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 has new predictions for forecasters' accuracy, which we test using micro forecast data. Domestic forecasters better predict their own country's economic outcomes, especially with increased global uncertainty. However, the US is an exception, where domestic forecasters do not outperform foreign institutions.

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1 Introduction

Capital flows across countries are a fundamental aspect of the global economy and play a crucial role for the fluctuation of output and asset prices. The recent literature on the global financial cycle, summarized in Coeurdacier and Rey (2013) and Miranda-Agrippino and Rey (2022), has documented that investors not only exhibit home bias in portfolio choices[1], but also retrench towards their own country and safer assets, particularly in the United States, during economic downturns. While home bias and capital flows have typically been studied in isolation, in this paper we test the hypothesis that a unique explanation, the heterogeneity across countries in information over asset payoffs, can rationalize all these empirical patterns.

To formalize the role of information heterogeneity in determining capital 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. Domestic 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 capital 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.[3] Figure 1 illustrates investor behavior during times of uncertainty, highlighting both retrenchment and the exceptionality of the United States. The left panel shows a general decline in foreign equity inflows as uncertainty increases. However, on the right panel, we can see that inflows towards the United States remain steady or even slightly increase when uncertainty is higher.

We rationalize these findings through a model with endogenous information acquisition in a multi-country setting, where investors face convex costs to learn about the fundamental value of domestic and foreign assets. We allow for arbitrarily heterogeneous information,

[1]We replicate the survey by Coeurdacier and Rey (2013) by extending the time frame in Appendix A.1.

[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.

[3]On average, equity outflows and equity inflows constitute around 55% and 40% of total capital flows. Our focus on equity flows, excluding bond transactions, is due to potential government interventions that might affect these transactions. Descriptive statistics of equity, bond, and capital flows can be found in Appendix (A.1).

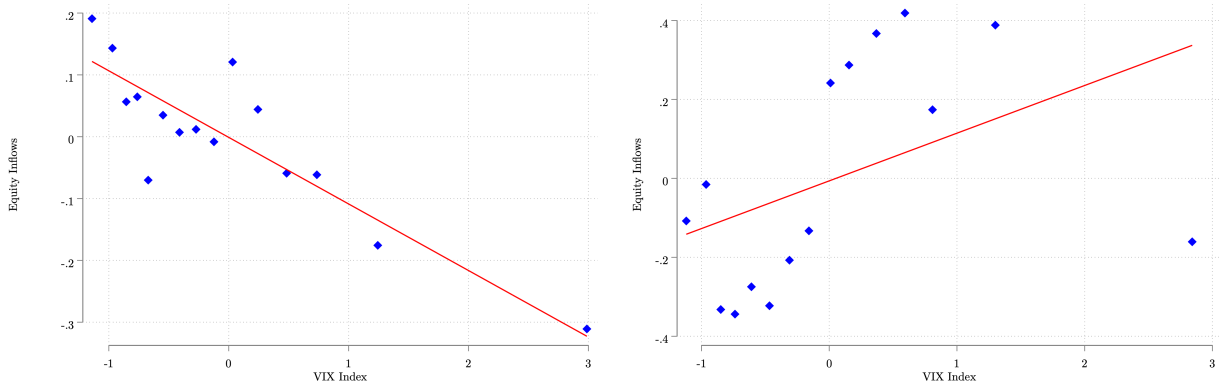
with learning costs varying by the pair of origin country (where the investor resides) and target country (where the asset is located). This general specification incorporates the key ideas that it is cheaper for an investor to learn about domestic assets and about the assets of transparent economies with ample news coverage, such as the United States, which we refer to as information havens. As in Veldkamp (2023) and De Marco et al. (2022), the model predicts that the informational advantage for domestic assets leads to home bias. Crucially, when uncertainty about the fundamental value of assets increases, there is an increased gain from specialization, leading investors to retrench towards their home countries. This behavior results in a decline in both inflows and outflows, consistent with the data. Concurrently, capital flows towards information havens, such as the United States. Hence, the model parsimoniously replicates the stylized facts of 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 then 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 of an information haven country in our model, where abundant and transparent information is available to all investors, domestic and foreign alike, isolating the country from capital outflows during uncertainty episodes.

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

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 left panel represents the correlation between these two variables across all 46 countries in our dataset, with the exception of the United States, which is shown in the right panel.

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.

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 Facts

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 primary 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, as discussed in Appendix A.1.

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 V_{it} is a measure of uncertainty (VIX, JLN, VSTOXX), the indicator function $\mathbb{1}_{\{\mathrm{US}\}}$ is instrumental in quantifying the marginal effect of US-specific uncertainty on its unique inflows and then 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, β 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[4]. 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 wide 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 9% 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, β_{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 9%.

[4] 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	-0.09***	-0.09***	-0.07***	-0.07***
	(0.01)	(0.01)	(0.02)	(0.02)
VIX Index × US	0.18***	0.18***	-0.05**	-0.05**
	(0.02)	(0.02)	(0.02)	(0.02)
GDP Δ%		0.01***		-0.00
		(0.00)		(0.00)
N	8003	7940	6506	6452
Country FEs	Yes	Yes	Yes	Yes

Notes: This table reports the OLS regression coefficients from Equation (1). Both dependent and independent 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. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level.

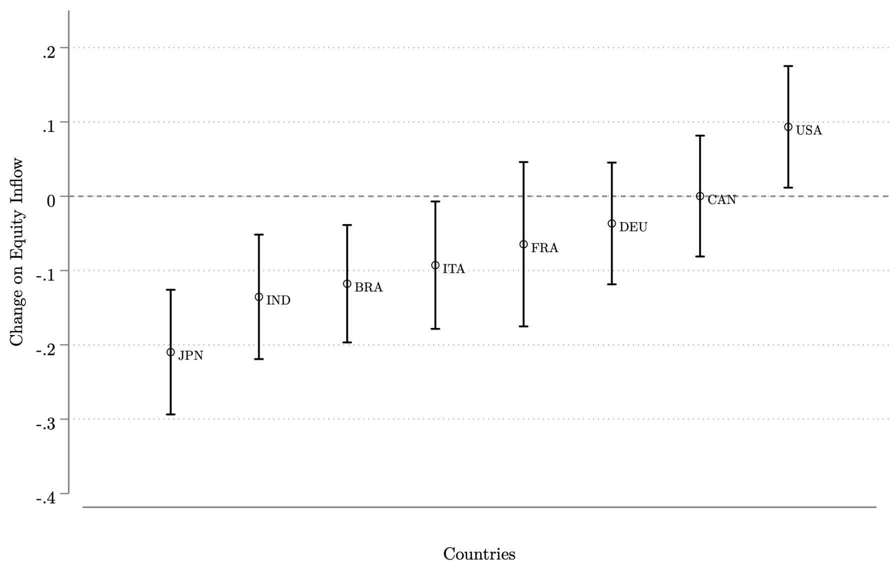
Column (3) explores the sensitivity of equity outflows to financial uncertainty, again including the interaction with the United States. On average, a one standard deviation increase in uncertainty is associated with a 7% decrease in outflows, indicating that domestic investors reduce their foreign equity 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.

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 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 β is the correlation coefficient between uncertainty and equity inflows. Figure 2 illustrates how this correlation

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%.

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.

Robustness Checks. In Appendix A.2.1, we show that our results are robust to using alternative measures of uncertainty, both global (the volatility of the global ACWI index, the financial uncertainty from Jurado (2015) and the European-wide VSTOXX) and country-specific (the volatility of country-specific stock indexes, and the uncertainty measures from Ozturk and Sheng (2017)). Additionally, in Section 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 extreme realizations, we reproduce our results excluding observations when uncertainty is beyond one standard deviation of its mean, and we include a dummy for recessionary periods, showing that our results are not dependent on these extreme events. We also reproduce Figure 2 for our entire sample of 47 countries, which again shows the unique exceptional pattern of the US.

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 κ 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 θ_{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: θ_{kk}, the cost of research for domestic assets, and θ_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 [5].

3.2 Portfolio Choice

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

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

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

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:

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

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 τ 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, θ_{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 (σ_k) is high or the cost to learn about the asset (θ_{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 θ_{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*

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

- *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 σ_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:

$$\mathbb{E}\int_S x_{i,k}^S dS = 1 + \frac{1}{2\theta_{ik}}\sigma_k^4 \left(\frac{1}{\eta} + \eta\sigma_k^2\right) \tag{11}$$

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 σ_k^2, can arise from various sources. Given our assumption of an independent payoff structure across assets, an increase in σ_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:

$$CF_k \equiv \frac{\partial}{\partial \sigma_k^2}\left(-x_{kk}^S + \frac{1}{N}\sum_{i=1}^{N} x_{ik}^S\right) \tag{12}$$

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

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

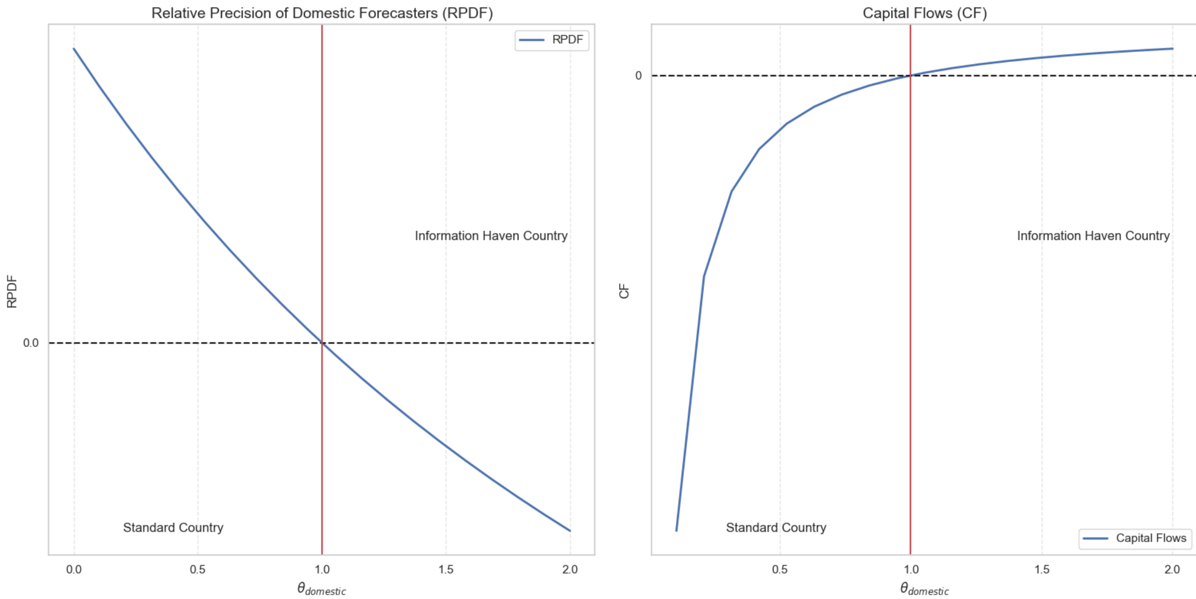
$$CF_k = \nu_k\left(\underbrace{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\theta_{ik}}}_{1/\theta_k} - \frac{1}{\theta_{kk}}\right) \tag{13}$$

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 (θ_{ik}). Whether this will result in inflows or outflows depend on the relative learning cost of domestic investors (θ_{kk}) and foreign investors, where the relevant statistic for foreign investors turns out to be their harmonic average learning cost θ_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.

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

Figure 3: RPDF and CF changing θ_d



Notes: This plot shows how relative precision of domestic forecasters and capital flows change in sign as θ_d increases. θ_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 $\theta_d \geq \theta_f$.

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 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.

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 $\theta_d \geq \theta_f$ [6]. In the Appendix B.2 we also show the dynamics of RPDF and CF for different values of σ^2.

[6]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 Analysis

In this section, we present novel empirical evidence on how the forecast accuracy of local investors relative to foreign forecasters fluctuates with varying levels of uncertainty, and we highlight distinctive patterns observed in the forecast data for the United States. Finally, we test whether equity flows empirically respond to the observed relative forecast precisions. 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.

In order to measure forecast precision and how it varies with uncertainty, we use data from Consensus Economics [7], 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 reflect the information accuracy available to the forecaster, serving as the empirical counterpart to the learning choice discussed in our model.

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[8]. Then, we define the Relative Precision of Domestic Forecasters (RPDF) as the difference between the average foreign forecast error and the average domestic forecast error, $\text{RPDF} = \text{RFE}^f - \text{RFE}^d$ [9]. To study the role of uncertainty, we separately construct RPDF during periods of high uncertainty and low uncertainty, with a period of high uncertainty defined as when the VIX is above one standard deviation of its average value. Additional details on the data and the methodology are available in Appendix C.2.

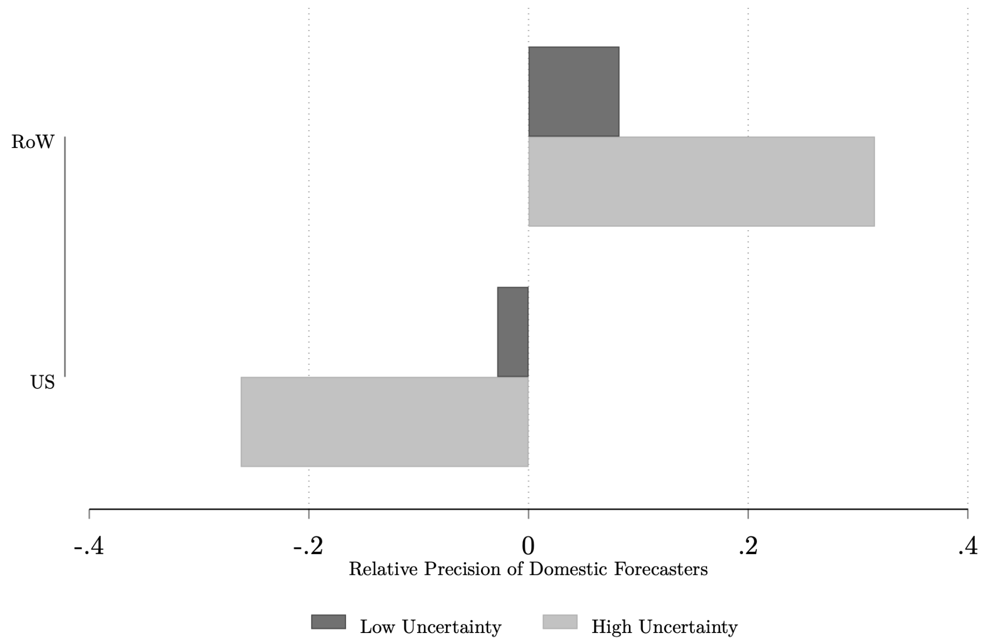
Figure 4 illustrates the relative precision of domestic forecasters across countries during

[7] 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).

[8] 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.

[9] Forecast errors are measured at a one period and two period horizon.

Figure 4: Uncertainty and RPDF



Notes: This plot shows how relative precision of domestic forecasters is distributed between rest of the world and United States, in case of high and low uncertainty. The measure we use to capture the relative precision is an Haltiwanger formula between foreign and local difference in forecast errors.

periods of low and high uncertainty[10], and comparing the rest of the world with the United States. 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 seem to even outperform domestic analysts in predicting economic variables during periods of high uncertainty. The special behavior of

[10]High uncertainty is defined as observations with more than one standard deviation of VIX in the distribution. This result remains robust even at higher levels in the distribution.

the United States is in line with the definition of an information haven in our model.

Regression Analysis. 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; D_{ic} is a dummy variable that defines which forecats are foreign and which are domestic; V_t is a countinuous variable that captures uncertainty. We use again the VIX as our main specification for V_t, but we show that our resuts are robust to several alternatives in Appendix C.4.1. More details on the data and the methodology are reported in Appendix (C.1).

There are two main set of results. First, independently of the level of the VIX, we find that there is a domestic information advantage $\beta < 0$, but that this is much weaker for the United States $\beta_{US} > 0$. Secondly, we find that when uncertainty increases, the relative precision of domestic forecasters increases ($\gamma < 0$), which validates the main testable prediction of our model. Furthermore, $\gamma_{US} > 0$ indicates that this result is reversed for the United States, that do not experience a relative domestic specialization in times of high uncertainty.

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 to 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 small and less sophisticated 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. This is because superior forecasting

Table 2: OLS Regression: FE^2

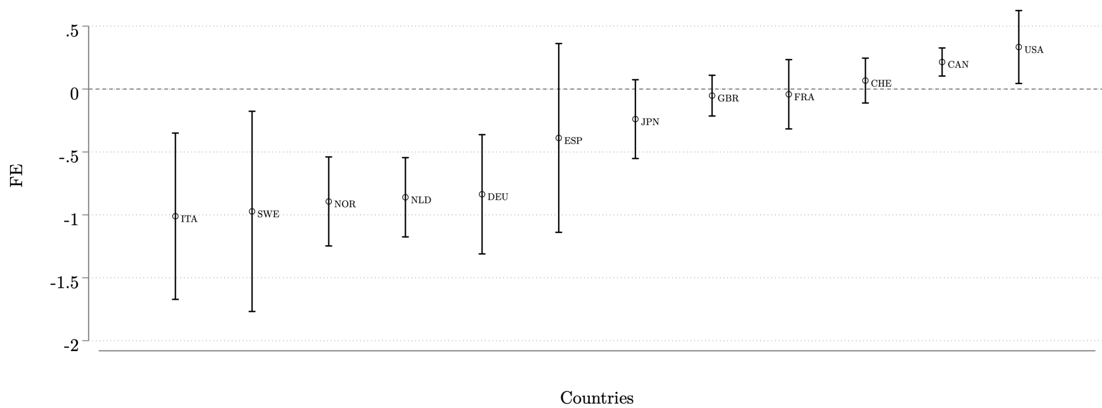
	FE^2 (1)	FE^2 (2)	FE^2 (3)
Domestic	-0.60***	-0.05	-0.51***
	(0.09)	(0.08)	(0.15)
VIX	3.34***	3.24***	3.15***
	(0.43)	(0.42)	(0.41)
Domestic × VIX	-0.54***	-0.53***	-0.54***
	(0.11)	(0.11)	(0.10)
US	-1.43***	0.00	-1.33***
	(0.25)	(.)	(0.29)
Domestic × US	0.82***	0.44***	0.19
	(0.15)	(0.14)	(0.29)
Domestic × VIX × US	0.85***	0.86***	0.59***
	(0.15)	(0.15)	(0.15)
N	213562	213562	213562
R^2	0.022	0.167	0.031
adj. R^2	0.022	0.166	0.030
FEs, Variable × Country	No	Yes	No
FEs, Bank ID	No	No	Yes
Clusters, Time	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 forecast errors, calculated as shows in this section of the appendix. We use the VIX index as a measure of uncertainty, but we check for many other masures of uncertainty in this appendix. Standard errors, clustered at time level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See the appendix for additional information on variables construction.

performance often results from greater resource investment in making those predictions.

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 γ, 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.

Figure 5: Country Specific Analysis



Notes: This plot captures the γ coefficient of our OLS specification, which is the effect of domestic forecasters in uncertainty on squared forecast error. Negative value represent a domestic advantage, or information home bias. This OLS specification is characterized by variable specific fixed effects and VIX is the measure of uncertainty. The confidence intervals are set at 95%.

Summary of the Results 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 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.

4.2 Robustness and Extensions

Throughout our analysis, we have relied on the VIX as our preferred measure of uncertainty. In Appendix C.4.1, we show that our results are robust to employing alternative measures of uncertainty, such as the volatility of the global ACWI index, the European VSTOXX, and the financial uncertainty measure in Jurado (2015). More importantly, we also show that our results are robust to using a measure of country-specific uncertainty, such as the measure by Ozturk and Sheng (2017) and the volatility of stock returns of each country in our sample by using Global Financial Data. Therefore, the predictions that tie surges in uncertainty to reduced equity inflows and increased relative domestic forecast precision carry over in the data both when the uncertainty surge is local or global, consistently with our model.

In Figure (4) and Table (2), we examined the relative precision of domestic forecasters by leveraging the forecasts for all the variables that are available in Consensus Economics. In Appendix C.4.2, we show that similar results can be obtained by isolating the different variables. Specifically, we separately analyze financial forecasts (T-bills), GDP forecasts, and other real economy forecasts (industrial production and unemployment), determining that our findings hold across these different economic dimensions.

To address potential biases that may arise in our estimates due to the correlation between adverse economic periods, such as recessions, and forecast errors, we incorporate a recession dummy variable into our regression model. This allows us to control for the effects of recessions and isolate the true relationship between our variables of interest. Furthermore, to reinforce the robustness of our model specification, we use an alternative measure of forecast errors, relying on the dispersion across forecasts [11]. This measure helps ensure that our results are not unduly influenced by outlier events or sudden economic changes. These comprehensive robustness checks are detailed in Appendix C.4.

Finally, in Appendix C.4.5, we show that we can go beyond the stark distinction between United States and rest of the world, and think of a continuum of countries based on their transparency and institutional quality. More specifically, we show that when we sort countries based on the relative precision of domestic forecasters, we obtain that countries with a large domestic advantage tend to suffer worst capital outflows when uncertainty increases.

[11] More details on this measure construction are available in the Appendix C.4.4

4.3 Forecast Precision and Equity Flows: Information Channel

In the previous section 4.1, we validated our model predictions on information, by showing that standard countries exhibit an increase in the relative precision of domestic forecasters in period of high uncertainty. Yet, so far, we have examined capital flows and relative precision separately. In this section, we directly test the information channel by verifying the ability of our measure of relative precision of domestic forecasters to explain capital flows.

In the first column of Table 3, we report the results of a regression of capital inflows on RPDF[12], where as in Section 4.1 RPDF is the difference between the average forecast error of foreign and domestic forecasters. To understand the negative sign of RPDF, consider the case of a country that is being forecasted at a certain month. A negative sign for RPDF suggest that if in that month domestic forecasters posted forecasts that ex-post turned out to be more precise than the forecasts made by foreigners (high RPDF), than in that month we are likely observing negative inflows, meaning that foreign investors are abandoning the country.

As additional evidence about the role of uncertainty for our mechanism, we use a two-stage approach. In the first stage, we isolate variation in forecast errors that is driven by the VIX. Such first-stage allows to construct a predicted forecast error for each forecaster-country pair, where all of the variation in forecast errors is driven by uncertainty. We then use these forecast errors to construct our measure of RPDF, analogous to the with the actual forecast errors. Finally, in the second-stage, we evaluate the effectiveness of such predicted RPDF in determining capital flows[13]. This test is described in more detail in Appendix C.3.

The results from these two exercises, displayed in Table 3, support our hypothesis that the relative domestic specialization can explain capital flows, in line with our key Proposition 2, and help us understand the equity flows patterns during periods of high uncertainty.

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 the new equity flow data

[12]Notice that here we do not distinguish between the US and rest of the world, as our model prediction is that RPDF in the US responds differently to uncertainty, as shown empirically in Section 4.1, and not that equity flows respond differently to RPDF in the US.

[13]To perform this step we need to combine the dataset on capital flows from Koepke and Paetzold (2022) with the forecast data from Consensus Economics.

Table 3: Testing the Information Channel

	Inflows OLS (1)	Inflows 2SLS (2)
RPDF	-0.01***	-0.17**
	(0.00)	(0.06)
N	870	870
Country FEs	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 fitted forecast error has on equity inflows, calculated as shown in this section of the Appendix (C.3). 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.

from Koepke and Paetzold (2022), 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.

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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 4, where we show how inflows and outflows are distributed for equity, bonds and capital (equity + bonds).

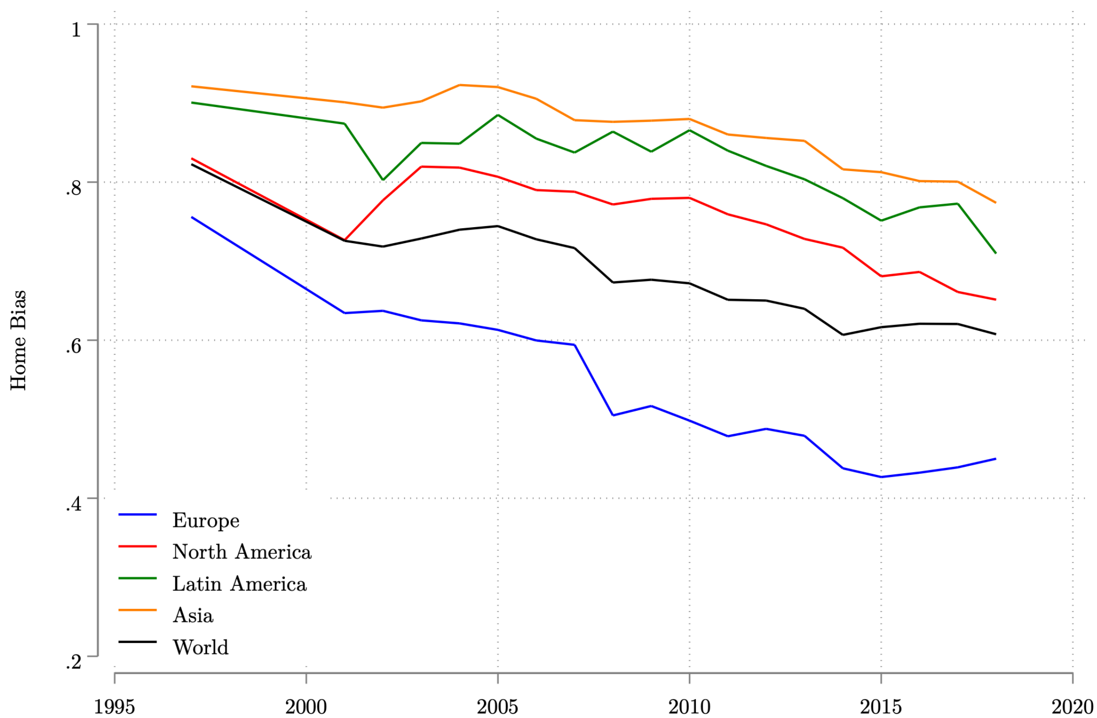
Table 4: Descriptive Statistics: Capital Flows

	Mean	SD	Median	Max	Min	N
Equity Inflows	0.54	12.29	0.01	300.34	-315.19	8524
Equity Outflows	1.61	10.90	0.04	185.50	-176.10	6911
Bonds Inflows	2.41	14.27	0.05	255.18	-403.60	8889
Bonds Outflows	1.53	9.26	0.05	174.17	-106.50	6911
Capital Inflows	2.84	18.49	0.11	443.64	-314.73	9752
Capital Outflows	2.70	14.16	0.11	298.15	-164.67	8572

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.

Equity Home Bias. We provide a figure that captures the equity home bias existing across different regions of the world, extending the evidence by Coeurdacier and Rey (2013) to a time series spanning from 1997 to 2018.

Figure 6: Equity Home Bias



Notes: This plot shows how equity home bias differs across regions in a time spanning from 1995 to 2020, following the same specifications as in Coeurdacier and Rey (2013).

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 5 shows how these measures are distributed.

Table 5: 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.

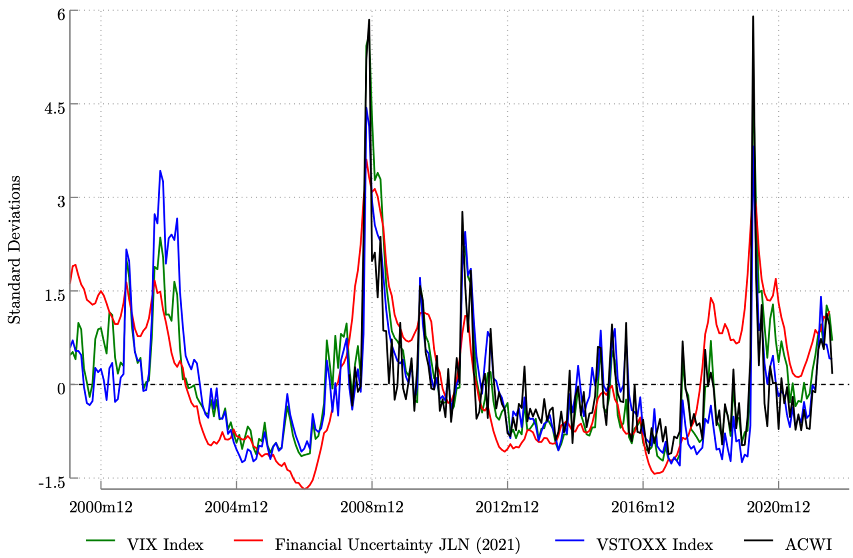
We also provide a table that shows how our main measure of uncertainty (VIX index) correlates with alternative measures.

Table 6: 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 7: 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 7: Equity Inflows and JLN

	Inflows (1)	Inflows (2)	Outflows (3)	Outflows (4)
Financial JLN (2021)	-0.06***	-0.06***	-0.03**	-0.03**
	(0.01)	(0.01)	(0.01)	(0.01)
Financial JLN (2021) × US	0.14***	0.14***	-0.07***	-0.07***
	(0.02)	(0.02)	(0.02)	(0.02)
GDP Δ%		0.01***		-0.00
		(0.00)		(0.00)
N	8003	7940	6506	6452
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.

Table 8: Equity Inflows and VSTOXX

	Inflows (1)	Inflows (2)	Outflows (3)	Outflows (4)
VSTOXX Index	-0.10***	-0.10***	-0.12***	-0.12***
	(0.01)	(0.01)	(0.02)	(0.02)
VSTOXX Index × US	0.16***	0.17***	-0.02	-0.02
	(0.01)	(0.01)	(0.02)	(0.02)
GDP Δ%		0.01***		-0.00
		(0.00)		(0.01)
N	7639	7639	6221	6221
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 VSTOXX 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.

Table 9: ACWI Volatility

	Inflows (1)	Inflows (2)	Outflows (3)	Outflows (4)
ACWI Volatility	-0.11***	-0.13***	-0.12***	-0.12***
	(0.02)	(0.02)	(0.03)	(0.04)
ACWI Volatility × US	0.25***	0.26***	0.02	0.02
	(0.02)	(0.02)	(0.03)	(0.04)
GDP Δ%		0.02***		0.00
		(0.01)		(0.01)
N	5711	5711	4626	4626
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 the ACWI index. 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.

We also check whether the result can be explained by using measures of local uncertainty (country specific), such as the measure by Ozturk and Sheng (2017) and a country specific volatility of stock returns, using Global Financial Data as our source.

Table 10: Country Specific Uncertainty (Ozturk)

	Inflows (1)	Inflows (2)	Outflows (3)	Outflows (4)
Country Uncertainty	-0.04**	-0.04**	-0.01	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)
Country Uncertainty × US	0.14***	0.14***	-0.06**	-0.07**
	(0.02)	(0.02)	(0.02)	(0.02)
GDP Δ%		0.01*		-0.01
		(0.00)		(0.00)
N	5071	5035	4231	4195
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 in Ozturk and Sheng (2017). 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.

Table 11: Country Specific Uncertainty (Volatility of Stock Returns)

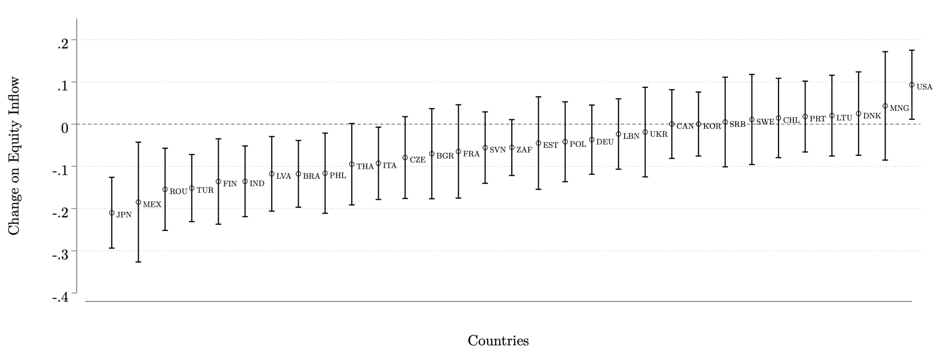
	Inflows (1)	Inflows (2)	Outflows (3)	Outflows (4)
Country Uncertainty	-0.14***	-0.14***	-0.11**	-0.11**
	(0.03)	(0.03)	(0.04)	(0.04)
Country Uncertainty × US	0.25***	0.25***	0.02	0.02
	(0.03)	(0.03)	(0.04)	(0.04)
GDP Δ%		0.01**		-0.01**
		(0.00)		(0.00)
N	4703	4699	3880	3876
Country FEs	Yes	Yes	Yes	Yes

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 8: 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 12, show that our estimates are very stable to adding this new set of controls.

Table 12: Equity Inflows and Additional Controls

	Inflows (1)	Inflows (2)	Inflows (3)	Inflows (4)
VIX	-0.10***	-0.10***	-0.10***	-0.10***
	(0.01)	(0.02)	(0.02)	(0.02)
VIX $\times$ US	0.20***	0.20***	0.20***	0.20***
	(0.02)	(0.02)	(0.02)	(0.02)
GDP Δ%	0.01***	0.01***	0.01***	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)
Size		0.06***	0.06**	0.06**
		(0.02)	(0.03)	(0.03)
EER			3.51**	3.48**
			(1.41)	(1.40)
Bond Inflows				0.00
				(0.00)
N	8033	7114	5985	5985
Country FEs	Yes	No	No	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 13: Equity Flows, Financial Uncertainty and Recession

	Inflows (1)	Inflows (2)	Inflows (3)
VIX Index	-0.09***		
	(0.01)		
VIX Index × US	0.18***		
	(0.02)		
Recession	0.00	-0.05	-0.05
	(0.04)	(0.05)	(0.04)
GDP Δ%	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)
Financial JLN (2021)		-0.05***	
		(0.01)	
Financial JLN (2021) × US		0.14***	
		(0.02)	
VSTOXX Index			-0.09***
			(0.01)
VSTOXX Index × US			0.16***
			(0.01)
N	7940	7940	7561
Country FEs	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 14: Equity Flows and Low Uncertainty

	Inflows (1)	Inflows (2)	Inflows (3)	Outflows (4)
VIX	-0.09***	-0.10***	-0.09***	-0.10***
	(0.02)	(0.02)	(0.02)	(0.03)
VIX × US	0.29***	0.29***	-0.04	-0.04
	(0.02)	(0.02)	(0.03)	(0.03)
GDP Δ%		0.01***		-0.00
		(0.00)		(0.01)
N	7619	7535	6174	6102
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:

$$U_i \equiv \mathbb{E}\left[\mathbb{E}_i\left(W_i\right) - \frac{\eta}{2}\mathbb{V}_i\left(W_i\right)\right] \tag{14}$$

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

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

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

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

Take expectation in the first period, we obtain

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

Under the assumption that risky asset payoffs are independently distributed, we can write the objective function 14 as:

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

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:

$$\max\ \frac{1}{2}\sum_{k=1}^{N}\left(\eta\frac{\tau_k + \tau_{ik,s}}{\tau_k^2} + \frac{1}{\eta}\frac{\tau_{ik,s}}{\tau_k}\right) - \sum_{k=1}^{N}\frac{\theta_{ik}}{2}\tau^2_{ik,s} \tag{15}$$

Information choice Solve for optimal $\tau_{ik,s}$ from 15, we get:

$$\tau_{ik,s} = \frac{1}{2\theta_{ik}}\left(\frac{\eta}{\tau_k^2} + \frac{1}{\eta\tau_k}\right) \tag{16}$$

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,

$$\widehat{r}_{ik} = \kappa_i s_{ik} + (1-\kappa_i)\mu_k \tag{17}$$

$$\widehat{\sigma}^2_{ik} = 1/\widehat{\tau}_{ik} = \frac{\sigma_k^2}{1 + \frac{1}{2\theta_{ik}}\sigma_k^4\left(\frac{1}{\eta} + \eta\sigma_k^2\right)} \tag{18}$$

Substitute 17 and 18 into the portfolio holdings in the second period 6, we get the aggregate demand for asset k of sophisticated investors in country i is:

$$\mathbb{E}\int_S x^S_{i,k}dS = \mathbb{E}\int_S \frac{\widehat{r}_{ik} - \mu_k + \eta\sigma_k^2}{\eta\widehat{\sigma}^2_{ik}}dS = 1 + \frac{1}{2\theta_{ik}}\left(\frac{\eta}{\tau_k^3} + \frac{1}{\eta\tau_k^2}\right) \tag{19}$$

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:

$$\frac{\partial}{\partial\sigma_k^2}\left(-x^S_{kk} + \frac{1}{N}\sum_{i=1}^{N}x^S_{ik}\right) = \frac{1}{2}\left(\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\theta_{ik}} - \frac{1}{\theta_{kk}}\right)\left(\frac{3\eta}{\tau_k^4} + \frac{2}{\eta\tau_k^3}\right) \tag{20}$$

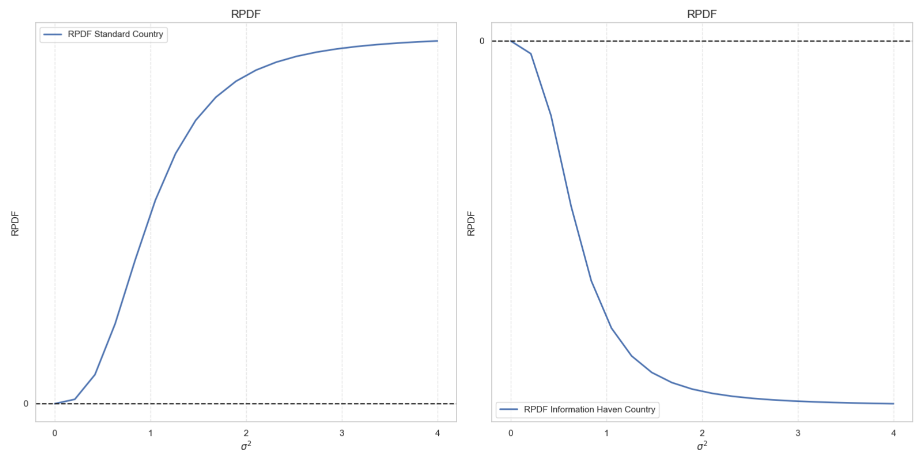
Hence,

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

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, σ^2, ranges from 0 to 4.

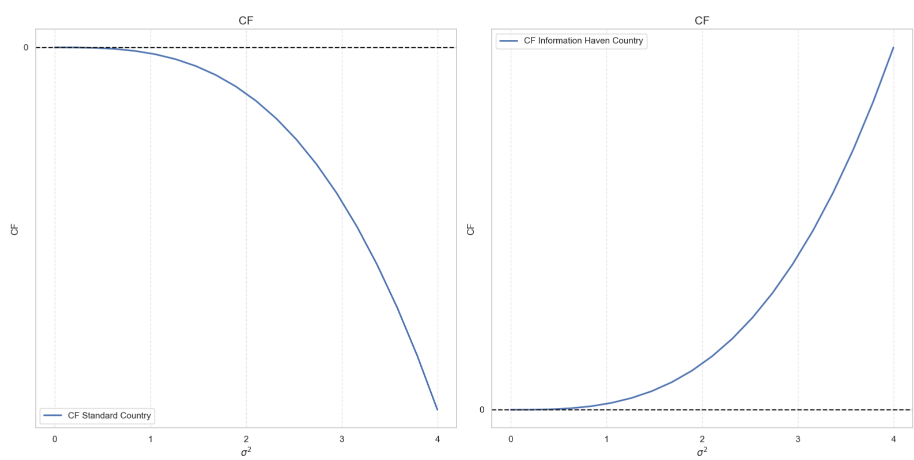
Figure 9: RPDF and CF changing σ^2



Notes: This plot shows how relative precision of domestic forecasters change in sign as σ^2 increases.

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

Figure 10: RPDF and CF changing σ^2



Notes: This plot shows how capital flows change in sign as σ^2 increases.

C Main Empirical Analysis

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.

- $\mathbb{E}_t[\mathbf{\Delta UNEMP}_{y,y-1}]$; $\mathbb{E}_t[\mathbf{\Delta UNEMP}_{y+1,y}]$ (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 15 and the resulting of a 1.5% trimming from both left and right tails in Table 16 [14]. Moreover, in Figure 11 we show the distributions of the variables we included in our dataset.

Table 15: 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.

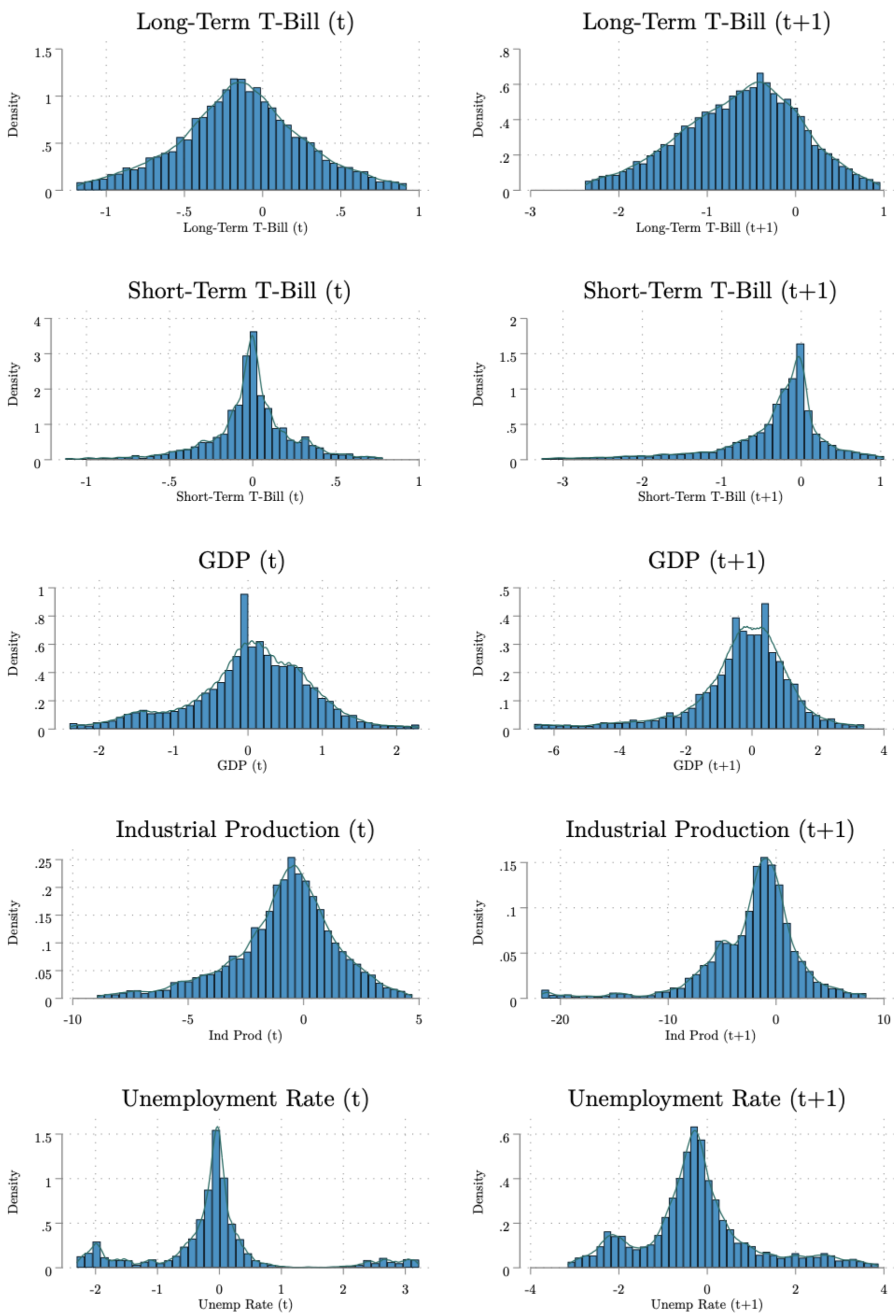
Table 16: Descriptive Statistics: Trimmed Data from Consensus Economics

	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.

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

Figure 11: 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:

$$\text{RPDF}_u^d = \text{RMSE}_u^f - \text{RMSE}_u^d \tag{21}$$

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

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

where FE is defined as in (22); 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.

Regression Analysis: Model Specification. 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:

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

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 $\mathbf{D} \in \{0,1\}$; $\mathbf{US}$ 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:

$$\mathrm{FE}^2_{i,j,c,t} = \Big\{\mathbf{x}_{i,j,c,t} - \mathbb{E}_{t-1}[\mathbf{x}_{i,j,c,t}]\Big\}^2 \tag{22}$$

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

Our coefficient of interest, in this case, is γ and γ_{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 2SLS: Testing the Information Channel.

We run, as a first stage of our 2SLS regression, the same specification we used before, as it follows:

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

We then collect the fitted values of this regression, $\hat{\mathrm{FE}}^2{}_{i,j,c,t}$, by computing the following average across countries:

$$\hat{\mathrm{FE}}^2{}_{c,t} = \frac{1}{\mathrm{I} \times \mathrm{J}} \sum_{i,j} \hat{\mathrm{FE}}^2{}_{i,j,c,t}$$

where I is the sum of forecasters and J is the sum of variables. We then use these country-time specific fitted values to see whether they explain the direction of equity flows in the following specification:

$$\mathrm{Y}_{c,t} = \alpha + \zeta_i + \xi \hat{\mathrm{FE}}^2{}_{c,t} + \mathrm{X}_{c,t} + \varepsilon_{ct}, \tag{23}$$

where $\mathrm{Y}_{c,t}$ captures equity inflows across countries c and time t.

C.4 Robustness Checks

C.4.1 Alternative Measures of Uncertainty

We replicate our analysis in Section 4.1, which relied on the VIX, using alternative measures of uncertainty, (such as Financial Uncertainty from Jurado (2015) and VSTOXX).

Table 17: OLS Regression: Alternative Measures of Uncertainty

	FE^2 JLN (1)	FE^2 VSTOXX (2)	FE^2 ACWI (3)
Domestic	-0.79***	-0.55***	-0.53***
	(0.10)	(0.09)	(0.07)
Uncertainty	3.95***	3.32***	3.53***
	(0.60)	(0.60)	(0.50)
Domestic × Uncertainty	-0.73***	-0.52***	-0.38***
	(0.10)	(0.12)	(0.10)
US	-1.93***	-1.38***	-1.48***
	(0.29)	(0.28)	(0.28)
Domestic × US	1.16***	0.80***	0.57***
	(0.17)	(0.16)	(0.13)
Domestic × Uncertainty × US	1.11***	0.89***	0.73***
	(0.13)	(0.13)	(0.16)
N	213562	213562	186922
R^2	0.027	0.015	0.024
adj. R^2	0.027	0.015	0.024
Clusters, Time	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 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. $* =$ 10% level, $** =$ 5% level, and $* * * =$ 1% level.

Controlling for Country Specific Uncertainty. We now want to check whether the results we have hold true even by controlling for country specific uncertainty, so that we can validate the results of the model for both global and local uncertainty shocks. We use the measures of country specific uncertainty, as in Ozturk and Sheng (2017) and volatility of stock return for each specific country in the sample, by using Financial Data.

Table 18: Country Specific Uncertainty

	FE^2 (Ozturk) (1)	FE^2 (Ret Vol) (2)
Domestic	-0.76***	-0.46***
	(0.12)	(0.09)
Country Uncertainty	4.50***	2.83***
	(0.71)	(0.59)
Domestic × Country Uncertainty	-0.70***	-0.32***
	(0.16)	(0.12)
US	-0.47	-0.78**
	(0.38)	(0.30)
Domestic × US	0.61***	0.63***
	(0.15)	(0.15)
Domestic × Country Uncertainty × US	0.68***	0.51*
	(0.19)	(0.26)
N	212958	197165
R^2	0.035	0.015
adj. R^2	0.035	0.015
Clusters, Time	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 local uncertainty has on forecast errors, calculated as shown in section 4. We use the country specific uncertainty index (Ozturk and Sheng (2017)) and country stock return volatility. Standard errors, clustered at time level, are reported in parentheses. $*$ = 10% level, $**$ = 5% level, and $***$ = 1% level.

C.4.2 Controlling for Specific Variables

Relative Precision of Domestic Forecasters: Specific Variables. We conduct a thorough examination of the results presented in Figure (4) by isolating different forecast variables. Specifically, we separately analyze financial indicators (such as T-bills), GDP, and real economy measures (industrial production and unemployment) to determine if our findings hold across these different economic dimensions. Both financial variables and real economy ones reflects the same sign we captured in Figure (4), while GDP shows same directions in times of heightened uncertainty, but not same sign for low uncertainty in the rest of the world.

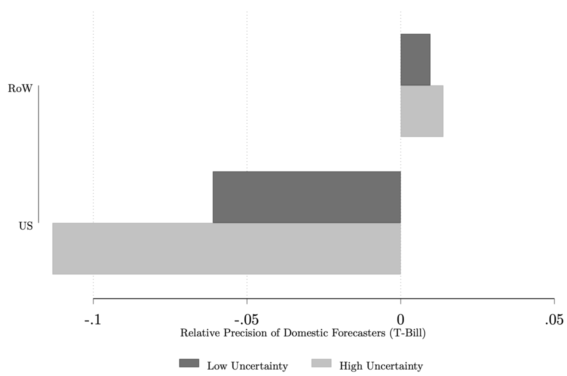


Figure 12: Financial Variables

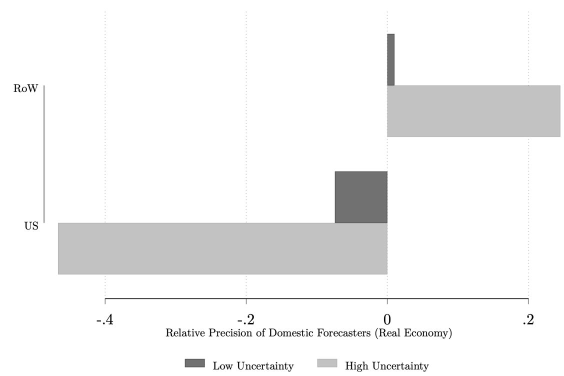


Figure 13: Real Economy Variables

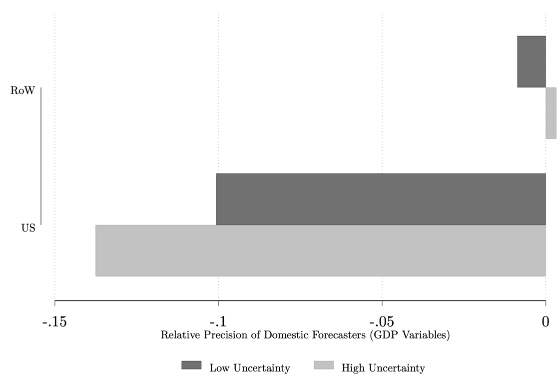


Figure 14: GDP Variables

Notes: This plot shows how forecast errors increase or decrease, depending on the forecast being domestic in higher times of uncertainty. Uncertainty is measured by the VIX Index, which is high when over one standard deviation in the distrbution.

Regression Analysis: Specific Variables. We conduct a thorough examination of the results presented in Table (2) by isolating different forecast variables. Specifically, we separately analyze financial indicators (such as T-bills), GDP, and real economy measures (including industrial production and unemployment) to determine if our findings hold across these different economic dimensions.

Table 19: OLS Regression: Specific Variables

	FE^2 Financial (1)	FE^2 GDP (2)	FE^2 Real (3)
Domestic	-0.02***	-0.03	-0.48***
	(0.01)	(0.03)	(0.18)
VIX	0.03**	1.27***	7.57***
	(0.02)	(0.19)	(0.88)
Domestic × VIX	-0.01	0.00	-0.62**
	(0.00)	(0.03)	(0.29)
US	0.06***	-0.85***	-4.30***
	(0.02)	(0.09)	(0.57)
Domestic × US	0.08***	0.27***	1.17***
	(0.02)	(0.07)	(0.29)
Domestic × VIX × US	0.03*	0.07	1.50***
	(0.02)	(0.07)	(0.34)
N	61815	56042	75759
R^2	0.007	0.084	0.047
adj. R^2	0.007	0.084	0.047
Clusters, Time	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 forecast errors, 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.4.3 Controlling for Recessionary Periods.

We now show that our results are robust to controlling for business cycle fluctuations, by looking at expansionary vs recessionary periods. We thus compute dispersion as it follows:

Table 20: OLS Regression: Controlling for Recession

	FE^2 (1)	FE^2 (2)	FE^2 (3)
Domestic	-0.65***	-0.09	-0.61***
	(0.10)	(0.08)	(0.18)
VIX	1.05**	0.93*	1.01**
	(0.48)	(0.48)	(0.49)
Domestic × VIX	-0.60***	-0.58***	-0.60***
	(0.12)	(0.12)	(0.12)
US	-1.19***	0.00	-1.20***
	(0.26)	(.)	(0.27)
Domestic × US	0.56***	0.16	0.31
	(0.11)	(0.11)	(0.30)
Domestic × VIX × US	0.82***	0.83***	0.69***
	(0.17)	(0.18)	(0.16)
Recession	13.77***	14.02***	13.33***
	(2.94)	(3.00)	(2.92)
N	213562	213562	213562
R^2	0.045	0.191	0.052
adj. R^2	0.045	0.190	0.051
FEs, Variable × Country	No	Yes	No
FEs, Bank ID	No	No	Yes
Clusters, Time	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 forecast errors, calculated as shown in section 4. 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.4.4 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 21: OLS Regression: Dispersion

	Dispersion (1)	Dispersion (2)	Dispersion (3)
Domestic	-0.12***	-0.08***	-0.19***
	(0.02)	(0.02)	(0.05)
VIX	0.26***	0.26***	0.27***
	(0.09)	(0.09)	(0.09)
Domestic × VIX	-0.04*	-0.04**	-0.06**
	(0.02)	(0.02)	(0.03)
US	-0.30***	0.00	-0.35***
	(0.08)	(.)	(0.10)
Domestic × US	0.11***	0.06***	0.28***
	(0.02)	(0.02)	(0.10)
Domestic × VIX × US	0.04	0.04*	0.06**
	(0.03)	(0.03)	(0.03)
N	220293	220293	220293
R^2	0.002	0.025	0.005
adj. R^2	0.002	0.025	0.004
FEs, Variable × Country	No	Yes	No
FEs, Bank ID	No	No	Yes
Clusters, Time	Yes	Yes	Yes

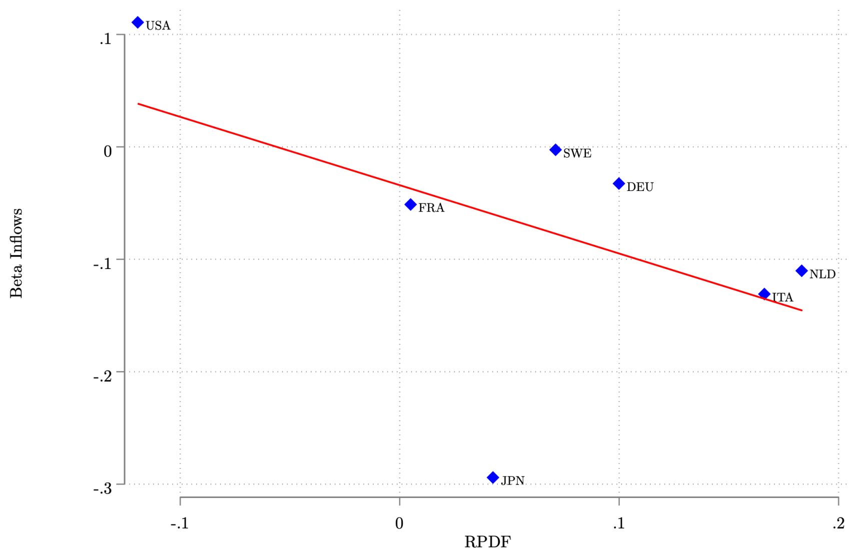
Notes: The Table reports the results of the model specification described in this section to capture the effect that a one standard deviation increase in uncertainty has on dispersion, calculated as shows in this section of the appendix. We use the VIX index as a measure of uncertainty. Standard errors,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

C.4.5 Equity Flows and Information: a Continuum of Countries

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 country, 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 cost for foreign (θ_{kk}) and domestic (θ_k) investors.

In this section, we test whether the countries that exhibit a greater domestic information advantage also exhibit stronger declines in capital inflows in periods of high uncertainty. In Figure 15, we show a scatterplot of countries that are in both our equity flows and forecast data, where on the x-axis we report the relative precision of domestic forecasters (RPDF), and in the y-axis the sensitivity of capital inflows to the VIX. While the sample of countries is small, there is a noticeable negative relationship, as predicted by our model: countries that have a stronger domestic information advantage (RPDF) exhibit a stronger reduction in inflows during periods of high uncertainty, while countries with a small domestic advantage, *in primis* the United States, are more insulated from such uncertainty episodes.

Figure 15: Information and Equity Inflows in Uncertain Times



Notes: This graph is a scatter capturing the correlation between equity inflows and RPDF. Each point represents a specific country in our merged dataset. In high uncertainty we end up with 7 countries, since 3 do not have observations with more than one standard deviation in uncertainty (limited sample), where uncertainty is measured by the VIX index.