Equity Flows in Uncertain Times: the Role of Heterogeneous Information

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This Draft: July 16, 2024

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 forecasting 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.

JEL Codes: E3, E7, F21, F36, G11, D82
Keywords: Home bias, Uncertainty shocks, Information asymmetries, Expectation formation, Capital flows.

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1 Introduction

Capital flows across countries are a fundamental aspect of the global economy and play a crucial role in fluctuations in output and asset prices. Recent literature, summarized in Coeurdacier and Rey (2013) and Miranda-Agrippino and Rey (2022), has documented the salient features of the global financial cycle, showing that not only investors tend to exhibit strong home bias in portfolio choices, [1] but that during downturns investors retrench towards their home country. Furthermore, episodes of global distress are typically associated with a 'flight to safety', with investors flowing towards safe assets and the United States. Yet, there is still no cohesive explanation for these phenomena.

We first outline the stylized facts of the global financial cycle that motivate this paper, which are are summarized in Figure 1. These results extend the literature by using equity flow data from Koepke and Paetzold (2022), and clearly show that when global uncertainty increases, as measured by the VIX, equity investors tend to retrench towards their home country, with the notable exception of the United States.[2]

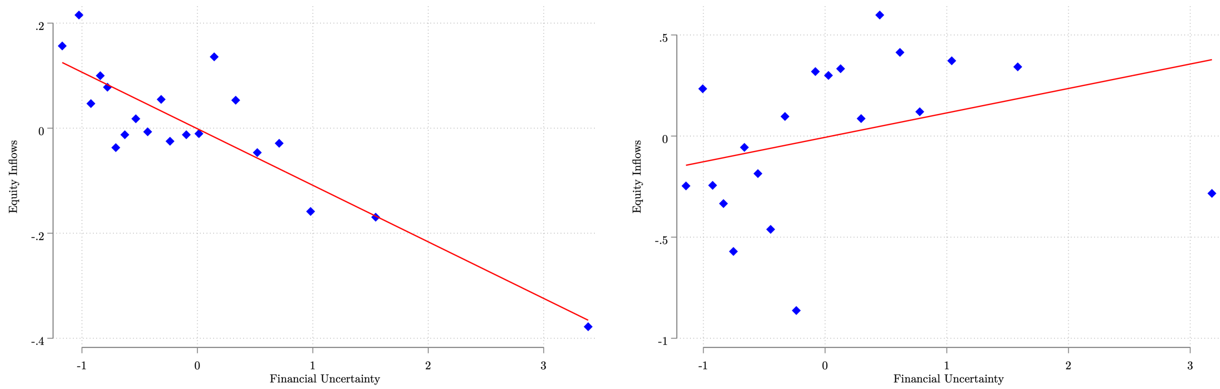
The core contribution of this paper is to formalize and empirically test the hypothesis that the heterogeneity in information across countries can explain the observed behavior of investors during periods of increased global uncertainty. The existing literature has explored alternative explanations for these phenomena, such as some countries being more exposed to global shocks, or the concepts of 'flight to quality' and 'flight to safety', which describe investors' tendencies to move their capital towards safer or higher-quality assets during times of economic stress. Our approach is to formalize a tractable model with endogenous learning in which the only source of heterogeneity is in the information access across investors in different countries, without relying on additional assumptions on differential exposure to global shocks, and to test the predictions of the model on information accuracy using microdata on forecaster accuracy.

We build a model of 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, with learning costs varying by

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

[2] 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).

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.

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 (2011) 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 observed 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.

We validate our model using data from *Consensus Economics*, which provides a measure of forecast precision across different pairs of countries categorized by the origin of the investor and the target asset. This data serves as the appropriate empirical counterpart to our theoretical concept of heterogeneous learning costs. Our analysis reveals that investors demonstrate greater accuracy when forecasting the economic conditions of their own country, which supports the notion of a home information advantage. Moreover, this superior forecasting ability of domestic investors becomes even more pronounced during periods of elevated global 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. Furthermore, when we isolate the data for the United States, we observe a different dynamic. There is no clear informational advantage for domestic forecasters in the U.S., nor is there a distinct pattern correlating increased uncertainty with forecast accuracy. This lack of a home information advantage in the United States is consistent with its characterization as an information haven, 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, which provides benchmark observations about their behavior under various economic conditions, as discussed in Caballero and Simsek (2020). Our contribution enriches this body of literature by focusing on the behavior of investors during times of uncertainty, in a manner similar to Akinci and Kalemli-Ozcan (2023), Choi et al. (2023). Our contribution consists in focusing on the impact of uncertainty on equity flows, highlighting 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.

Third, we contribute to the literature that studies empirically the existence of local information advantage, such as in Benhima and Bolliger (2023) [3]. We contribute in this literature by using *Consensus Economics* data to provide evidence of local information advantages in times of uncertainty, with the exception of the United States. We then claim that the information channel is able to explain capital flows in times of uncertainty, raising a similar point such as in Chahrour et al. (2021).

Outline. The paper is organized as it 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 works in explaining capital flows in an uncertainty environment. Section 4 uses *Consensus Economics* data to provide support to the prediction highlighted in the model. Section 5 concludes.

2 Motivating Facts

In this section, we aim to present foundational evidence for our entire paper. 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 main dataset is a country-month level panel data from the work of Koepke and Paetzold (2022), covering the period from 1997 to 2023. This dataset contains information on each country equity inflows and outflows, which is based on the IMF balance of payment definition of portfolio equity. We also include several measures of uncertainty: VIX index, VSTOXX index and financial and macroeconomics uncertainty from Jurado et al. (2015). More information about the structure of this dataset are in Appendix (A.1). In this initial analysis, we concentrate on examining the relationship between uncertainty and equity flows.

[3]Several papers have contributed in this stream of the literature, as in Coibion and Gorodnichenko (2015), Bordalo et al. (2020).

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):

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

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 U_{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. In this case, if β captures the sensitivity of equity flows to uncertainty on average. $\beta < 0$ would suggest that foreigners reduce their investments in a specific country i when uncertainty is higher. On the other hand, the sensitivity to uncertainty of inflows in the US will be given by $\beta + \beta_{US}$. So that if $\beta_{US} > 0$ would suggest that flows in the US are less sensitive to the level of uncertainty. 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.

Table 1, shows evidence of equity fickleness (negative inflows) and retrenchment (negative outflows) when the economy experiences higher volatility [4]. Here we use the VIX index to measure uncertainty, probably the most common measure exploited in the literature. In column 1 we just look at unconditional correlation between equity inflows and financial uncertainty, adding the interaction with the United States. On average a one standard deviation shock of uncertainty relates negatively with inflows, by around 6%, meaning that foreigners reduce their holdings abroad. This results is confirmed in column 2, where we control for GDP growth. It is interesting to notice that, on the converse, β_{US} is positive, and it remains positive even when we subtract the the average effect, meaning that foreigners do not reduce their equities in the United States in more uncertain time. On the opposite, they tend to increase them, by around 8%. Column 3 shows the unconditional correlation between equity outflows and financial uncertainty, adding the interaction with the United States. On average a one standard deviation shock of uncertainty relates negatively with outflows, by around 3%, meaning that domestic reduce their holdings abroad. This results is confirmed in column 4, where we control for GDP growth. Column 3 and 4 confirm that equity flows are subject to retrenchment in bad times, a benchmark case in the literature, as in Miranda-Agrippino and Rey (2015) and Caballero and Simsek (2020). In this case there is no asymmetry between the United States and the other countries, on average, meaning

[4] The equity inflows of a country are the net purchases of domestic equity by foreign investors. The equity outflows of a country are the net purchases of foreign equity from domestic investors.

Table 1: Uncertainty and Equity Flows

	Inflows (1)	Inflows (2)	Outflows (3)	Outflows (4)
VIX Index	-0.088***	-0.091***	-0.067***	-0.068***
	(0.014)	(0.014)	(0.016)	(0.017)
VIX Index × US	0.177***	0.182***	-0.048**	-0.048**
	(0.018)	(0.018)	(0.018)	(0.018)
GDP Δ%		0.010***		-0.001
		(0.003)		(0.004)
N	8003	7940	6506	6452
Country FEs	Yes	Yes	Yes	Yes

Notes: This table reports the correlation coefficients of the specified OLS regression. Both dependent and indepentent variables are standardized to the mean and GDP % is yearly GDP growth. As an additional control, there is also lagged inflows. Data are from Koepke and Paetzold (2022), collected from 47 countries, as shown in A.1. We use VIX index as a measure of uncertainty. Standard errrors, clustered at country level, are reported in parenthesis. $*$ = 10% level, $**$ = 5% level, and $***$ = 1% level. See the appendix for additional information on variables construction.

that all countries, on average, retrench as uncertainty goes up.

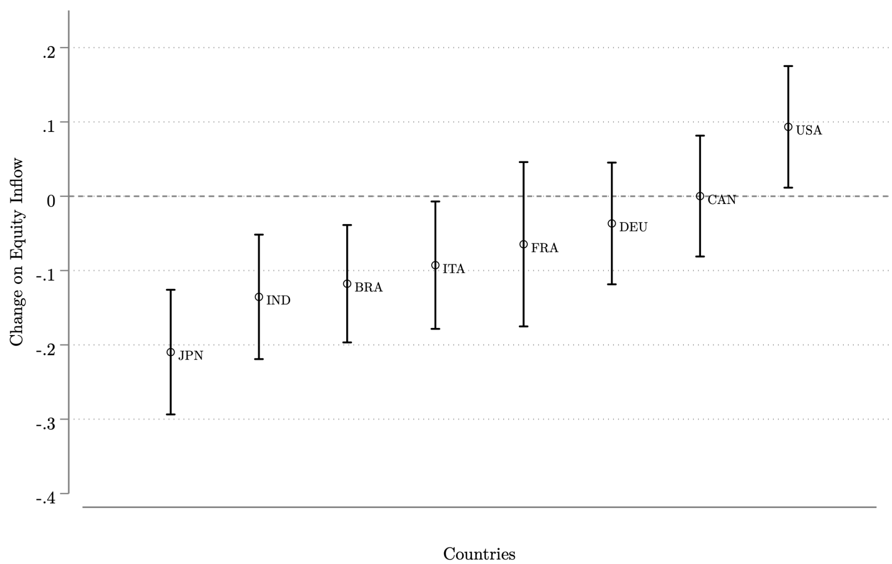
We then want to perform a simple model specification, to check whether this result is consistent across countries and not biased by some outliers. Therefore we perform the following regression method to each specific country in our sample:

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

where also in this case we restrict our Y_{it} to be equity inflows, β be the correlation coefficient between uncertainty and equity inflows and X_{it} be a set of controls, such as lagged Y_{it} and GDP growth. Figure 2 shows how β varies depending on the country, and it is possible to see that this relation is consistent when comparing the G7 countries. In the Appendix (A.2) we also look at the consistency of these results for the entire sample of 47 countries, leaving the United States as 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

Figure 2: Uncertainty and Equity Inflows



Notes: This plot shows the relation between uncertainty and equity inflows, comparing the G7 countries. Data are from Koepke and Paetzold (2022), collected from 47 countries, as shown in A.1. Both dependent and independent variables are standardized to the mean. The confidence intervals are set at 95%.

States from other countries during periods of heightened economic volatility.

Robustness Checks. To ensure the robustness of our results, we perform a comprehensive battery of robustness checks. First, we examine whether the observed correlations remain consistent when employing alternative measures of uncertainty, both global (VSTOXX and Financial Uncertainty from Jurado et al. (2015)) and local. We obtain similar results when using a measure of local uncertainty, as outlined in Ozturk and Sheng (2017), which is important for interpreting our model accurately. Additionally, 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.

Furthermore, we assess whether our results hold true across the entire sample of countries, thereby eliminating potential outliers that might skew our findings. We also verify the consistency of our results when controlling for recessionary periods specifically in the United States, ensuring that the observed patterns are not merely driven by economic downturns.

Lastly, we examine the impact of limiting the distribution's tail in uncertainty by excluding observations beyond one standard deviation. This test is essential to determine whether the information channel, as proposed in our hypothesis, operates independently of the well-documented flight-to-quality narrative. Similarly, we check whether recessionary period might absorb this effect, thus testing if an alternative story to the already known 'flight to quality' channel exists.

These extensive robustness checks are detailed in Appendix (A.2).

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 heterogenous forecast accuracy towards asset payoffs and equity flows. 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 in the first period, in the form of a 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 ik 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 (*e.g.* domestic investors, or neighboring 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, it is useful to refer to *standard countries* as those countries that have $\theta_{kk} < \theta_k$, exhibiting to domestic information advantage. That is, for a standard country information is cheaper to collect for domestic investors. Instead, we will refer to *information haven countries* as those countries that behave exceptionally, and have $\theta_{kk} \geq \theta_k$. In the Section 4, we will connect our theoretical definition of an *information haven country* to the empirical behavior of the United States, but we keep the more general term of *information haven country* throughout the theory section.

We will now formally present the investor problem proceeding backward. We will start with the investment decision in the second period, which is standard, and then move to the research decision problem in first period, where we will discuss the information heterogeneity in greater detail.

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 $\{x_{i,k}\}_{k=1}^{N}$ to maximized expected utility over the next period:

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

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

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

$$x^U_{i,k} = \frac{\mu_k - r^f p_k}{\eta \sigma^2_k} \tag{2}$$

Under the assumption that $\kappa \to 1$, the market-clearing price for each asset is determined by the demand of unsophisticated investors in all countries, which suggests

$$\sum_{i=1}^{N} \int_U x^U_{i,k} dU = 1 \tag{3}$$

and yields the equilibrium asset price p_k as

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

Equilibrium prices only contain information of the prior distribution, as they only aggregate the unsophisticated investors' information sets. Therefore, despite prices being public signals, investors don't learn additional information about the stochastic payoffs from prices. This is crucial since it allows us to break the no-trade theorems, and have trading and capital flows in equilibrium.

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

$$x^S_{i,k} = \frac{\widehat{r}_{ik} - \mu_k + \eta \sigma^2_k}{\eta \widehat{\sigma}^2_{ik}} \tag{6}$$

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

$$
\begin{bmatrix}
\theta_{11} & \cdots & \theta_{1k} & \cdots & \theta_{1n} \\
\vdots & \ddots & \vdots & & \vdots \\
\theta_{i1} & & \theta_{kk} & & \theta_{in} \\
\vdots & & \vdots & \ddots & \vdots \\
\theta_{n1} & \cdots & \theta_{nk} & \cdots & \theta_{nn}
\end{bmatrix}
$$

$$
\begin{bmatrix}
\theta_1 & \cdots & \underbrace{\theta_k}_{\frac{N}{\sum_i \frac{1}{\theta_{ik}}}} & \cdots & \theta_n
\end{bmatrix}
$$

Table 2: Information Cost Matrix. θ_{ik} captures the cost for investors located in country i to acquire information about the assets of country k. θ_{kk} is thus the cost of research for domestic investors in country k. $\theta_k = \frac{N}{\sum_i \frac{1}{\theta_{ik}}}$ is the harmonic average information cost about country k among all world's investors.

3.3 Information Choice

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

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

The cost function is additive separable in signal precision for each asset and takes the form

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

The key assumption for the cost function is that investors in different countries face different information acquisition cost or research cost. In principle, this specifies N^2 parameters. However, we will show that capital flows 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. These elements are visually summarized in the information cost matrix in Table 2.

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, when $k = i$, the inequality implies that it is easier for country i's investors to learn about the domestic asset than foreign assets. In addition, the cost may not be symmetric, θ_{ik} is not the same as θ_{ki} for $k \neq i$. When discussing capital flows in Section 3.4, we will show that θ_k and θ_{kk} are the two relevant summary statistics to determine the sign and magnitude of capital flows in country k during episodes of aggregate uncertainty, and we will distinguish between two types of countries. For the first type, a *standard country* labeled by s, we will assume that domestic investors have a learning cost θ_{ss} that is lower than the harmonic average cost for worldwide investors θ_s: $\theta_{ss} < \theta_s$. For the second type, an *information haven country* labeled by h, the reverse holds and $\theta_{hh} \geq \theta_h$.

The following result then 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.

From the optimal information decision, an immediate implication is that investors in different countries may learn differently about assets. In our model setup, such difference arises from varying learning costs $\{\theta_{ik}\}$. The relative forecast precision, which is of particular interest to us, depends on both investors' learning cost and the asset's prior uncertainty.

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 consider the capital flows after the uncertainty of asset k increases. We define capital inflow for country k as:

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

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:*

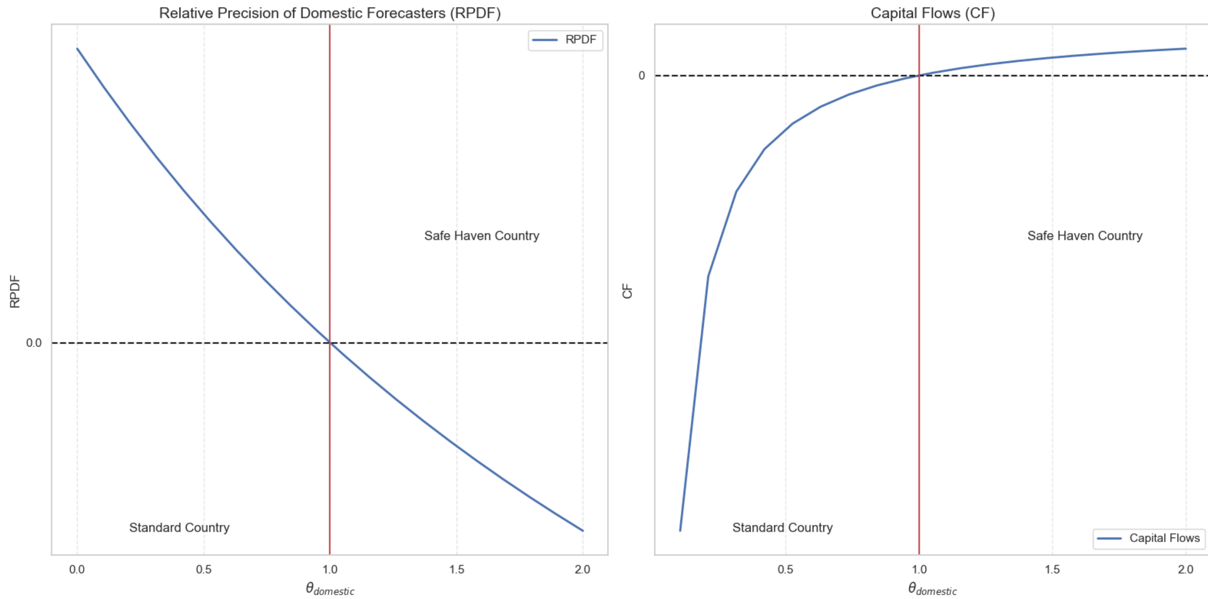
$$CF_k \propto \underbrace{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\theta_{ik}}}_{1/\theta_k} - \frac{1}{\theta_{kk}} \tag{13}$$

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}). For the case of a *standard country* with $\theta_k < \theta_{kk}$, domestic investors have an information advantage, and they thus hold a larger fraction of the outstanding domestic assets when uncertainty increase, triggering the capital flows patterns.

Summary of model predictions. We end this section by comparing the results for two types of countries that differ in their patterns of $\{\theta_{ik}\}$. Recall that for the first type, a standard country labeled by s, domestic investors have a learning cost θ_{ss} that is lower than the harmonic average cost for worldwide investors $\theta_s \equiv \frac{N}{\sum_{i=1}^{N}\frac{1}{\theta_{is}}}$. For the second type, an information-haven country labeled by h, the reverse holds and $\theta_{hh} \geq \theta_h \equiv \frac{N}{\sum_{i=1}^{N}\frac{1}{\theta_{ih}}}$.

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 a safe haven country, with $\theta_d \geq \theta_f$.

From Proposition 1 and Proposition 2, domestic investors in country s have higher forecast precision of domestic assets than foreign investors. In addition, when uncertainty for asset payoff r_s increases, such information superiority for domestic investors is more salient, while at the same time country s experiences negative capital inflow. The opposite is true for 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 carachterized by $\theta_d < \theta_f$, into a safe haven country environment, which is carachterized by $\theta_d \geq \theta_f$ [5]. In the Appendix B we also show the dynamics of RPDF and CF for different values of σ^2.

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

4 Empirical Analysis

What is the relative performance of foreign and domestic forecasters when predicting an economy? And if there is a domestic information advantage, does this change across different countries and with the level of uncertainty? Our illustrative model has shown that heterogeneous learning on assets between local and foreign investors can generate equity flows in times of heightened uncertainty, tying together the sign of equity flows and the relative forecast accuracy between local and foreign investors. In this section, we provide novel empirical evidence on how local investors' forecast accuracy relative to foreigners vary with uncertainty, and on the special patterns in the forecast data of the United States.

In order to measure forecast precision and how it varies with uncertainty, we use data from *Consensus Economics*[6], as in related work by De Marco et al. (2022) and Benhima and Bolliger (2023). The data contains country-specific forecasts provided by public and private institutions, such as investment banks, universities, research organizations, and large corporations. The magnitude of forecast errors 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

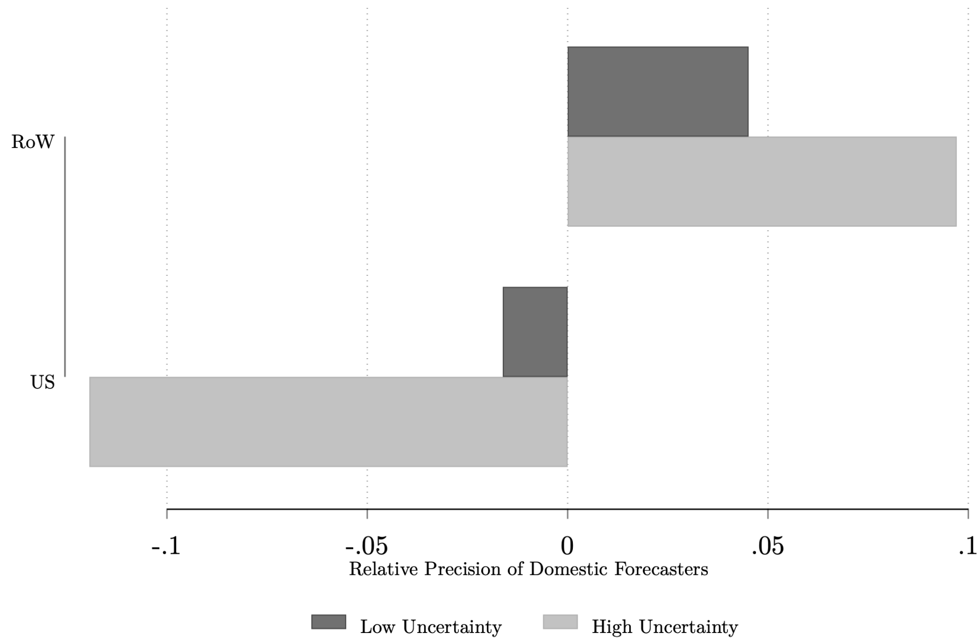
To study the information advantage of domestic investors, we construct a measure of forecast precision for each country for domestic and foreign forecasters over the five variables available in the forecast data[7]. Then, we define as Relative Precision of Domestic Forecasters (RPDF) as the percentage difference between the average foreign forecast error and the average domestic forecast error[8]. 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.

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

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

[8] Since forecast errors are prone to outliers and numbers close to zero, we use the ratio popularized by Haltiwanger to deal with zeros, $RPDF = 2 \times \frac{RFE^f - RFE^d}{RFE^f + RFE^d}$, which approximates a percentage difference between RFE^f and RFE^d when the two numbers are close, but is bounded between -2 and +2.

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.

Figure 4 illustrates the relative precision of domestic forecasters across countries during periods of low and high uncertainty[9], and comparing the rest of the world with the United States. Focusing first on countries other than the US, we first 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 low and heightened uncertainty. Such evidence is consistent with our model predictions when the cost of research is higher for foreign economies than for domestic ones, i.e., Proposition 1 in the Theoretical Analysis (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

[9]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.

in predicting economic variables during periods of high uncertainty. The special behavior of the United States is in line with the definition of an *information haven* in our model.

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 time-specific and forecaster-specific effects.

In Table 3, we demonstrate the robustness of our findings using the OLS specification (22) reported in the Appendix (C.2). Specifically, we estimate the average effect of domestic forecasters on forecast errors during periods of uncertainty and the marginal effect for the United States, respectively. 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 forecaster-specific variables and the country of prediction. The inclusion of forecaster-specific fixed effects is crucial to mitigate potential biases arising from consistently superior forecasters. For instance, if Goldman Sachs consistently outperforms the University of Colorado in economic predictions, this fixed effect accounts for Goldman Sachs' informational advantage. It is important to note, however, 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 performance often results from greater resource investment in making those predictions.

Main Results To sum up, both approaches suggest 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 the Theoretical Analysis (3) [10].

Specifically for the United States, this superior performance by foreign investors may be

[10] We also control for each country-specific coefficient, as shown in Appendix C.3. Notably, Canada, Switzerland, and the United States are the only countries showing a positive coefficient. Various factors might explain why not only the United States benefit from better forecasts from foreign institutions. Since our focus is on explaining positive changes in equity inflows into the United States, we do not deepen further into this evidence.

Table 3: Second approach: OLS and FE[2]

	SD Forecast Error (1)	SD Forecast Error (2)	SD Forecast Error (3)
Domestic	-0.603***	-0.772***	-0.052
	(0.089)	(0.218)	(0.078)
VIX	3.337***	0.000	3.244***
	(0.431)	(.)	(0.417)
Domestic × VIX	-0.541***	-1.031***	-0.526***
	(0.114)	(0.321)	(0.106)
US	-1.432***	-1.855***	0.000
	(0.251)	(0.329)	(.)
Domestic × US	0.822***	0.772**	0.437***
	(0.146)	(0.362)	(0.136)
Domestic × VIX × US	0.845***	1.413**	0.861***
	(0.152)	(0.545)	(0.146)
N	213562	83533	213562
R^2	0.022	0.701	0.167
adj. R^2	0.022	0.601	0.166
FEs, Variable × Bank ID × Time	No	Yes	No
FEs, Variable × Country	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.

attributed to significant investments by major institutions and banks headquartered outside the U.S. These entities often station numerous forecasters in American branches and allocate substantial resources to research focused on the U.S. 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 Forecast Precision and Equity Flows: Information Channel

We now aim to empirically test whether the information channel can explain, at least in part, investor behavior during periods of increased uncertainty, reflecting similar patterns in terms of equity inflows across countries.

Our empirical results have suggested that for a standard country, the domestic cost of

Table 4: Second approach: OLS and FE[2]

	Inflows (1)	Inflows (2)	Inflows (3)
ξ	-0.028**	-0.030**	-0.031**
	(0.012)	(0.011)	(0.012)
ξ × US		0.077***	0.078***
		(0.013)	(0.013)
N	891	870	870
Country FEs	Yes	No	Yes

Notes: The Table reports the results of the model specification described in this section to capture the effect that a one standard deviation increase in fitted forecast error has on equity inflows, calculated as shows in this section of the Appendix (C.2). We use the VIX 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.

research is lower than foreign costs, i.e., $\theta_d < \theta_f$. In this scenario, we would expect equity retrenchment during times of uncertainty for foreigners. However, in the case of the United States, which is an information safe haven, foreigners may have even better information about the economy. This could predict foreign investors to either maintaining or increasing their investments in the United States when uncertainty spikes.

To empirically test these predictions in the data, we need to merge our dataset on capital flows with data on forecast errors. This integration will allow us to isolate the information channel as effectively as possible and determine whether forecast errors, serving as a proxy for signal precision during times of uncertainty, can explain equity flows as predicted in our model and as suggested by the broader literature on capital flows. This final piece of evidence would be crucial, as it would validate our model's predictions along with our motivational evidence.

We thus implement a 2SLS model to determine whether this channel exists and its sign. We first run the same OLS specification we used to test the correlation between forecast errors and local forecasters in uncertain times. We then collect the fitted values of this specification to check on their correlation with equity inflows. Details on this empirical specifications can be found in Appendix (C.2).

As shown in Table 4, our hypothesis aligns with the correlation coefficients obtained through our 2SLS model. Indeed, columns 1, 2, and 3 consistently demonstrate the same sign and similar magnitude of correlation between equity inflows and fitted values of squared forecast errors. This evidence further confirms that information plays a critical role and significantly influences capital flow directions, in line with Proposition 2 in the Theoretical Analysis (3). Specifically, we have shown that during periods of increased uncertainty, the direction of flows is generally negatively affected by an increase in relative domestic forecast errors, except in the case of the United States.

4.3 Robustness Checks

We begin our robustness analysis by verifying whether the correlations in our initial results retain the same sign and significance when using alternative measures of uncertainty, to ensure that our findings are not dependent on a specific definition of uncertainty. Additionally, we conduct a thorough examination of the results presented in Figure (4) and Table (3) by isolating different forecast variables. Specifically, we separately analyze financial variables (T-bills), GDP variables, and real economy variables (industrial production and unemployment) to determine if 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 introduce a measure of dispersion, which serves to mitigate the impact of unexpected economic shocks. This measure helps ensure that our results are not unduly influenced by outlier events or sudden economic changes. Finally, we also look at how these results look like when isolating our attention to specific countries in our sample. These comprehensive robustness checks, detailed in Appendix C.3, provide strong validation for our findings and underscore the reliability of our model's predictions.

We also examine whether these results hold true when employing measures of country-specific uncertainty, as in Ozturk and Sheng (2017). In Appendix C.3, we validate our predictions using this local proxy of uncertainty.

To further validate our findings across a broader range of countries, beyond just comparing the United States with the rest of the sample, we assess whether this pattern persists. As demonstrated in Appendix C.4, our findings support the hypothesis that the information channel explains equity flows during uncertain times. This extended analysis strengthens our conclusions and underscores the robustness of our results.

To mitigate potential biases in our estimates, such as a flight-to-quality effect driving equity flows into the United States, we include a variable representing consumer confidence across countries and different time periods. We re-estimate our 2SLS regression model, incorporating this variable in the second stage. This analysis is detailed in Appendix C.3. Ideally, if the theory of 'flight to quality' fully explains the effect of our information channel, this variable of consumer confidence will capture the impact. These supplementary tests further validate our findings and underscore the reliability of our model's predictions.

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 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. Furthermore, the model predicts that capital should flow towards *information haven* countries - transparent countries that do not have a home information advantage - during episodes of uncertainties.

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.

Finally, we also uncover an intriguing exception to our forecast accuracy results. In the case of 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. This anomaly suggests unique dynamics at play within the US, potentially due to its prominent role in the global economy and the widespread availability of information about its economic conditions. The US behaves in line with the *information haven* country in our model, and this can rationalize why - unlike other countries - the US does 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:

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

This 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.

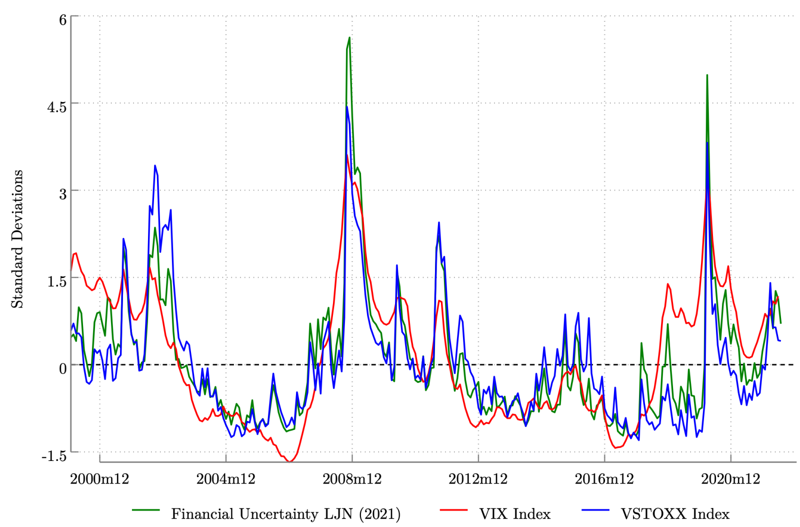
Merging the dataset with uncertainty measures. We then merge this data with uncertainty measures at monthly level, by using Jurado et al. (2015) measure, updated in 2021, VIX and VSTOXX, from Fred. Table 5 shows how these measures are distributed.

Table 5: Descriptive Statistics: Uncertainty

	Max	Min	N
VIX Index	5.628	-1.239	391
Financial Uncertainty JLN (2021)	3.608	-1.676	390
VSTOXX Index	4.436	-1.298	283
Global EPU	3.991	-1.194	307

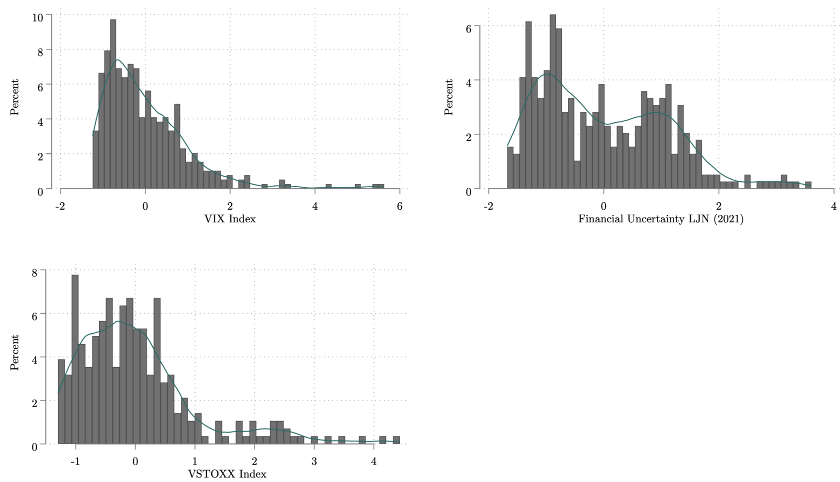
Notes: The Table reports the descriptive statistics of different measure of uncertainty. These measures are standardized to the mean.

Figure 5: Time Series: Uncertainty Measures



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

Figure 6: Distributions: Uncertainty Measures



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

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.

Dataset. We thus provide a descriptive statistics in Table 6, where we show how inflows and outflows are distributed for equity, bonds and capital (equity + bonds).

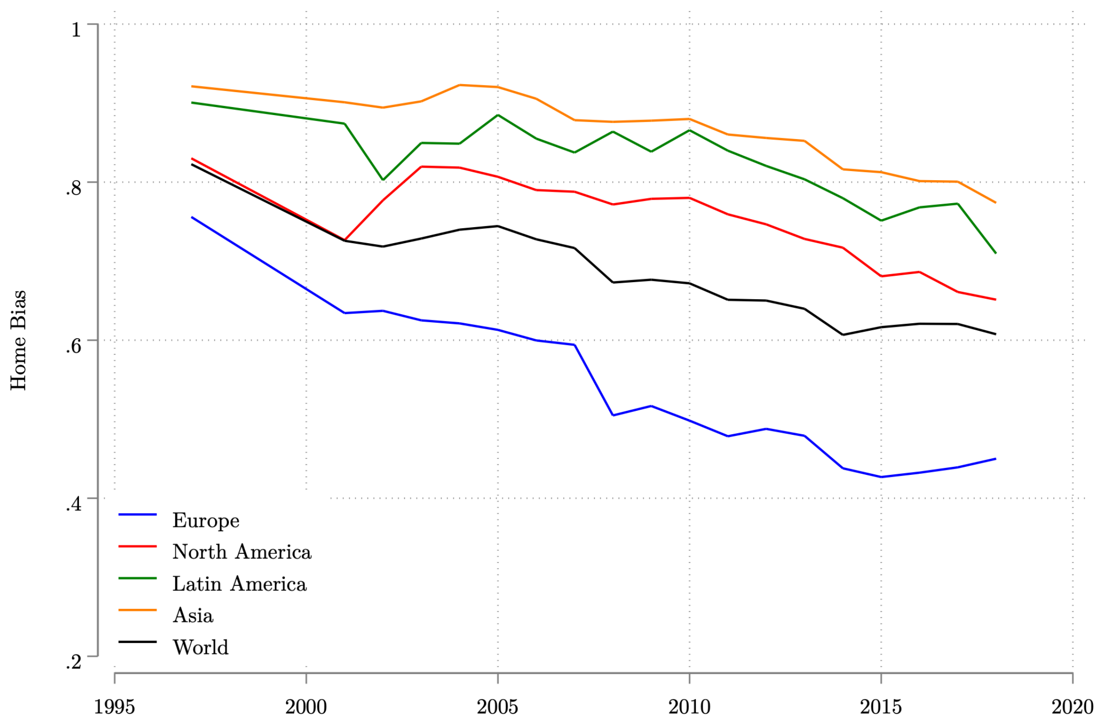
Table 6: Descriptive Statistics: Capital Flows

	Mean	SD	Median	Max	Min	N
Equity Inflows	0.541	12.291	0.006	300.336	-315.194	8524
Equity Outflows	1.610	10.900	0.038	185.502	-176.105	6911
Bonds Inflows	2.411	14.272	0.048	255.183	-403.597	8889
Bonds Outflows	1.526	9.263	0.049	174.174	-106.498	6911
Capital Inflows	2.842	18.489	0.111	443.645	-314.732	9752
Capital Outflows	2.700	14.157	0.111	298.151	-164.667	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 7: 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).

A.2 Robustness Checks

Alternative measures of uncertainty. We check whether ou results hold true when comparing different measures of uncertainty. We thus use both VIX and VSTOXX measures and implement the same regression specification as in section (2):

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

Table 7: Equity Inflows and VIX

	Inflows (1)	Inflows (2)	Outflows (3)	Outflows (4)
Financial JLN (2021)	-0.061***	-0.060***	-0.026**	-0.029**
	(0.012)	(0.012)	(0.013)	(0.012)
Financial JLN (2021) × US	0.137***	0.139***	-0.067***	-0.067***
	(0.015)	(0.015)	(0.016)	(0.016)
GDP Δ%		0.009***		-0.002
		(0.003)		(0.004)
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	-0.097***	-0.099***	-0.116***	-0.116***
	(0.013)	(0.014)	(0.025)	(0.025)
VSTOXX Index × US	0.164***	0.168***	-0.016	-0.016
	(0.015)	(0.015)	(0.025)	(0.025)
GDP Δ%		0.013***		-0.002
		(0.003)		(0.005)
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.

Additional Control Variables. We add some control variables, such as size of the stock market in each country (market capitalization), effective exchange rate and bond inflows, to check whether the results hold true even by increasing the boundle of control variables.

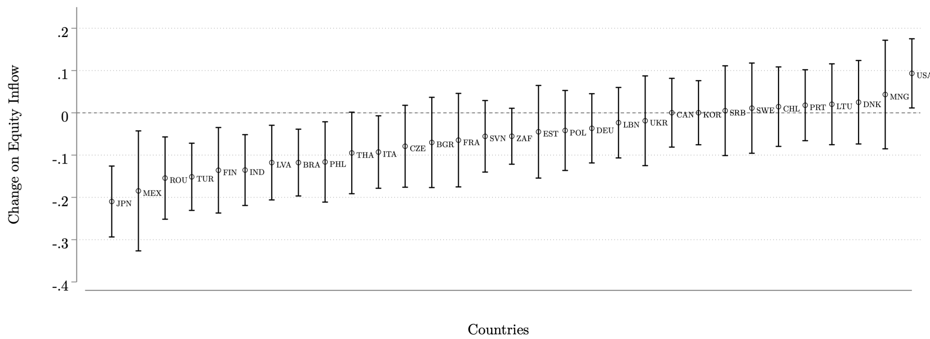
Table 9: Equity Inflows and Additional Controls

	Inflows (1)	Inflows (2)	Inflows (3)	Inflows (4)
VIX	-0.100***	-0.103***	-0.102***	-0.102***
	(0.014)	(0.015)	(0.018)	(0.018)
VIX $\times$ US	0.200***	0.201***	0.200***	0.200***
	(0.017)	(0.018)	(0.021)	(0.021)
GDP Δ%	0.012***	0.011***	0.010***	0.010**
	(0.003)	(0.003)	(0.004)	(0.004)
Size		0.055***	0.058**	0.058**
		(0.019)	(0.026)	(0.026)
EER			3.507**	3.483**
			(1.410)	(1.404)
Bond Inflows				0.001
				(0.003)
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.

Entire Sample: Equity Flows and Uncertainty. We now want to check whether 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%.

Controlling for Country Specific Uncertainty. We check whether the evidence holds true even by controlling for local uncertainty, using the measure of country specific uncertainty, as in Ozturk and Sheng (2017).

Table 10: Country Specific Uncertainty

	Inflows (1)	Inflows (2)	Inflows (3)
Country Uncertainty	-0.032*	-0.042**	-0.045**
	(0.017)	(0.015)	(0.016)
Country Uncertainty × US		0.149***	0.153***
		(0.021)	(0.022)
GDP Growth			0.009*
			(0.005)
N	5107	5107	5063
Country FEs	No	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.

Including a Control Variable for Recession. We check whether the evidence holds true even by including recession as a control variable in our specification model, in order to convince that there is a story beyond the channel of flight to quality.

Table 11: Equity Flows, Financial Uncertainty and Recession

	Inflows (1)	Inflows (2)	Inflows (3)
VIX Index	-0.091***		
	(0.014)		
VIX Index × US	0.182***		
	(0.018)		
Recession	0.002	-0.051	-0.049
	(0.040)	(0.047)	(0.042)
GDP Δ%	0.010***	0.009***	0.011***
	(0.003)	(0.003)	(0.003)
Financial JLN (2021)		-0.054***	
		(0.014)	
Financial JLN (2021) × US		0.139***	
		(0.015)	
VSTOXX Index			-0.086***
			(0.013)
VSTOXX Index × US			0.156***
			(0.015)
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 12: Equity Flows and Low Uncertainty

	Inflows (1)	Inflows (2)	Inflows (3)	Outflows (4)
VIX	-0.095***	-0.097***	-0.091***	-0.097***
	(0.017)	(0.017)	(0.025)	(0.026)
VIX $\times$ US	0.289***	0.293***	-0.043	-0.040
	(0.021)	(0.021)	(0.027)	(0.028)
GDP $\Delta\%$		0.012***		-0.000
		(0.003)		(0.006)
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

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

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

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

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

Take expectation in the first period, we obtain

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

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

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

To simplify notation, rewrite the equation above in terms of precisions, i.e. $\tau_k = 1/\sigma^2_k$ and $\widehat{\tau}_{ik} = \widehat{\sigma}^2_{ik}$, then

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

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

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

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,

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

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

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:

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

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:

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

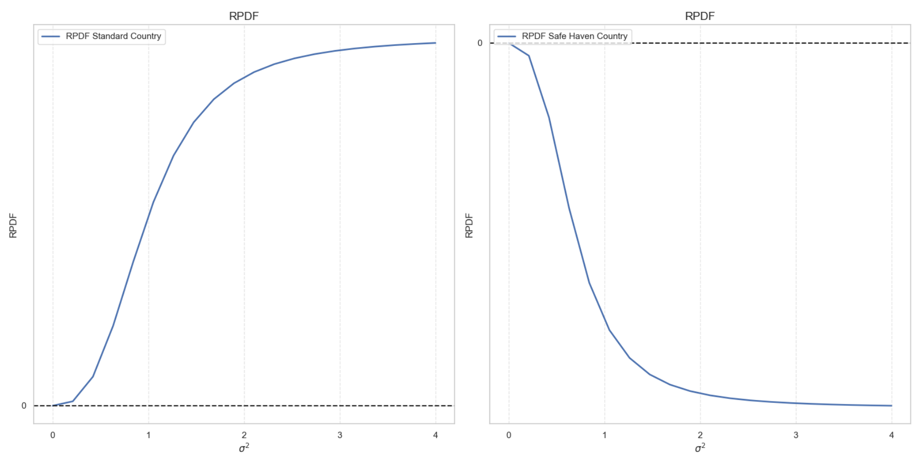
Hence,

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

B.1 Comparative Statics of the Model

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

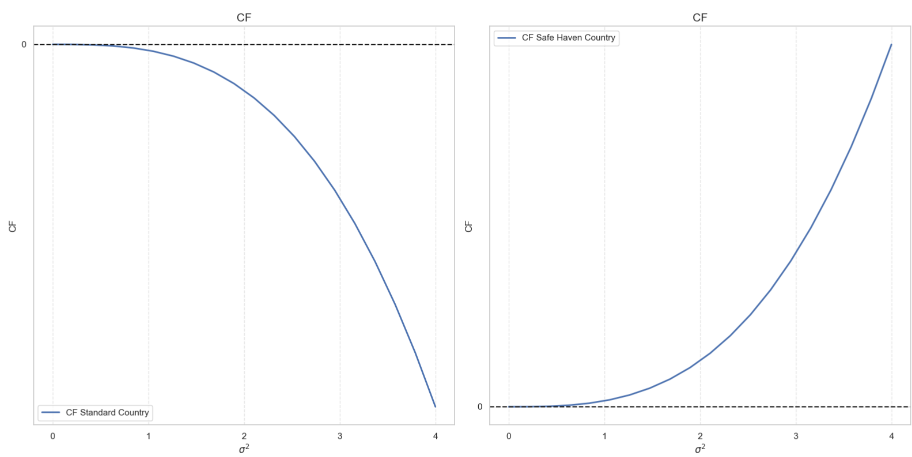
Figure 9: RPDF and CF changing σ^2



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 safe 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 (C.1). 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), industrial production, and GDP. 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. More details on the data construction are available in the Appendix (C.1).

- $\mathbb{E}_t(\%\mathbf{B}_{t+4,t});\mathbb{E}_t\%\mathbf{B}_{t+12,t})$ (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.

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

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

- $\mathbb{E}_t(\Delta\%\mathbf{UNEMP}_{y,y-1})$; $\mathbb{E}_t(\Delta\%\mathbf{UNEMP}_{y+1,y})$ (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 report descriptive statistics of the data in Table 13 and the resulting of a 1% trimming from both left and right tails in Table 14. Moreover, in Figure 11 we show the distributions of the variables we included in our dataset.

Table 13: Descriptive Statistics: Data from Consensus Economics

	Mean	Median	Max	Min	N
Long-Term T-Bills ($\Delta\%$ $m, m+4$)	-0.137	-0.138	3.399	-2.353	23800
Short-Term T-Bills ($\Delta\%$ $m, m+4$)	-0.028	-0.005	1.957	-4.250	23044
GDP $\Delta\%$ ($\Delta\%$ m, y)	0.039	0.100	6.743	-9.300	33330
FE1_IP	-0.932	-0.589	12.605	-45.405	23056
Unemployment Rate ($\Delta\%$ y)	-0.079	-0.075	4.125	-3.446	20987
Long-Term T-Bills ($\Delta\%$ $m, m+12$)	-0.622	-0.570	3.520	-3.758	23264
Short-Term T-Bills ($\Delta\%$ $m, m+12$)	-0.372	-0.171	2.347	-5.229	22638
GDP $\Delta\%$ ($\Delta\%$ $m, y+1$)	-0.377	-0.100	6.905	-8.600	32837
FE2_IP	-2.378	-1.465	23.554	-31.105	22525
Unemployment Rate ($\Delta\%$ $y+1$)	-0.203	-0.292	5.425	-4.958	20574

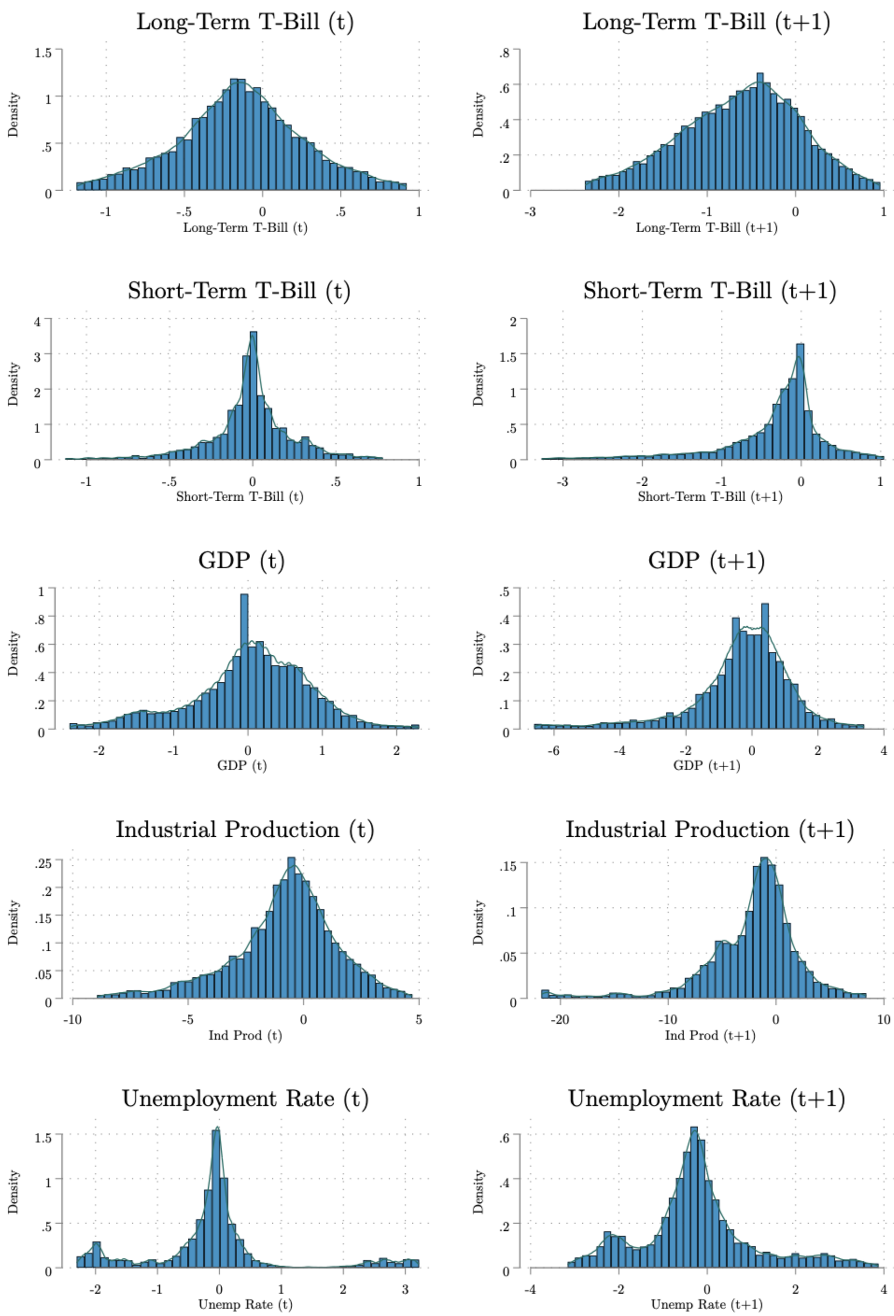
Notes: The Table reports a descriptive statistics of the variables we included in our dataset from *Consensus Economics* survey. We report mean, median, max, min and number of observations. In appendix ()C.1) we report the list of countries included in our dataset.

Table 14: Descriptive Statistics: Trimmed Data from Consensus Economics

	Mean	Median	Max	Min	N
Long-Term T-Bills ($\Delta\%$ $m, m+4$)	-0.138	-0.138	0.921	-1.189	23085
Short-Term T-Bills ($\Delta\%$ $m, m+4$)	-0.014	-0.005	0.782	-1.127	22361
GDP $\Delta\%$ ($\Delta\%$ m, y)	0.032	0.100	2.300	-2.400	32351
FE1_IP	-0.850	-0.589	4.710	-8.947	22366
Unemployment Rate ($\Delta\%$ y)	-0.096	-0.075	3.221	-2.304	20358
Long-Term T-Bills ($\Delta\%$ $m, m+12$)	-0.622	-0.570	0.958	-2.384	22569
Short-Term T-Bills ($\Delta\%$ $m, m+12$)	-0.345	-0.171	1.042	-3.269	21961
GDP $\Delta\%$ ($\Delta\%$ $m, y+1$)	-0.348	-0.100	3.400	-6.600	31871
FE2_IP	-2.253	-1.467	8.354	-21.758	21856
Unemployment Rate ($\Delta\%$ $y+1$)	-0.219	-0.292	3.875	-3.159	19962

Notes: The Table reports a descriptive statistics of the trimmed variables we included in our dataset from *Consensus Economics* survey. We trimmed 1% from both tails of teh distribution. We report mean, median, max, min and number of observations. In appendix ()C.1) we report the list of countries included in our dataset.

Figure 11: Uncertainty and Equity Inflows



Notes: Distributions of the main variables we included in our dataset from *Consensus Economics*. Data are 1% 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 an Haltiwanger measure comparing domestic and foreign forecast errors as it follows:

$$\mathrm{RP}_u^d = 2 \times \frac{\mathrm{RFE}_u^f - \mathrm{RFE}_u^d}{\mathrm{RFE}_u^f + \mathrm{RFE}_u^d} \tag{21}$$

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

$$\mathrm{RFE}_{H,L}^{f,d} = \sqrt{\frac{1}{I+J+C+T} \sum_{i,j,c,t} \mathrm{FE}_{i,j,c,t}^2 \mathbb{1}_{\{i=\text{Foreign},\mathbf{SD}_{H,L}\}}}$$

where FE is defined as in (23); I is the sum of individual forecasters; J is the sum of the forecast's variables, C is the sum of the forecasts over countries, T is the sum of the forecasts over time, H corresponds to any observation with more than one standard deviation of uncertainty from the norm and L corresponds to any observation with less than one standard deviation of uncertainty from the norm.

OLS regression of FE^2. 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 with a positive shock to uncertainty. What we expect is to obtain similar results, compared to the first approach, as we show later in the next paragraph. Thus, what we implement here is a typical OLS specification, as it follows:

$$\mathrm{FE}^2_{i,j,c,t} = \alpha + \alpha_{1j} + \beta\mathbf{D}_{i,c} + \beta_{US}\mathbf{D}_{i,c}\times\mathbf{US}_i + \tau\mathbf{US}_i + \gamma\mathbf{D}_{i,c}\times\mathbf{U}_t + \gamma_{US}\mathbf{D}_{i,c}\times\mathbf{U}_t\times\mathbf{US}_i + \varepsilon_{i,c,t} \quad (22)$$

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:

$$\mathrm{FE}^2_{i,j,c,t} = \left\{ \mathbf{x}_{i,j,c,t} - \mathbb{E}_{t-1}[\mathbf{x}_{i,j,c,t}] \right\}^2 \quad (23)$$

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.

2SLS: Testing the Information Channel

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

We then collect the fitted values of this regression, $\hat{\mathrm{FE}}^2{}_{ct}$, to see whether they explain the direction of equity flows in the following specification:

$$\mathrm{Y}_{c,t} = \alpha_{1i} + \xi\hat{\mathrm{FE}}^2{}_{c,t} + \xi_{US}\hat{\mathrm{FE}}^2{}_{c,t} \times \mathbf{US} + \mathrm{X}_{c,t} + \varepsilon_t, \quad (24)$$

where $\mathrm{Y}_{c,t}$ captures equity inflows across countries c and time t. This regression aims to quantify the impact of forecast errors during periods of heightened uncertainty on equity inflows. Specifically, we seek to determine whether ξ is positive or negative, indicating the presence or absence of fickleness in a specific country as prediction errors increase. The model predicts that, on average, countries should experience fickleness whenever the cost of research is lower in domestic economies than in foreign ones, as in a ‘regular’ country. If this holds true, we should expect $\xi \leq 0$. Conversely, for the United States, the marginal effect ξ_{US} should be positive and significantly different from zero, assuming it is an information haven.

C.3 Robustness Checks

Alternative measures of uncertainty. We now check whether the results hold true by using alternative measures of uncertainty, such as Financial Uncertainty and VSTOXX.

Table 15: OLS Regression: Financial Uncertainty

	SD Forecast Error (1)	SD Forecast Error (2)	SD Forecast Error (3)
Domestic	-0.787***	-0.965***	-0.211**
	(0.101)	(0.293)	(0.086)
Financial JLN (2021)	3.950***	0.000	3.859***
	(0.602)	(.)	(0.587)
Domestic × Financial JLN (2021)	-0.733***	-1.099***	-0.674***
	(0.104)	(0.388)	(0.100)
US	-1.929***	-2.247***	0.000
	(0.289)	(0.364)	(.)
Domestic × US	1.160***	0.913*	0.750***
	(0.170)	(0.466)	(0.160)
Domestic × Financial JLN (2015) × US	1.110***	1.434**	1.078***
	(0.132)	(0.625)	(0.130)
N	213562	83533	213562
R^2	0.027	0.701	0.172
adj. R^2	0.027	0.601	0.172
FEs, Variable × Bank ID × Time	No	Yes	No
FEs, Variable × Country	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 financial uncertainty index (Jurado et al. (2015)) as a measure of uncertainty. 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.

Table 16: OLS Regression: VSTOXX

	SD Forecast Error (1)	SD Forecast Error (2)	SD Forecast Error (3)
Domestic	-0.551***	-0.660***	0.002
	(0.091)	(0.210)	(0.072)
VSTOXX	3.318***	0.000	3.212***
	(0.598)	(.)	(0.587)
Domestic × VSTOXX	-0.519***	-0.923**	-0.507***
	(0.119)	(0.393)	(0.112)
US	-1.383***	-1.594***	0.000
	(0.283)	(0.339)	(.)
Domestic × US	0.797***	0.420	0.408***
	(0.157)	(0.327)	(0.139)
Domestic × VSTOXX × US	0.888***	1.051*	0.892***
	(0.133)	(0.630)	(0.127)
N	213562	83533	213562
R^2	0.015	0.700	0.160
adj. R^2	0.015	0.601	0.160
FEs, Variable × Bank ID × Time	No	Yes	No
FEs, Variable × Country	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 financial VSTOXX index as a measure of uncertainty. 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.

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 (including 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 relative more uncertainty, but not same sign for low uncertainty in the rest of the world.

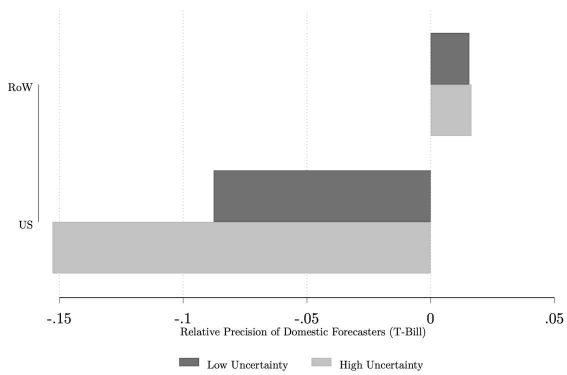


Figure 12: Financial Variables (T-Bills)

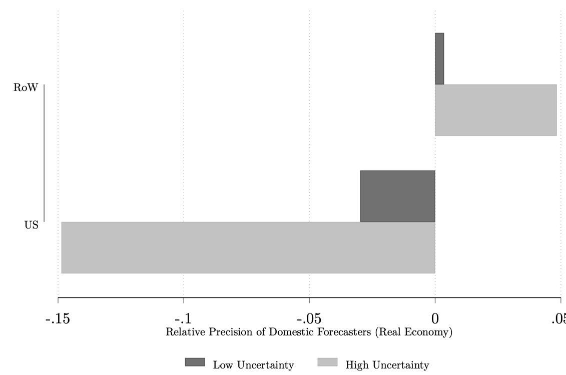


Figure 13: Real Economy Variables

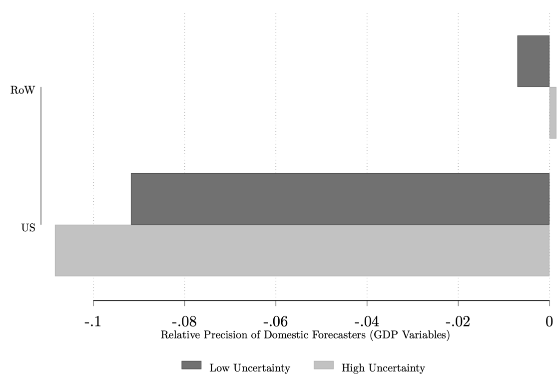


Figure 14: GDP Variables

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 (3) 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 17: OLS Regression: Specific Variables

	SD Forecast Error Financial Variables (1)	SD Forecast Error GDP Variables (2)	SD Forecast Error Real Economics Variables (3)
Domestic	-0.026***	-0.061*	-0.690***
	(0.006)	(0.036)	(0.204)
Financial Uncertainty (JLN 2021)	0.052***	1.518***	9.037***
	(0.016)	(0.277)	(1.276)
Domestic × Financial Uncertainty (JLN 2021)	-0.013***	-0.027	-0.912***
	(0.005)	(0.041)	(0.244)
US	0.067***	-1.063***	-5.504***
	(0.023)	(0.118)	(0.633)
Domestic × US	0.088***	0.356***	1.729***
	(0.021)	(0.087)	(0.330)
Domestic × Financial Uncertainty (JLN 2021) × US	0.031**	0.143*	1.998***
	(0.015)	(0.076)	(0.280)
N	61815	56042	75759
R^2	0.010	0.105	0.059
adj. R^2	0.010	0.104	0.059
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. See the appendix for additional information on variables construction.

Controlling for Recessionary Periods. We now want to check whether the results we have hold true even by controlling for business cycle fluctuations, by looking at expansionary vs recessionary periods. We thus compute dispersion as it follows:

Table 18: OLS Regression: Controlling for Recession

	SD Forecast Error (1)	SD Forecast Error (2)	SD Forecast Error (3)
Domestic	-0.648***	-0.772***	-0.092
	(0.098)	(0.218)	(0.084)
VIX	1.052**	0.000	0.934*
	(0.482)	(.)	(0.482)
Domestic × VIX	-0.601***	-1.031***	-0.582***
	(0.124)	(0.321)	(0.116)
US	-1.192***	-1.855***	0.000
	(0.256)	(0.329)	(.)
Domestic × US	0.559***	0.772**	0.158
	(0.111)	(0.362)	(0.115)
Domestic × VIX × US	0.819***	1.413**	0.827***
	(0.174)	(0.545)	(0.175)
Recession	13.770***	0.000	14.024***
	(2.943)	(.)	(3.005)
N	213562	83533	213562
R^2	0.045	0.701	0.191
adj. R^2	0.045	0.601	0.190
FEs, Variable × Bank ID × Time	No	Yes	No
FEs, Variable × Country	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. See the appendix for additional information on variables construction.

A measure of dispersion. We now want to check whether the results we have hold true even by using an alternative measure of forecast surprise. 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.

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

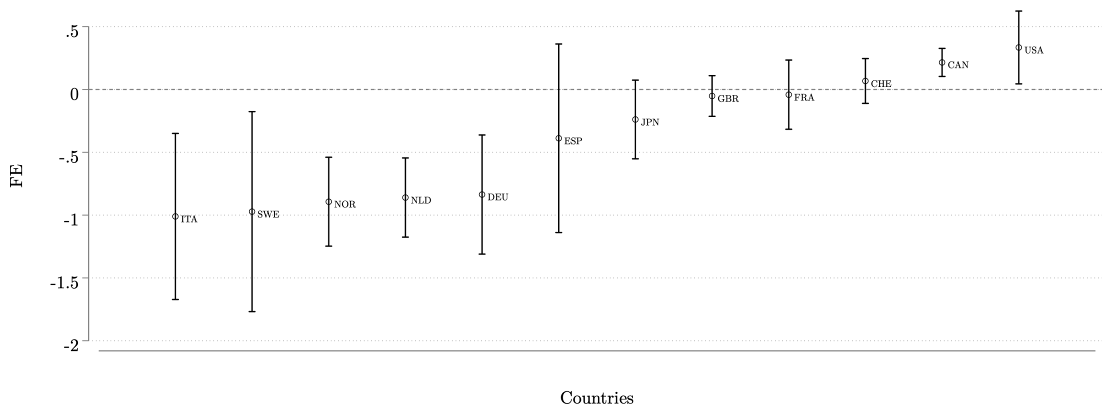
Table 19: OLS Regression: Dispersion

	SD Dispersion (1)	SD Dispersion (2)	SD Dispersion (3)
Domestic	-0.124***	-0.310**	-0.075***
	(0.020)	(0.123)	(0.016)
VIX	0.264***	0.000	0.258***
	(0.086)	(.)	(0.085)
Domestic × VIX	-0.043*	-0.214**	-0.045**
	(0.023)	(0.102)	(0.022)
US	-0.302***	-0.434***	0.000
	(0.081)	(0.116)	(.)
Domestic × US	0.106***	0.351***	0.063***
	(0.021)	(0.094)	(0.016)
Domestic × VIX × US	0.042	0.457***	0.045*
	(0.026)	(0.130)	(0.026)
N	220293	86351	220293
R^2	0.002	0.363	0.025
adj. R^2	0.002	0.153	0.025
FEs, Variable × Bank ID	No	Yes	No
FEs, Variable × Country	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. See the appendix for additional information on variables construction.

Regression Analysis: Country Specific. We now run the same OLS regression specification as in (22) for each country of our sample and capture the coefficient of domestic forecasters in uncertainty, on squared forecats errors. The figure below shows that the United States are the country with the highest foreign adavantage, as opposed to the rest of the sample.

Figure 15: Country Specific Analysis



Notes: This plot captures the γ coefficient of regression (22), 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 carachterized by variable specific fixed effects and VIX is the measure of uncertainty. The confidence intervals are set at 95%.

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).

Table 20: Country Specific Uncertainty

	SD Forecast Error (1)	SD Forecast Error (2)	SD Forecast Error (3)
Domestic	-0.758***	-0.996***	-0.221**
	(0.117)	(0.273)	(0.086)
Country Uncertainty	4.500***	0.823***	4.587***
	(0.709)	(0.240)	(0.710)
Domestic × Country Uncertainty	-0.700***	-1.311***	-0.639***
	(0.158)	(0.403)	(0.145)
US	-0.475	-2.453***	0.000
	(0.384)	(0.425)	(.)
Domestic × US	0.610***	1.561***	0.257*
	(0.148)	(0.477)	(0.140)
Domestic × Country Uncertainty × US	0.683***	1.998***	0.678***
	(0.191)	(0.599)	(0.198)
N	212958	83192	212958
R^2	0.035	0.701	0.180
adj. R^2	0.035	0.600	0.180
FEs, Variable × Bank ID × Time	No	Yes	No
FEs, Variable × Country	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 local uncertainty has on forecast errors, calculated as shown in section 4. We use the country specific uncertainty index (Ozturk and Sheng (2017)). 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.

An additional test for the information channel. We now aim to verify whether our results remain consistent when incorporating an additional variable to account for consumer confidence across countries. Specifically, we will examine the Consumer Confidence Index (CCI) to capture the direction and significance of the ξ and ξ_{US} coefficients. If the CCI index adequately represents these coefficients, it suggests that the observed phenomena might be explained by a 'flight to quality' theory alone. This would imply that consumer confidence within a specific country and time frame is the sole driver of the observed effects. However, as illustrated in the table below, our findings remain robust even after including the CCI. This confirms the presence of an information effect on equity inflows, both across the country average and within the United States.

Table 21: CCI and the Information Channel

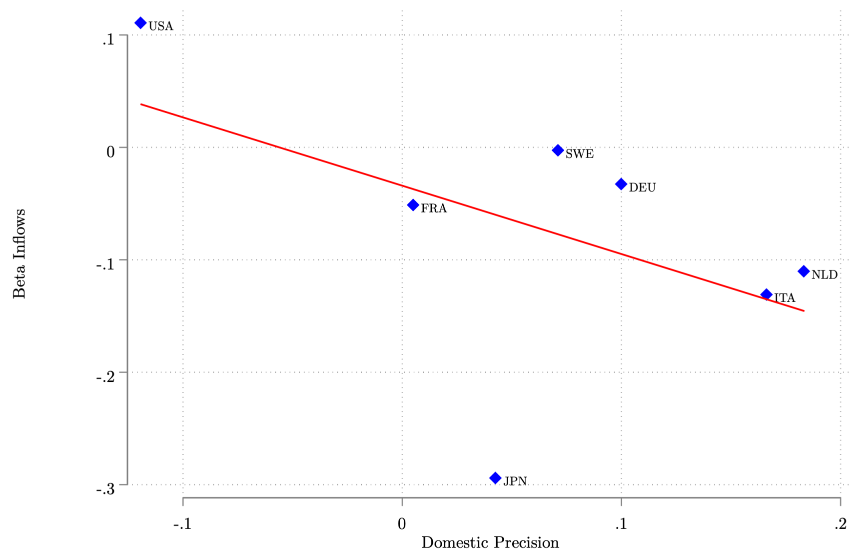
	Inflows (1)	Inflows (2)	Inflows (3)
CCI	-0.026	0.006	0.007
	(0.143)	(0.157)	(0.158)
CCI $\times$ US	0.061	0.071	0.069
	(0.146)	(0.161)	(0.161)
ξ	-0.028**	-0.030**	-0.031**
	(0.012)	(0.011)	(0.011)
ξ $\times$ US		0.078***	0.080***
		(0.012)	(0.013)
N	891	870	870
Country FEs	Yes	No	Yes

Notes: The Table reports the results of the model specification described in this section to capture the effect that a one standard deviation increase in fitted forecast error has on equity inflows, calculated as shows in this section of the appendix. 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.

C.4 Equity Flows and Information: a Continuum of Countries

We now check whether the countries we have merged between the equity flows dataset and the Consensus Economics forecasts have a correlation in explaining how higher uncertainty leads to smaller capital inflows and to larger relative domestic accuracy. If this relation holds we can thus say that our information channel is relevant not only to explain how United States differ from the other countries, but the entire sample. In our analysis we look at how the coefficient we get from the regression model we specified in the motivating evidence, by looking at the correlation between uncertainty and equity inflows, is correlated with the relative precision of domestic forecasters (RPDF) across countries. From the two binscatter below it is possible to see that this negative relation exists and is able to validate our hypothesis that in general the information channel is able to explain equity flows in uncertain times.

Figure 16: Information and Equity Inflows in Uncertain Times



Notes: This graph is a binscatter capturing the correlation between equity inflows and RPDF. Each point represents a specific country in our merged dataset. The dataset we use is by Koepke and Paetzold (2022) and Consensus Economics. 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.