# Equity Flows in Uncertain Times: the Role of Heterogeneous Information

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**Abstract**

We study the role of information heterogeneity in determining capital flows during the global financial cycle. When global uncertainty increases, investors retrench toward their home country and the United States. We build a model of portfolio choice and information acquisition with varying learning costs across countries. Our model replicates the global financial cycle's stylized facts and delivers new predictions for forecasts' accuracy, which we test using micro forecast data. Domestic forecasters better predict their own country's economic outcomes, especially with increased global uncertainty. We further document that the United States is an exception, where domestic forecasters do not outperform foreign institutions. Finally, the model predicts and the data confirm that bilateral capital reallocations also depend on relative information costs across country pairs: flows increase toward destinations where foreign investors hold a comparative informational advantage during periods of heightened uncertainty.

**JEL Codes:** F32, F36, G11, D82
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# 1 Introduction

Equity flows across countries are a fundamental aspect of the global economy and play a crucial role for the fluctuation of output and asset prices. They represent a large share of total capital movements, with inflows and outflows together accounting on average for nearly half of all cross-border capital flows [1]. The recent literature on the global financial cycle, summarized in Coeurdacier and Rey (2013) and Miranda-Agrippino and Rey (2022), has documented that equity investors not only exhibit home bias in portfolio choices, but also retrench towards their own country and safer assets, particularly in the United States, during economic downturns. While home bias and equity flows have typically been studied in isolation, in this paper we test the hypothesis that a possible channel, the heterogeneity across countries in information over asset payoffs, can rationalize all these empirical patterns.

The research question we address is important for at least three reasons. First, equity flows are massive and highly volatile. Annual gross inflows alone often exceed ten percent of GDP in many countries, and during financial crises retrenchments and reversals have reached hundreds of billions of dollars. For instance, in the aftermath of the Lehman collapse global equity investors withdrew approximately 430 billion USD in only two quarters (Caballero and Simsek, 2020). Second, equity flows are very sensitive to uncertainty shocks. A one standard deviation increase in global volatility reduces institutional equity inflows by about two percentage points per quarter, with effects that are several times larger in emerging markets and that become even more pronounced at the investor-firm level (Kacperczyk et al., 2025). Third, the policy stakes are substantial. Even seemingly modest percentage changes in equity flows translate into hundreds of billions of dollars in reallocations, raising concerns about financial stability, the scope for capital flow management, and the design of transparency and disclosure regulation. Understanding what drives equity flows, and how they respond to uncertainty, is therefore of central importance both for researchers and policymakers.

To formalize the role of information heterogeneity in determining equity flows, we develop a tractable model of portfolio choice and information acquisition with varying learning costs across countries. Our model replicates the global financial cycle's stylized facts and has new predictions for forecasting accuracy, which we test using micro forecast data. Do-

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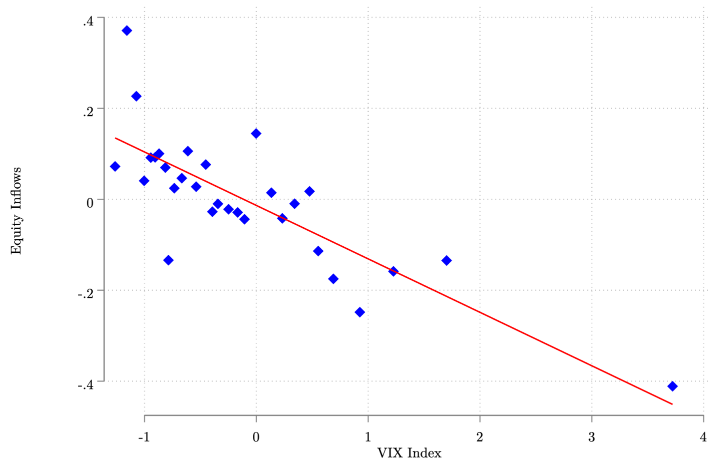
mestic forecasters better predict their own country's economic outcomes and, crucially, their information advantage becomes larger when global uncertainty is high. However, the United States is an exception, as domestic forecasters do not outperform foreign institutions.

To motivate our work, we first summarize the key findings of the global financial cycle for equity flows, and in doing so we extend the literature by using equity flow data from Koepke and Paetzold (2022). We clearly show that when global uncertainty increases, as measured by the VIX,[2] equity investors tend to retrench towards their home country, with the notable exception of the United States. In what follows, we use the standard convention that equity *inflows* into a country capture increases in foreign holdings of its domestic equity, while equity *outflows* represent increases in residents' holdings of foreign equity.

Figure 1 illustrates investor behavior during times of uncertainty, highlighting investors' fickleness, as documented in Caballero and Simsek (2020).

Figure 1: Uncertainty and Equity Inflows




**Notes**: This graph is a binscatter capturing the correlation between equity inflows and financial uncertainty. Each point represents a specific moment in time for a particular country, with monthly data. The dataset we use is by Koepke and Paetzold (2022). Each point in time is associated with a specific level of uncertainty, measured using the VIX index. The binscatter represents the correlation between these two variables across all 46 countries in our dataset.

We rationalize these findings through a model with endogenous information acquisition in a multi-country setting, where investors face heterogeneous costs of learning about domestic and foreign assets. The framework captures the idea that investors know more about their

[2] Our results are robust to a wide array of uncertainty measures, both global, such as ACWI, and country-specific. We document these robustness checks in Appendix A.2.1.

own markets and about particularly transparent economies, such as the United States. The model predicts that rising uncertainty amplifies these differences, leading to retrenchment towards home countries and to sustained inflows into information havens. At the bilateral level, it further implies that capital flows respond systematically to which investors hold an informational advantage, providing a micro-foundation for the aggregate patterns observed in the global financial cycle.

Finally, we validate our model using data from Consensus Economics, which contains forecast data about several country-level variables. We categorize forecasters as either domestic or foreigners, depending on whether the institution making the forecast is headquartered in the country for which the forecast is made. We show that analysts exhibit greater accuracy when forecasting the economic conditions of their own country, which supports the notion of a home information advantage. Moreover, and crucially for our mechanism, the superior forecasting ability of domestic investors becomes even more pronounced during periods of elevated uncertainty. This observation aligns with our model's prediction that changes in the relative specialization of domestic and foreign investors can explain capital flow patterns. Specifically, as global uncertainty rises, the benefits of specialization increase, leading domestic investors to perform better relative to their foreign counterparts.

When we isolate the data for the United States, we observe a different dynamic. There is no clear informational advantage for domestic forecasters in this case, nor is there a distinct pattern correlating increased uncertainty with forecast accuracy. If anything, domestic forecasters seem to do worse than foreigners when forecasting the US in periods of high uncertainty. This lack of a home information advantage in the United States is consistent with its characterization as an information haven in our model, where abundant and transparent information is available to all investors, domestic and foreign alike, insulating the country from capital outflows during uncertainty episodes.

To further validate our mechanism, we combine these forecast data with bilateral investment flows. Using bilateral alongside unilateral flows allows us to capture both the aggregate retrenchment patterns and the cross-country reallocations predicted by the model, providing direct evidence that the information channel is a central driver of capital movements in times of uncertainty.

**Relation to the Literature.** We contribute to three main literatures. First, our work is connected to the literature examining capital flows during global financial cycles, as in Caballero and Simsek (2020), Akinci and Kalemli-Ozcan (2023), and Choi et al. (2023). Our motivating findings build upon this literature, by studying the response of equity flows to uncertainty, which highlight both a clear retrenchment pattern when uncertainty increases, and the different behavior of safe havens, such as the United States, with respect to the rest of the world.

Second, our paper relates to studies that analyze the interaction between investors' endogenous information choice and portfolio decisions, as in Van Nieuwerburgh and Veldkamp (2009), Van Nieuwerburgh and Veldkamp (2010), Mondria (2010), Mondria and Wu (2010), Dziuda and Mondria (2012), Valchev (2017), Kacperczyk et al. (2019), De Marco et al. (2022), Veldkamp (2023). Existing work has studied the role of information choices and advantages in explaining the seemingly under-diversified and differentially concentrated portfolio holdings across investors. Our work contributes to the literature by demonstrating that heterogeneity in investors' learning technology, and thus beliefs, can also help explain the observed heterogeneous international equity flow patterns. Kacperczyk et al. (2024) investigates the equity flows of institutional investors in periods of high global uncertainty, when foreign and domestic institutional investors differ in their size and information processing capacities. Our model allows investors to acquire information for multiple assets in equilibrium, allowing for a different behavior of investors, which may vary across countries. Our information mechanism is also related to Malmendier et al. (2020), which studies the role of past investor experiences in explaining capital flows. We instead emphasize the role of endogenous information acquisition and, most importantly, we test in the data the predictions of the model on heterogeneous forecast precision. Closely related, Saka (2020) introduces the concept of "information closeness," defined as a *bilateral* information set shaping cross-country bank exposures during the Eurozone crisis. In contrast, our mechanism is based on a comparison between the information cost for the home country and the *average* foreign country information cost, highlighting a different aggregation of information frictions.

Third, we contribute to a literature that studies empirically the existence of local information advantage, as in Batchelor (2007), Ager et al. (2009), Mehrotra and Yetman (2014), Coibion and Gorodnichenko (2015), Bordalo et al. (2020), Gemmi and Valchev (2023), and Benhima and Bolliger (2023). We contribute to this literature by providing evidence that not only there is a local information advantage, but that this becomes more marked in times of uncertainty. We also show that the United States does not display a local information advantage, behaving consistently with our theoretical notion of information haven.

**Outline.** The paper is organized as follows. Section 2 presents our motivational evidence on the behavior of capital flows in times of uncertainty across countries. Section 3 presents the model to understand how the information channel can explain capital flows. Section 4 uses Consensus Economics data to provide support for the predictions highlighted in the model. Section 5 concludes.

# 2 Motivating Evidence

In this section, we examine the effect of foreign equity holdings in the context of a shock to global uncertainty, and we show that, on average, uncertainty drives negative inflows, with the notable exception of the United States. This mirrors the 'flight to safety' mechanism, which characterizes investor behavior worldwide, as described in Miranda-Agrippino and Rey (2015), and the role of local uncertainty as a local pull-factor for capital emphasized in Choi et al. (2023). While our finding is reminiscent of empirical patterns documented in the literature, our contribution lies in using equity flow data, and in clearly highlighting the exceptional behavior of the United States. This evidence serves as a motivation for our main research question, which seeks to determine the role of heterogeneous information as a key driver of investor behavior during adverse times.

Our dataset is a country-month panel sourced from Koepke and Paetzold (2022), covering 47 countries for the period from 1997 to 2023. This dataset includes information on equity inflows and outflows by country, adhering to the IMF's balance of payments definition of portfolio equity. A detailed description of the dataset structure is provided in Appendix A.1. The study primarily investigates the relationship between equity flows and uncertainty, with uncertainty measured by the VIX, which captures global volatility. Additionally, we examine alternative measures of uncertainty, including those at local level.

To estimate how equity flows react to uncertainty we rely on a specification in line with the existing work by Akinci and Kalemli-Ozcan (2023) and Choi et al. (2023):

$$\mathrm{Y}_{it} = \alpha_i + \beta \mathrm{V}_{it} + \beta_{US} \mathrm{V}_{it} \times \mathbb{1}\{\mathrm{i} = \mathrm{US}\} + \mathrm{X}_{it} + \varepsilon_{it}, \tag{1}$$

In this model, the variable $Y_{it}$ is either equity inflows or equity outflows for a specific country $i$ at a specific month $t$; the variable $\mathrm{V}_{it}$ is a measure of uncertainty, the indicator function $\mathbb{1}_{\{\mathrm{US}\}}$ is instrumental in quantifying the marginal effect of US-specific uncertainty on its unique inflows and then $\mathrm{X}_{it}$ are control variables. We control for country specific fixed effect and for additional variables, such as GDP growth and lagged $Y_{it}$, to check for potential autocorrelation in the time series, similarly to the specification used in Choi et al. (2023).

In this case, $\beta$ captures the average response of equity flows to uncertainty. To give an example, if we look at equity inflows, a $\beta < 0$ suggests that foreigners reduce their investments in a specific country $i$ when uncertainty is higher. Conversely, to analyze the specific case of the United States, we examine $\beta + \beta_{US}$. If this is positive, it indicates that equity inflows into the United States are positively correlated with rising uncertainty, implying an increase in foreign equity holdings.

Table 1 provides evidence of equity fickleness (negative inflows) and retrenchment (negative outflows) during periods of increased volatility[3]. In our main analysis, we use the VIX index, a commonly used measure of financial uncertainty, but in Appendix A.2.1 we show that our results are robust to a more generic array of uncertainty measures, both global and country-specific.

In column (1), we examine the sensitivity of equity inflows to financial uncertainty, including the interaction with the United States. On average, a one standard deviation increase in uncertainty is associated with a 10% decrease in inflows, indicating that foreign investors reduce their equity holdings abroad. This finding is confirmed in column (2), where we control for GDP growth. Notably, $\beta_{US}$ is positive and remains so even after accounting for the average effect, suggesting that foreign investors do not reduce their equity holdings in the United States during times of heightened uncertainty. Instead, they tend to increase them by approximately 6%.

Column (3) explores the sensitivity of equity outflows to financial uncertainty, again including the interaction with the United States. On average, a one standard deviation increase in uncertainty is associated with a 7% decrease in outflows, indicating that domestic investors reduce their foreign equity holdings. This result is corroborated in column (4), where we control for GDP growth. Columns 3 and 4 confirm that equity flows are subject to retrenchment during periods of high uncertainty, a well-established finding in the literature Miranda-Agrippino and Rey (2015); Caballero and Simsek (2020). Unlike inflows, there is no significant asymmetry between the United States and other countries in terms of outflows, indicating that all countries tend to retrench as uncertainty increases. That is, in uncertain times also American investors reduce their foreign investments, but foreigners do not leave the United States.

[3] Equity inflows refer to net purchases of domestic equity by foreign investors, while equity outflows refer to net purchases of foreign equity by domestic investors.

Table 1: Uncertainty and Equity Flows

| | Inflows (1) | Inflows (2) | Outflows (3) | Outflows (4) |
|---|---|---|---|---|
| VIX Index | -0.10 | -0.11 | -0.07 | -0.07 |
| | (0.01) | (0.01) | (0.02) | (0.02) |
| VIX Index × US | 0.16 | 0.17 | -0.04 | -0.04 |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| GDP $\Delta$% | | 0.01 | | 0.00 |
| | | (0.00) | | (0.00) |
| $N$ | 7484 | 7349 | 6326 | 6218 |
| Country FEs | Yes | Yes | Yes | Yes |

**Notes**: This table reports the OLS regression coefficients from Equation (1). Both dependent and indepentent variables are standardized to the mean and GDP % is yearly GDP growth. We control for one lag of the dependent variable. Standard errrors, clustered at country level, are reported in parenthesis.

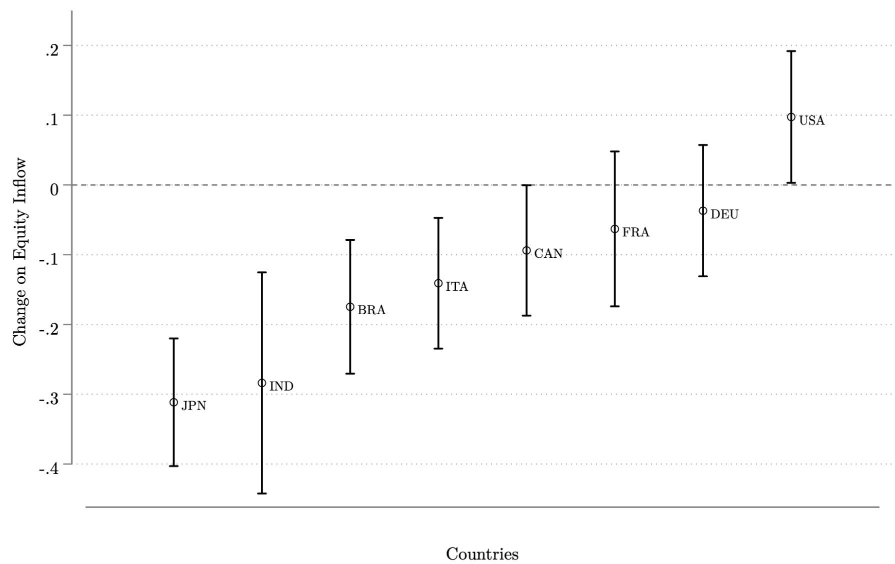
We aim to verify the consistency of our results across different countries and to ensure that our findings are not biased by outliers. To this end, we perform the following regression method for each specific country $i$ in our sample:

$$\mathrm{Y}_{it} = \alpha_i + \beta \mathrm{V}_{it} + \mathrm{X}_{it} + \varepsilon_t,$$

where we focus on $Y_{it}$ be equity inflows, the variable $\mathrm{V}_{it}$ be the VIX index, and $X_{it}$ including a set of controls such as lagged $Y_{it}$ and GDP growth. In this case $\beta$ is the correlation coefficient between uncertainty and equity inflows. Figure 2 illustrates how this correlation varies by country, demonstrating consistency among the G7 countries. In the Appendix A.3, we further examine the robustness of these results for the entire sample of 47 countries, with the United States being the only exception.

Our findings in this motivating section corroborate the results in previous literature, as in Akinci and Kalemli-Ozcan (2023) and Choi et al. (2023), using new data that focus exclusively on equity inflows. Specifically, we documented that when global uncertainty increases, investors retrench towards their own country and towards the United States. Our primary objective in the rest of the paper is to study the role of information heterogeneity in driving these patterns, and to understand through such lenses what distinguishes the United States from other countries during periods of heightened economic volatility.

Figure 2: Uncertainty and Equity Inflows




**Notes**: This plot shows the sensitivity of the equity inflows of each G7 country to financial uncertainty.Both dependent and independent variables are standardized to the mean. The confidence intervals are set at 95%.

**Robustness Checks.** In Appendix A.2.1, we show that our results are robust to using alternative measures of uncertainty, both global and country-specific. Additionally, in A.3.1, we incorporate various controls, such as the effective exchange rate and the size of the country's stock market, to account for potential confounding factors. To control for potential business-cycle effects, we first include a dummy for recessionary periods and confirm that our results remain unchanged. We then check for the influence of extreme realizations by excluding observations in which uncertainty exceeds two standard deviations above its mean. Both exercises show that our findings are not driven by recessions or by tail events in uncertainty. Finally, we reproduce Figure 2 for our entire sample of 47 countries, which again highlights the unique exceptional pattern of the United States.

# 3 Model

In this section we outline a theoretical framework to understand how endogenous information acquisition might have an impact on equity flows across countries. Investors across countries differ in their cost function of acquiring information about various assets in our model, which generate equity flows and heterogenous forecast accuracy towards asset payoffs. To simplify the analysis and provide clear analytical expressions for portfolio positions and capital flows, we focus on a limiting case with a small fraction of sophisticated investors that engage in learning, without qualitatively affecting our results.

## 3.1 Setup

The model features three periods. In the first period, investors choose information allocation to each asset. In the second period, they receive private signals about asset payoffs and make their portfolio choice. In the last period, payoff realizations are revealed and investors consume their wealth.

The world economy consists of $N$ countries. Each country $k \in \{1, 2, ...N\}$ has a risky asset with stochastic payoff $r_k$ and unit total supply. An additional risk-free asset pays off $r^f$, known to all investors in the second period. The prices of risky assets are $\{p_k\}_{k=1}^N$.

There are a continuum of investors with measure $\frac{1}{N}$ in each country, who have the same initial wealth $W_0$ and can invest in a portfolio of all assets. We distinguish investors by two types: a fraction $\kappa$ are unsophisticated and the remaining $1-\kappa$ are sophisticated. Both types know the true distribution of the payoff for each risky asset, $r_k \sim \mathcal{N}(\mu_k, \sigma_k^2)$, and thus have common prior about $r_k$. The unsophisticated investors cannot invest in research to learn about the assets, and therefore rely fully on their prior to make investment decisions. The sophisticated investors in a generic country $i$ can choose to acquire additional information of any asset $k$ in the first period, in the form of an unbiased and normally distributed signal with precision $\tau_{ik,s}$, subject to a convex cost $\theta_{ik}\tau_{ik,s}^2$, which is additive across assets for each investor. Then, investors receive the private signals about asset payoffs in the second period and use this additional information to make their portfolio decisions. Finally, uncertainty is realized and consumption takes place in the final period.

We assume that heterogeneity among investors in different countries stems from the differences in the cost of acquiring information about various assets, so that $\theta_{ik}$ - the cost for investors in country $i$ to acquire information about assets of country $k$- can vary across all $(i, k)$ pairs. We interpret such heterogeneity as a way to capture both the differences in the overall level of transparency of a country, and the possible relative information advantage of some investors when studying certain countries. While in principle this leads to a large number of parameters, in Section 3.3 we will show that the patterns of capital flows for each country are entirely pinned down by two summary statistics: $\theta_{kk}$, the cost of research for domestic assets, and $\theta_k$, the average cost of acquiring information about country $k$ among all world's investors. For illustrative purposes, we refer to *standard countries* as those countries that have $\theta_{kk} < \theta_k$, exhibiting domestic information advantage. That is, it is less costly for domestic investors to acquire information for a standard country than foreigners. If $\theta_{k'k'} \geq \theta_{k'}$ for country $k'$, we call it an information haven country. In the Section 4, we will connect our theoretical definition of an information haven to the empirical behavior of the United States, but we keep the more general term of information haven throughout the theory section.

We now formally present the investor problem proceeding backward. We will start with the standard investment decision in the second period, and then move to the information choice problem in the first period [4].

## 3.2 Portfolio Choice

Each investor in country $i$ has mean-variance preference with risk-aversion $\eta$. In the second period, investor $i$ optimally chooses asset holdings $\{x_{ik}\}_{k=1}^{N}$ to maximized expected utility over the next period:

$$\max \mathbb{E}_i[W_i] - \frac{\eta}{2}\mathbb{V}_i[W_i]$$
$$s.t. \quad W_i = r^f W_0 + x_i'(r - r^f p)$$

where $r$, $x_i$ and $p$ denote the vectors of risky asset payoffs, investor's portfolio holdings and risky asset prices respectively. We assume that asset payoffs are independently distributed.

The optimal portfolio holding of country $k$'s asset for the unsophisticated investor in country $i$ is given by:

$$x_{ik}^U = \frac{\mu_k - r^f p_k}{\eta\sigma_k^2} \tag{2}$$

Under the assumption that the mass of unsophisticated investors tends to one ($\kappa \to 1$), the price for each asset is determined by the demand of unsophisticated investors in all countries, and the market-clearing condition for the asset of country $k$ reads:

$$\sum_{i=1}^{N} \int_U x_{ik}^U dU = 1 \tag{3}$$

[4] Details on the derivations are provided in Appendix B.

and yields the equilibrium asset price $p_k$ as

$$p_k = \frac{\mu_k - \eta\sigma_k^2}{r^f} \tag{4}$$

Equilibrium prices only contain information of the prior distribution, as they only aggregate the unsophisticated investors' information. Therefore, despite prices being public signals, investors don't learn additional information about the stochastic payoffs from prices.

The sophisticated investors in country $i$ can receive private signals of asset payoffs in the second period:

$$s_{ik} = r_k + \epsilon_{ik} \tag{5}$$

where $\epsilon_{ik} \sim \mathcal{N}(0, {\sigma_{ik}^s}^2)$ is the i.i.d. signal noise, and $\tau_{ik,s} = \frac{1}{{\sigma_{ik}^s}^2}$ is the signal precision. To ease notation, we have omitted the individual $j$ index for signal, $s_{ik}^j$. Taking into account the equilibrium prices, the demand for asset $k$ of the sophisticated investor in country $i$ is given by:

$$x_{ik}^S = \frac{\widehat{r}_{ik} - \mu_k + \eta\sigma_k^2}{\eta\widehat{\sigma}_{ik}^2} \tag{6}$$

where $\widehat{r}_{ik} = \mathbb{E}[r_k|s_{ik}]$ and $\widehat{\sigma}_{ik}^2 = \mathbb{V}[r_k|s_{ik}]$ are posterior mean and variance for payoff $r_k$ after observing the private signal.

## 3.3 Information Choice

In the first period, sophisticated investors in country $i$ optimally choose the precision of private signals $\{\tau_{ik,s}\}_{k=1}^N$ to maximize ex ante expected utility, anticipating their future optimal investment choices:

$$\max_{\{\tau_{ik,s}\}_{k=1}^N} \mathbb{E}\left[\mathbb{E}_i\left(W_i\right) - \frac{\eta}{2}\mathbb{V}_i\left(W_i\right)\right] - C_i(\tau) \tag{7}$$

where $\tau$ is the vector of signal precision for all assets, and the cost function is quadratic and additive separable in signal precision for each asset

$$C_i(\tau) = \sum_{k=1}^{N} \frac{\theta_{ik}}{2}\tau_{ik,s}^2. \tag{8}$$

The key assumption for the cost function is that investors in different countries face different information acquisition cost or research cost. This is illustrated in the information cost matrix below, where each row corresponds to the learning costs for investors in a given country to learn about assets of all countries, and each column specifies the costs associated with learning about the assets of one specific country for all world investors:

$$\begin{bmatrix} \theta_{11} & \cdots & \theta_{1k} & \cdots & \theta_{1N} \\ \vdots & \ddots & \vdots & & \vdots \\ \theta_{k1} & & \theta_{kk} & & \theta_{kN} \\ \vdots & & \vdots & \ddots & \vdots \\ \theta_{N1} & \cdots & \theta_{Nk} & \cdots & \theta_{NN} \end{bmatrix}$$

For different assets $k$ and $k'$, $\theta_{ik} < \theta_{ik'}$ captures that it is easier for investors in country $i$ to conduct research and obtain information about $r_k$. For example, $\theta_{ii} < \theta_{ik'}$ ($\forall\ k' \neq i$) implies that it is easier for country $i$'s investors to learn about the domestic asset than foreign assets. In addition, the cost matrix may not be symmetric. In principle, this specifies $N^2$ parameters. However, we will show in Section 3.4 that the sign and magnitude of capital flows for country $k$ ultimately depend only on two summary statistics: the cost of research for domestic investors, $\theta_{kk}$, and the average cost of acquiring information about country $k$ for all investors, $\theta_k \equiv \frac{N}{\sum_i^N \frac{1}{\theta_{ik}}}$.

The following equation characterizes the optimal information choices for the sophisticated investor:

$$\tau_{ik,s} = \frac{1}{2\theta_{ik}} \sigma_k^2 \left( \frac{1}{\eta} + \eta \sigma_k^2 \right) \tag{9}$$

When the prior uncertainty for an asset ($\sigma_k$) is high or the cost to learn about the asset ($\theta_{ik}$) is low, the sophisticated investors will optimally choose more precise signals for that asset. Even though we have assumed common prior across investors, the heterogeneity in cost $\theta_{ik}$ implies that investors in different countries may learn differently about assets. Denote $\widehat{\tau}_{ik}$ as the inverse of country $i$'s sophisticated investors' posterior variance of payoff $r_k$. We derive the comparison of the relative forecast precision for asset $k$ between sophisticated investors in countries $i$ and $j$ in the following proposition.

**Proposition 1.** *The relative forecast precision for asset $k$'s payoff of investors in country $i$ and $j$ is:*

$$\frac{\widehat{\tau}_{ik}}{\widehat{\tau}_{jk}} = \frac{1 + \frac{1}{2\theta_{ik}} \sigma_k^4 \left( \frac{1}{\eta} + \eta \sigma_k^2 \right)}{1 + \frac{1}{2\theta_{jk}} \sigma_k^4 \left( \frac{1}{\eta} + \eta \sigma_k^2 \right)} \tag{10}$$

*The relative forecast precision for asset k's payoff between investors in country i and j reacts to uncertainty as follows:*

$$\frac{\partial}{\partial \sigma_k^2}\left(\frac{\widehat{\tau}_{ik}}{\widehat{\tau}_{jk}}\right) > 0 \quad \Longleftrightarrow \quad \theta_{ik} < \theta_{jk}. \tag{11}$$

- When $\theta_{ik} < \theta_{jk}$, investors in country $i$ have better forecast on $r_k$ than investors in country $j$, i.e. $\frac{\widehat{\tau}_{ik}}{\widehat{\tau}_{jk}} > 1$.
- When $\theta_{ik} < \theta_{jk}$, $\frac{\widehat{\tau}_{ik}}{\widehat{\tau}_{jk}}$ is increasing in the prior variance $\sigma_k^2$.

## 3.4 Capital Flows

Before analyzing capital flows, we first characterize the aggregate demand for asset $k$ of sophisticated investors in country $i$ after they have received private signals with optimally chosen precision:

$$\mathbb{E}\int_S x_{i,k}^S dS = 1 + \frac{1}{2\theta_{ik}}\sigma_k^4\left(\frac{1}{\eta} + \eta\sigma_k^2\right) \tag{12}$$

We observe from this result that when the uncertainty of asset $k$ increases, sophisticated investors demand more of it, especially those with lower costs to learn about the asset. Without any initial adjustment of research activity, sophisticated investors increase their demand for these assets because their hedge compared to unsophisticated investors improves. Higher portfolio holdings make it more desirable to learn about the asset, leading to an endogenous research adjustment and further increasing the holdings. The higher uncertainty of asset $k$, modeled as an increase in its prior variance $\sigma_k^2$, can arise from various sources. Given our assumption of an independent payoff structure across assets, an increase in $\sigma_k^2$ due to heightened local or global uncertainty will produce the same model results.

We then study how an increase in the uncertainty of asset $k$ affect capital flows in our model. As our model is static, we define capital inflow for country $k$ as the change in portfolio holdings between foreigners and domestic investors in response to a unit increase in asset volatility:

$$CF_k \equiv \frac{\partial}{\partial \sigma_k^2}\left(-x_{kk}^S + \frac{1}{N}\sum_{i=1}^{N} x_{ik}^S\right) \tag{13}$$

The following proposition illustrates how capital flows are related to the cost of information acquisition.

**Proposition 2.** *Denote $IF_k$ as the capital inflow for asset $k$ when its uncertainty increases, then:*

$$IF_k = \nu_k \left( \underbrace{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\theta_{ik}}}_{1/\theta_k} - \frac{1}{\theta_{kk}} \right) \tag{14}$$

*where $\nu_k = \frac{1}{2}\left(\frac{3\eta}{\tau_k^4} + \frac{2}{\eta\tau_k^3}\right)$. Country $k$ experiences negative capital inflows, when its domestic investors face lower-than-average cost in learning about the domestic risky asset than foreign investors.*

The intuition for Proposition 2 is as follows. When uncertainty about assets in country $k$ increases, this will trigger an increase in the relative specialization of investors with a low cost of learning about asset $k$ ($\theta_{ik}$). Whether this will result in inflows or outflows depend on the relative learning cost of domestic investors ($\theta_{kk}$) and foreign investors, where the relevant statistic for foreign investors turns out to be their harmonic average learning cost $\theta_k$. In the case of a *standard country* with $\theta_{kk} < \theta_k$, domestic investors have an information advantage. Therefore, when uncertainty increases, they become relatively more specialized in domestic assets and hold a larger fraction of such assets, triggering the capital flows patterns summarized in Proposition 2.

### 3.4.1 Bilateral Flows

We next extend our analysis from unilateral to bilateral capital flows. While unilateral inflows capture the aggregate difference between domestic and foreign investors' responses to higher uncertainty, they do not reveal which countries adjust their positions relative to one another. To better understand the cross-country reallocation of portfolios, we characterize bilateral flows between a specific investor country $i$ and destination country $k$.

In analogy with the definition of unilateral inflows in 3.4, we define bilateral flows as the change in the portfolio holdings of investors from country $i$ in asset $k$, relative to the global average, when the uncertainty of asset $k$ increases. This bilateral perspective highlights how information asymmetries shape not only whether foreign investors as a whole retrench from a country, but also which foreign investors do so more strongly.

Formally, the bilateral flow from country $i$ to country $k$ is given by:

$$CF_{ik} = \nu_k \left( \frac{1}{\theta_{ik}} - \underbrace{\frac{1}{N} \sum_{j=1}^{N} \frac{1}{\theta_{jk}}}_{1/\theta_k} \right), \tag{15}$$

where $\nu_k$ is the same scaling factor as in Proposition 2.

The following proposition summarizes the dependence of bilateral flows on information acquisition costs.

**Proposition 3.** *Consider the bilateral flow $CF_{ik}$ from country $i$ to country $k$ in response to an increase in the uncertainty of asset $k$. Then:*

$$CF_{ik} = \nu_k \left( \frac{1}{\theta_{ik}} - \frac{1}{\theta_k} \right). \tag{16}$$

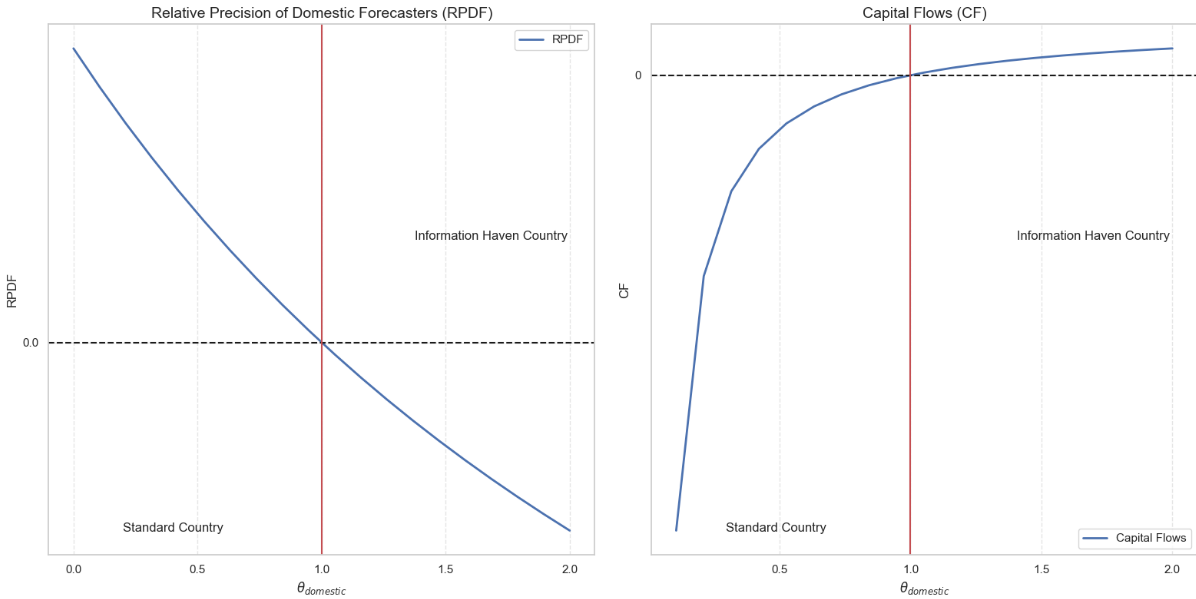
*Capital flows from country $i$ into country $k$ are positive if investors in $i$ face a lower learning cost for asset $k$ than the world average, $\theta_{ik} < \theta_k$, and negative otherwise.*

When the uncertainty of asset $k$ increases, investors with a relative informational advantage (low $\theta_{ik}$) reallocate towards $k$, while those with a disadvantage (high $\theta_{ik}$) reduce their exposure. The benchmark is not given by domestic investors, as in unilateral flows, but by the harmonic average learning cost $\theta_k$ across all investors. Thus, bilateral flows are positive whenever country $i$ is "better than average" at learning about country $k$.

## 3.5 Summary of model predictions.

We end this section by comparing the results for two types of countries that differ in their patterns of $\{\theta_{ik}\}$. For the first type, a standard country labeled by $s$, the learning cost for domestic investors satisfies $\theta_{ss}^{-1} > \theta_s^{-1} \equiv \frac{1}{N}\sum_{i=1}^{N} \theta_{is}^{-1}$. That is, domestic investors have lower learning cost than foreign investors on domestic asset payff. For the second type, an information-haven country labeled by $h$, the reverse holds and $\theta_{hh}^{-1} \geq \theta_h^{-1} \equiv \frac{1}{N}\sum_{i=1}^{N} \theta_{ih}^{-1}$. From Proposition 1 and Proposition 2, domestic investors in country $s$ have higher forecast precision of domestic assets than foreign investors. In addition, when uncertainty for asset payoff $r_s$ increases, such information superiority for domestic investors is more salient, while at the same time country $s$ experiences negative capital inflow. The opposite is true for

Figure 3: RPDF and CF changing $\theta_d$




**Notes**: This plot shows how relative precision of domestic forecasters and capital flows change in sign as $\theta_d$ increases. $\theta_f$ is normalized to one. On the left side of the vertical red line it is represented a standard country, with $\theta_d < \theta_f$, while on the right side of the vertical line it is represented an information haven country, with $\theta_d \geq \theta_f$.

the special country $h$. Foreign investors have better forecasts on $r_h$ than domestic investors. Such forecasting discrepancy further widens and country $h$ experiences positive capital inflow when $r_h$ is more uncertain.

Proposition 3 further refines these predictions by showing that, when uncertainty rises, bilateral flows from country $i$ to $k$ are positive if $i$'s learning cost is below the world average for asset $k$ ($\theta_{ik} < \theta_k$), and negative otherwise. Thus, uncertainty reallocates capital not only between domestic and foreign investors in the aggregate, but also across specific country pairs according to their relative informational advantage.

Figure 3 shows how relative precision of domestic forecasters and capital flows change in sign as we move from a standard country environment, which is characterized by $\theta_d < \theta_f$, into an information haven country environment, which is characterized by $\theta_d \geq \theta_f$ [5]. In the Appendix B.2 we also show the dynamics of RPDF and CF for different values of $\sigma^2$.

[5]This numerical representation is made by assuming that risk aversion $\eta = 2$ and volatility $\sigma^2 = 0.5$, with $\theta_f = 1$ fixed, while changing $\theta_d \in [0, 2]$.

# 4 Empirical Validation

In this section, we present novel empirical evidence to test the three central predictions of our model. We first show how the forecast accuracy of local investors relative to foreign forecasters fluctuates with varying levels of uncertainty, and we highlight the distinctive pattern for the United States, which stands out as an information haven. Finally, we test whether equity flows empirically respond to the observed relative forecast precisions, confirming that countries with a stronger domestic informational advantage experience weaker foreign inflows. Our empirical results are in line with the illustrative model in Section 3, which formalizes how heterogeneous learning between local and foreign investors can influence both forecast precision and equity flows during periods of heightened uncertainty, and links the direction of these flows to the comparative forecast accuracy of local versus foreign investors. We also provide direct evidence for the information channel, showing that bilateral capital flows move in line with our prediction that investors with a relative informational advantage increase their exposure while others retrench.

In order to measure forecast precision and how it varies with uncertainty, we use data from Consensus Economics [6], as in related work by De Marco et al. (2022) and Benhima and Bolliger (2023). The data contains country-specific forecasts provided by public and private institutions, such as investment banks, universities, research organizations, and large corporations. The magnitude of forecast errors reflects the information accuracy available to the forecaster, serving as the empirical counterpart to the learning choice discussed in our model.

In addition, we use bilateral investment data from the JRC-ECFIN Finflows database by Nardo et al. (2017). This dataset provides yearly bilateral positions and flows of cross-border investment up to 2020, covering both private and official transactions. It reports financial stocks (the gross bilateral international investment position) as well as financial flows (gross bilateral financial account transactions) between reporting and partner countries. The database includes more than 80 reporting and partner countries, allowing us to map the cross-country patterns of capital reallocation in response to changes in uncertainty and relative forecast precision.

[6] Consensus Economics compiles forecasts of macroeconomic variables from analysts in various countries, originating from diverse professional backgrounds such as banks, universities, and forecast centers. The dataset covers a decade, from 2006 to 2018, and is formatted as a time panel with monthly frequency. More details on the data construction are available in the Appendix C.1.

## 4.1 Relative Forecast Accuracy

To study the information advantage of domestic investors, we construct a measure of forecast precision for each country for domestic and foreign forecasters over the five variables available in the forecast data.[7]

For each country $k$ and forecast horizon $h$, we define forecast errors as

$$\mathrm{FE}^{j}_{k,h,t} = \left( y_{k,t+h} - \hat{y}^{j}_{k,t+h|t} \right)^2, \tag{17}$$

where $j \in \{d, f\}$ denotes domestic ($d$) or foreign ($f$) forecasters. Forecast errors are squared and trimmed both sides by 1% of their distribution.

We then compute the average forecast error for domestic and foreign forecasters, denoted $\mathrm{RFE}^{d}_{k,h}$ and $\mathrm{RFE}^{f}_{k,h}$, and define the Relative Precision of Domestic Forecasters (RPDF) as

$$\mathrm{RPDF}_{k,h} = \mathrm{RFE}^{f}_{k,h} - \mathrm{RFE}^{d}_{k,h}. \tag{18}$$

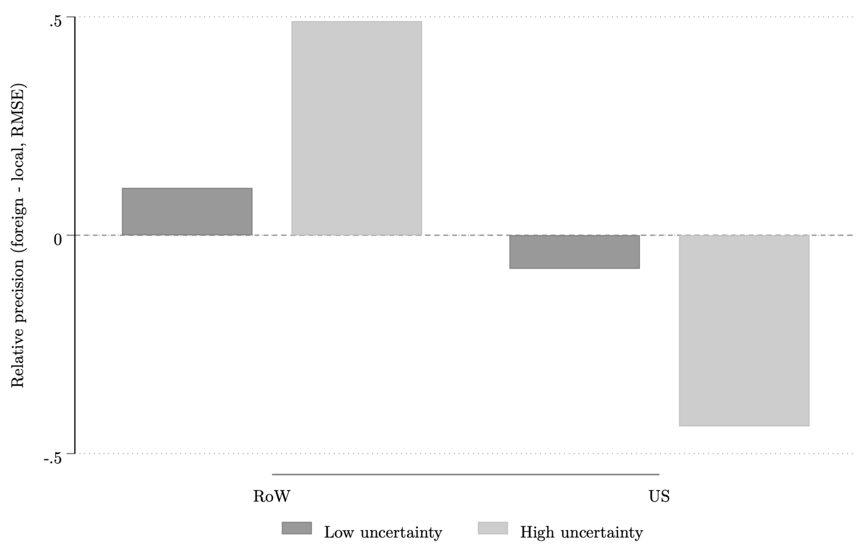
To study the role of uncertainty, we compute $\mathrm{RPDF}_{k,h}$ separately for periods of high and low uncertainty, with high uncertainty defined as months when the VIX is more than one standard deviation above its average value. Additional details on the data and methodology are available in Appendix C.2.

Figure 4 illustrates the relative precision of domestic forecasters across countries during periods of low and high uncertainty. Focusing first on countries other than the US (RoW), we notice that there is an information advantage of domestic forecasters even in low uncertainty periods. Notably, in relative terms, domestic forecast accuracy improves during periods of heightened uncertainty. Such evidence is consistent with our model predictions when the cost of research is higher for foreign investors than for domestic ones, as outlined in Proposition 1 of Section 3. While domestic information advantage has been documented in previous studies, our findings extend the results by highlighting a pronounced information home bias that intensifies with increased uncertainty.

Moving to the results for the United States, we find that there is no clear domestic information advantage, and that foreign forecasters even outperform domestic analysts in predicting economic variables during periods of high uncertainty. The special behavior of the United States is in line with the definition of an information haven in our model.

[7] The five variables we observe forecasts for in Consensus Economics are short-term and long-term treasury bills, GDP growth, industrial production growth and unemployment rate.

Figure 4: Uncertainty and RPDF




**Notes**: This plot shows how the relative precision of domestic forecasters is distributed between the rest of the world and the United States in periods of high and low uncertainty. The measure is the difference between foreign and local forecast errors.

We now use the full microdata to study in a regression framework the effect of uncertainty on forecast accuracy and on the domestic information advantage which are outlined in Figure 4. This allows both to assess the significance of the domestic information advantage, and to control for variable-specific and forecaster-specific effects.

In Table 2, we demonstrate the robustness of our findings using the following OLS specification:

$$\mathrm{FE}^2_{i,j,c,t} = \alpha + \zeta_j + \beta \mathrm{D}_{i,c} + \beta_{US} \mathrm{D}_{i,c} \times \mathbb{1}_{\{\mathrm{c=US}\}} + \tau \mathbb{1}_{\{\mathrm{c=US}\}} + \gamma \mathrm{D}_{i,c} \times \mathrm{V}_t + \gamma_{US} \mathrm{D}_{i,c} \times \mathrm{V}_t \times \mathbb{1}_{\{\mathrm{c=US}\}} + \varepsilon_{i,j,c,t}$$

where $i$ = forecaster; $j$ = variable; $c$ = country; $t$ = monthly date; $\mathrm{D}_{ic}$ is a dummy variable for domestic forecasts; and $V_t$ is our measure of uncertainty. We use the VIX as our main specification for $V_t$, and show robustness to alternatives in Appendix C.3.1. More details on the data and methodology are reported in Appendix C.1.

There are two main results. First, the unconditional domestic effect, $\beta$, is small and statistically indistinguishable from zero in both specification so there is no baseline domestic advantage once we abstract from uncertainty. This baseline term is not economically relevant for our mechanism. Second, the interaction with uncertainty is the key margin. The coefficient $\gamma$ on Domestic $\times$ Uncertainty is negative and significant ($\gamma = -0.03$), implying that a one standard deviation increase in the VIX improves domestic relative precision by 0.03 standard deviations. For the United States, the triple interaction reverses the sign: $\gamma_{\text{US}} = 0.09$ without bank fixed effects and $\gamma_{\text{US}} = 0.04$ with bank fixed effects (both significant), meaning that when uncertainty rises, domestic forecasters lose precision relative to foreign ones in the US. Since both outcomes and regressors are standardized, these coefficients have a direct SD interpretation.

To summarize, our results indicate that, on average, local forecasters are more accurate in predicting their own economies compared to foreign forecasters when uncertainty increases by one standard deviation. Conversely, for the United States, foreign forecasters outperform domestic ones under similar conditions. This result is in line with what we just showed in Figure 4, and can be considered as an additional test of our model prediction.

We then incorporate fixed effects, including variable-country and forecaster-specific. The latter is crucial to mitigate potential biases arising from consistently superior forecasters. For instance, if a large international bank is consistently outperforming a smaller local research institute, this could lead us to erroneously detect a foreign information advantage. Table 2 shows that our results are robust to such controls. It is important to note that while these fixed effects control for forecaster-specific biases, they may also reduce some of the variation we aim to capture in our analysis, since superior forecasting often reflects greater resources invested in information acquisition.

Similarly to our motivation section 2, we also aim to verify whether our findings are robust across different countries and not influenced by outliers. To accomplish this, we employ the same OLS specification as previously discussed, but conduct separate analyses for each country within our sample. Specifically, we focus on estimating the coefficient $\gamma$, which captures the correlation between squared forecast errors and domestic forecasters during uncertain periods. The goal is to examine how this coefficient varies across different countries.

Figure 5 illustrates that in most countries, when uncertainty increases, domestic investors have a milder increase in their forecast errors. That is, the domestic information advantage becomes larger when uncertainty increases. The United States again stands out as the country with the highest foreign advantage, with foreign forecasters becoming, if anything, more precise than domestic ones when uncertainty increases. The only other exception to this pattern is Canada, which is also not too far to the United States in terms of sensitivity

Table 2: OLS Regression: $FE^2$

| | Forecast Errors$^2$ (1) | Forecast Errors$^2$ (2) |
|---|---|---|
| Domestic | 0.01 | 0.03 |
| | (0.02) | (0.04) |
| VIX | 0.31 | 0.29 |
| | (0.03) | (0.03) |
| Domestic × VIX | -0.03 | -0.03 |
| | (0.01) | (0.01) |
| US | -0.12 | -0.10 |
| | (0.06) | (0.06) |
| Domestic × US | 0.08 | 0.02 |
| | (0.02) | (0.07) |
| Domestic × VIX × US | 0.08 | 0.04 |
| | (0.01) | (0.01) |
| $N$ | 106723 | 106723 |
| $R^2$ | 0.074 | 0.108 |
| adj. $R^2$ | 0.074 | 0.106 |
| FEs, Bank ID | No | Yes |

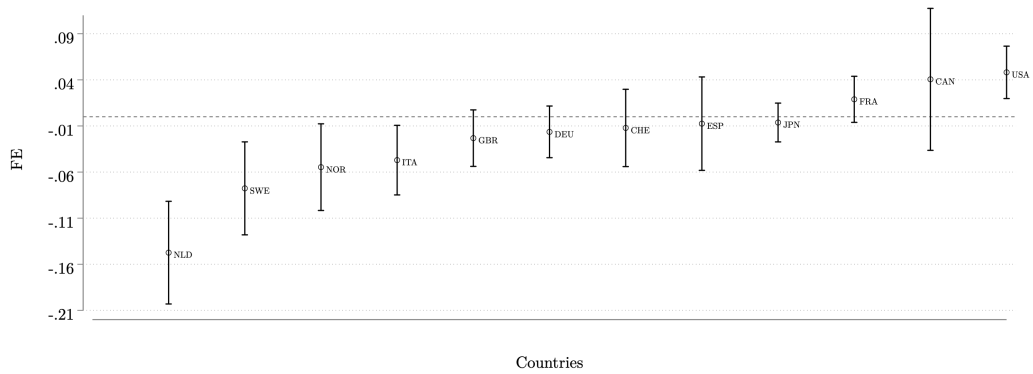
**Notes**: The table reports the results of the specification described in this section. The dependent variable is the normalized squared forecast error. Column (1) reports results without bank fixed effects; Column (2) includes bank fixed effects. Standard errors, clustered at the time level, are reported in parentheses.

of capital inflows to uncertainty, as highlighted in Figure 2.

Similarly to our motivation section 2, we also aim to verify whether our findings are robust across different countries and not influenced by outliers. To accomplish this, we employ the same OLS specification as previously discussed, but this time we conduct separate analyses for each country within our sample. Specifically, we focus on estimating the coefficient $\gamma$, which captures the correlation between squared forecast errors and domestic forecasters during uncertain periods. The goal is to examine how this coefficient varies across different countries. Figure 5 illustrates that in most countries, when uncertainty increases, domestic investors have a milder increase in their forecast errors. That is, the domestic information advantage becomes larger when uncertainty increases. The United States again stands out as the country with the highest foreign advantage, with foreign forecasters becoming, if anything, more precise than domestic when uncertainty increases. The only other exception to this pattern is Canada, which is also close to the United States in terms of sensitivity of capital inflows to uncertainty, as highlighted in Figure 2.

We provided evidence that, on average, forecasters tend to be more precise in predicting domestic economies than foreign ones during periods of heightened uncertainty. This implies that domestic economies experience a relatively higher increase in research during uncertain

Figure 5: Country Specific Analysis




**Notes**: This plot captures the $\gamma$ coefficient of our OLS specification, which is the effect of domestic forecasters in uncertainty on squared forecast error. Negative values represent a domestic advantage, or information home bias. The specification includes variable-specific fixed effects, and the VIX is used as the measure of uncertainty. Confidence intervals are at 95%.

times compared to foreign economies, with the United States being an exception, as predicted by Proposition 1 in Section 3.

Our model explains the exceptional behavior of the United States through its greater openness and transparency, which is reflected in the lack of a domestic learning advantage. This greater transparency could be the results of better institutions, but also ultimately reflect other forces at play that make the United States so central in the financial system. Indeed, major institutions and banks headquartered outside the United States typically allocate substantial resources to research focused on the United States economy compared to other regions. Such strategic deployment underscores the phenomena of 'flight to safety' and 'flight to home,' as documented by Miranda-Agrippino and Rey (2015). In each country, individuals tend to concentrate their research efforts on their own nation and on regions perceived as safe, such as the United States. This provides a plausible explanation for the distinct forecasting dynamics observed in the United States relative to other countries.

As robustness, we show in Appendix C.3 that our results are unchanged when using an alternative measure of uncertainty. In addition we show that the findings remain when forecast precision is measured through the dispersion across forecasters rather than ex-post forecast errors. These checks confirm that our main results are not driven by the specific choice of uncertainty or precision measure.

## 4.2 Testing the Information Channel

The theoretical model developed above highlights a simple but powerful prediction: when some investors enjoy an informational advantage, they increase their holdings of the asset they understand better, while those at an informational disadvantage reduce their positions. Crucially, in periods of heightened uncertainty these informational differences widen, amplifying the role of information heterogeneity in driving capital flows. The logic of our empirical tests follows directly from this mechanism. We first establish that when global or local uncertainty rises, equity inflows into a country decline on average, reflecting the fact that foreign investors retrench in response to an informational disadvantage. We then show that, at the same time, the relative precision of domestic forecasters systematically improves in periods of high uncertainty, confirming that informational advantages shift in favor of local investors when risks rise. Putting these pieces together, the model predicts two distinct capital flow responses: (i) at the aggregate level, if domestic forecasters are more accurate than foreign ones, foreign inflows should weaken, since investors facing an informational disadvantage reduce their holdings; (ii) at the bilateral level, if investors from country $i$ forecast country $k$ more accurately than the global average, then flows from $i$ into $k$ should increase during uncertainty shocks, reflecting reallocations toward destinations where investors hold a comparative informational edge. In this way, our empirical strategy directly tests the information channel: by linking variation in forecast precision to observed equity flows, both in aggregate retrenchments and in bilateral reallocations, we can verify that uncertainty-induced changes in relative information advantage are a key driver of capital flows in uncertain times.

### 4.2.1 Aggregate Inflows

In Section 3.3, we validated the model's information mechanism by showing that in standard countries domestic forecasters gain relative precision in periods of high uncertainty. We now connect this mechanism to equity flows. The hypothesis is simple: months in which domestic forecasters are relatively more precise should coincide with lower equity inflows, since foreigners facing an informational disadvantage reduce their positions. To test this, we construct a monthly measure of the Relative Precision of Domestic Forecasters ($\text{RPF}_{ii}$). For each country-month, $\text{RPF}_{ii}$ is defined as the difference between the average squared forecast error of foreign forecasters and that of domestic forecasters, winsorized at the 1-99 percentile and then standardized. Positive values of $\text{RPF}_{ii}$ indicate that domestic forecasters are more

Table 3: Aggregate Inflows and Relative Precision

| | Inflows (1) | Inflows (2) |
|---|---|---|
| RPF | -0.05 | -0.05 |
| | (0.01) | (0.01) |
| $N$ | 861 | 861 |
| Country FE | No | Yes |
| Cluster (Country) | Yes | Yes |
| p-value | 0.007 | 0.008 |

**Notes**: The table reports regressions of standardized equity inflows on standardized relative precision of domestic forecasters (RPF). Column (1) shows OLS without country fixed effects. Column (2) includes country fixed effects and clusters standard errors at the country level. RPF is constructed by computing average squared forecast errors for domestic and foreign institutions within each country-month, taking their difference, and then standardizing across the panel.

accurate than foreign ones. We then estimate the following regression:

$$\text{Inflows}_{i,t} = \alpha + \xi \, \text{RPF}_{ii,t} + \varepsilon_{i,t}, \tag{19}$$

first without country fixed effects and then with country fixed effects and clustering at the country level. Table 3 shows that the coefficient on $\text{RPF}_{ii}$ is consistently around -0.05 across specifications. Since both the dependent variable (equity inflows) and the regressor ($\text{RPF}_{ii}$) are standardized, the coefficient has a direct interpretation: a one standard deviation increase in domestic relative precision is associated with a reduction of about 5 percent of a standard deviation in equity inflows. In other words, whenever domestic forecasters outperform foreign forecasters more strongly, foreign investors reduce their net purchases of local equity.

Although modest in magnitude, this effect is economically meaningful given the monthly frequency and volatility of equity flows. The result is robust to the inclusion of country fixed effects, confirming that we exploit within-country time variation. Together, these findings provide direct support for the mechanism highlighted in Proposition 2: when domestic investors enjoy a relative informational advantage, foreign inflows weaken.

### 4.2.2 Bilateral Inflows

We next move from the aggregate distinction between domestic and foreign investors to the bilateral dimension of equity flows. The model predicts that when global uncertainty

Table 4: Bilateral Inflows and Relative Precision

| | Inflows (1) | Inflows (2) |
|---|---|---|
| RPF (i) | 0.23 | 0.23 |
| | (0.14) | (0.13) |
| $N$ | 156 | 156 |
| Cluster (Country) | No | Yes |
| p-value | 0.093 | 0.108 |

**Notes**: The table reports regressions of standardized bilateral equity inflows on standardized bilateral relative precision ($\text{RPF}_{ik}$). Column (1) includes controls for GDP growth and lagged inflows. Column (2) adds country-pair fixed effects. Standard errors are clustered at the country-pair level. Bilateral RPF is constructed as the difference between average squared forecast errors of origin $i$ forecasters and the global benchmark for destination $k$, standardized to zero mean and unit variance.

rises, capital is reallocated toward investors with a relative informational advantage and away from those with a disadvantage. To test this prediction, we construct a bilateral version of the RPF measure. For each origin $i$ and destination $k$, we compute the average squared forecast error of forecasters located in $i$ about country $k$ and compare it to the benchmark average error across all origins for $k$. We then standardize this bilateral $\text{RPF}_{ik}$ across the panel so that values above zero indicate above-average precision for origin $i$ about destination $k$. The regression specification is:

$$\text{Inflows}_{ik,t} = \alpha_i + \xi \,\text{RPF}_{ik,t} + \gamma \,\text{Inflows}_{ik,t-1} + \varepsilon_{ik,t}, \tag{20}$$

where $\text{Inflows}_{ik,t}$ are standardized annual bilateral inflows from origin $i$ to destination $k$, scaled by the trend GDP of the destination, and standardized within origin $i$. We exclude conduit financial centers to avoid artificial financial flows. Table 4 shows that the coefficient on bilateral $\text{RPF}_{ik}$ is positive and statistically significant, around 0.2. This implies that a one standard deviation increase in an origin's relative precision about a given destination is associated with an increase of about 20 percent of a standard deviation in bilateral inflows from that origin into that destination. In other words, investors expand their exposure precisely where they enjoy an informational advantage.

Taken together, the aggregate and bilateral results provide a consistent picture: informational advantages and disadvantages drive systematic capital reallocations. When domestic investors gain precision, foreigners retrench, reducing aggregate inflows. At the same time, at the bilateral level, investors increase exposures toward those countries they can forecast more accurately. The information channel is therefore not only a micro-foundation for home bias, but also a central driver of the dynamics of capital flows in uncertain times.

# 5 Conclusion

There is a growing interest to understand the forces shaping the cyclical fluctuations in capital flows, and the differential exposure across countries. Using aggregate equity flow data, we first summarize the stylized facts of the global financial cycle, clearly showing that during periods of heightened global uncertainty, investors retrench towards their own countries and towards the United States. Motivated by these findings, we study the role of information heterogeneity across countries in explaining such patterns. To do so, we build a model with heterogeneous investors and endogenous learning and test the model mechanism using micro forecast data from Consensus Economics.

Our model replicates the stylized facts observed in the global financial cycle, showing that a unique mechanism can rationalize these complex dynamics. Domestic information advantage generates not only home bias, but also capital flows in line with the data when uncertainty increases, as the information advantage of domestic investors becomes larger.

The model generates new, testable predictions regarding the accuracy of economic forecasts, which we test by leveraging micro forecast data on the performance of multiple countries. Our findings confirm that domestic forecasters have a distinct advantage in predicting the economic outcomes of their own countries, and that, crucially, such advantage becomes larger as global uncertainty rises, in line with our mechanism.

Furthermore, the model predicts that, during episodes of global uncertainty, capital should flow towards information haven countries, which are transparent countries that do not have a home information advantage. In the data, we show that for the United States domestic forecasters do not exhibit a significant edge over foreign institutions in predicting their own country's economic outcomes, and if anything the domestic advantage deteriorates in times of uncertainty. The United States thus behave in line with the information haven country in our model, which can help to rationalize why, unlike other countries, they do not experience capital outflows when uncertainty increases.

Finally, we directly test the information channel by linking relative forecast precision to actual capital flows. At the aggregate level, we find that when domestic forecasters are relatively more accurate than foreign ones, foreign inflows decline, consistent with the idea that informational disadvantage leads to retrenchment. At the bilateral level, the model predicts and the data confirm that when country $i$ has lower information costs to learn about country $k$ than the global average, bilateral flows from $i$ to $k$ increase during uncertainty shocks, while they retrench otherwise. We validate this bilateral channel empirically, showing that country pairs where investors hold such informational advantages indeed exhibit stronger inflow responses to global uncertainty. This joint evidence, aggregate retrenchment where foreigners face an informational disadvantage, and bilateral reallocations toward destinations where an informational edge exists, complements our unilateral results and further supports the central role of information heterogeneity in shaping international capital flows during periods of heightened global risk.

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# Appendix

## A Motivating Empirics

### A.1 Dataset Construction

We use the dataset provided by Koepke and Paetzold (2022), collecting data on equity flows from 47 countries. A list of those included in our sample is available in this section. Data are spanning from 1997 to 2023 and are expressed in nominal values, in USD. We then standardize the data in the following way, to have a more consistent measure, to be compared in our empirical specification models:

$$Z_{it} = \frac{X_{it} - \mathbb{E}[X_{it}]}{\sigma_{X_{it}}}$$

where $X_{it}$ is either equity inflows or equity outflows in a specific country $i$ at a specific time $t$. This transformation allows us to compare both dependent and independent variables in our OLS regression specification, with a clear interpretation on the coefficients we get.

The list of countries that are in our dataset, which are 47, is the following: Belgium, Bulgaria, Brazil, Canada, Chile, China, Colombia, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Greece, Croatia, Hungary, Indonesia, India, Iceland, Italy, Japan, Korea, Lebanon, Sri Lanka, Lithuania, Latvia, Mexico, Mongolia, Malaysia, Netherlands, Pakistan, Philippines, Poland, Portugal, Romania, Serbia, Slovenia, Sweden, Thailand, Turkey, Ukraine, United States, South Africa.

**Equity inflows and equity outflows: Definitions.** We define equity inflows (BoP) as the net transaction between non-residents and residents in a specific country. Positive equity inflows mean that foreigners are purchasing, net of sales, domestic equities. We define equity outflows (BoP) as the net transaction between residents and non-residents in all countries except the domestic country. Positive equity outflows mean that residents are purchasing, net of sales, foreign equities.

**Descriptive Statistics.** We thus provide a descriptive statistics in Table 5, where we show how inflows and outflows are distributed for equity, bonds and capital (equity + bonds).

Table 5: Descriptive Statistics: Capital Flows

| | Mean | SD | Median | Max | Min | N |
|---|---|---|---|---|---|---|
| Equity Inflows | 1.01 | 12.93 | 0.01 | 300.34 | -315.19 | 8774 |
| Equity Outflows | 1.73 | 10.98 | 0.04 | 185.50 | -176.10 | 7161 |
| Bonds Inflows | 2.43 | 14.36 | 0.05 | 255.18 | -403.60 | 9139 |
| Bonds Outflows | 1.72 | 9.79 | 0.05 | 174.17 | -141.35 | 7161 |
| Capital Inflows | 3.27 | 18.96 | 0.13 | 443.64 | -314.73 | 10002 |
| Capital Outflows | 2.96 | 14.75 | 0.12 | 298.15 | -201.88 | 8822 |

**Notes**: The Table reports the descriptive statistics of capital flows, splitting them into two subgroups: equity and bonds. We report the mean, standard deviation, median, max, min and number of observations in the sample. There are 47 countries in the dataset and they are all reported in this table.

**Measures of Uncertainty.** We collect several measures of uncertainty at monthly level: the VIX index, the Jurado et al. (2015) measure of financial uncertainty (updated in 2021), the VSTOXX index, the volatility of the ACWI index and also country level uncertainty measures, such as the one from Ozturk and Sheng (2017) and the volatility of stock market returns at country level. Table 6 shows how these measures are distributed.

Table 6: Descriptive of Uncertainty Measures

| | Max | Min | N |
|---|---|---|---|
| VIX Index | 5.63 | -1.24 | 2984 |
| Financial Uncertainty JLN (2021) | 3.61 | -1.43 | 2984 |
| VSTOXX Index | 4.44 | -1.30 | 2984 |
| ACWI | 5.90 | -1.12 | 2984 |
| Local Uncertainty (Ozturk) | 6.26 | -1.79 | 2984 |
| Local Uncertainty (Return Volatility) | 7.73 | -1.58 | 2984 |

**Notes**: The Table reports the descriptive statistics of different measure of uncertainty. These measures are standardized to the mean.

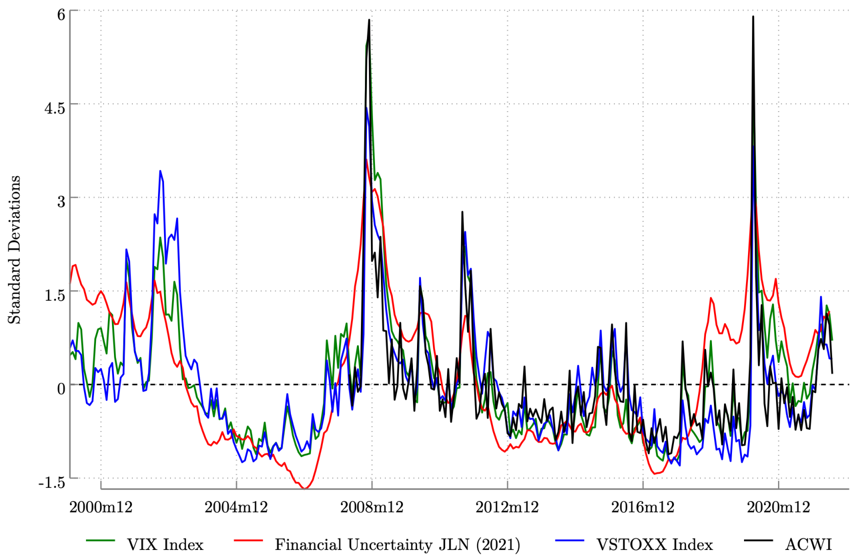
We also provide a table that shows how our main measure of uncertainty (VIX index) correlates with alternative measures.

Table 7: Correlation of VIX Index with Uncertainty Measures

| | VIX Index |
|---|---|
| Financial Uncertainty JLN (2021) | 0.81*** |
| VSTOXX Index | 0.94*** |
| ACWI | 0.91*** |
| Local Uncertainty (Ozturk) | 0.59*** |
| Local Uncertainty (Return Volatility) | 0.78*** |

**Notes**: The Table reports the correlation between the VIX Index and alternative measures of uncertainty.

Figure 6: Time Series of Uncertainty Measures




**Notes**: This plot shows the time series between 1997 and 2023 for different measures of uncertainty, all standardized to the mean.

## A.2 Robustness

### A.2.1 Alternative measures of uncertainty.

We replicate the analysis in Section 2, which relied on the VIX, using different measures of uncertainty: Jurado et al. (2015) measure of financial uncertainty (updated in 2021), the VSTOXX index, the ACWI Volatility, implementing the same OLS regression specification as in (1).

Table 8: Equity Inflows and JLN

| | Inflows (1) | Inflows (2) | Outflows (3) | Outflows (4) |
|---|---|---|---|---|
| Financial JLN (2021) | -0.08 | -0.08 | -0.04 | -0.04 |
| | (0.01) | (0.01) | (0.02) | (0.02) |
| Financial JLN (2021) × US | 0.14 | 0.14 | -0.06 | -0.07 |
| | (0.01) | (0.01) | (0.02) | (0.02) |
| GDP Δ% | | 0.01 | | -0.00 |
| | | (0.00) | | (0.00) |
| $N$ | 7484 | 7349 | 6326 | 6218 |
| Country FEs | Yes | Yes | Yes | Yes |

**Notes**: The Table reports the results of the model specification described in this section to capture the effect that a one standard deviation increase in uncertainty has on equity inflows. Both dependent and indepentent variables are standardized to the mean and GDP % is yearly GDP growth. We use the financial uncertainty index (Jurado et al. (2015)) as a measure of uncertainty. Standard errors, clustered at country level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See the appendix for additional information on variables construction.

We also check whether the result can be explained by using measures of local uncertainty (country specific), such as by computing country specific volatility of stock returns, using Global Financial Data as our source.

Table 9: Country Specific Uncertainty (Volatility of Stock Returns)

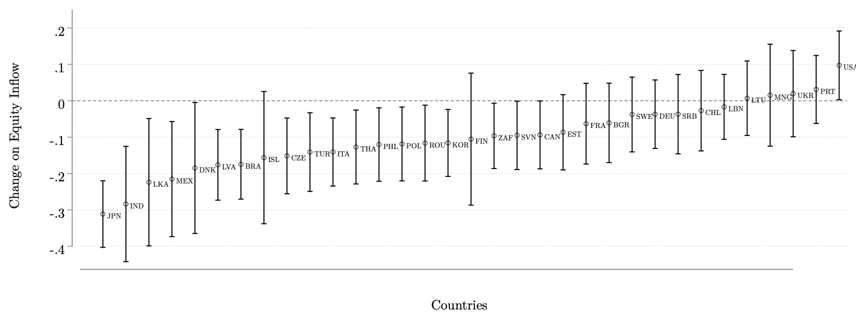
| | Inflows (1) | Inflows (2) | Outflows (3) | Outflows (4) |
|---|---|---|---|---|
| Country Uncertainty | -0.13 | -0.14 | -0.14 | -0.14 |
| | (0.02) | (0.03) | (0.04) | (0.04) |
| Country Uncertainty $\times$ US | 0.21 | 0.23 | 0.05 | 0.06 |
| | (0.02) | (0.03) | (0.03) | (0.04) |
| GDP $\Delta\%$ | | 0.01 | | -0.01 |
| | | (0.01) | | (0.01) |
| $N$ | 3756 | 3639 | 2876 | 2786 |
| Country FEs | Yes | Yes | Yes | Yes |

**Notes**: The Table reports the results of the model specification described in this section to capture the effect that a one standard deviation increase in country specific uncertainty has on equity inflows, measured as the volatility of stock return for each country in our sample. Both dependent and indepentent variables are standardized to the mean and GDP % is yearly GDP growth. Standard errors, clustered at country level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See the appendix for additional information on variables construction.

## A.3 Full Set of Countries

We now extend Figure 2, which only displayed results for G7 countries, to our entire sample of 47 countries, excluding only those country with less than 2 years of observations. We use the same specification (2). Again, the United States is the only country with a significant positive change in equity inflows when VIX index increases by one standard deviation.

Figure 7: Uncertainty and Equity Inflows




**Notes**: This plot shows the relation between uncertainty and equity inflows, comparing the entire sample of countries in the dataset. Uncertainty is measured using the VIX index and changes are in standard deviations. The confidence intervals are set at 95%.

### A.3.1 Additional Controls

**Additional Control Variables.** We add some control variables to equation (1), such as size of the stock market in each country (market capitalization), effective exchange rate and bond inflows. The results, reported in Table 10, show that our estimates are very stable to adding this new set of controls.

Table 10: Equity Inflows and Additional Controls

| | Inflows (1) | Inflows (2) | Outflows (3) | Outflows (4) |
|---|---|---|---|---|
| VIX | -0.10 | -0.11 | -0.07 | -0.08 |
| | (0.01) | (0.02) | (0.02) | (0.02) |
| VIX $\times$ US | 0.16 | 0.17 | -0.04 | -0.04 |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| GDP $\Delta\%$ | | 0.01 | | -0.00 |
| | | (0.00) | | (0.00) |
| EER | | 0.03 | | 0.04 |
| | | (0.02) | | (0.01) |
| Bond Inflows | | 0.00 | | 0.00 |
| | | (0.00) | | (0.00) |
| $N$ | 7484 | 6375 | 6326 | 5523 |
| Country FEs | Yes | No | Yes | No |

**Notes**: The Table reports the results of the model specification described in this section to capture the effect that a one standard deviation increase in uncertainty has on equity inflows. Both dependent and indepentent variables are standardized to the mean and GDP % is yearly GDP growth. We use the VIX index as a measure of uncertainty. Standard errors, clustered at country level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See the appendix for additional information on variables construction.

**Including a Control Variable for Recession.** We check whether the results from (1) are robust to the inclusion of a recession dummy as a control variable.

Table 11: Equity Flows, Financial Uncertainty and Recession

| | Inflows VIX (1) | Inflows JLN (2) | Outflows VIX (3) | Outflows JLN (4) |
|---|---|---|---|---|
| Uncertainty Index | -0.10 | -0.07 | -0.08 | -0.03 |
| | (0.01) | (0.02) | (0.02) | (0.02) |
| Uncertainty Index × US | 0.17 | 0.14 | -0.04 | -0.07 |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| Recession | -0.08 | -0.10 | 0.05 | -0.01 |
| | (0.04) | (0.05) | (0.04) | (0.05) |
| GDP $\Delta$% | 0.01 | 0.01 | 0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| $N$ | 7349 | 7349 | 6218 | 6218 |
| Country FEs | Yes | Yes | Yes | Yes |

**Notes**: The Table reports the results of the model specification described in this section to capture the effect that a one standard deviation increase in uncertainty has on Equity Inflows. We use the VIX index as a measure of uncertainty. Both dependent and indepentent variables are standardized to the mean and GDP % is yearly GDP growth. Standard errors, clustered at country level, are reported in parentheses. $*$ = 10% level, $**$ = 5% level, and $***$ = 1% level. See the appendix for additional information on variables construction.

**Excluding Extreme Events.** We want to assess whether our results remain valid in the absence of extreme events. This examination can help us determine if a 'flight to quality' narrative primarily drives investor behavior, suggesting that only extreme events influence equity flow directions. We thus investigate if our results hold even when excluding periods of high uncertainty, defined as observations exceeding more than two standard deviations in the VIX index distribution. Our findings remain robust even when applying different thresholds for high uncertainty.

Table 12: Equity Flows and Low Uncertainty

| | Inflows (1) | Inflows (2) | Inflows (3) | Outflows (4) |
|---|---|---|---|---|
| VIX | -0.10*** | -0.10*** | -0.06* | -0.06** |
| | (0.02) | (0.02) | (0.03) | (0.03) |
| VIX $\times$ US | 0.37*** | 0.37*** | -0.07** | -0.07* |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| GDP $\Delta\%$ | | 0.01*** | | -0.00 |
| | | (0.00) | | (0.01) |
| $N$ | 7578 | 7494 | 6144 | 6072 |
| Country FEs | Yes | Yes | Yes | Yes |

**Notes**: The Table reports the results of the model specification described in this section to capture the effect that a one standard deviation increase in uncertainty has on Equity Inflows. We use the VIX index as a measure of uncertainty. Both dependent and indepentent variables are standardized to the mean and GDP % is yearly GDP growth. Standard errors, clustered at country level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See the appendix for additional information on variables construction.

# B Theoretical Analysis

## B.1 Derivations

**Objective in the first period** In the first period, the objective function for the sophisticated investor $i$ is:

$$U_i \equiv \mathbb{E}\left[\mathbb{E}_i\left(W_i\right) - \frac{\eta}{2}\mathbb{V}_i\left(W_i\right)\right] \tag{21}$$

Substitute investor $i$'s optimal portfolio choices in equilibrium 6, we get

$$\mathbb{E}_i\left[x_{ik}(r_k - r^f p_k)\right] = \frac{\left(\widehat{r}_{ik} - r^f p_k\right)^2}{\eta\widehat{\sigma}_{ik}^2} = \frac{(\kappa_i s_{ik} + (1-\kappa_i)\mu_k - \mu_k + \eta\sigma_k^2)^2}{\eta\widehat{\sigma}_{ik}^2} = \frac{(\kappa_i(s_{ik} - \mu_k) + \eta\sigma_k^2)^2}{\eta\widehat{\sigma}_{ik}^2}$$

where the second equality has used $\widehat{r}_{ik} = \kappa_i s_{ik} + (1-\kappa_i)\mu_k$ with $\kappa_i \equiv \frac{\sigma_k^2}{\sigma_k^2 + \sigma_{ik}^{s\ 2}}$. Similarly, we also have

$$\mathbb{V}_i\left[x_{ik}(r_k - r^f p_k)\right] = \frac{\left(\widehat{r}_{ik} - r^f p_k\right)^2}{\eta^2\widehat{\sigma}_{ik}^2} = \frac{(\kappa_i(s_{ik} - \mu_k) + \eta\sigma_k^2)^2}{\eta^2\widehat{\sigma}_{ik}^2}$$

Take expectation in the first period, we obtain

$$\begin{aligned}\mathbb{E}\left[\mathbb{E}_i\left[x_{ik}(r_k - r^f p_k)\right]\right] &= \mathbb{E}\left[\frac{(\kappa_i(s_{ik} - \mu_k) + \eta\sigma_k^2)^2}{\eta\widehat{\sigma}_{ik}^2}\right] = \mathbb{E}\left[\frac{(\kappa_i(r_k + \epsilon_{ik} - \mu_k) + \eta\sigma_k^2)^2}{\eta\widehat{\sigma}_{ik}^2}\right] \\ &= \frac{\kappa_i^2(\sigma_k^2 + \sigma_{ik}^{s\ 2}) + \eta^2\sigma_k^4}{\eta\widehat{\sigma}_{ik}^2}\end{aligned}$$

Under the assumption that risky asset payoffs are independently distributed, we can write the objective function 21 as:

$$\begin{aligned}U_i &= \sum_{k=1}^{N}\mathbb{E}\left\{\mathbb{E}_i\left[x_{ik}(r_k - r^f p_k)\right] - \frac{\eta}{2}\mathbb{V}_i\left[x_{ik}(r_k - r^f p_k)\right]\right\} + r^f W_0 \\ &= \sum_{k=1}^{N}\frac{\kappa_i^2(\sigma_k^2 + \sigma_{ik}^{s\ 2}) + \eta^2\sigma_k^4}{2\eta\widehat{\sigma}_{ik}^2} + r^f W_0 = \sum_{k=1}^{N}\frac{\sigma_k^4/(\sigma_k^2 + \sigma_{ik}^{s\ 2}) + \eta^2\sigma_k^4}{2\eta\widehat{\sigma}_{ik}^2} + r^f W_0\end{aligned}$$

To simplify notation, rewrite the equation above in terms of precisions, i.e. $\tau_k = 1/\sigma_k^2$ and

$\widehat{\tau}_{ik} = \widehat{\sigma}^2_{ik}$, then

$$U_i = \frac{1}{2}\sum_{k=1}^{N}\left(\eta\frac{\tau_k + \tau_{ik,s}}{\tau_k^2} + \frac{1}{\eta}\frac{\tau_{ik,s}}{\tau_k}\right) + r^f W_0$$

Then the objective in the first period can be simplifies as choosing $\{\tau_{ik,s}\}_{k=1}^N$ to maximize:

$$\max\ \frac{1}{2}\sum_{k=1}^{N}\left(\eta\frac{\tau_k + \tau_{ik,s}}{\tau_k^2} + \frac{1}{\eta}\frac{\tau_{ik,s}}{\tau_k}\right) - \sum_{k=1}^{N}\frac{\theta_{ik}}{2}\tau^2_{ik,s} \tag{22}$$

**Information choice** Solve for optimal $\tau_{ik,s}$ from 22, we get:

$$\tau_{ik,s} = \frac{1}{2\theta_{ik}}\left(\frac{\eta}{\tau_k^2} + \frac{1}{\eta\tau_k}\right) \tag{23}$$

When the payoff of asset $k$ is more uncertain, sophisticated investors increase their research effort on that asset.

**Optimal portfolio** With the optimal information allocation, in the second period,

$$\widehat{r}_{ik} = \kappa_i s_{ik} + (1-\kappa_i)\mu_k \tag{24}$$

$$\widehat{\sigma}^2_{ik} = 1/\widehat{\tau}_{ik} = \frac{\sigma_k^2}{1 + \frac{1}{2\theta_{ik}}\sigma_k^4\left(\frac{1}{\eta} + \eta\sigma_k^2\right)} \tag{25}$$

Substitute 24 and 25 into the portfolio holdings in the second period 6, we get the aggregate demand for asset $k$ of sophisticated investors in country $i$ is:

$$\mathbb{E}\int_S x^S_{i,k} dS = \mathbb{E}\int_S \frac{\widehat{r}_{ik} - \mu_k + \eta\sigma_k^2}{\eta\widehat{\sigma}^2_{ik}} dS = 1 + \frac{1}{2\theta_{ik}}\left(\frac{\eta}{\tau_k^3} + \frac{1}{\eta\tau_k^2}\right) \tag{26}$$

We observe from this equation that, when uncertainty for asset $k$ increases, sophisticated investors demand more of it.

**Capital flows** Denote $CF_k$ as the capital inflow for asset $k$. We consider the capital flows after the local uncertainty in country $k$ increases. Approximately, it is:

$$\frac{\partial}{\partial\sigma_k^2}\left(-x^S_{kk} + \frac{1}{N}\sum_{i=1}^{N}x^S_{ik}\right) = \frac{1}{2}\left(\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\theta_{ik}} - \frac{1}{\theta_{kk}}\right)\left(\frac{3\eta}{\tau_k^4} + \frac{2}{\eta\tau_k^3}\right) \tag{27}$$

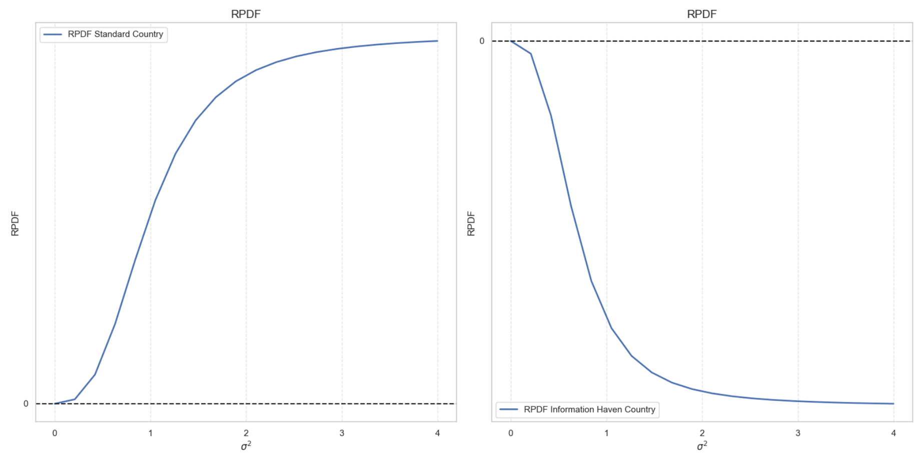
Hence,

$$\frac{\partial}{\partial \sigma_k^2}\left(-x_{kk}^S + \frac{1}{N}\sum_{i=1}^{N} x_{ik}^S\right) \propto \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\theta_{ik}} - \frac{1}{\theta_{kk}}$$

## B.2 Comparative Statics of the Model

**Relative Precision of Domestic Forecasters.** We show how RPDF changes in both a standard country and information haven country when uncertainty, $\sigma^2$, ranges from 0 to 4.

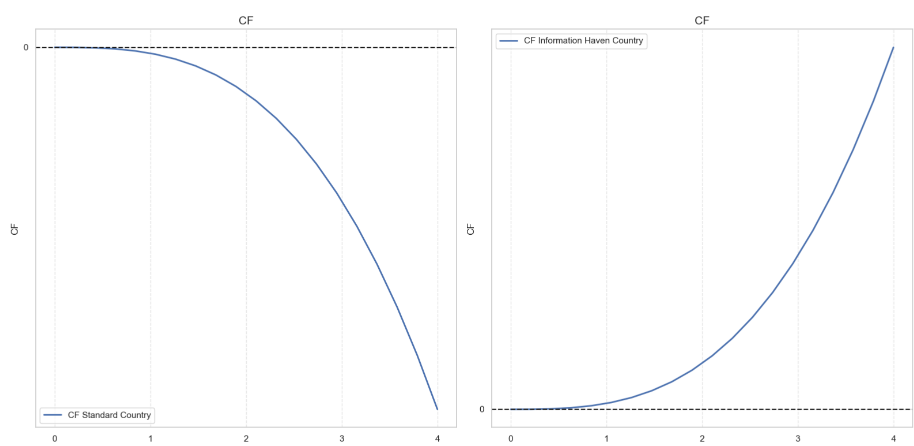
Figure 8: RPDF and CF changing $\sigma^2$




**Notes**: This plot shows how relative precision of domestic forecasters change in sign as $\sigma^2$ increases.

**Capital Flows.** We show how CF changes in both a standard country and information haven country when uncertainty, $\sigma^2$, ranges from 0 to 4.

Figure 9: RPDF and CF changing $\sigma^2$




**Notes**: This plot shows how capital flows change in sign as $\sigma^2$ increases.

# C Empirical Validation

## C.1 Dataset Construction

Consensus Economics compiles forecasts of macroeconomic variables from analysts in various countries, originating from diverse professional backgrounds such as banks, universities, and forecast centers. The dataset covers a decade, from 2006 to 2018, and is formatted as a time panel with monthly frequency. More details on the data construction are available in the Appendix (**??**). A distinctive feature of this dataset is the categorization of forecasters based on their origin, distinguishing between domestic and foreign analysts, as in Benhima and Bolliger (2023). This categorization is determined by the location of the forecasting institution's headquarters, while also accounting for their subsidiaries. Our primary objective is to calculate the forecast error and dispersion for both groups of forecasters. The macroeconomic variables analyzed include long-term treasury bills (10 years), short-term treasury bills (3 months), GDP growth, industrial production growth and unemployment rate. We include only forecasts made for periods longer than two years. The resulting data forms a comprehensive panel encompassing forecasts from 12 different countries, allowing for a comparative analysis over the decade in question. Below a description of the variables we use in our dataset and in parenthesis the corresponding name of the variable you find in the code:

- $\mathbb{E}_t[\%\mathbf{B}_{t+4,t}]$;$\mathbb{E}_t[\%\mathbf{B}_{t+12,t}]$ (10 yrs Long Term Treasury Bills, Y1 and Y2), where $t$ is monthly date.

- $\mathbb{E}_t[\%\mathbf{b}_{t+4,t}]$; $\mathbb{E}_t[\%\mathbf{b}_{t+12,t}]$ (3 months Short Term Treasury Bills, M1 and M2), where $t$ is monthly date.

- $\mathbb{E}_t[\Delta\%\mathbf{GDP}_{y,y-1}]$; $\mathbb{E}_t[\Delta\%\mathbf{GDP}_{y+1,y}]$ (Gross Domestic Product, GDP1 and GDP2), where $t$ is monthly date and $y$ yearly date.

- $\mathbb{E}_t[\Delta\%\mathbf{IP}_{y,y-1}]$; $\mathbb{E}_t[\Delta\%\mathbf{IP}_{y+1,y}]$ (Industrial Production, IP1 and IP2), where $t$ is monthly date and $y$ yearly date.

- $\mathbb{E}_t[\Delta\mathbf{UNEMP}_{y,y-1}]$; $\mathbb{E}_t[\Delta\mathbf{UNEMP}_{y+1,y}]$ (Unemployment Rate, UNEMP1 and UNEMP2), where $t$ is monthly date and $y$ yearly date.

The list of the 20 countries included in our sample is the following: Austria, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Ireland, Israel, Italy, Japan, Netherlands, Norway, Portugal, Sweden, United States. We exclude from the sample countries with less than 2 years of observations (Israel and Portugal), restricting our sample to 18 countries.

**Descriptive Statistics.** We report descriptive statistics of the data in Table 13 and the resulting of a 1.5% trimming from both left and right tails in Table 14 [8]. Moreover, in Figure 10 we show the distributions of the variables we included in our dataset.

Table 13: Descriptive Statistics: Data from Consensus Economics

| | Mean | Median | Max | Min | N |
|---|---|---|---|---|---|
| Long-Term T-Bills ($\Delta\%$ $m, m+4$) | -0.14 | -0.14 | 3.40 | -2.35 | 23800 |
| Long-Term T-Bills ($\Delta\%$ $m, m+12$) | -0.62 | -0.57 | 3.52 | -3.76 | 23264 |
| Short-Term T-Bills ($\Delta\%$ $m, m+4$) | -0.03 | -0.00 | 1.96 | -4.25 | 23044 |
| Short-Term T-Bills ($\Delta\%$ $m, m+12$) | -0.37 | -0.17 | 2.35 | -5.23 | 22638 |
| GDP $\Delta\%$ ($\Delta\%$ $m, y$) | 0.04 | 0.10 | 6.74 | -9.30 | 33330 |
| GDP $\Delta\%$ ($\Delta\%$ $m, y+1$) | -0.38 | -0.10 | 6.90 | -8.60 | 32837 |
| IP $\Delta\%$ ($\Delta\%$ $m, y$) | -0.93 | -0.59 | 12.61 | -45.41 | 23056 |
| IP $\Delta\%$ ($\Delta\%$ $m, y+1$) | -2.38 | -1.47 | 23.55 | -31.11 | 22525 |
| Unemployment Rate ($\Delta\%$ $y$) | -0.08 | -0.07 | 4.12 | -3.45 | 20987 |
| Unemployment Rate ($\Delta\%$ $y+1$) | -0.20 | -0.29 | 5.43 | -4.96 | 20574 |

**Notes**: The Table reports a descriptive statistics of the variables we included in our dataset from *Consensus Economics* survey. We report mean, median, max, min and number of observations.

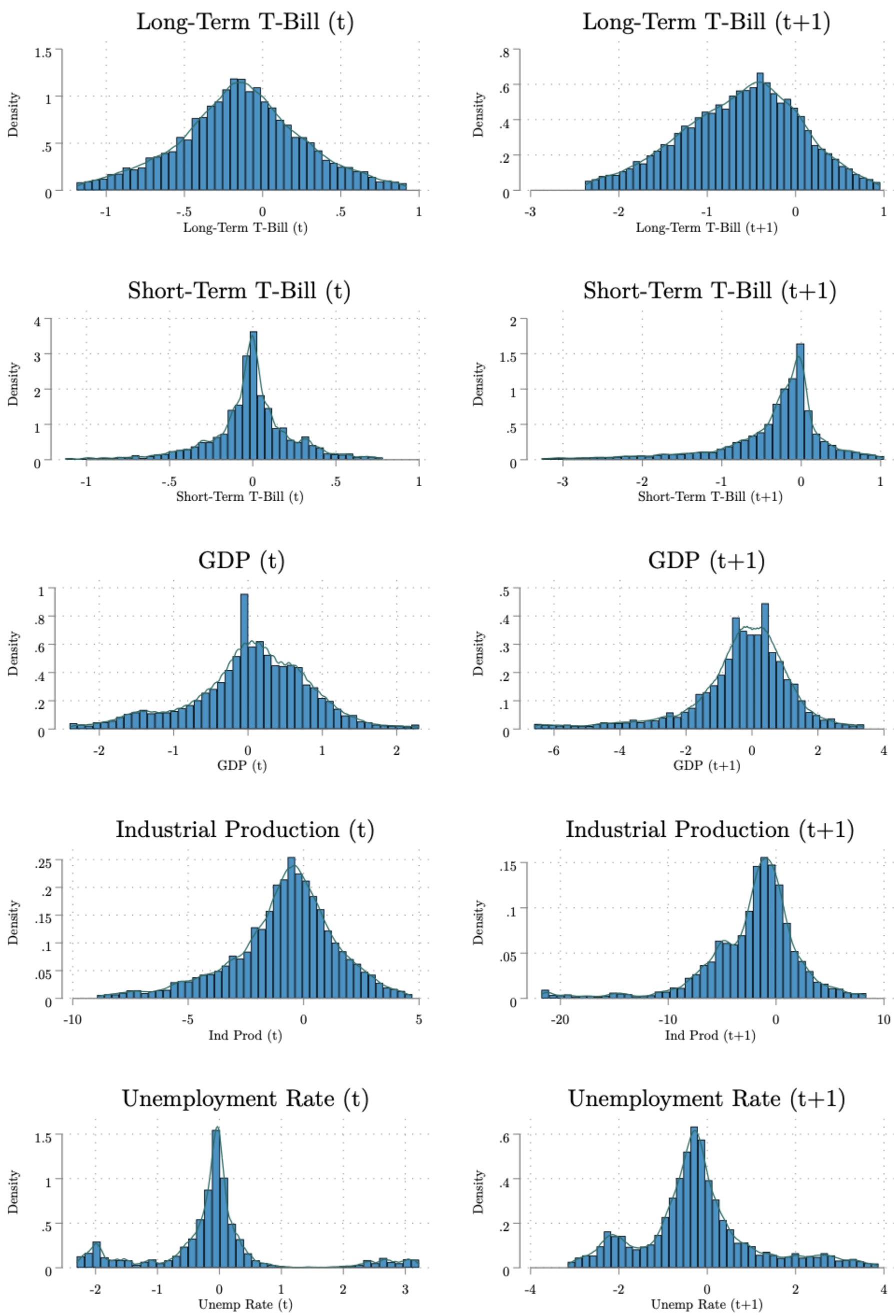
Table 14: Descriptive Statistics: Trimmed Data from Consensus Economics

| | Mean | Median | Max | Min | N |
|---|---|---|---|---|---|
| Long-Term T-Bills ($\Delta\%$ $m, m+4$) | -0.14 | -0.14 | 0.92 | -1.19 | 23085 |
| Long-Term T-Bills ($\Delta\%$ $m, m+12$) | -0.62 | -0.57 | 0.96 | -2.38 | 22569 |
| Short-Term T-Bills ($\Delta\%$ $m, m+4$) | -0.01 | -0.00 | 0.78 | -1.13 | 22361 |
| Short-Term T-Bills ($\Delta\%$ $m, m+12$) | -0.34 | -0.17 | 1.04 | -3.27 | 21961 |
| GDP $\Delta\%$ ($\Delta\%$ $m, y$) | 0.03 | 0.10 | 2.30 | -2.40 | 32351 |
| GDP $\Delta\%$ ($\Delta\%$ $m, y+1$) | -0.35 | -0.10 | 3.40 | -6.60 | 31871 |
| IP $\Delta\%$ ($\Delta\%$ $m, y$) | -0.85 | -0.59 | 4.71 | -8.95 | 22366 |
| IP $\Delta\%$ ($\Delta\%$ $m, y+1$) | -2.25 | -1.47 | 8.35 | -21.76 | 21856 |
| Unemployment Rate ($\Delta\%$ $y$) | -0.10 | -0.07 | 3.22 | -2.30 | 20358 |
| Unemployment Rate ($\Delta\%$ $y+1$) | -0.22 | -0.29 | 3.88 | -3.16 | 19962 |

**Notes**: The Table reports a descriptive statistics of the trimmed variables we included in our dataset from *Consensus Economics* survey. We trimmed 1.5% from both tails of the distribution. We report mean, median, max, min and number of observations.

[8] Notice that results are robust to smaller trimming, such as 1% or 0.5% on each tail.

Figure 10: Histogram of Forecast Variables




**Notes**: Distributions of the main variables we included in our dataset from *Consensus Economics*. Data are 1.5% trimmed from both left and right tails.

## C.2 Measures of Forecast Precision

We use two approaches to capture the effect of higher uncertainty on forecast precision, one is a measure of relative precision of domestic forecaster (RPDF) and the other is by using an OLS specification.

**Relative Precision of Domestic Forecasters (RPDF).** In this case we compute an aggregate measure of relative precision of domestic forecasters by computing the average across several variables, such as short-term and long-term treasury bills, GDP growth, industrial production growth and unemployment rate, both one period and two periods ahead. This measure is obtained by computing the difference between domestic and foreign forecast errors as it follows:

$$\mathrm{RPDF}_u^d = \mathrm{RMSE}_u^f - \mathrm{RMSE}_u^d \tag{28}$$

where $\mathrm{RMSE}_u^f$ is root mean squared error of foreign economy; $\mathrm{RMSE}_u^f$ is root mean squared error of domestic economy and $u$ is uncertainty, which can be either low or high. We define $\mathrm{RMSE}_u^f$ and $\mathrm{RMSE}_u^d$, by aggregating forecast errors observations by individual forecasters, variable, country and time, as it follows:

$$\mathrm{RMSE}_{H,L}^{f,d} = \sqrt{\frac{1}{N}\sum_{i,j,c,t} \mathrm{FE}_{i,j,c,t}^2 \mathbb{1}_{\{i=\text{Foreign},\mathbf{SD}_{H,L}\}}}$$

where $FE$ is defined as in (29); $N$ is the sum of the entire sample observations, H corresponds to any observation with more than one standard deviation of uncertainty and L corresponds to any observation with less than one standard deviation of uncertainty.

**Squared Forecast Errors** We now show how we address the same question, by using a second approach, which is based on an OLS specification, to capture with individual forecasts across time how squared forecast error correlates with domestic forecasters when hit by a positive shock to uncertainty. The specification we use in our analysis is the following:

$$\mathrm{FE}_{i,j,c,t}^2 = \alpha + \zeta_j + \beta \mathrm{D}_{i,c} + \beta_{US} \mathrm{D}_{i,c} \times \mathbb{1}\{\mathrm{c} = \mathrm{US}\} + \tau \mathbb{1}\{\mathrm{c} = \mathrm{US}\} + \gamma \mathrm{D}_{i,c} \times \mathrm{V}_t + \gamma_{US} \mathrm{D}_{i,c} \times \mathrm{V}_t \times \mathbb{1}\{\mathrm{c} = \mathrm{US}\} + \varepsilon_{i,j,c,t}$$

where $i$ = forecaster; $j$ = variable; $c$ = country; $t$ = monthly date; $\mathbf{D}$ is a dummy variable that defines which forecats are foreign and which are domestic, respectivly $\mathbf{D} \in \{0, 1\}$; **US** is a dummy variable that defines which forecats are not about the US economy and which are about the US economy, respectivly $\mathbf{US} \in \{0, 1\}$; $\mathbf{U}$ is a countinuous variable that captures uncertainty.

Notice that squared forecast errors (FE) is empirically defined in the following way:

$$\mathrm{FE}^2_{i,j,c,t} = \Big\{ \mathbf{x}_{i,j,c,t} - \mathbb{E}_{t-1}[\mathbf{x}_{i,j,c,t}] \Big\}^2 \tag{29}$$

where $i$ = forecaster, $j$ = variable, $c$ = country and $t$ = monthly date.

Our coefficient of interest, in this case, is $\gamma$ and $\gamma_{US}$, which capture the average effect of domestic forecasters with a positive shock to uncertainty and the marginal effect when considering the american economy. Thus, having $\gamma \geq 0$ means that, on average, domestic forecasters increase forecast errors in times of uncertainty, with respect to the foreigners and the converse if $\gamma < 0$. Similarly, by adding the marginal effect for the United States to the average we can get the overall effect for the american economy. In the next paragraph we show the results we get by implementing this specification method.

## C.3 Robustness Checks

### C.3.1 Alternative Measures of Uncertainty

We replicate our analysis in Section **??**, which relied on the VIX, using alternative measures of uncertainty, (such as Financial Uncertainty from Jurado (2015) and VSTOXX).

Table 15: OLS Regression: Alternative Measures of Uncertainty

| | Forecast Errors$^2$ VIX (1) | Forecast Errors$^2$ JLN (2) |
|---|---|---|
| Domestic | 0.03 | 0.02 |
| | (0.04) | (0.04) |
| Uncertainty | 0.29 | 0.33 |
| | (0.03) | (0.03) |
| Domestic × Uncertainty | -0.03 | -0.05 |
| | (0.01) | (0.02) |
| US | -0.10 | -0.12 |
| | (0.06) | (0.06) |
| Domestic × US | 0.02 | 0.03 |
| | (0.07) | (0.07) |
| Domestic × Uncertainty × US | 0.04 | 0.06 |
| | (0.01) | (0.02) |
| $N$ | 106723 | 106723 |
| $R^2$ | 0.108 | 0.123 |
| adj. $R^2$ | 0.106 | 0.121 |
| FEs, Bank ID | Yes | Yes |

**Notes**: The Table reports the results of the model specification described in this section to capture the effect that a one standard deviation increase in uncertainty has on forecast errors, calculated as shown in section 4. We use the financial uncertainty index (Jurado et al. (2015)), VSTOXX Index and ACWI volatility as alternative measures of uncertainty. Standard errors, clustered at time level, are reported in parentheses.

### C.3.2 Alternative Measure of Forecast Precision: Dispersion

**A measure of dispersion.** We reproduce our results using an alternative measure of forecast error. We thus compute dispersion as it follows:

$$\text{Dispersion}_{i,j,c,t} = \left\{ \mathbb{E}_t[\mathbf{x}_{i,j,c,t}] - \mathbb{E}_t[\bar{\mathbf{x}}_t] \right\}^2$$

where $i$ = forecaster, $j$ = variable, $c$ = country and $t$ = monthly date and $\bar{x}_t$ is the average across forecaster, variable and country at each time $t$.

$$\text{Dispersion}_{i,j,c,t} = \alpha + \alpha_{1j} + \beta \mathbf{D}_{i,c} + \beta_{US} \mathbf{D}_{i,c} \times \mathbf{US}_i + \tau \mathbf{US}_i + \gamma \mathbf{D}_{i,c} \times \mathbf{U}_t + \gamma_{US} \mathbf{D}_{i,c} \times \mathbf{U}_t \times \mathbf{US}_i + \varepsilon_{i,c,t}$$

Table 16: OLS Regression: Dispersion

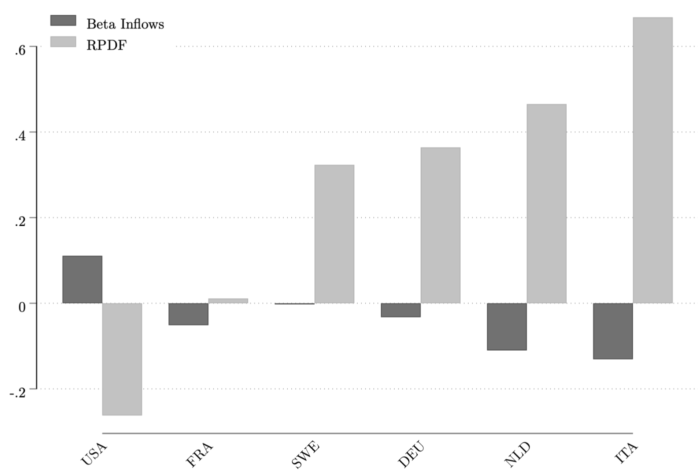
| | Dispersion (1) | Dispersion (2) |
|---|---|---|
| Domestic | -0.54 | -0.40 |
| | (0.15) | (0.29) |
| VIX | 0.86 | 0.89 |
| | (0.18) | (0.18) |
| Domestic × VIX | -0.22 | -0.27 |
| | (0.14) | (0.16) |
| US | -0.71 | -0.77 |
| | (0.23) | (0.45) |
| Domestic × US | 0.27 | 0.12 |
| | (0.15) | (0.74) |
| Domestic × VIX × US | 0.21 | 0.28 |
| | (0.14) | (0.16) |
| $N$ | 108841 | 108841 |
| $R^2$ | 0.006 | 0.017 |
| adj. $R^2$ | 0.006 | 0.014 |
| FEs, Bank ID | No | Yes |

**Notes**: The Table reports the results of the model specification described in this section to capture the effect that a one standard deviation increase in uncertainty has on dispersion, calculated as shows in this section of the appendix. We use the VIX index as a measure of uncertainty. Standard errors, clustered at time level, are reported in parentheses. $*$ = 10% level, $**$ = 5% level, and $***$ = 1% level.

## C.4 Testing the Information Channel

In our main analysis, we have shown the sharply different patterns of equity flows and domestic information advantage for the United States compared to the rest of the world. However, one may postulate that, rather than the United States being the only special case, there might be a continuum of countries ranked by their transparency and institutional quality, which in our model is captured by the ratio of learning costs for foreign ($\theta_{kk}$) and domestic ($\theta_k$) investors.

Figure 11: Information and Equity Inflows in Uncertain Times




**Notes**: This figure reports a bar chart comparing, for each country, the estimated sensitivity of unilateral equity inflows to the VIX ($\beta_i^{CF,vix}$) with the relative precision of domestic forecasters (RPDF). The sample consists of the six countries for which both inflow and forecast data are available: USA, FRA, SWE, DEU, NLD, and ITA.

To construct $\beta_i^{\text{Inflows},vix}$, we run for each country $i$ the regression

$$\text{Inflows}_{i,t} = \alpha_i + \beta_i^{CF,vix} VIX_t + \delta_1 \Delta GDP_{i,t} + \delta_2 \text{Inflows}_{i,t-1} + \varepsilon_{i,t}, \tag{30}$$

where $\text{Inflows}_{i,t}$ denotes standardized equity inflows into country $i$, $VIX_t$ captures global uncertainty, and controls include GDP growth and lagged inflows. Thus, $\beta_i^{\text{Inflows},vix}$ measures how strongly foreign inflows into country $i$ respond to a one-standard deviation increase in global uncertainty.

RPDF is computed as the difference between the average forecast error of foreign and domestic forecasters for each country-month, based on Consensus Economics forecasts for

GDP, industrial production, unemployment, and treasury bills, and then standardized across the panel. A higher RPDF indicates a stronger domestic informational advantage.

Figure 11 shows that as RPDF increases, the corresponding $\beta_i^{\text{Inflows},vix}$ becomes more negative: countries with stronger domestic information advantage (ITA, NLD, DEU) suffer sharper declines in inflows during uncertainty spikes, while countries with weaker or absent domestic advantage (notably the USA) remain more resilient. This evidence mirrors our bilateral results, but here at the unilateral level: information asymmetries shape how capital flows respond to global uncertainty.

**Bilateral Flows.** We provide a bilateral test of the information channel in three steps that mirror our data construction and the empirical code, while keeping the country-pair list explicit.

- **Step 1: Constructing bilateral relative precision $RPF_{ik}$.** Starting from Consensus Economics forecast microdata, we (i) compute squared forecast errors for each institution and variable, winsorize at the 1st–99th percentiles to limit outliers; (ii) reshape to a long format across variables; (iii) standardize forecast errors *within destination country and forecasted variable* so that errors are comparable; (iv) average over time and institutions to obtain, for each origin–destination $(i, k)$, the mean error $\overline{FE}_{ik}$; and (v) compute the destination-wide benchmark $\overline{FE}_{\cdot k}$ as the mean across all origins. We define

$$RPF_{ik} \equiv \overline{FE}_{\cdot k} - \overline{FE}_{ik}, \tag{31}$$

  so that positive values indicate that investors from $i$ forecast $k$ more accurately than the world average. We harmonize identifiers with the bilateral flows dataset and standardize $RPF_{ik}$ to zero mean and unit variance.

  After merging, 37 country pairs remain with sufficient data:

  > USA-CHE, DNK-USA, DNK-FIN, FRA-USA, FRA-ITA, FRA-NLD, FRA-CHE, DEU-USA, DEU-FRA, DEU-ITA, DEU-NLD, DEU-SWE, DEU-CHE, ITA-USA, ITA-FRA, ITA-NLD, ITA-CHE, NLD-USA, NLD-FRA, NLD-CHE, NLD-JPN, SWE-USA, SWE-DNK, SWE-FRA, SWE-NLD, SWE-CHE, SWE-FIN, CAN-USA, CAN-CHE, JPN-DEU, JPN-CHE, FIN-USA, FIN-SWE, ESP-USA, ESP-ITA, ESP-NLD, ESP-CHE.

  These surviving pairs are those with at least three annual observations and variation in $V_t$. The pattern is consistent with the bilateral model prediction: when uncertainty rises, capital reallocates toward destinations for which the origin has an informational edge.

- **Step 2: Bilateral regression.** We merge $RPF_{ik}$ with annual bilateral equity inflows (JRC–ECFIN Finflows), scaled by destination GDP and standardized within origin country. We exclude conduit centers (BMU, CYM, CUW, HKG, IRL, JEY, LUX, PAN, VGB, SGP) to avoid distortions. Our baseline specification is

$$\text{Inflows}_{ik,t} = \alpha_i + \xi \, RPF_{ik,t} + \gamma \, CF_{ik,t-1} + \varepsilon_{ik,t}, \tag{32}$$

where $\text{Inflows}_{ik,t}$ are standardized bilateral inflows. A positive $\xi$ indicates that investors direct flows toward destinations they forecast with greater relative precision.