Equity Flows in Uncertain Times: the Role of Heterogeneous Information

Francesco Beraldi
Yale University

Alessandro Dario Lavia*
Boston College

Chenping Yang
Yale University

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Abstract

We study the role of information heterogeneity in determining capital flows during the global financial cycle. When global uncertainty increases, investors retrench toward their home country and the United States. We build a model of portfolio choice and information acquisition with varying learning costs across countries. Our model replicates the global financial cycle's stylized facts and has new predictions for 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.

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*Corresponding author: Alessandro Dario Lavia, alessandrodario.lavia@bc.edu. Contact: Francesco Beraldi, francesco.beraldi@yale.edu. Chenping Yang, chenping.yang@yale.edu. We benefited from discussions with many including Peter Ireland, Jaromir Nosal, Rosen Valchev, Eduardo Dávila, Giuseppe Moscarini, Stefano Giglio, Zhen Huo, Alp Simsek, Michele Boldrin, Susanto Basu, Fabio Bagliano, Roberto Billi, Ulf Söderström, Silvia Miranda-Agrippino, Christoph Bertsch, Cristina Cella, Jens Christensen, Chris Foote, Georgios Georgiadis, Elisa Luciano, Roberto Marfè, Giovanna Nicodano, Kris Nimark, Valerio Nispi Landi, Federico Ravenna, Xin Zhang, Falk Bräuning, Chris Cotton, Pablo Guerron, Marco Errico, Luigi Pollio and the seminar participants at the Sveriges Riksbank and at the University of Turin. Part of the research was conducted while Alessandro Dario Lavia was visiting the Federal Reserve Bank of Boston and the Sveriges Riksbank.

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, such as Coeurdacier and Rey (2013) and Miranda-Agrippino and Rey (2022), has documented the salient features of the global financial cycle, showing that during downturns, investors retrench towards their home country.[1] Such contractionary movements are often linked to the increased risks and uncertainties associated with recessions, leading both domestic and international investors to adopt a more cautious approach. This shift towards safer assets, widely known as 'flight to safety', is a key feature highlighted in Miranda-Agrippino and Rey (2022), Brunnermeier et al. (2012), Bruno and Shin (2015), Gabaix and Maggiori (2015), and Fostel et al. (2015).

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 how 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]

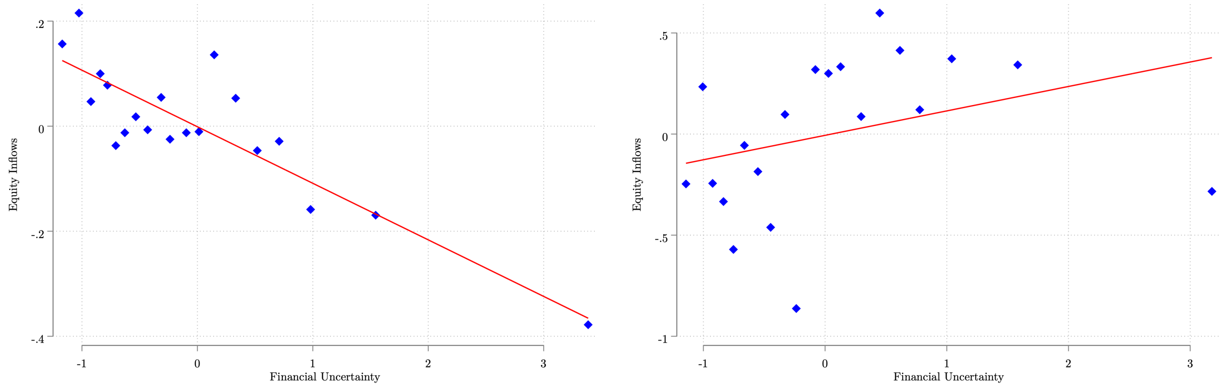
The core contribution of this paper is to formalize and empirically test the hypothesis that the heterogeneity in information across countries can explain the observed behavior of investors during periods of increased global uncertainty. The existing literature has explored alternative explanations for 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] An extension of the survey by Coeurdacier and Rey (2013) 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, whuch 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 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). While our finding is not novel in the sense that we do not identify any anomalous capital movements due to increased volatility, a phenomenon already documented in the existing literature, our contribution lies in isolating this evidence within a specific framework. We examine the effect of foreign equity holdings in the context of a shock to global uncertainty. This evidence serves as a motivation for our main research question, which seeks to determine one of the possible key drivers 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 specific equity inflows and outflows. 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, juxtaposing our findings with pre-existing research in the literature, such as in Choi et al. (2023). We assert the novelty of our contribution by being the first to

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

uncover this evidence through a dataset explicitly targeting equity flows across 47 countries.

As already mentioned, our main question is related to understand how capital flows, in particular equity, correlates with uncertainty and see whether we find a pattern in line with the existing literature of flight to safety, as in Miranda-Agrippino and Rey (2015), Miranda-Agrippino and Rey (2022) and Forbes and Warnock (2012). Moreover, we want to see whether the Unites States are once again the special country, which captures part of the flows that are going to safer areas in more uncertain time. This literature has been widely deepened in the last years, ending up with a study by Choi et al. (2023), who clearly states that local uncertainty acts as a local pull-factor for capital. However, we claim to be the first ones to check how equity flows, defined as IMF Bops portfolio equities, change to a shock of several uncertainty measures.

To estimate how equity flows correlates with uncertainty we need to build a correct model specification, in line with the existing works by Akinci and Kalemli-Ozcan (2023) and Choi et al. (2023).

More specifically, we begin with the following specification, to capture the effect of uncertainty on both equity inflows and outflows:

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

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 $\beta > 0$, then this suggests that on average, foreigners increase their investments in a specific country i. On the other hand, if $\beta_{US} > 0$, it means that the US correlates with a marginal increase in inflows, to be added to the average effect of all the countries in β. Therefore, the correlation between uncertainty and inflows in the US will be given by $\beta + \beta_{US}$. 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 experience higher volatility. Here we use the VIX index, probably the most common measure exploited so far 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

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 $\times$ 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. Standard errrors, clustered at country level, are reported in parenthesis.

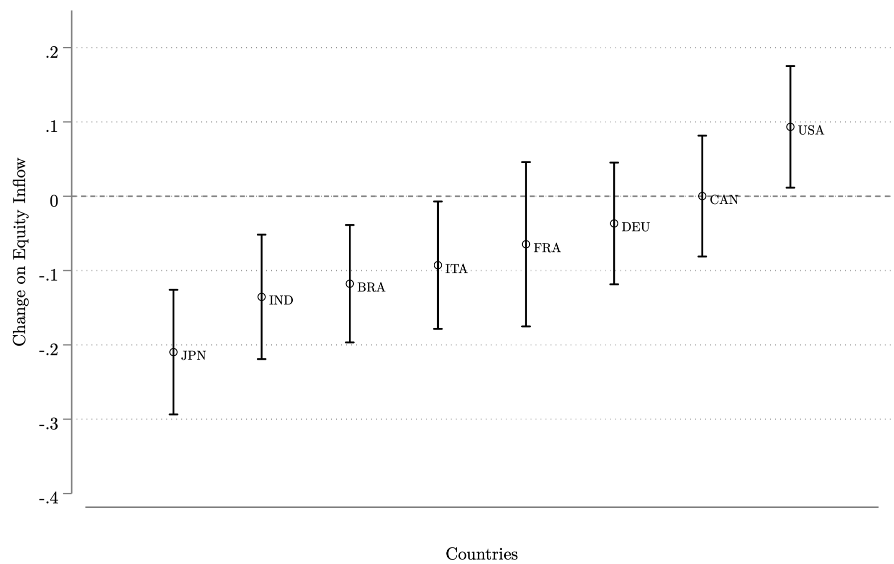
holdings abroad. This results is confirmed in column 2, where we control for GDP growth. It is interesting to notice that, on the converse, β_{US} is positive, and by adding the average effect to the marginal effect it does not change the overall result, meaning that foreigners do not reduce their equities 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 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

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%.

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.

In light of this evidence, we can conclude that our findings corroborate what has been demonstrated in previous literature, such as in Akinci and Kalemli-Ozcan (2023) and Choi et al. (2023). Specifically, we confirm these results within our dataset, making a significant contribution by being the first to focus exclusively on equity inflows. Our primary objective is to understand what distinguishes the United States from other countries during periods of heightened economic volatility. This differentiation is crucial for our analysis, as we emphasize the role of the information channel as a key driver of these observed patterns. Our hypothesis posits that the research choices made by investors might influence their domestic investment decisions differently in the United States compared to the rest of the world.

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. 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. To further validate our findings, we utilize a measure of local uncertainty, as outlined in Ozturk and Sheng (2017), ensuring that the effect persists even when using localized measures of uncertainty. This step is crucial for interpreting our simple model accurately.

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), providing confidence in the validity and generalizability of our results.

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 (eg 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 $\theta_{kk} < \theta_k$. 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:

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

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:

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

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

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

and yields the equilibrium asset price p_k as

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

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

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

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

where $\epsilon_{ik} \sim \mathcal{N}(0, {\sigma^s_{ik}}^2)$ is the i.i.d. signal noise. 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.

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

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

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}

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

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

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.

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. 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.

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

When the prior uncertainty for an asset is high or the cost to learn about the asset 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:

$$\mathbb{E}\int_S x_{i,k}^S dS = 1 + \frac{1}{2\theta_{ik}}\left(\frac{\eta}{\tau_k^3} + \frac{1}{\eta\tau_k^2}\right) \tag{11}$$

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 approximately as:

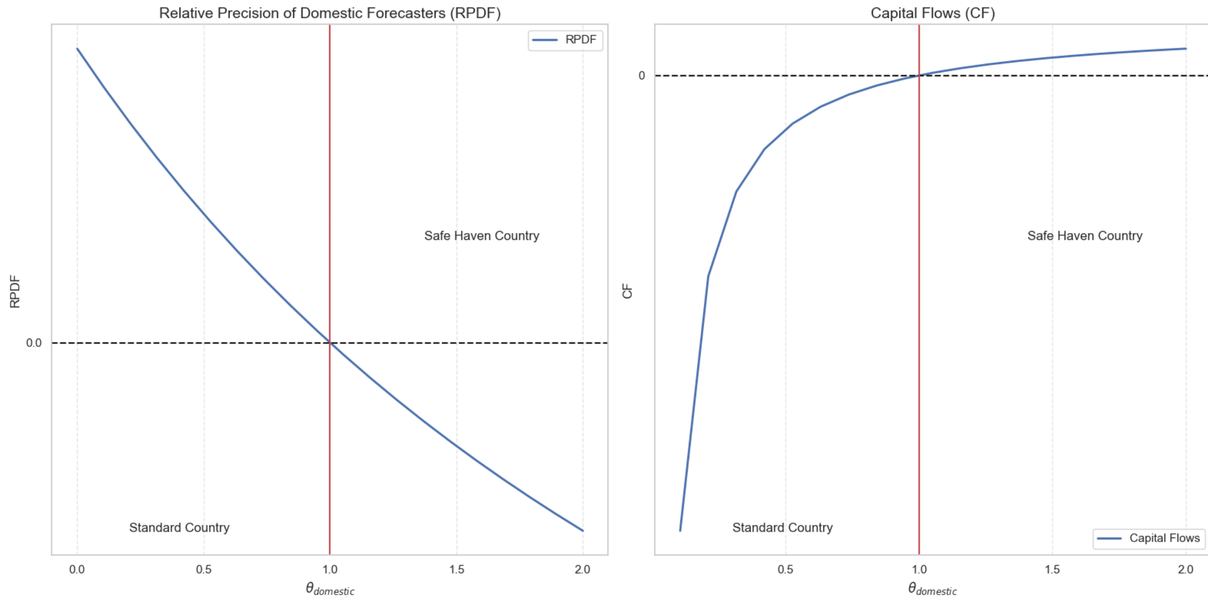
$$CF_k \equiv \frac{\partial}{\partial\sigma_k^2}\left(-x_{kk}^S + \frac{1}{N}\sum_{i=1}^N x_{ik}^S\right) \tag{12}$$

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:*

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

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. 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 $\theta_d \geq \theta_f$.

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.

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 $\theta_{hh} \geq \theta_h \equiv \frac{N}{\sum_{i=1}^{N} \frac{1}{\theta_{ih}}}$. 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 $\theta_d \geq \theta_f$ [4]. In the Appendix B we also show the dynamics of RPDF and CF for different values of σ^2.

4 Empirical Analysis

In this section, we empirically test the prediction derived from the theoretical analysis presented at the end of the previous section. To achieve this, we require a measure that captures how investors make their investment decisions based on their information research. We utilize data from *Consensus Economics*, as employed in related studies by De Marco et al. (2022) and Benhima and Bolliger (2023). Specifically, we collect country-specific forecasts provided by public and private institutions, including investment banks, universities, research organizations, and large corporations. The rationale is that forecast errors reflect the information accuracy available to the forecaster, serving as the empirical counterpart to the learning choice discussed in our model. [5]

4.1 Cost of Research: Standard vs Safe Haven Countries

In order to capture how forecast precision correlates with higher and lower uncertainty, we compute two different approaches, which are described in Appendix C.2. The first approach examines how an aggregate measure of forecast precision, namely the relative precision of domestic forecasters (RPDF), varies when comparing periods of high and low uncertainty in the United States and other countries in our sample. The second approach aims to determine whether time-dependent components and forecaster specific features might affect our estimation by analyzing the correlation between forecast errors and local forecasters during times of uncertainty. We now compare these two results and discuss their implications for our model predictions.

Relative Precision of Domestic Forecasters. On average, the cost of research is higher for foreign economies than for domestic ones. This phenomenon, known as information home

[4] 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 $\theta_d \in [0, 2]$.

[5] *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).

bias, is supported by both theoretical and empirical studies, such as those by Veldkamp (2011) and Benhima and Bolliger (2023). This finding aligns with our interpretation of the θ parameter in our theoretical framework. Accordingly, we seek to empirically validate Proposition 1 in the Theoretical Analysis (3).

Figure 4 illustrates the relative precision of domestic forecasters across countries during periods of low and high uncertainty[6], comparing the rest of the world with the United States. Notably, in relative terms, domestic forecast accuracy improves during periods of low and heightened uncertainty. This trend does not hold for the United States, where foreign forecasters consistently outperform domestic analysts in predicting economic variables during periods of high uncertainty. This divergent behavior in predictions suggests that the United States can be viewed as an information haven.

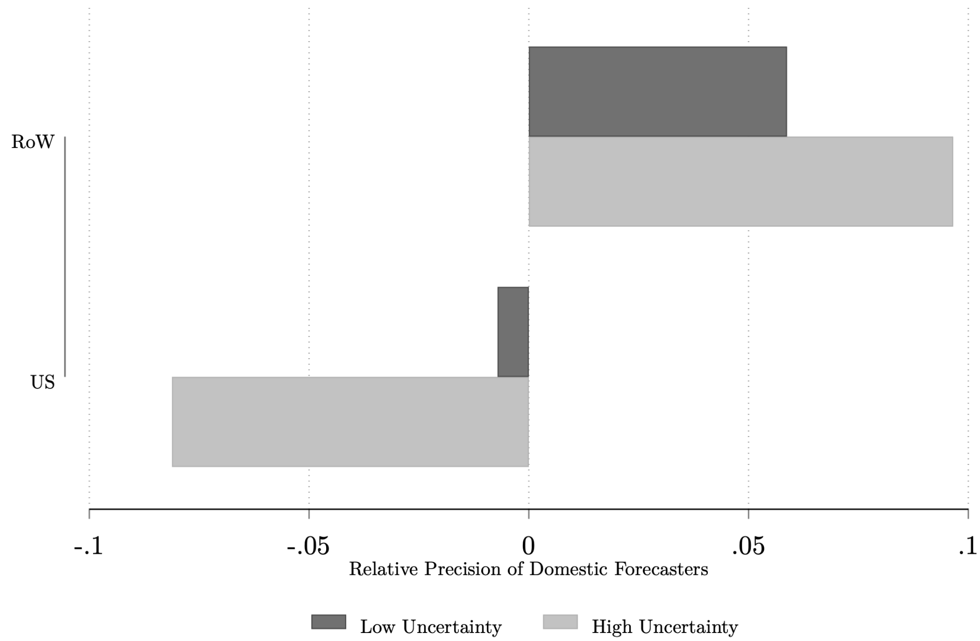
These findings extend the results of Benhima and Bolliger (2023) by highlighting a pronounced information home bias that intensifies with increased uncertainty. Furthermore, we present novel evidence indicating that investors can surpass domestic forecasters in accuracy when predicting risk factors related to the United States.

Forecast Errors and Local Forecasters: OLS Approach. In Table 3, we demonstrate the robustness of our findings using the OLS specification (22) introduced in the Appendix (C.2). Specifically, we estimate the coefficients γ and γ_{US}, which represent 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.

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.

[6] 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.

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.

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) [7].

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

[7] 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	-0.779***	-0.338*	-0.157
	(0.132)	(0.182)	(0.100)
VIX	3.736***	3.408***	3.580***
	(0.357)	(0.344)	(0.329)
Domestic × VIX	-0.705***	-0.676***	-0.657***
	(0.155)	(0.156)	(0.135)
US	-1.987***	-1.785***	0.000
	(0.535)	(0.493)	(.)
Domestic × US	1.000***	-0.883**	0.539***
	(0.162)	(0.435)	(0.151)
Domestic × VIX × US	1.019***	0.678***	0.996***
	(0.183)	(0.196)	(0.166)
N	217335	217303	217335
R^2	0.022	0.205	0.170
adj. R^2	0.022	0.198	0.170
FEs, Variable - Bank ID	No	Yes	No
FEs, Country × Variable × Time	No	No	Yes
Clusters, Country - 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, but we check for many other masures of uncertainty in this appendix. 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.

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 main predictions derived from our model hold true in our empirical analysis. Specifically, we want to examine 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.

Given that θ varies across countries, for a standard country, the domestic cost of research is lower than foreign costs, where $\theta_d < \theta_f$. In this scenario, during times of uncertainty, foreigners may disinvest in the foreign country due to fickleness. However, in the case of the United States, which is an information safe haven, foreigners may have even better

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

	Inflows (1)	Inflows (2)	Inflows (3)
ξ	-0.027**	-0.027**	-0.029**
	(0.011)	(0.010)	(0.011)
$\xi \times$ US		0.075***	0.077***
		(0.011)	(0.012)
N	909	887	887
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 (Jurado et al. (2015)), but we check for many other masures of uncertainty in this appendix. 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.

information about the economy. This could lead to either maintaining or increasing their investments in the United States when uncertainty spikes.

To empirically test these predictions, 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 founs on 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 Cheks

We first verify whether our correlations maintain the same sign and significance using alternative measures of uncertainty. To control for potential biases in our estimates arising from the correlation between adverse periods, such as recessions, and forecast errors, we include a recession dummy variable in our regression model. Additionally, to confirm the robustness of our specification, we introduce a measure of dispersion aimed at mitigating the impact of unexpected economic shocks. These robustness checks are detailed in Appendix C.3.

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 incorporate a variable capturing consumer confidence across countries and different time periods. We re-estimate our 2SLS regression model, including this variable in the second stage. This analysis is shown in Appendix C.3. These supplementary tests further validate our findings and emphasize 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.

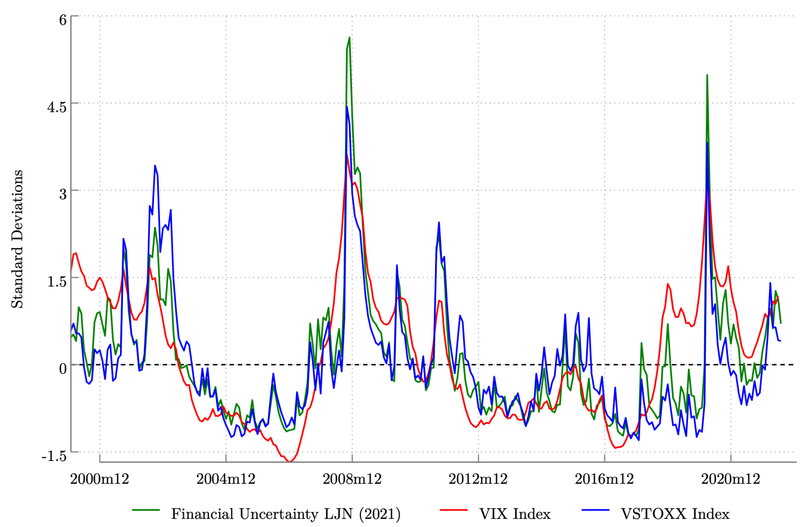
Merging the dataset with uncertainty measures. We then merge this data with uncertainty measures at monthly level, by using Jurado et al. (2015) measure, updated in 2021, VIX and VSTOXX, from Fred. Table 5 shows how these measures are distributed.

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

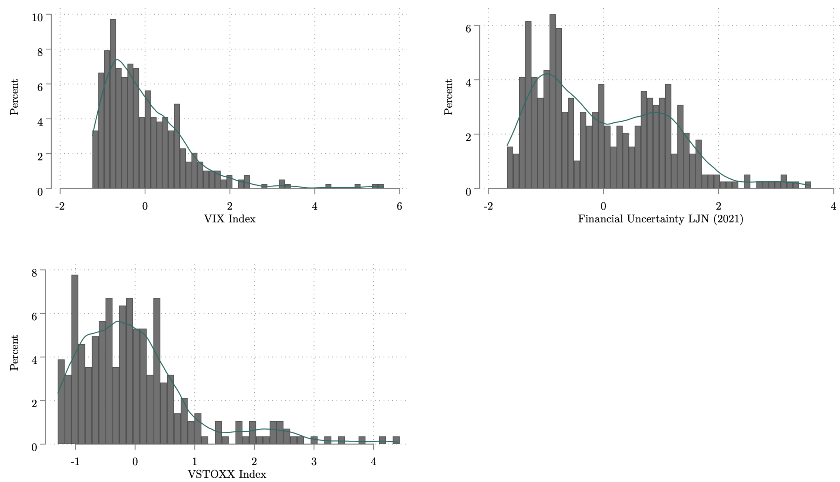
Notes: The Table reports the descriptive statistics of different measure of uncertainty. These measures are standardized to the mean.

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).

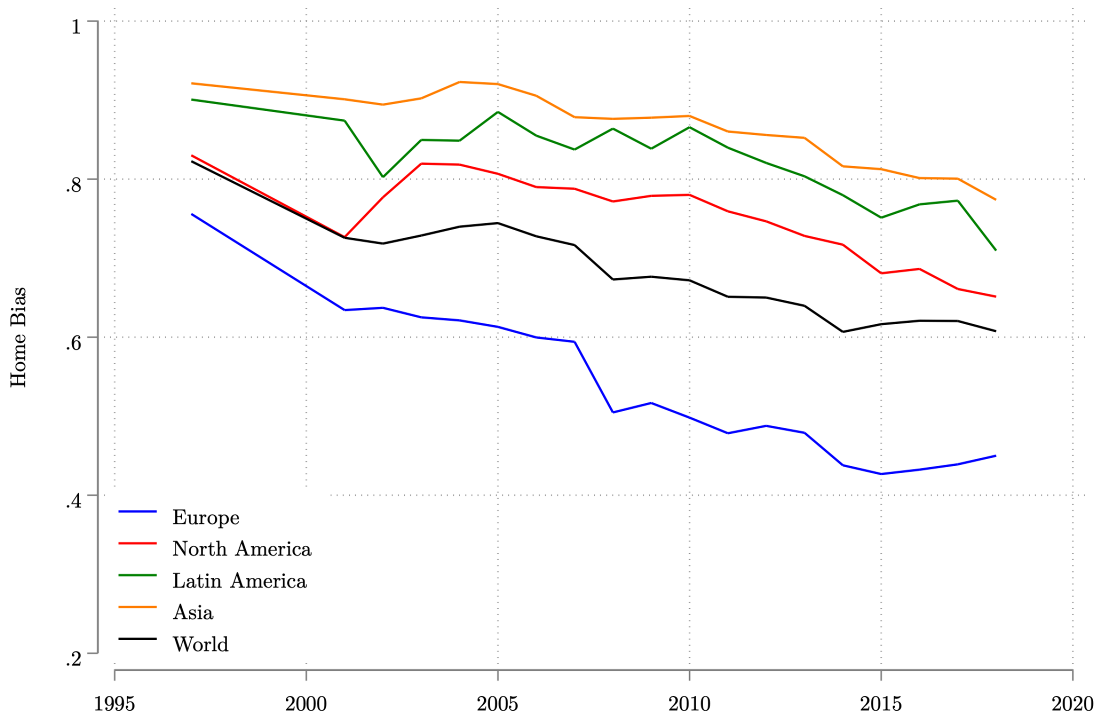
Table 6: Descriptive Statistics: Capital Flows

	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: Extension from Coeurdacier. 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).

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 Flows 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. We use the financial uncertainty index (Jurado et al. (2015)), but we check for many other measures of uncertainty in this appendix (robustness checks). 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 Flows 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. We use the financial uncertainty index (Jurado et al. (2015)), but we check for many other measures of uncertainty in this appendix (robustness checks). 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.

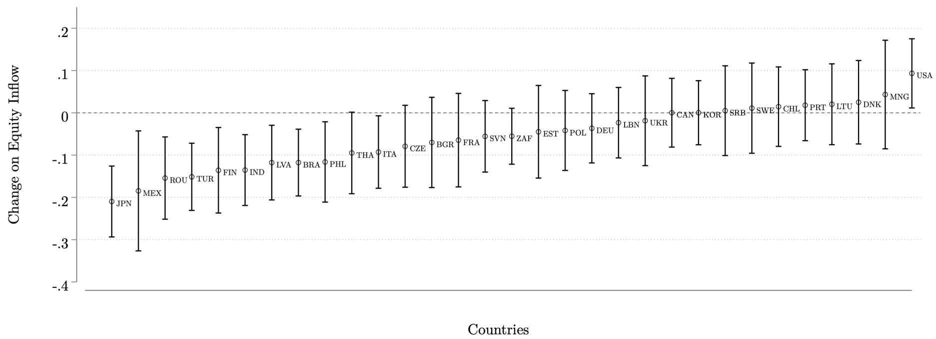
Table 9: Equity Flows and Additional Controls

	Inflows (1)	Inflows (2)	Outflows (3)	Outflows (4)
VIX	-0.100***	-0.103***	-0.102***	-0.102***
	(0.014)	(0.015)	(0.018)	(0.018)
VIX × 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. We use the VIX index. 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 Local Economic Policy 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 RoW (1)	Inflows RoW (2)	Inflows US (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 counry specific uncertainty has on Equity Inflows. We use different measures of uncertainty. Standard errors, clustered at country level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See the appendix for additional information on variables construction.

Including a Control Variable for Recession. We check whether the 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 financial uncertainty index (Jurado et al. (2015)), but we check for many other measures of uncertainty in the appendix (robustness checks). 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.

Low Uncertainty: Reducing the Distribution of a SD. We check whether the evidence holds true even by reducing the distribution of financial uncertainty of a standard deviation, in order to convince that there is a story beyond the channel of flight to quality.

Table 12: Equity Flows and Low Uncertainty

	Inflows (1)	Inflows (2)	Outflows (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 financial uncertainty index (Jurado et al. (2015)), but we check for many other measures of uncertainty in the appendix (robustness checks). 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

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

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

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

Take expectation in the first period, we obtain

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

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

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

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

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

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

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

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:

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

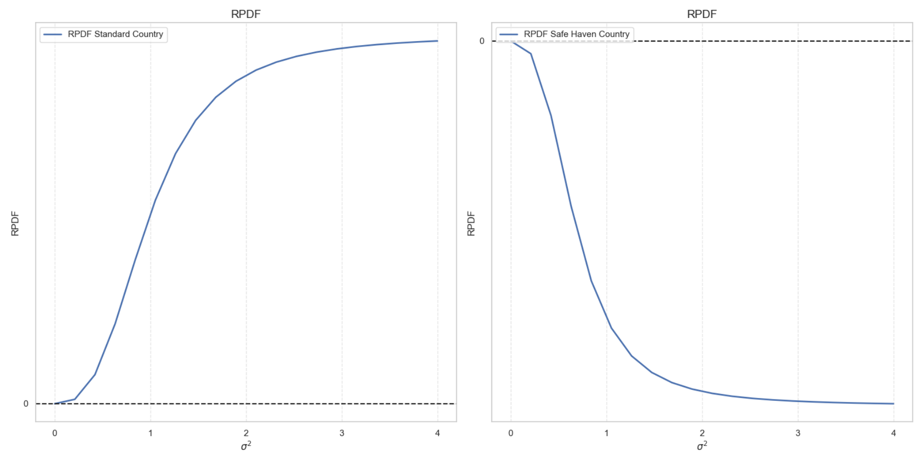
Hence,

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

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.

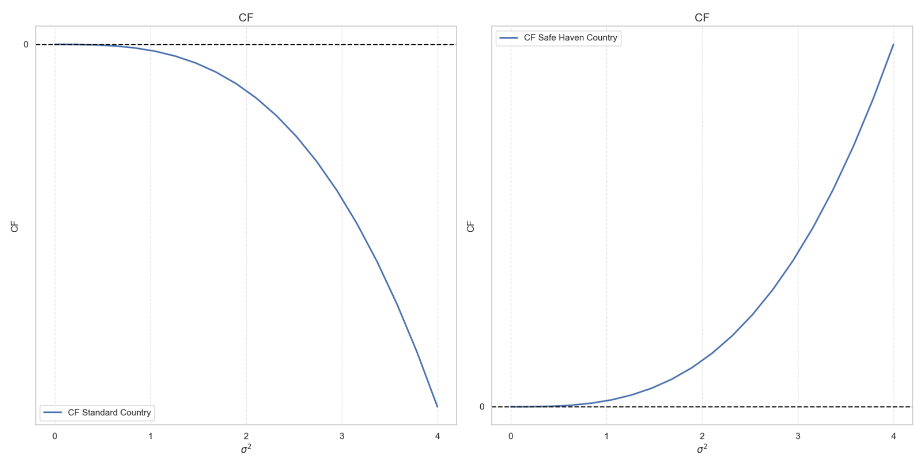
Figure 9: RPDF and CF changing σ^2



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

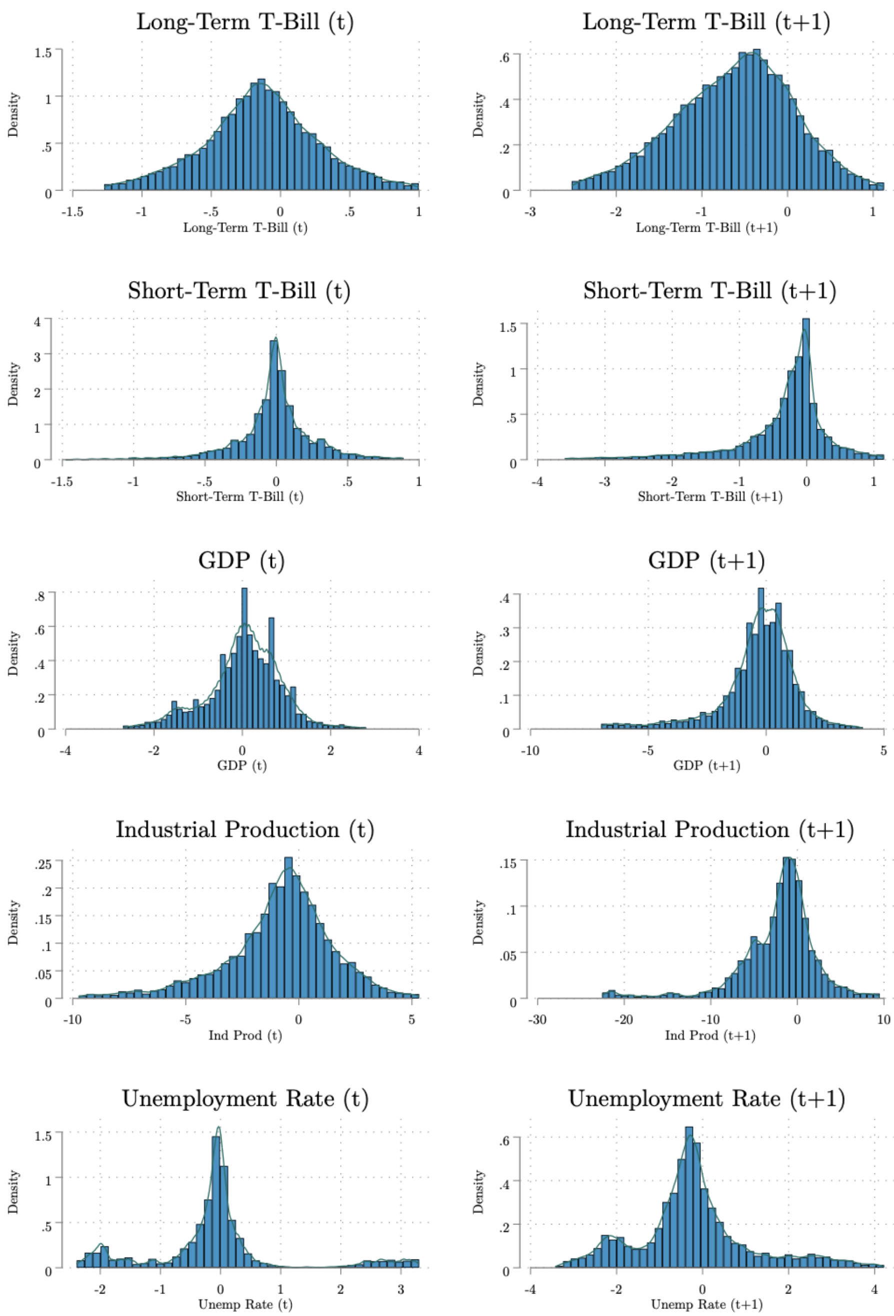
Notes: The Table reports a descriptive statistics of the variables we included in our dataset from *Consensus Economics* survey. We report mean, median, max, min and number of observations. In appendix ()C.1) we report the list of countries included in our dataset.

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	0.998	-1.273	23325
Short-Term T-Bills ($\Delta\%$ $m, m+4$)	-0.016	-0.005	0.892	-1.477	22584
GDP $\Delta\%$ ($\Delta\%$ m, y)	0.033	0.100	2.800	-2.700	32666
FE1_IP	-0.863	-0.589	5.313	-9.734	22597
Unemployment Rate ($\Delta\%$ y)	-0.089	-0.075	3.300	-2.392	20619
Long-Term T-Bills ($\Delta\%$ $m, m+12$)	-0.623	-0.570	1.126	-2.520	22800
Short-Term T-Bills ($\Delta\%$ $m, m+12$)	-0.353	-0.171	1.148	-3.594	22186
GDP $\Delta\%$ ($\Delta\%$ $m, y+1$)	-0.361	-0.100	4.100	-7.000	32204
FE2_IP	-2.292	-1.465	9.514	-22.541	22075
Unemployment Rate ($\Delta\%$ $y+1$)	-0.212	-0.292	4.216	-3.421	20152

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 $\mathbf{FE}^2$. 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 VIX and VSTOXX.

Table 15: Second Approach: Using VIX

	SD Forecast Error (1)	SD Forecast Error (2)	SD Forecast Error (3)
Domestic	-1.017***	-0.604***	-0.350***
	(0.161)	(0.199)	(0.121)
Financial JLN (2021)	4.522***	4.221***	4.364***
	(0.406)	(0.380)	(0.377)
Domestic × Financial JLN (2021)	-0.913***	-0.825***	-0.824***
	(0.172)	(0.161)	(0.146)
US	-2.607***	-2.399***	0.000
	(0.614)	(0.574)	(.)
Domestic × US	1.393***	-0.410	0.888***
	(0.194)	(0.393)	(0.176)
Domestic × Financial JLN (2015) × US	1.296***	0.916***	1.225***
	(0.191)	(0.193)	(0.168)
N	217335	217303	217335
R^2	0.028	0.211	0.177
adj. R^2	0.028	0.204	0.176
FEs, Variable - Bank ID	No	Yes	No
FEs, Country × Variable × Time	No	No	Yes
Clusters, Country - 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)), but we check for many other masures of uncertainty in this appendix. 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.

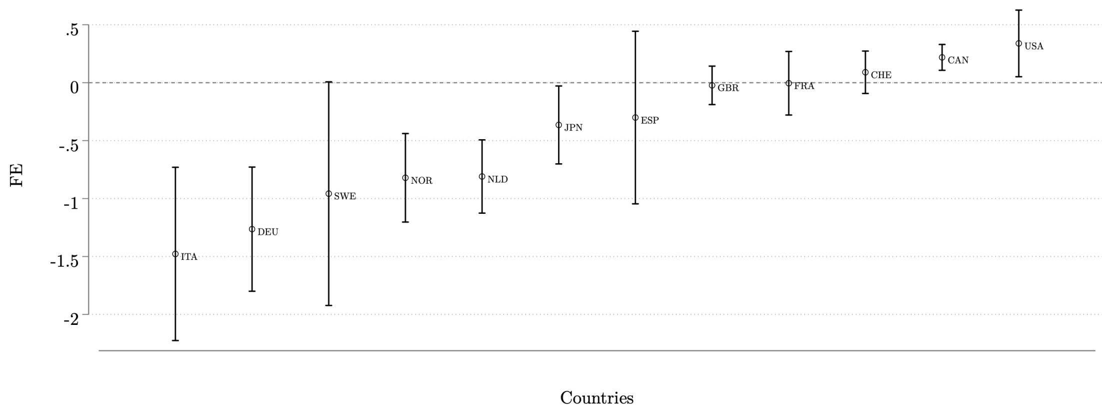
Table 16: Second Approach: Using VSTOXX

	SD Forecast Error (1)	SD Forecast Error (2)	SD Forecast Error (3)
Domestic	-0.724***	-0.186	-0.095
	(0.129)	(0.183)	(0.095)
VSTOXX	3.689***	3.352***	3.526***
	(0.407)	(0.395)	(0.384)
Domestic × VSTOXX	-0.673***	-0.660***	-0.634***
	(0.169)	(0.170)	(0.150)
US	-1.931***	-1.617***	0.000
	(0.523)	(0.472)	(.)
Domestic × US	0.970***	-1.323***	0.501***
	(0.164)	(0.454)	(0.155)
Domestic × VSTOXX × US	1.053***	0.772***	1.026***
	(0.189)	(0.210)	(0.172)
N	217335	217303	217335
R^2	0.015	0.199	0.164
adj. R^2	0.015	0.192	0.163
FEs, Variable - Bank ID	No	Yes	No
FEs, Country × Variable × Time	No	No	Yes
Clusters, Country - 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)), but we check for many other masures of uncertainty in this appendix. 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.

Country Specific Analysis. We now check whether the results hold true when controlling the impact of domestic forecasters across each specific country, when absorbing the variable fixed effect.

Figure 12: Relative Precision of Domestic Forecasters: Average



Notes: This plot shows how forecast errors increase or decrease, depending on the forecaste being domestic in higher times of uncertainty. Uncertainty is measured by VIX Index.

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 17: Second Approach: Controlling for Recession

	SD Forecast Error (1)	SD Forecast Error (2)	SD Forecast Error (3)
Domestic × Financial JLN (2021)	-0.705***	-0.756***	-0.731***
	(0.155)	(0.157)	(0.138)
US	-1.987***	-1.632***	0.000
	(0.535)	(0.416)	(.)
Domestic × VIX × US	1.019***	0.823***	0.976***
	(0.183)	(0.207)	(0.190)
Recession		16.366***	16.732***
		(1.679)	(1.667)
N	217335	217303	217335
R^2	0.022	0.231	0.198
adj. R^2	0.022	0.224	0.198
FEs, Variable - Bank ID	No	Yes	No
FEs, Country × Variable × Time	No	No	Yes
Clusters, Country - 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, but we check for many other masures of uncertainty in this appendix. 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.

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.

Table 18: Country Specific Uncertainty

	SD Forecast Error (1)	SD Forecast Error (2)	SD Forecast Error (3)
Domestic	-0.983***	-0.886***	-0.365***
	(0.161)	(0.210)	(0.123)
Country Uncertainty	5.300***	5.096***	5.308***
	(0.463)	(0.438)	(0.451)
Domestic × Country Uncertainty	-0.954***	-0.776***	-0.829***
	(0.221)	(0.188)	(0.180)
US	-1.175*	-1.444**	0.000
	(0.695)	(0.702)	(.)
Domestic × US	0.853***	0.009	0.411**
	(0.225)	(0.407)	(0.191)
Domestic × Country Uncertainty × US	0.959***	0.532**	0.881***
	(0.301)	(0.266)	(0.270)
N	215406	215374	215406
R^2	0.037	0.218	0.185
adj. R^2	0.037	0.211	0.184
FEs, Variable - Bank ID	No	Yes	No
FEs, Country × Variable × Time	No	No	Yes
Clusters, Country - 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 country 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: Second Approach: Dispersion

	SD Dispersion (1)	SD Dispersion (2)	SD Dispersion (3)
Domestic	-0.142***	-0.088***	-0.091***
	(0.026)	(0.019)	(0.018)
Domestic × VIX	-0.053**	-0.051*	-0.047*
	(0.026)	(0.026)	(0.025)
US		-0.319***	0.000
		(0.077)	(.)
Domestic × US		0.089***	0.079***
		(0.022)	(0.020)
Domestic × VIX × US		0.052*	0.047*
		(0.028)	(0.027)
N	221714	221714	221714
R^2	0.002	0.014	0.027
adj. R^2	0.002	0.014	0.026
FEs, Variable	No	Yes	No
FEs, Country × Variable × Time	No	No	Yes
Clusters, Country - 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 financial uncertainty index (Jurado et al. (2015)), but we check for many other masures of uncertainty in this appendix. 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.

An additional test for the information channel. We now want to check whether the results we have hold true even by using an additional variable to capture consumer confidence across countries.

Table 20: Second approach: OLS and FE[2]

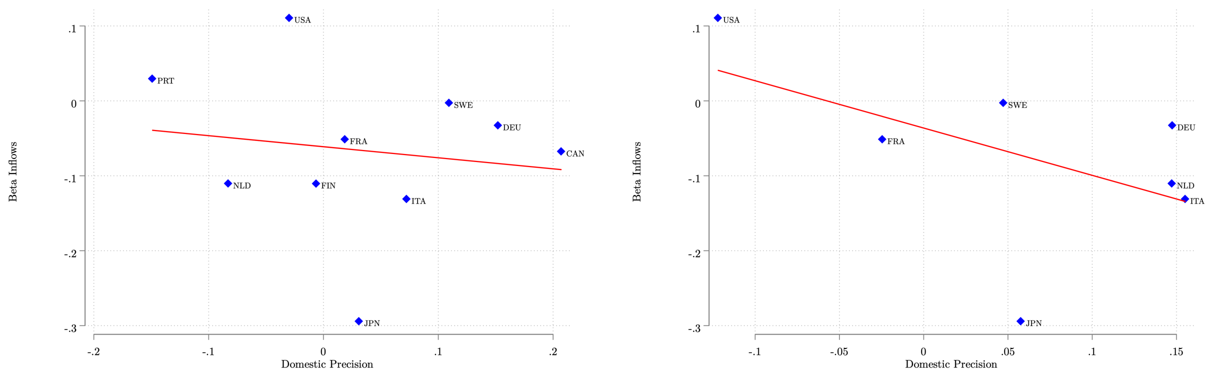
	Inflows (1)	Inflows (2)	Inflows (3)
Consumer Confidence Index	-0.033	-0.000	0.001
	(0.142)	(0.156)	(0.156)
Confidence Index $\times$ US	0.068	0.074	0.072
	(0.145)	(0.159)	(0.160)
ξ	-0.027**	-0.027**	-0.029**
	(0.010)	(0.010)	(0.010)
$\xi\times$ US		0.077***	0.078***
		(0.011)	(0.012)
N	909	887	887
Country 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 financial uncertainty index (Jurado et al. (2015)), but we check for many other masures of uncertainty in this appendix. 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, stronger in the right panel, where we look at RPDF in higher uncertainty setting, is there, validating our hypothesis that in general the information channel is able to explain equity flows in uncertain times.

Figure 13: 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, on the right panel, we end up with 7 countries, since 3 do not have observations with more than one standard deviation in uncertainty (limited sample). The left panel represents the correlation between these two variables without separating RPDF in high or low uncertainty, while on the right we just look at countries in a sample with more than one standard deviation in uncertainty, measured by the VIX index.