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

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First Draft: June 14, 2024

**Abstract**

We study the role of information heterogeneity across countries in shaping the patterns of capital flows during the global financial cycle. We first point out an exception to the known fickleness phenomenon, when looking at equity flows: foreigners tend to increase their investments in the United States in times of higher uncertainty. We build a model of portfolio choice and endogenous information acquisition with heterogeneous learning costs across countries. Our model predicts that in periods of global uncertainty investors retrench toward their home country and that capital flows toward the United States, parsimoniously replicating the stylized facts of the global financial cycle. Finally, we use forecast data on the macroeconomic and financial performance of several countries. We find that domestic forecasters have a superior ability to predict the economic outcomes of their own country and that this advantage increases with global uncertainty. We then show that the US is an exception to these patterns, as domestic forecasters do not outperform foreign institutions when forecasting their own country.

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

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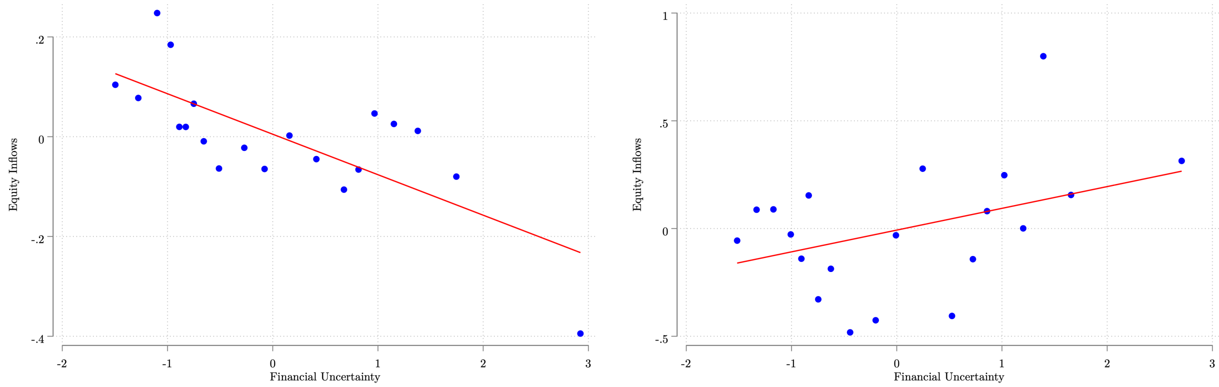
# 1 Introduction

Capital flows across countries are a fundamental aspect of the global economy, and play an important role for fluctuations in output and asset prices. We examine how heterogeneity in access to information across countries influences the patterns of capital flows during the global financial cycle. It is well known that investors have a bias for holding assets of their home countries. Furthermore, 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. In this paper, we propose and empirically test that a unique explanation, the heterogeneity in information across countries, can rationalize both of these findings.

We first use data from Koepke and Paetzold (2022) to summarize the key features of the global financial cycle, which are displayed in Figure 1. Building on recent literature, we show that when global uncertainty increases, investors retrench towards their home country, but we highlight the exceptional behavior of the United States, which instead receives net capital inflows. This is definitely a story of flight to quality, where investors look at how to optimize their asset portfolio, given their risk aversion. There is an huge literature that tries to find out the key drivers of this behavior, as summarized in Coeurdacier and Rey (2013). Motivated by these findings, 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 pair of origin country, where the investor resides, and target country of the asset under consideration. This general specification nests the two 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 safe 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, and investors retrench towards their home countries, generating a decline in inflows and outflows as in the data. At the same time, capital flows towards information safe havens, such as the United States. The model is thus able to parsimoniously replicate the stylized facts of the global financial cycle.

We use data from *Consensus Economics* to measure the forecast precision across different pairs of countries by investor origin and target asset, which is the correct empirical

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 financial uncertainty, measured using Jurado et al. (2015). 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.

counterpart of the heterogeneous learning costs. We then use these measures to validate the model mechanism. In the data, investors are more accurate at forecasting their own country, which suggest the presence of an home information advantage. Furthermore, this superior forecasting ability of domestic forecasters strenghtens when global uncertainty is high. This finding validates the model prediction that capital flows can be explained as changes in the relative specialization of domestic and foreign investors. Finally, when isolating the United States, we show that there is no informational advantage of domestic forecasters, and no clear pattern when uncertainty increases, which is consistent with the notion of the United States as an information safe haven.

Our paper is structured in three main parts. In the first we focus our attention on equity flows [1] and try to understand how do they move depending on the state of the world. With a dataset from Koepke and Paetzold (2022) spanning between 1997 and 2023, we compare how these flows experienced different movements depending on the economic period. It is possible to notice that in all the three recessionary periods, 2001, 2008 and 2020, there

[1] On average, equity outflows and equity inflows constitute around 55% and 40% of the total capital flows. Moreover, our choice of focusing on equity flows, not incorporating bond transactions into the analysis is not only due to the weigh that this flows have, but also for the potential interventions by governments, which might affect this transactions. A descriptive statistics of equity, bond and capital flows can be seen in the appendix (A).

has been a negative spike for both outflows and inflows. This is an evidence in line with the existing literature. Notice that in expansionary periods both flows tend to be positive, while the opposite happens in time of recession. Interestingly, when comparing how the rest of the world behave with respect to the United States, it is possible to see that inflows are asymmetric. It looks like foreigners increase their equity holdings in the United States in bad time. This is a quite well known fact, as already documented in Caballero and Simsek (2020). From an empirical perspective, numerous investigations have consistently demonstrated a significant and durable inverse relationship between higher volatility in the economy and the movement of cross-border bank and portfolio investments, such as in Forbes and Warnock (2012), Ahmed and Zlate (2012), Bruno and Shin (2015), Miranda-Agrippino and Rey (2015), Choi et al. (2023). This empirical evidence is even clearer when focusing on uncertainty and looking at how higher volatility in the economy correlates with equity inflows. In this part of the analysis, we also point out an exception to the known fickleness phenomenon, when looking at equity flows: foreigners tend to increase their investments in the United States in times of higher uncertainty. This is not a completely new fact, as already documented in Akinci and Kalemli-Ozcan (2023). However, we claim to be the first to show this pattern for the United States, isolating bond and equity flow dynamics.

Second, we build a model of portfolio choice and information acquisition with heterogeneous learning costs, similarly to Neuwerburgh and Veldkamp (2011) and De Marco et al. (2022), which we use to understand the logic behind our empirical findings. The agents are investors, either sophisticated or unsophisticated. The latter are endowed, in a multicountry context, with an amount of time to be spent to learn about either their domestic economy or foreign ones. Each country has a specific cost of research, which can be related to the investment needed to learn about country-specific risk factors. Our model predicts that investors increase their research in times of uncertainty, especially in those countries with a lower cost of research. Ideally, we link these to domestic economies, in line with the theory of information home bias, by Neuwerburgh and Veldkamp (2011) and Coeurdacier and Rey (2013). Moreover, we show that the portfolio composition of sophisticated investors, who make research choices, is positively related to uncertainty and negatively related to the country-specific cost of research. We then predict that in periods of global uncertainty, investors retrench toward their home country or to countries where the research cost is low, such as the United States, thus parsimoniously replicating the stylized facts of the global financial cycle.

Finally, we use *Consensus Economics* data on the macroeconomic and financial performance of several countries to test the predictions in our model. We use this survey as a proxy of information accuracy and derive the forecast errors, which can be considered to be an inverse function of signal precision of investors. This would then reflect how much investors dedicate to study about their own economy and foreign ones. We find that domestic forecasters have a superior ability to predict the economic outcomes of their own country and that this advantage increases with global uncertainty. We then show that the United States are an exception to these patterns, as domestic forecasters do not outperform foreign institutions when forecasting their own country. These evidence are in line with the predictions we get from the theoretical analysis. Indeed, we document the existence of a higher signal precision (smaller forecast errors) in domestic economies, as opposed to the foreign ones. This is because investors increase their information acquisition when uncertainty goes up, especially in their own local economies and the United States, where research costs are lower. Moreover, we also show that there is a channel that links information and capital flows. In particular we can provide evidence of a negative equity flows when the economy is more volatile, due to a smaller signal precision in predicting economic variables. This mirrors our prediction in the model, stating that countries with smaller research costs (domestic and United States) experience higher flows of capital when uncertainty over the economy goes up.

**Contribution 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). Such contractionary movements are often linked to the increased risks and uncertainties associated with recessions, leading both domestic and international investors to take 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). 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) [2]. 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 Fact

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

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

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: financial and macroeconomics uncertainty from Jurado et al. (2015), VIX and VSTOXX. 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 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 $\mathrm{U}_{it}$ is a measure of uncertainty (JLN 2021, VIX, 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 $\beta$. 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 financial uncertainty, the most exogenous measure exploited so far in the literature, by Jurado et al. (2015). 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, $\beta_{US}$ 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, $\beta$ 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 $\beta$ varies depending on the country, and it is possible to see that this relation is consistent when comparing the G7 countries. In the

Table 1: Uncertainty and Equity Flows

| | 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) $\times$ US | 0.137*** | 0.139*** | -0.067*** | -0.067*** |
| | (0.015) | (0.015) | (0.016) | (0.016) |
| GDP $\Delta\%$ | | 0.009*** | | -0.002 |
| | | (0.003) | | (0.004) |
| $N$ | 8003 | 7940 | 6506 | 6452 |
| Country FEs | Yes | Yes | Yes | Yes |

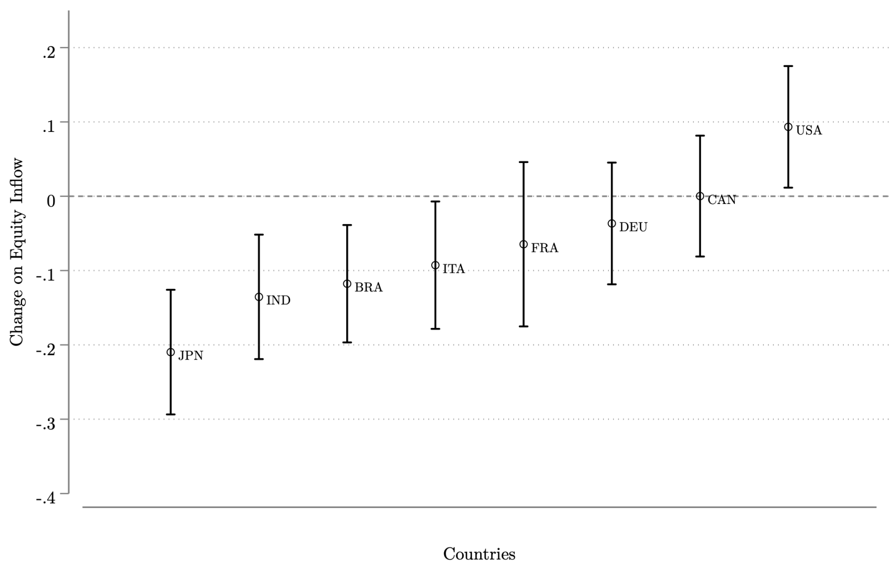
**Notes**: This table reports the correlation coefficients of the specified OLS regression. Both dependent and indepentent variables are standardized to the mean and GDP % is yearly GDP growth. As an additional control, there is also lagged inflows. Data are from Koepke and Paetzold (2022) and Jurado et al. (2015), collected from 47 countries, as shown in A.1. Standard errrors, clustered at country level, are reported in parenthesis.

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 these evidence we can conclude that what already shown in previous literature, such as in Akinci and Kalemli-Ozcan (2023) and Choi et al. (2023), is confirmed in our data. Interestingly, we point out in our entire empirical analysis how the United States differs from the other country when the economy is more volatile. This fact is important for our understanding, as we try to use the information channel as a key driver of these results. Our guess is that research choice might affect differently how peope choose to invest domestically, in the United States and in the rest of the world. Moreover, to double check if our results are only driven in period of recession or in the entire business cycle framework, we do also control for this, as shown in the Appendix (A.2). To see whether this result is consistent with both the theory and the empirics, we first employ an information choice model and set it in an uncertainty environment and then test its predictions with data on forecasts and equity flows.

**Robustness Checks.** We then perform a battery of robustness checks to confirm this results. We first check whether these correlations are consistent when using alternative measures of uncertainty and by adding controls, such as effective exchange rate and size of the country stock market. Then we also check whether our results are consistent for the

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) and Jurado et al. (2015), 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%.

entire country sample, to get rid of potential outliers in our results. We finally check whether we do get the same results when controlling for recessionary periods in the United States. Last, but not least, we also check on whether limiting the tail of distribution in uncertainty, by cutting a standard deviation, we still get the same results. This test is needed to be sure that an alternative channel, such as the information, might exist in addition to a story of flight to quality. These robustness checks can be found in the 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.

## 3.1 Setup

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

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

There are a continuum of investors with measure $\frac{1}{N}$ in each country, who have the same initial wealth $W_0$ and can invest in a portfolio of all assets. We distinguish investors by two types: a fraction $\kappa$ are unsophisticated and the remaining $1-\kappa$ are sophisticated. Both types know the true distribution of the payoff for each risky asset, $r_k \sim \mathcal{N}(\mu_k, \sigma_k^2)$, and thus have common prior about $r_k$. The unsophisticated investors cannot invest in research to learn about the assets, and therefore rely fully on their prior to make investment decisions. The sophisticated investors in a generic country $i$ can choose to acquire additional information 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 $\theta_{ik}$ - 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: $\theta_{kk}$, the cost of research for domestic assets, and $\theta_k$, the average cost of acquiring information about country $k$ among all world's investors. For illustrative purposes, 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 $\eta$. 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 $\{\tau_{ik,s}\}^N_{k=1}$ to maximize expected utility, anticipating their future optimal investment decisions.

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

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, $\theta_{kk}$, and the average cost of acquiring information about country $k$. These elements are visually summarized in the information cost matrix in Table 2.

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

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

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

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, $\theta_{ik}$ is not the same as $\theta_{ki}$ for $k \neq i$.

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 $\sigma_k^2$.*

### 3.4 Capital Flows

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

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

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 $\sigma_k^2$, can arise from various sources. Given our assumption of an independent payoff structure across assets, an increase in $\sigma_k^2$ due to heightened local or global uncertainty will produce the same model results.

We then consider the capital flows after the uncertainty of asset $k$ increases.

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

$$CF_k \propto \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\theta_{ik}} - \frac{1}{\theta_{kk}} \tag{12}$$

*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.*

We end this section by comparing the results for two types of countries that differ in their patterns of $\{\theta_{ik}\}$. Assume for the first type, a 'regular' country labeled as $r$, domestic investors have a learning cost $\theta_{rr}$ that is lower than the average cost for worldwide investors $\bar{\theta}_r \equiv \sum_{i=1}^{N}\frac{1}{\theta_{ir}}$. For the second type, a 'special information-haven' country labeled as $s$, the reverse holds and $\theta_{ss} > \bar{\theta}_s \equiv \sum_{i=1}^{N}\frac{1}{\theta_{is}}$. From Proposition 1 and Proposition 2, domestic investors in country $r$ have higher forecast precision of domestic assets than foreign investors. In addition, when uncertainty for asset payoff $r_r$ increases, such information superiority for domestic investors is more salient, while at the same time country $r$ experiences negative capital inflow. The opposite is true for the special country $s$. Foreign investors have better forecasts on $r_s$ than domestic investors. Such forecasting discrepancy further widens and country $s$ experiences positive capital inflow when $r_s$ is more uncertain.

# 4 Empirical Analysis

In this section, we test the prediction we get from the theoretical analysis. We need to use a dataset that is able to capture how investors make their investment decision based on their information research. Inspired by a similar analysis by De Marco et al. (2022) and Benhima and Bolliger (2023), we use *Consensus Economics* data, collecting country specific forecasts made by public and private institutions, such as universities, research organizations, bank of investiment and firms. The idea is that forecast errors will be a proxy of signal precision, given that the former is a decreasing function of the latter.

## 4.1 Dataset

*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 the dispersion for both groups of forecasters. The macroeconomic variables analyzed include long-term treasury bills spanning 10 years, short-term treasury bills spanning 3 months, industrial production and GDP. The central focus of our study is on evaluating the discrepancies in mean squared error between domestic and foreign forecasters for these variables, particularly during periods of significant uncertainty shocks, defined as exceeding one standard deviation from the norm, which affect the respective countries' economies. The resulting data forms a comprehensive panel encompassing forecasts from 12 different countries, enabling a comparative analysis over the decade in question. More details on the data construction are available in the Appendix (C.1).

**Forecast Errors: an inverse measure of signal precision.** As already introduced in the previous paragraph we need to find a way to compare signal precision with this data. We show in the Appendix (C.1) how we derive this inverse relation between $\tau_{ik,s}$ and squared forecast errors (FE), which is empirically defined in the following way:

$$\mathrm{FE}^2_{i,j,c,t} = \left\{ \mathbf{x}_{i,j,c,t} - \mathbb{E}_{t-1}[\mathbf{x}_{i,j,c,t}] \right\}^2 \tag{13}$$

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

**A proxy of signal precision.** We then want to find a proxy to capture how investment in research is related to uncertainty and see whether this precision is higher for domestic or foreign economies. To do this, we assume that each country can be interpreted as a representative investor, who makes investments in studying the risk factors of specific economies. We can think of forecast errors as an inverse function of signal precision, as we do in our model, by exploiting forecast precision $\hat{\tau_{ik}}$. Recalling our model, we are thus examining how signal precision varies depending on the investor's country perspective. Our hypothesis is that domestic economies tend to be preferred in times of uncertainty when making decisions on how much research to allocate across countries, that is, $\theta_{ii} < \theta_{ik} \forall k \neq i \rightarrow \tau_{ik,s} \uparrow$.

To assess the validity of our hypothesis, we implement two different specifications. First, we look at the average across countries on a single measure of forecast precision by computing root mean squared errors, based on high and low uncertainty. As a second method, we examine how squared forecast errors correlate with domestic forecasters in times of uncertainty.

## 4.2 Empirical Specification

**First approach: relative precision of domestic forecasters.** Let's start with the first methodology. We thus use a measure of relative precision of domestic forecast errrors, which is obtained by computing an Haltiwanger measure comparing domestic and foreign forecast errors as it follows:

$$\mathrm{RP}^d_u = 2 \times \frac{\mathrm{RFE}^f_u - \mathrm{RFE}^d_u}{\mathrm{RFE}^f_u + \mathrm{RFE}^d_u} \tag{14}$$

where $\mathrm{RFE}^f_u$ is root mean squared error of foreign economy; $\mathrm{RFE}^f_u$ is root mean squared error of domestic economy and $u$ is uncertainty, which can be either low or high. We define $\mathrm{RFE}_u^f$ and $\mathrm{RFE}_u^d$, 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 (13); $I$ 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.

**Second approach: 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:

$$\mathrm{FE}_{i,j,c,t}^2 = \alpha+\alpha_{1j}+\beta\mathbf{D}_{i,c}+\beta_{US}\mathbf{D}_{i,c}\times\mathbf{US}_i+\tau\mathbf{US}_i+\gamma\mathbf{D}_{i,c}\times\mathbf{U}_t+\gamma_{US}\mathbf{D}_{i,c}\times\mathbf{U}_t\times\mathbf{US}_i+\varepsilon_{i,c,t} \quad (15)$$

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

## 4.3 Results

**Cost of research: an interpretation.** On average, the cost of research is higher for foreign economies than for domestic ones. This finding is reflected in both theoretical and empirical studies, such as those by Veldkamp (2011) and Benhima and Bolliger (2023), and is known as information home bias. Thus, we can easily relate this to our interpretation of the $\theta$ parameter in our theoretical framework.

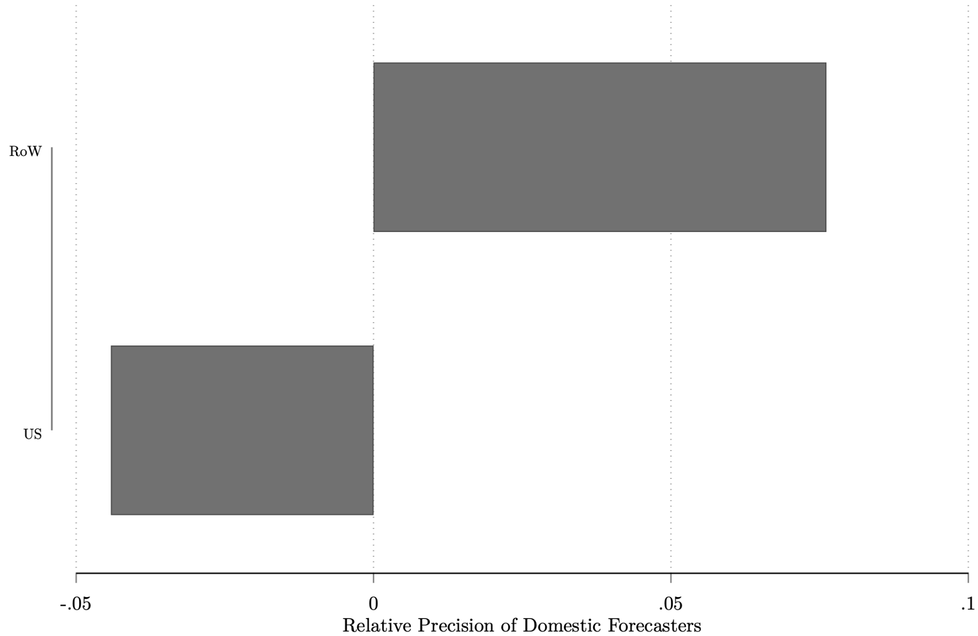
We also test this finding using our first approach, checking how the relative precision of domestic forecasts is distributed on average in our dataset. Figure 3 illustrates this by comparing how all the countries in our sample behave relative to the United States. It is evident that, on average, the rest of the world makes better predictions for domestic economies, with the exception of the United States. Our assumption is that for 'regular' countries, where the domestic cost of research is lower, forecast precision will be higher in the domestic economy. This result is completely reversed for an information haven country, such as the United States. This finding aligns with **Proposition 1** in the theoretical analysis, where we show that for 'regular' countries, forecast precision will be higher for domestic investors than for foreign investors, and vice versa for information haven countries.

**Forecast precision: domestic vs foreign economy.** In Figure 4, we illustrate the variations in the relative precision of domestic forecasters across different countries during periods of low and high uncertainty, comparing the rest of the world with the United States. In our analysis, consistent with the motivating fact, we use an alternative measure of uncertainty as detailed in Appendix C.3. Following the theoretical analysis, we aim to test whether **Proposition 1** is confirmed empirically.

Our findings indicate that, in relative terms, domestic forecast accuracy improves during periods of heightened uncertainty. This trend does not hold for the United States, where foreign forecasters consistently outperform domestic analysts in predicting economic variables during both low and high uncertainty periods. This different behavior in predictions reflects the fact that the United States can be interpreted as an information haven country. These findings extend the results of Benhima and Bolliger (2023) by demonstrating a pronounced information home bias that intensifies with increased uncertainty. Furthermore, we present novel evidence that foreign investors can surpass domestic forecasters in accuracy when predicting risk factors pertaining to the United States.

This superior performance by foreign investors may be attributed to significant invest-

Figure 3: Uncertainty and Equity Inflows



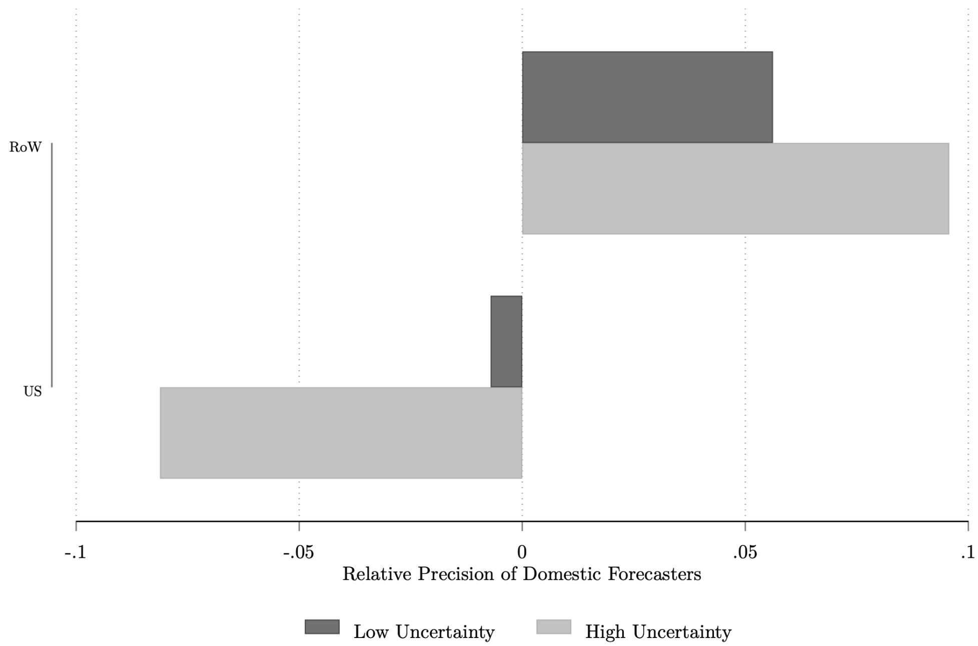

**Notes**: This plot shows the relation between uncertainty and equity inflows, comparing the G7 countries. Uncertainty is measured using the VIX index and changes are in standard deviations. The confidence intervals are set at 95%.

ments by major institutions and banks headquartered outside of the United States. 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 in the literature 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, providing a plausible explanation for the distinct forecasting dynamics observed in the U.S. relative to other countries.

In Figure 5 we show how relative precision of domestic forecasters differs across countries when uncertainty is high. As you can notice, the United States are an exception, while for the rest of the worls, the domestic predictions dominates the foreign ones.

In Table 3, we demonstrate that the same result holds even when performing the OLS specification (15) introduced in the previous paragraph. We focus on capturing the coefficient $\gamma$ and the coefficient $\gamma_{US}$, which represent the average effect of domestic forecasters in times

Figure 4: Uncertainty and Equity Inflows



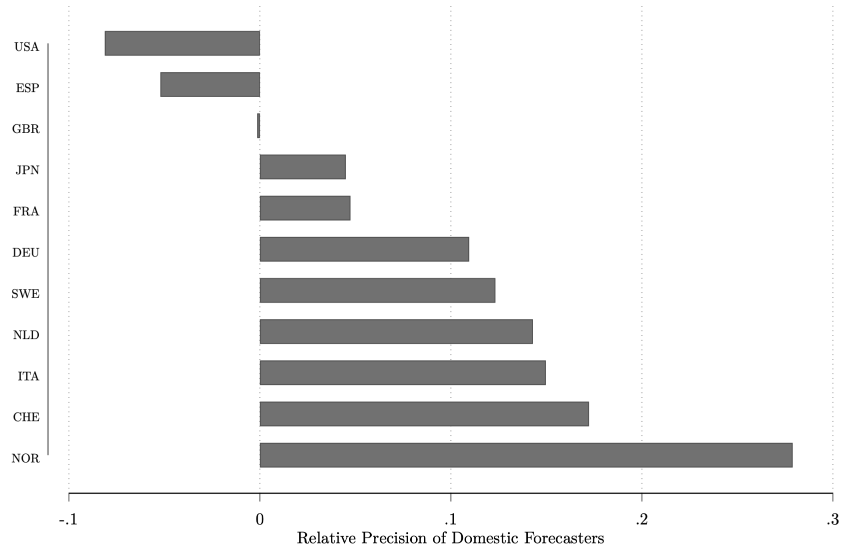

**Notes**: This plot shows how relative precision of domestic forecasters is distributed between rest of the world and United States, in case of high and low uncertainty. The measure we use to capture the relative precision is an Haltiwanger formula between foreign and local difference in forecast errors.

of uncertainty on forecast errors and the marginal effect of the United States, respectively.

Column 1 captures only the average effect, without distinguishing the United States from the cross-country average. The first row of this regression table captures $\beta$, the unconditional effect of domestic forecasters on forecast errors. In this case, $\beta \leq 0$ aligns with Benhima and Bolliger (2023), suggesting that domestic forecasts are on average more accurate than foreign ones. The second row captures the $\gamma$ we are interested in. A $\gamma \leq 0$ indicates that local forecasters are on average more accurate in predicting their own economy compared to foreign forecasters when uncertainty spikes by one standard deviation.

Column 2 includes the dummy variable **US**, thus controlling for the marginal effects of the United States, as shown in our empirical specification (15). We show that $\beta_{US} > 0$, suggesting that in normal times, foreign forecasts about the United States tend to be marginally more precise compared to the cross-country average, with variable and forecaster-specific fixed effects. This is crucial because it mitigates potential biases that might arise from forecasters who periodically make better predictions about the economy. For instance,

Figure 5: Uncertainty and Equity Inflows




**Notes**: This plot shows how relative precision of domestic forecasters is distributed across countries, in conditions of high uncertainty. The measure we use to capture the relative precision is an Haltiwanger formula between foreign and local difference in forecast errors.

if Goldman Sachs consistently outperforms the University of Colorado in making predictions, this fixed effect should eliminate Goldman Sachs' informational advantage.

Column 3 differs from column 2 only by controlling for country-specific fixed effects. The results in this regression table are consistent with those obtained when computing the measure of relative precision of domestic forecasters.

To sum up, both of these approaches suggest that, on average, forecasters tend to be more precise in predicting domestic economies than foreign ones during periods of heightened uncertainty. Given that forecast errors are inversely proportional to signal precision, we can relate our model predictions to these empirical findings. Indeed, by assuming that domestic research is less costly than foreign research, except in the case of the United States, where $\theta_{ii} < \theta_{ik} \forall k \neq \text{US}$[3]. This suggests that domestic economies experience a relatively higher increase in research during times of uncertainty compared to foreign economies, with the United States being an exception, as predicted by **Proposition 1**.

[3]The fact that $\theta_{ii} < \theta_{ik} \forall k \neq \text{US}$ aligns with the literature by Nieuwerburgh and Veldkamp (2009) and Benhima and Bolliger (2023), as information home bias is reflected in a higher cost to study foreign risk factors. Moreover, we also document this in our previous section.

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

| | SD Forecast Error (1) | SD Forecast Error (2) | SD Forecast Error (3) |
|---|---|---|---|
| Domestic | -0.946*** | -0.595*** | -0.331*** |
| | (0.162) | (0.199) | (0.121) |
| Domestic × Financial JLN (2021) | -0.896*** | -0.796*** | -0.797*** |
| | (0.173) | (0.162) | (0.147) |
| US | | -2.397*** | 0.000 |
| | | (0.574) | (.) |
| Domestic × US | | -0.420 | 0.868*** |
| | | (0.393) | (0.176) |
| Domestic × Financial JLN (2015) × US | | 0.887*** | 1.198*** |
| | | (0.194) | (0.169) |
| $N$ | 217187 | 217155 | 217187 |
| $R^2$ | 0.027 | 0.211 | 0.176 |
| adj. $R^2$ | 0.027 | 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 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.

We first look at how this results hold true across different measures of uncertainty. We then also want to control for potential bias in our estimates, since we might have correlation between bad periods, such as recessionary, and forecast errors, we do implement an additional specification, by including recession dummy variable in our regression model. Futher, we also want to double check on this specification, by creating a measure of dispersion, which might be able to get rid of this surprise effect. These robustness checks can be found in Appendix (C.3).

**Testing the 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 $\theta$ varies across countries, for a 'regular' country, we have that 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 country, foreigners may have even better predictions 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 in (15):

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

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

$$\mathrm{Y}_{c,t} = \alpha_{1i} + \xi \hat{\mathrm{FE}^2}_{c,t} + \xi_{US} \hat{\mathrm{FE}^2}_{c,t} \times \mathbf{US} + \mathrm{X}_{c,t} + \varepsilon_t, \tag{16}$$

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 $\xi$ is positive or negative, which would indicate 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 $\xi_{US}$ should be positive and significantly different from zero, assuming that it is an information haven country.

As shown in Table 18, 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. Consequently, we have $\xi < 0$ and $\xi_{US} > 0$, even when controlling for additional variables such as GDP growth. 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. Specifically, we have shown that during periods of increased

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

| | Inflows (1) | Inflows (2) | Inflows (3) |
|---|---|---|---|
| $\xi$ | -0.018** | -0.016*** | -0.018*** |
| | (0.006) | (0.004) | (0.005) |
| $\xi\times$ US | | 0.059*** | 0.060*** |
| | | (0.006) | (0.006) |
| $N$ | 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.

uncertainty, the direction of flows is generally negatively affected by an increase in relative domestic forecast errors, as opposed to the rest of the world. As an additional test, to be

In order to control for potential bias in our estimates, since we might have some sort of flight to quality channel to drive the equity in the United States, we want to test whether by introducing some sort of variable that captures this index of confidence across countries in different period of times our results still hold true. We thus use an index of consumer confidence across country and run again our 2SLS regression specfication, including this variable in our second stage. These robustness check can be found in Appendix (C.3).

# 5 Conclusion

This paper explores the compelling fact that rising uncertainty leads to negative capital inflows worldwide, with the notable exception of the United States. Recognizing this as a 'flight to quality' phenomenon, we make a deeper analysis to uncover an additional mechanism driving this behavior. Our approach combines both theoretical and empirical analyses to support our thesis.

We develop a model of endogenous information acquisition within a multi-country framework, where investors incur convex costs to learn about the fundamental values of domestic and foreign assets. Our model accounts for diverse information environments, with learning costs varying by the investor's home country and the target country's assets.

Our empirical analysis verifies the model's predictions, demonstrating that in normal countries, domestic forecasts are more precise, whereas the United States, an information haven, exhibits the opposite, as in **Proposition 1**. We further validate the information channel using a two-stage least squares method, capturing the correct inflow signs for both the average effect and the United States. This finding aligns with our model's predictions, in particular with **Proposition 2**.

Our contribution lays the groundwork for advancing three major literature streams, suggesting potential extensions to further investigate this behavior and its implications for investors. However, this paper is already able to replicate some predictions coming from a theoretical framework, where we isolate our attention to the information channel only. The goal is to focus exclusively to the investor asymmetries in terms of information and how these are amplified in times of uncertainty. This contribution can be considered an additional piece of literature to be added to the existing handbook on capital flows by Miranda-Agrippino and Rey (2022), in an environment of uncertainty.

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# Appendix

## A Motivation

### 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:

- BEL Belgium
- BGR Bulgaria
- BRA Brazil
- CAN Canada
- CHL Chile
- CHN China
- COL Colombia
- CZE Czech Republic
- DEU Germany
- DNK Denmark

- ESP Spain
- EST Estonia
- FIN Finland
- FRA France
- GRC Greece
- HRV Croatia
- HUN Hungary
- IDN Indonesia
- IND India
- ISL Iceland
- ITA Italy
- JPN Japan
- KOR Korea
- LBN Lebanon
- LKA Sri Lanka
- LTU Lithuania
- LVA Latvia
- MEX Mexico
- MNG Mongolia
- MYS Malaysia
- NLD Netherlands
- PAK Pakistan

- PHL Philippines
- POL Poland
- PRT Portugal
- ROU Romania
- SRB Serbia
- SVN Slovenia
- SWE Sweden
- THA Thailand
- TUR Turkey
- UKR Ukraine
- USA United States
- ZAF South Africa

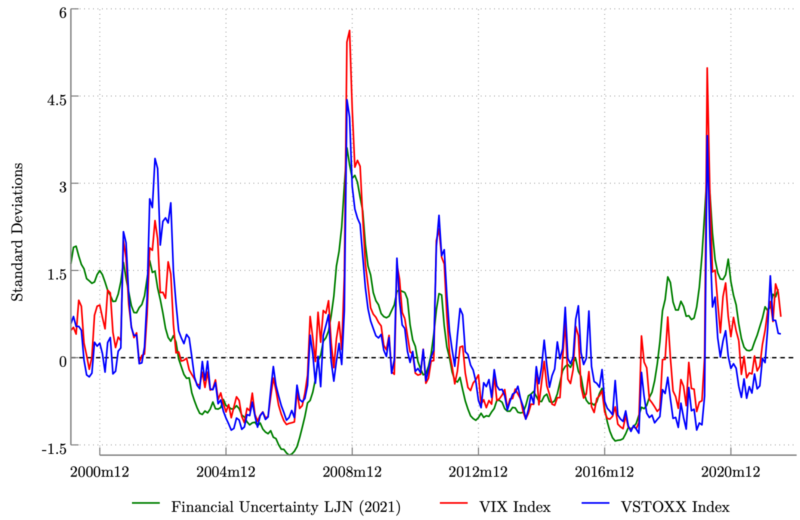
**Merging the dataset with uncertainty measures.** We then merge this data with uncertainty measures at monthly level, by using Jurado et al. (2015) measure, updated in 2021, VIX and VSTOXX, from Fred. Table 5 shows how these measures are distributed. Figure 6 plots time series for alternative measures of uncertainty, while Figure 7 their distributions.

Table 5: Descriptive Statistics: Uncertainty

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

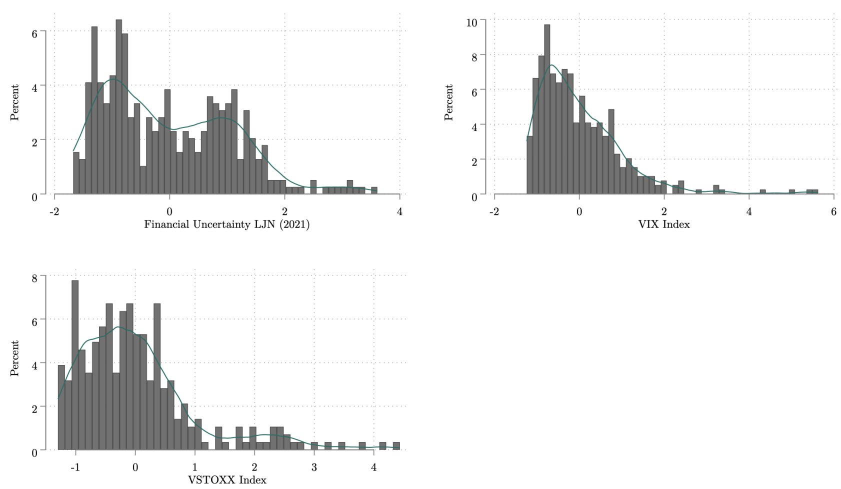
**Notes**: The Table reports the descriptive statistics of different measure of uncertainty. These measures are standardized to the mean.

Figure 6: 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 7: 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.

## 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):

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

Table 7: Equity Flows and VIX

| | 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**: 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.

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 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.

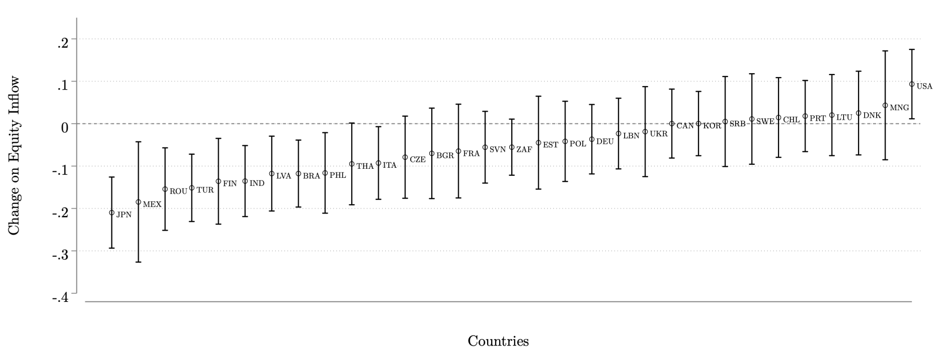
**Additional Control Variables.** We add some control variables, such as size of the stock market in each country (market capitalization), effective exchange rate and bond inflows, to check whether the results hold true even by increasing the boundle of control variables.

Table 9: Equity Flows and Additional Controls

| | Inflows (1) | Inflows (2) | Outflows (3) | Outflows (4) |
|---|---|---|---|---|
| Financial LJN (2021) | -0.070*** | -0.074*** | -0.068*** | -0.068*** |
| | (0.013) | (0.014) | (0.016) | (0.016) |
| Financial LJN (2021) × US | 0.157*** | 0.161*** | 0.155*** | 0.155*** |
| | (0.014) | (0.015) | (0.018) | (0.018) |
| GDP Δ% | 0.011*** | 0.009*** | 0.008** | 0.008** |
| | (0.003) | (0.003) | (0.004) | (0.004) |
| Size | | 0.045*** | 0.048** | 0.048** |
| | | (0.016) | (0.023) | (0.023) |
| EER | | | 3.855** | 3.825** |
| | | | (1.466) | (1.461) |
| Bond Inflows | | | | 0.002 |
| | | | | (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 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.

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%.

**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 10: Equity Flows, Financial Uncertainty and Recession

| | Inflows (1) | Inflows (2) | Inflows (3) |
|---|---|---|---|
| Financial JLN (2021) | -0.054*** | | |
| | (0.014) | | |
| Financial JLN (2021) × US | 0.139*** | | |
| | (0.015) | | |
| Recession | -0.051 | 0.002 | -0.049 |
| | (0.047) | (0.040) | (0.042) |
| GDP Δ% | 0.009*** | 0.010*** | 0.011*** |
| | (0.003) | (0.003) | (0.003) |
| VIX Index | | -0.091*** | |
| | | (0.014) | |
| VIX Index × US | | 0.182*** | |
| | | (0.018) | |
| 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 11: Equity Flows and Low Uncertainty

| | Inflows (1) | Inflows (2) | Outflows (3) | Outflows (4) |
|---|---|---|---|---|
| Financial LJN (2021) | -0.044*** | -0.039** | -0.007 | -0.012 |
| | (0.014) | (0.015) | (0.023) | (0.022) |
| Financial LJN (2021) × US | 0.141*** | 0.137*** | -0.117*** | -0.120*** |
| | (0.015) | (0.016) | (0.025) | (0.026) |
| GDP Δ% | | 0.011*** | | -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:

$$U_i \equiv \mathbb{E}\left[\mathbb{E}_i\left(W_i\right) - \frac{\eta}{2}\mathbb{V}_i\left(W_i\right)\right] \tag{17}$$

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

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

Under the assumption that risky asset payoffs are independently distributed, we can write the objective function 17 as:

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

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:

$$
\max \; \frac{1}{2}\sum_{k=1}^{N}\left(\eta\frac{\tau_k + \tau_{ik,s}}{\tau_k^2} + \frac{1}{\eta}\frac{\tau_{ik,s}}{\tau_k}\right) - \sum_{k=1}^{N}\frac{\theta_{ik}}{2}\tau_{ik,s}^2 \tag{18}
$$

**Information choice** Solve for optimal $\tau_{ik,s}$ from 18, we get:

$$
\tau_{ik,s} = \frac{1}{2\theta_{ik}}\left(\frac{\eta}{\tau_k^2} + \frac{1}{\eta\tau_k}\right) \tag{19}
$$

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,

$$
\widehat{r}_{ik} = \kappa_i s_{ik} + (1-\kappa_i)\mu_k \tag{20}
$$

$$
\widehat{\sigma}_{ik}^2 = 1/\widehat{\tau}_{ik} = \frac{\sigma_k^2}{1 + \frac{1}{2\theta_{ik}}\sigma_k^4\left(\frac{1}{\eta} + \eta\sigma_k^2\right)} \tag{21}
$$

Substitute 20 and 21 into the portfolio holdings in the second period 6, we get the aggregate demand for asset $k$ of sophisticated investors in country $i$ is:

$$
\mathbb{E}\int_S x_{i,k}^S dS = \mathbb{E}\int_S \frac{\widehat{r}_{ik} - \mu_k + \eta\sigma_k^2}{\eta\widehat{\sigma}_{ik}^2} dS = 1 + \frac{1}{2\theta_{ik}}\left(\frac{\eta}{\tau_k^3} + \frac{1}{\eta\tau_k^2}\right) \tag{22}
$$

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:

$$\frac{\partial}{\partial \sigma_k^2}\left(-x_{kk}^S + \frac{1}{N}\sum_{i=1}^{N} x_{ik}^S\right) = \frac{1}{2}\left(\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\theta_{ik}} - \frac{1}{\theta_{kk}}\right)\left(\frac{3\eta}{\tau_k^4} + \frac{2}{\eta\tau_k^3}\right) \tag{23}$$

Hence,

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

# C Empirical Analysis

## C.1 Dataset Construction

We build our dataset from *Consensus Economics*, by collecting data of 14 countries, from 2006 to 2018. We include the following variables in our dataset:

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

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

The list of countries included in our sample is the following:

- AUT Austria
- BEL Belgium
- CAN Canada
- CHE Switzerland
- DEU Germany
- DNK Denmark
- ESP Spain
- FIN Finland
- FRA France
- GBR United Kingdom
- GRC Greece
- IRL Ireland
- ISR Israel
- ITA Italy
- JPN Japan
- NLD Netherlands
- NOR Norway
- PRT Portugal
- SWE Sweden
- USA United States

We report descriptive statistics of the data in Table 12 and the resulting of a 1% trimming from both left and right tails in Table 13. Moreover, in Figure 9 we show the distributions of the variables we included in our dataset.

Table 12: 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 |

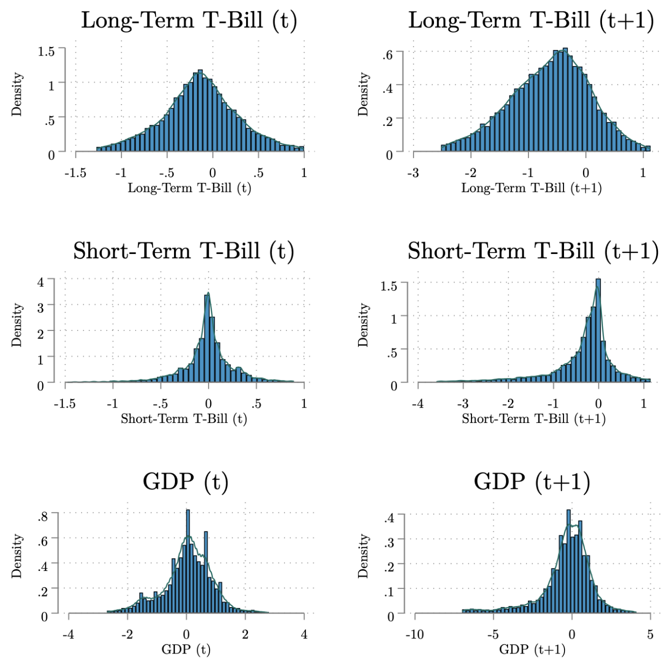
**Notes**: The Table reports a descriptive statistics of the variables we included in our dataset from *Consensus Economics* survey. We report mean, median, max, min and number of observations. In appendix ()C.1) we report the list of countries included in our dataset.

Table 13: 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 9: Uncertainty and Equity Inflows

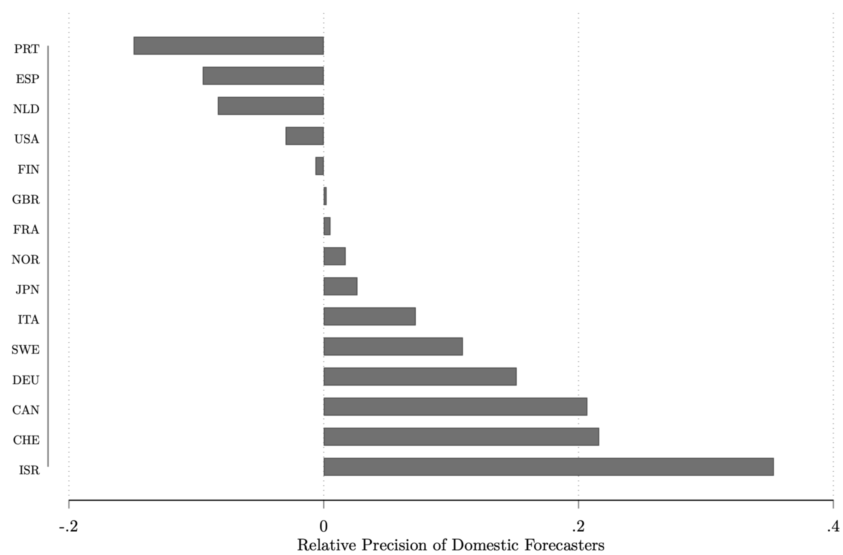



**Notes**: Distributions of the main variables we included in our dataset from *Consensus Economics*. Data are 1% trimmed from both left and right tails.

## C.2 Cost of Research

We show how relative precision of domestic forecasters is distributed across countries on average. Most of the countries show that domestic forecasters are more precise than foreigners. This has implications, in ine with the Information Home Bias literature. Thus, we can use that to interpret how $\theta$ in our theoretical framework will mostly be intepreted such that $\theta_d < \theta_f$ since cost of research looks to be cheaper in the domestic economy. An exception, confirmed also in Figure 10 is for the United States.

Figure 10: Relative Precision of Domestic Forecasters: Average




**Notes**: This plot shows how relative precision of domestic forecasters is distributed across countries, on average. The measure we use to capture the relative precision is an Haltiwanger formula between foreign and local difference in forecast errors.

## 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 14: Second Approach: Using VIX

| | SD Forecast Error (1) | SD Forecast Error (2) | SD Forecast Error (3) |
|---|---|---|---|
| Domestic | -0.750*** | -0.332* | -0.140 |
| | (0.136) | (0.182) | (0.100) |
| Domestic × VIX | -0.728*** | -0.641*** | -0.623*** |
| | (0.160) | (0.158) | (0.136) |
| US | | -1.782*** | 0.000 |
| | | (0.493) | (.) |
| Domestic × US | | -0.890** | 0.523*** |
| | | (0.434) | (0.151) |
| Domestic × VIX × US | | 0.643*** | 0.962*** |
| | | (0.198) | (0.168) |
| $N$ | 217187 | 217155 | 217187 |
| $R^2$ | 0.021 | 0.204 | 0.170 |
| adj. $R^2$ | 0.021 | 0.197 | 0.169 |
| 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 15: Second Approach: Using VSTOXX

| | SD Forecast Error (1) | SD Forecast Error (2) | SD Forecast Error (3) |
|---|---|---|---|
| Domestic | -0.687*** | -0.181 | -0.079 |
| | (0.133) | (0.184) | (0.096) |
| Domestic × VSTOXX | -0.701*** | -0.623*** | -0.596*** |
| | (0.170) | (0.172) | (0.151) |
| US | | -1.616*** | 0.000 |
| | | (0.472) | (.) |
| Domestic × US | | -1.328*** | 0.486*** |
| | | (0.454) | (0.156) |
| Domestic × VSTOXX × US | | 0.735*** | 0.989*** |
| | | (0.212) | (0.173) |
| $N$ | 217187 | 217155 | 217187 |
| $R^2$ | 0.014 | 0.199 | 0.163 |
| adj. $R^2$ | 0.014 | 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.

**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 16: Second Approach: Controlling for Recession

| | SD Forecast Error (1) | SD Forecast Error (2) | SD Forecast Error (3) |
|---|---|---|---|
| Domestic | -0.946*** | -0.681*** | -0.370*** |
| | (0.162) | (0.202) | (0.118) |
| Domestic × Financial JLN (2021) | -0.896*** | -0.864*** | -0.842*** |
| | (0.173) | (0.162) | (0.146) |
| US | | -2.073*** | 0.000 |
| | | (0.495) | (.) |
| Domestic × US | | -0.410 | 0.399*** |
| | | (0.375) | (0.144) |
| Domestic × Financial JLN (2015) × US | | 0.911*** | 1.088*** |
| | | (0.204) | (0.189) |
| Recession | | 14.988*** | 15.387*** |
| | | (1.570) | (1.551) |
| $N$ | 217187 | 217155 | 217187 |
| $R^2$ | 0.027 | 0.231 | 0.199 |
| adj. $R^2$ | 0.027 | 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 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.

**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 $t$.

We then implement the following OLS specification to capture the effect of uncertainty, depending on being local forecasters, on dispersion:

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

Table 17: Second Approach: Dispersion

| | SD Dispersion (1) | SD Dispersion (2) | SD Dispersion (3) |
|---|---|---|---|
| Domestic | -0.148*** | -0.094*** | -0.094*** |
| | (0.029) | (0.022) | (0.021) |
| Domestic × Financial JLN (2015) | -0.061** | -0.057** | -0.054* |
| | (0.030) | (0.029) | (0.028) |
| US | | -0.365*** | 0.000 |
| | | (0.090) | (.) |
| Domestic × US | | 0.101*** | 0.088*** |
| | | (0.025) | (0.022) |
| Domestic × Financial JLN (2015) × US | | 0.065** | 0.061** |
| | | (0.031) | (0.029) |
| $N$ | 221525 | 221525 | 221525 |
| $R^2$ | 0.004 | 0.016 | 0.029 |
| adj. $R^2$ | 0.003 | 0.016 | 0.028 |
| 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 18: Second approach: OLS and FE[2]

| | Inflows (1) | Inflows (2) | Inflows (3) |
|---|---|---|---|
| Consumer Confidence Index | -0.014 | 0.015 | 0.017 |
| | (0.140) | (0.153) | (0.153) |
| Confidence Index × US | 0.061 | 0.048 | 0.046 |
| | (0.141) | (0.156) | (0.156) |
| $\xi$ | -0.018$^{**}$ | -0.016$^{***}$ | -0.018$^{***}$ |
| | (0.006) | (0.004) | (0.005) |
| $\xi\times$ US | | 0.059$^{***}$ | 0.061$^{***}$ |
| | | (0.006) | (0.006) |
| $N$ | 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.