The coefficient ψ governs the shares of the response to local shocks in liability flows vs. asset flows. It is difficult to bound ψ for the general case due to terms from the covariance matrix. Nevertheless, we can consider two extremes of the international market to provide intuitions.

First, consider the case of a frictionless foreign-exchange market where $\zeta = \infty$. In this case, bankers have infinite capacity (or completely risk-neutral) to channel cross-border lending without moving the exchange rate. The exchange rate is pinned down at its long-run rate of 1.

Setting $\zeta \to \infty$, we can solve Equations (C.29)-(C.38) in a closed form:

$$\begin{aligned}
\alpha_e &= 0 \\
\sigma_e &= 0 \\
e_I &= 0 \\
p_{Ir} &= 0 \\
p_{Id} &= \frac{\alpha\theta}{2(r+\alpha)\,(r+\kappa)} \\
\Sigma_d &= \frac{\left(\sigma_g^2+\sigma^2\right)(\theta+2\kappa+2r)^2}{4(\alpha+r)^2(\kappa+r)^2} \\
\Sigma_c &= \frac{\sigma_g^2(\theta+2\kappa+2r)^2}{4(\alpha+r)^2(\kappa+r)^2} \\
\Sigma_r &= \frac{\left(\sigma_g^2+\sigma^2\right)(\theta+2\kappa+2r)^2}{4(\alpha+r)^2(\kappa+r)^2}.
\end{aligned}$$

Plug the solutions to Equations (C.29)-(C.38) in the expression for $\mathbf{Q}_t$, we can express coefficients for flows as:

$$\bar{f} = \bar{P}\frac{2\theta(\alpha+r)(\kappa+r)^2}{\gamma\sigma^2(\theta+2\kappa+2r)^2} \tag{C.41}$$

$$\frac{1}{2} \leq \psi = \frac{\sigma_g^2+\sigma^2}{2\sigma_g^2+\sigma^2} \leq 1. \tag{C.42}$$

Plug them into (C.39) and (C.40), we have:

$$\begin{aligned}
dF_{L,t} = dF^*_{A,t} = \mu_{F_L,t}dt + \frac{2\theta^2(\alpha+r)(\kappa+r)^2}{\gamma\sigma^2(\theta+2\kappa+2r)^2}\left(\frac{\sigma_g^2+\sigma^2}{2\sigma_g^2+\sigma^2}\sigma dZ_{US,t} + \frac{\sigma_g^2}{2\sigma_g^2+\sigma^2}\sigma dZ_{EU,t} + \sigma_g dZ_{g,t}\right) \\
dF_{A,t} = dF^*_{L,t} = \mu_{F_A,t}dt + \frac{2\theta^2(\alpha+r)(\kappa+r)^2}{\gamma\sigma^2(\theta+2\kappa+2r)^2}\left(\frac{\sigma_g^2}{2\sigma_g^2+\sigma^2}\sigma dZ_{US,t} + \frac{\sigma_g^2+\sigma^2}{2\sigma_g^2+\sigma^2}\sigma dZ_{EU,t} + \sigma_g dZ_{g,t}\right).
\end{aligned}$$

In this limiting case, the exchange rate is constant as bankers can absorb infinite flows without moving the exchange rate. Therefore, the model is akin to a closed-economy model with two assets and two investors who have symmetric biases. In this economy, when the US tree is negatively shocked, European investors will withdraw from the US tree. They take the proceeds and partly invest into the European tree, and lend the rest to the US investors for them to buy back the US tree. European investors rebalance toward to the European tree because the European tree and US tree are exposed to the common global shock and therefore are substitutes. As indicated by the expression of ψ in Equation (C.42), if σ_g^2 is set to zero, $\psi = 1$ and European investors lend all proceeds to US investors.

Consider the other extreme where the cross-border lending is completely frictional ($\zeta = 0$) and the trade friction is also infinitely large ($\chi \to \infty$), so the goods-market arbitrage is infinitesimally small. In this world, cross-border lending is completely shut down ($B_t = 0$) and a one-dollar portfolio liability flow has to be matched with a one-dollar portfolio asset flow. In the limit, the exchange-rate dynamics is characterized as:

$$\begin{aligned}
\alpha_e &= 0 \\
\sigma_e &= -\frac{\theta\sigma}{2\bar{P}(\alpha+r)(\kappa+r)} \\
e_I &= \frac{\alpha\theta\kappa}{2\bar{P}(\alpha+r)(\kappa+r)}.
\end{aligned}$$

Hence, in the limit, we have:

$$\begin{aligned}
d\hat{E}_t &= \frac{\alpha\theta}{2\bar{P}(\alpha+r)(\kappa+r)}\left[\kappa\left(\hat{\mathcal{I}}_{h,t} - \hat{\mathcal{I}}_{f,t}\right)dt + \frac{\sigma}{\alpha}\left(-dZ_{h,t} + dZ_{f,t}\right)\right] \\
&= -\frac{\alpha\theta}{2\bar{P}(\alpha+r)(\kappa+r)}\left[d\hat{\mathcal{I}}_{h,t} - d\hat{\mathcal{I}}_{f,t}\right].
\end{aligned}$$

That is, in the limit, the exchange rate perfectly co-moves with the sentiment differentials. Therefore, we can solve the equilibrium "as if" there are only four state variables $\left(\tilde{D}_{h,t}, \tilde{D}_{f,t}, \tilde{\mathcal{I}}_{h,t}, \tilde{\mathcal{I}}_{f,t}\right)$ by substituting $\hat{E}_t$with $-\frac{\alpha\theta}{2\bar{P}(\alpha+r)(\kappa+r)}\left(\hat{\mathcal{I}}_{h,t} - \hat{\mathcal{I}}_{f,t}\right)$. The limiting equilibrium is characterized by:

$$\begin{aligned}
d\hat{P}_{h,t} &= \frac{1}{r+\alpha}d\tilde{D}_{h,t} + \frac{\alpha\theta}{2(\alpha+r)(\theta+2\kappa+2r)}\left(\sigma dZ_{h,t} + \sigma dZ_{f,t} + 2\sigma_g dZ_{g,t}\right) \\
d\hat{P}^*_{f,t} &= \frac{1}{r+\alpha}\tilde{D}_{f,t} + \frac{\alpha\theta}{2(\alpha+r)(\theta+2\kappa+2r)}\left(\sigma dZ_{h,t} + \sigma dZ_{f,t} + 2\sigma_g dZ_{g,t}\right) \\
\Sigma_d &= \frac{\frac{\theta\left(2\sigma_g^2+\sigma^2\right)(3\theta+4\kappa+4r)}{2(\theta+2\kappa+2r)^2} + \sigma_g^2 + \sigma^2}{(\alpha+r)^2} \\
\Sigma_c &= \frac{(\theta+\kappa+r)\left(8\sigma_g^2(\kappa+r)(\theta+\kappa+r) - \theta^2\sigma^2\right)}{2(\alpha+r)^2(\kappa+r)(\theta+2\kappa+2r)^2} \\
\Sigma_r &= \frac{\frac{\theta\left(2\sigma_g^2+\sigma^2\right)(3\theta+4\kappa+4r)}{(\theta+2\kappa+2r)^2} + 2\sigma_g^2 + \frac{\sigma^2\left(\theta^2+2\theta\kappa+2\kappa^2+2r^2+2r(\theta+2\kappa)\right)}{(\kappa+r)^2}}{2(\alpha+r)^2}.
\end{aligned}$$

Coefficients governing the capital flows can be solved as:

$$\begin{aligned}
\bar{f} &= \bar{P}\frac{2\theta(\alpha+r)(\kappa+r)^2}{\gamma\sigma^2(\theta+2\kappa+2r)^2} \\
\psi &= \frac{1}{2}.
\end{aligned}$$

Plug them into (C.39) and (C.40), we have:

$$dF_{L,t} = dF^*_{A,t} = \mu_{F_L,t}dt + \frac{\theta^2(\alpha+r)(\kappa+r)^2}{\gamma\sigma^2(\theta+2\kappa+2r)^2}\left(\sigma dZ_{US,t} + \sigma dZ_{EU,t} + 2\sigma_g dZ_{g,t}\right)$$
$$dF_{A,t} = dF^*_{L,t} = \mu_{F_A,t}dt + \frac{\theta^2(\alpha+r)(\kappa+r)^2}{\gamma\sigma^2(\theta+2\kappa+2r)^2}\left(\sigma dZ_{US,t} + \sigma dZ_{EU,t} + 2\sigma_g dZ_{g,t}\right).$$

As no cross-border lending is allowed, the asset flows and liability flows in and out of a country has to be matched one-to-one. Therefore, shocks to either country trigger global capital flows of the same size. □

C.2.4 Proof of Lemma 1 and Proposition 2

Proof. I first derive the equations of coefficients under heterogeneous parameterizations, $\theta_{EU} = \theta$ and $\theta_{US} \equiv \theta + \Delta\theta$, as outlined in C.2.1. I then take the partial derivative of coefficients with respect to $\Delta\theta$, and evaluate the partial derivatives at the symmetric case where $\Delta\theta = 0$. Use $e'_g(\Delta\theta)$ to denote partial derivatives with respect to $\Delta\theta$, We have:

$$e'_g(\Delta\theta)\mid_{\Delta\theta=0} = -\frac{\bar{P}\sigma_g}{(\alpha+r)\left(2\bar{P}^2(\alpha_e+\kappa+r)+\gamma\zeta(\alpha_e+\kappa)(2\Sigma_c+\Sigma_d+\Sigma_r)\right)} -$$
$$\theta\times\frac{\sigma_g\left(\bar{P}\left(\left((\Sigma^*_d)'(0)-(\Sigma^*_r)'(0)-\Sigma'_d(0)+\Sigma'_r(0)\right)\right)-(2\Sigma_c+\Sigma_d+\Sigma_r)\left(\overline{P_f}'(0)-\overline{P_h}'(0)\right)\right)}{(\alpha+r)(-2\Sigma_c+\Sigma_d+\Sigma_r)\left(2\bar{P}^2(\alpha_e+\kappa+r)+\gamma\zeta(\alpha_e+\kappa)(2\Sigma_c+\Sigma_d+\Sigma_r)\right)},$$

and

$$\Delta f^{*'}_g(\Delta\theta)\mid_{\Delta\theta=0} = -\zeta(\alpha_e+\kappa)\times e'_g(\Delta\theta)\mid_{\Delta\theta=0}.$$

With $\theta\to 0$, we have

$$e'_g(0)\mid_{\theta=0} = -\frac{\bar{P}\sigma_g}{(\alpha+r)\left(2\bar{P}^2(\alpha_e+\kappa+r)+\gamma\zeta(\alpha_e+\kappa)(2\Sigma_c+\Sigma_d+\Sigma_r)\right)} < 0.$$

Therefore, by continuity, with θ close enough to zero, we have $\frac{\partial e_g}{\partial\Delta\theta}\mid_{\Delta\theta=0} < 0$ and $\frac{\partial\Delta f^*_g}{\partial\Delta\theta}\mid_{\Delta\theta=0} > 0$. □

C.2.5 Converting Model Parameters to Moments

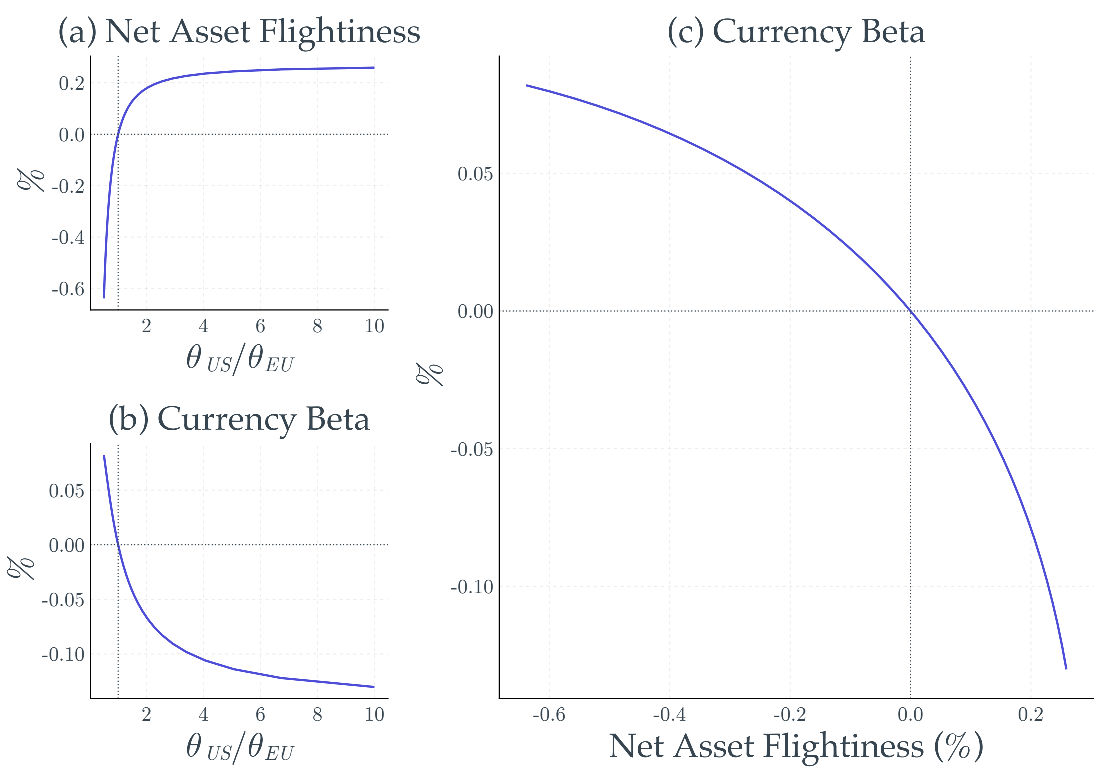
Lemma 1 and Proposition 2 are stated in terms of loadings on global shocks $dW_{g,t}$ and the flightiness parameter θ , which are not directly observed in data. With numerical exercises, I show that the analytical results hold when the loading on global shocks is replaced with comovement, or *beta*, on global asset returns. Specifically, I estimate *net asset flightiness* and *currency beta* from the following regressions in the model:

$$dF^*_{A,t} - dF^*_{L,t} = \beta_{NAF} \times dR^{global}_t + \varepsilon_t \tag{C.43}$$

$$dE_t = \beta_{FX} \times dR^{global}_t + \varepsilon_t. \tag{C.44}$$

Figure 17 shows numerically the comparative statics on net asset flightiness and currency beta while varying relative flightiness parameters between Europe and the US. Consistent with my analytical results, Panel (a) and (b) shows that as foreign flightiness toward Europe increases θ_{US} while fixing θ_{EU}, Europe's net asset flightiness estimated from flows increases, while its currency beta also decrease: when Europe's external assets are flightier than its external liabilities, the euro also becomes safer. This relationship holds robustly across a wide range of parameterizations. Panel (c) plots the currency beta against the net asset flightiness. As both variables can be estimated empirically, Panel (c) provides a testable hypothesis: currency beta is higher (currency is riskier) if the country has low net asset flightiness.

Figure 17: Comparative Statics: Currency Beta and Flow Beta



D Appendix to Currency Risk

D.1 Construction of Net Asset Flightiness

Data sources. In order to capture cross-border flows for the aggregate economy, I use aggregate datasets to construct net asset flightiness. The backbone datasets are the Balance of Payment (BOP) and the International Investment Position (IIP) published by the IMF. The BOP captures gross inflows and outflows in different instruments for each country reporting to the IMF, and IIP reports the levels of external assets and liabilities in financial instruments. Both datasets are updated at the quarterly frequency. The IIP has a relatively short history. Many countries, including the US, only only started reporting external positions to IMF after 2005. Therefore, I limit the time periods in this section between 2000Q1-2021Q4. I impute missing values in external positions using last nonmissing values. Missing flows are not imputed.

One limitation of the BOP/IIP is that they are unilateral: they report the flows and positions between the given country and the rest of the world but do not tell us where investments come from or go to. To augment BOP/IIP, I further use the Coordinated Portfolio Investment Survey (CPIS), which further breaks down external investments into destination countries. The CPIS is also published by IMF semiannually, and I impute it to the quarterly frequency using last nonmissing values.

Estimate Asset Specific Foreign Flightiness. Recall the definition of net asset flightiness:

$$NAF_{c,t} = \frac{(\sum_s A_{c,s,t-1}\Delta\theta_s - \sum_s L_{c,s,t-1}\Delta\theta_s)}{(A_{c,t-1} + L_{c,t-1})/2}, \tag{D.1}$$

where s represents each asset type. I classify assets in different asset types by asset classes (public portfolio debt, private portfolio debt, equity, etc.) and issuing country type (core advanced economies versus emerging markets).[36] As discussed in the main text, the asset-specific flightiness can be estimated using the following specification pooling from all countries in the Balance of Payment data:

$$f^{foreign}_{c,s,t} = \tilde{\theta}_s \times r^{global}_t + \epsilon_{c,s,t}, \tag{D.2}$$

where $f^{foreign}_{c,s,t} \equiv \frac{F^{foreign}_{c,s,t}}{A^{foreign}_{c,s,t-1}}$ is dollar flows into asset type s issued by country c normalized by the outstanding amount. $F_{c,s,t}$ can be directly observed from BOP as the gross inflows of each instrument s, and $L_{c,s,t-1}$ is observed from IIP. Equation (D.2) is weighted by sizes $L_{c,s,t-1}$ to improve precision, as the report of flows from small countries tend to be noisier. The results are to equally-weighted regressions with outliers winsorized.

[36] Core advanced economies here refer to Australia, Austria, Belgium, Canada, Denmark, France, Germany, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, United Kingdom, and United States. I do not include Italy, Ireland, Portugal, Spain and Greece here as these countries encountered debt crises during the sample period and have relatively lower sovereign debt ratings. This choice is not crucial for my results as these countries are not used for currency risk analysis later due to being part of the euro area.

In contrast to specification using mutual fund flows in Section 2, the coefficient $\tilde{\theta}_s$ in (D.2) already captures the differences between foreign and domestic investors, without being directly compared to domestic counterparts. This is because the BOP reports aggregate flows into each economy. With a constant supply of securities, a one-dollar foreign inflow is matched with a one-dollar domestic outflow by market clearing. However, the supply is not always constant throughout the business business cycle. Particularly, governments typically issue more public debt to finance stimulus during downturns. This will induce positive correlation between foreign government debt inflows and stock-market returns even if foreign and domestic investors are alike.

To adjust for supply-driven foreign debt flows, I utilize the debt supply data from the Quarterly Public Sector Debt (QPSD) from the World Bank and the Global Debt Database from the IMF. The former reports the public sector debt outstanding at the quarterly frequency for selected countries, while the latter reports debt issued by the public sector and the private sector respectively at the yearly frequency. Both datasets in principle report debt in the nominal value, and hence the changes are immune from valuation effect. I use quarterly data whenever feasible, and linearly impute the yearly data to the quarterly frequency otherwise.

Denote $D_{c,s,t}$ as the nominal value of debt issued by country c's sector s. I compute the growth rate of debt $g_{c,s,t}$ and the supply-adjusted foreign flows $\tilde{f}_{c,s,t}$:

$$
\begin{aligned}
g_{c,s,t} &= \frac{D_{c,s,t} - D_{c,s,t-1}}{D_{c,s,t-1}} \\
\tilde{f}_{c,s,t} &\equiv f_{c,s,t} - g_{c,s,t}
\end{aligned}
$$

To understand the supply-adjusted foreign flows, $\tilde{f}_{c,s,t}$, consider the scenario that foreign and domestic investors are homogeneous. In this case, when the supply of securities increases, the new issuance is absorbed by domestic and foreign investors in proportion to their relative sizes in the market, and hence $f_{c,s,t} = g_{c,s,t}$ and $\tilde{f}_{c,s,t} = 0$. Therefore, after adjusting for the supply growth, the coefficient $\tilde{\theta}_s$ captures the relative flightiness between foreign and domestic investors. I use $\tilde{f}_{c,s,t}$ in estimation of $\tilde{\theta}_s$ whenever available.

Table 17 reports the full table of flow flightiness for each asset type s. Some countries, such as Japan, do not report their external holdings of government debt and private debt separately, but only report the overall assets in portfolio debt. Therefore, I also estimate the average debt flightiness in the fourth column pooling government debt and private debt together.

The focus of this paper is on portfolio assets. In the construction of net asset flightiness, I only include portfolio flows and omit other types of flows. In fact, including other types of flows does not change net asset flightiness, because other types of flows are not particularly flighty, as reported in the last two columns in Table 17. The point estimates for bank loans and FDI are close to zero and insignificant. Therefore, loans and FDI enter the construction of net asset flightiness (5.1) with zero weights regardless.

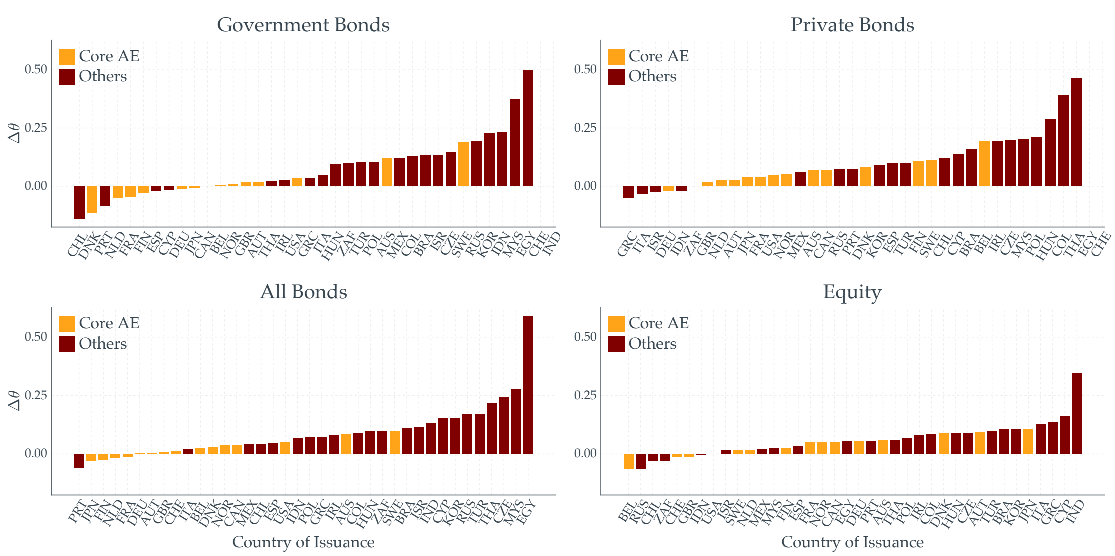
Table 17: Foreign Flightiness Estimates by Asset Types

	Public Debt	Private Debt	Debt	Equity	Loan	FDI
Core Advanced Economies	-0.00	0.04*	0.03*	0.03**	-0.00	-0.02
	(0.053)	(0.021)	(0.013)	(0.010)	(0.088)	(0.017)
Others	0.05	0.07**	0.06**	0.09***	-0.00	0.00
	(0.033)	(0.026)	(0.021)	(0.012)	(0.030)	(0.018)

Note. This table reports flow flightiness by asset type. Asset types are defined by issuance country types and asset classes. Flow betas are estimated by regressions $f_{i,s,t} = \tilde{\theta}_s \times r_t^{global} + \epsilon_{i,s,t}$, pooling from all countries for the same type of flows between 2000Q1–2021Q4. Flows are computed using the Balance of Payment by the IMF. Core advancecd economies here refer to Australia, Austria, Belgium, Canada, Denmark, France, Germany, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, United Kingdom, and United States. Standard errors are reported in parentheses, clustered at the quarter level. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

To estimate the asset-specific flightiness, I make the assumption that the same type of asset issued by countries in the same group (core advanced economies vs. others) have the same foreign flightiness. To evaluate the validity of this assumption, I estimate the foreign flightiness by both country and asset class. The coefficients are reported in Figure 18. As shown in the plots, countries in the same group indeed tend to have similar foreign flightiness coefficients as they cluster together, and core advanced economies overall are subject to lower foreign flightiness than other economies.

Figure 18: Foreign Flightiness Estimates by Countries



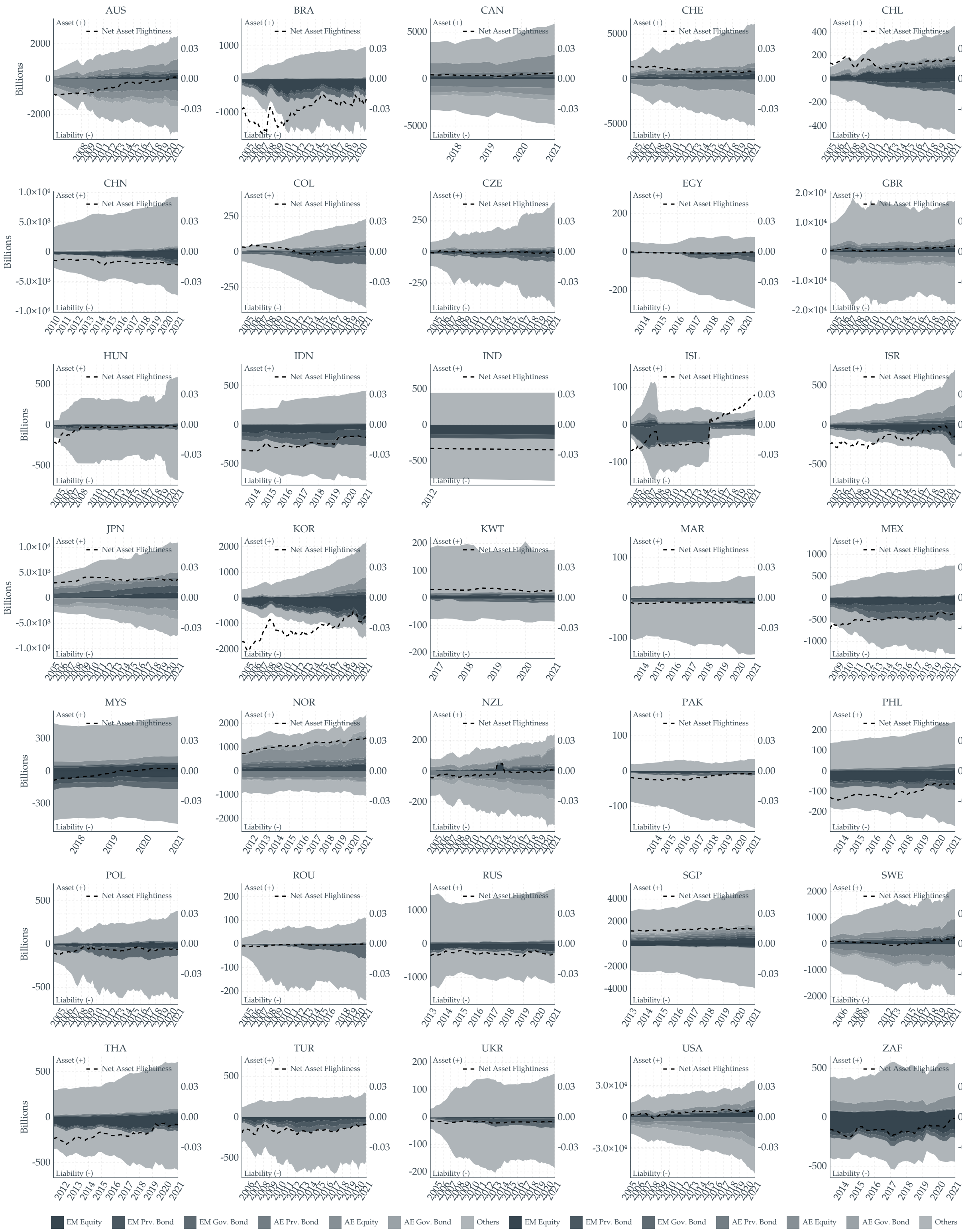
Note. This figure reports flow flightiness by country and asset class, estimated from $f_{c,s,t} = \Delta\theta_s \times r_t^{global} + \epsilon_{c,s,t}$ for each country c and asset class s between 2000Q1-2021Q4. Flows are computed using the Balance of Payment by the IMF. Core advancecd economies here refer to Australia, Austria, Belgium, Canada, Denmark, France, Germany, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, United Kingdom, and United States.

Aggregating asset-specific flightiness to net asset flightiness. Net asset flightiness is then constructed as the weighted external assets $A_{c,s,t}$ minus external liabilities $L_{c,s,t}$, with weights being asset-specific flightiness β_s reported in Table 17.

The external liability $L_{c,s,t}$ can be observed directly from the IIP. On the external asset side, the IIP only offers breakdowns into asset classes but not the destination countries. To use the correct $\Delta\theta_s$ requires information on the type of issuing countries. I use the Coordinated Portfolio Investment Survey (CPIS) to augment the IIP. The CPIS reports bilateral holdings of portfolio securities for each participating countries. The survey is conducted semiannually. From the CPIS I can compute the share of external portfolio assets invested in core advanced economies for each asset class, and use the relevant shares to compute the weighted average in the construction of net asset flightiness. For countries that do not report to CPIS, I impute the share of core advanced economy using world averages.

Figure 19 plots the detailed external balance sheet composition together with net asset flightiness for each country in the final sample. In each panel, I plot external assets on the positive y-axis and external liabilities on the negative y-axis, consistent with the construction of net asset flightiness. For both assets and liabilities, I decompose them into different asset types. The darkness of the color corresponds to the asset-specific foreign flightiness report in Table 17. The darker the color, the flightier foreign investors are for the asset type. The net asset flightiness, reported on the right axes, is the difference of assets and liabilities weighted by the asset-specific beta.

Figure 19: External Balance Sheet Composition and Net Asset Flightiness



Notes. This figure plots the external balance sheets of each country in the final sample and corresponding net asset flightiness. It plots external liabilities in the positive y-axis and external assets in the negative y-axis. The darkness of color indicates the asset-specific flightiness, reported in Table 5. The black dotted line (right axes) reports net asset flightiness, computed following (5.1).

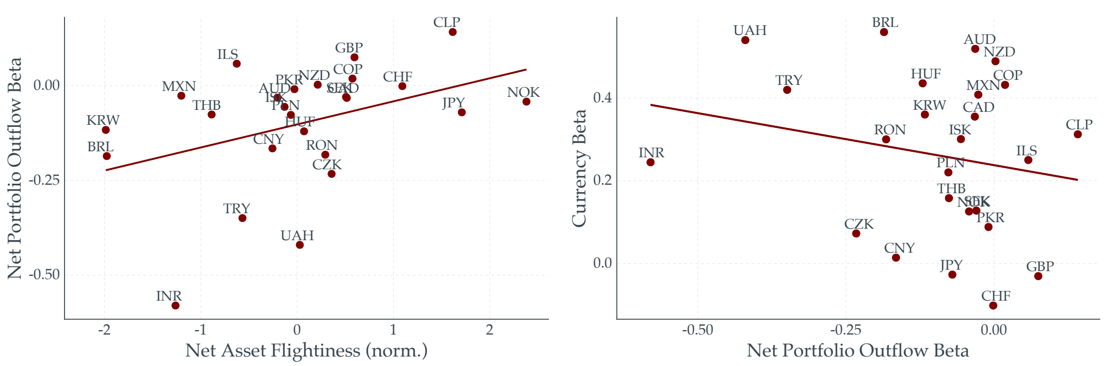
Estimate Flow Flightiness by Country. An alternative approach of constructing net asset flightiness is to estimate the country-specific net portfolio flow flightiness directly, using the following specification:

$$f_{c,t}^{net} = \Delta\theta_c^{net} r_t^{global} + \varepsilon_{c,t}, \tag{D.3}$$

where $f_{c,t}^{net} \equiv \frac{F_{A,c,t}^{portfolio} - F_{L,c,t}^{portfolio}}{\left(A_{c,t}^{portfolio} + L_{c,t}^{portfolio}\right)/2}$ is the net portfolio outflows from country c at quarter t, and the coefficient $\Delta\theta_c^{net}$ is referred to as *net portfolio outflow beta*. As discussed in the main text, this approach suffers from several drawbacks: first, country-specific flightiness may be driven by its currency risk; second, relatively short sample periods also make the estimation noisier. Regardless, below I estimate $\Delta\theta_c^{net}$ from Equation (D.3) for countries with more than 40 quarters of observations and show its relation to net asset flightiness.

In the left panel of Figure D.3 I compare the estimates of net portfolio outflow beta $\Delta\theta_c^{net}$ with net asset flightiness NAF for countries in my sample. These two variables do exhibit positive correlation. For countries with higher net asset flightiness measured by their balance sheet composition, the net portfolio outflows are indeed flightier. The right panel plots the currency beta against the estimated net portfolio outflow beta for each country. These two variables also exhibit a slight negative correlation, similar to my baseline results, but the correlation is much weaker, potentially due to measurement errors in the net portfolio outflow beta.

Figure 20: Direct Estimates of Net Portfolio Outflow Beta



Note. This figure report the results using the net portfolio outflow beta, directly estimated from (D.3) for countries with at least 40 quarters of observations. The left panel plots net portfolio outflow beta with net asset flightiness used in the main text, and the right panel plots currency beta against net portfolio outflow beta.