Equity Flows in Uncertain Times: the Role of Heterogeneous Information

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Abstract

We study the role of information heterogeneity in shaping capital flows during the global financial cycle. When global uncertainty rises, investors retrench toward their home country and the United States. We build a model of portfolio choice and information acquisition with heterogeneous learning costs across countries. The model replicates key features of the global financial cycle and generates two testable predictions. First, domestic forecasters are more accurate in predicting their own country's economic conditions, and this informational advantage strengthens with higher global uncertainty. Second, differences in learning costs translate into systematic patterns of equity flows: capital moves toward destinations where investors hold a relative informational advantage. Using Consensus Economics forecast data and both aggregate and bilateral equity inflows, we find empirical support for these predictions, showing that informational frictions help explain the reduction of foreign equity holdings during uncertain times, except in information-haven countries such as the United States.

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1 Introduction

Equity flows across countries are a fundamental aspect of the global economy and play a crucial role for the fluctuation of output and asset prices. They represent a large share of total capital movements, with inflows and outflows together accounting on average for nearly half of all cross-border capital flows.[1]

The recent literature on the global financial cycle, summarized in Coeurdacier and Rey (2013) and Miranda-Agrippino and Rey (2022), has documented that equity investors not only exhibit home bias in portfolio choices, but also reduce their exposure to foreign markets and shift towards safer assets, particularly in the United States, during episodes of global uncertainty. In line with this evidence, Caballero and Simsek (2020) and Akinci and Kalemli-Ozcan (2024) show that increases in uncertainty are systematically associated with declines in equity inflows across most countries, while the United States remains an exception that continues to attract foreign capital. This asymmetric behavior suggests that informational conditions may play a role in explaining cross-country differences in investor responses to global shocks.

The central question we address is whether these differences in information across countries can explain the heterogeneous response of equity inflows to global uncertainty. Specifically, we ask whether cross-country variation in the cost and precision of information acquisition can account for the broad contraction of foreign equity investment observed during periods of high uncertainty, and the relative resilience of certain economies.

This question matters for several reasons. Equity flows are massive and highly volatile. Annual gross inflows alone often exceed ten percent of GDP in many countries, and during financial crises declines in inflows have reached hundreds of billions of dollars, as shown in Caballero and Simsek (2020). They are also extremely sensitive to uncertainty shocks, a one standard deviation increase in global volatility reduces institutional equity inflows by about two percentage points per quarter, with effects several times larger in emerging markets and that become even more pronounced at the investor-firm level, as shown by Kacperczyk et al. (2025). Even seemingly modest changes in equity inflows translate into hundreds of billions of dollars in reallocations, with significant implications for financial stability, capital flow

[1] Following the balance of payments convention, we define equity inflows as the net transactions between nonresidents and residents of a given country that lead to changes in the ownership of domestic equities. Positive inflows indicate that foreign investors are, on net, purchasing domestic equities from residents, while negative inflows reflect net sales of domestic equities by nonresidents, implying a withdrawal of foreign capital. This definition follows the official convention of the TIC US system.

management, and disclosure regulation. Understanding what drives equity inflows, and how they respond to uncertainty, is therefore central for both researchers and policymakers.

Building on this motivation, we develop a multi-country portfolio choice model with endogenous information acquisition. A fraction of investors are sophisticated and can acquire costly information about domestic and foreign assets, while the remaining unsophisticated investors do not invest in research and only base their decision on the prior distributions of asset returns. Information costs differ across countries, so the ability to learn about foreign assets is heterogeneous. Sophisticated investors choose how much information to acquire about each country's risky asset before forming portfolios, trading off higher signal precision against its cost. Information shapes expected returns and allocations, so the global pattern of equity holdings reflects how well investors in each country understand each destination. When either global or local uncertainty rises, the value of information increases, and investors shift both learning and investment toward markets they can research more cheaply.

The model delivers three key predictions. First, investors with lower learning costs for a given market acquire more precise information and gain a relative information advantage, and this advantage becomes stronger as uncertainty increases. Second, higher uncertainty affects foreign equity inflows at the aggregate level, as the net change in total foreign investment into a country. Countries where domestic investors have a clear information advantage experience a fall in aggregate foreign inflows in such episodes. Third, beyond aggregate inflows, the model also characterizes bilateral inflows, which capture how individual foreign countries adjust their positions. Whether investors from a specific country increase or reduce their holdings depends on how their learning cost compares with the world average. Markets that are relatively easy for all investors to research behave as information havens and remain resilient during global volatility.

We then test these predictions empirically using both aggregate and bilateral data on equity inflows. The aggregate series are taken from De Crescenzio and Lepers (2025) and cover 46 economies from 2000 to 2022. Bilateral equity flow data come from the JRC ECFIN Finflows database by Nardo et al. (2017), which provides yearly bilateral positions and flows of cross border investment up to 2020 for more than 80 reporting and partner countries. To measure informational heterogeneity, we use forecasts from Consensus Economics, which collect monthly projections from a large set of institutions on key macroeconomic variables such as GDP growth, inflation, interest rates, industrial production, and unemployment. We focus on one year ahead horizons for comparability across variables and countries. The panel spans 2006 to 2018 and, after standard sample filters, covers 18 advanced economies with a clear classification of forecasters as domestic or foreign based on the location of the headquarters, accounting for international subsidiaries as in Benhima and Bolliger (2025). We compute forecast errors and construct relative precision measures for domestic versus foreign institutions that serve as empirical proxies for information precision.

Empirically, we first examine how the forecast accuracy of domestic relative to foreign institutions varies with global uncertainty. We show that domestic forecasters are systematically more accurate about their own country, and that this informational advantage widens during periods of high volatility, while in the United States the advantage weakens or reverses, consistent with its interpretation as an information haven.

Then we test whether these informational differences translate into observable patterns in equity inflows. At the aggregate level, we find that when domestic institutions become relatively better informed, foreign equity inflows into that country weaken, consistent with the idea that foreign investors reduce their participation when they are informationally disadvantaged. At the bilateral level, we show that investors channel more equity toward destinations they understand better, as measured by their relative forecast precision about those countries. Both results hold when we include country pair fixed effects and controls for persistence, confirming that information frictions systematically shape both the level and the geography of equity inflows when uncertainty rises.

Taken together, the evidence confirms the central mechanism of the model and shows that information heterogeneity is a first order determinant of how equity capital is allocated across countries. By documenting the asymmetric response of equity inflows to uncertainty, and by linking it to measurable differences in forecast precision, we deliver a unified explanation for three core facts, the sensitivity of inflows to global volatility, the persistence of home bias, and the special role of the United States as an information haven. The combination of aggregate and bilateral tests makes the mechanism transparent and directly testable, while the Consensus Economics measures of relative precision provide a clean proxy for information gaps.

Relation to the Literature. We contribute to three main literatures. First, our work is connected to the literature examining capital flows during global financial cycles, as in Caballero and Simsek (2020), Akinci and Kalemli-Ozcan (2024), and Choi et al. (2023). Our motivating findings build upon this literature, by studying the response of equity flows to uncertainty, which highlight both a clear retrenchment pattern when uncertainty increases, and the different behavior of safe havens, such as the United States, with respect to the rest of the world. Second, our paper relates to studies that analyze the interaction between investors' endogenous information choice and portfolio decisions, as in Van Nieuwerburgh and Veldkamp (2009), Van Nieuwerburgh and Veldkamp (2010), Mondria (2010), Mondria and Wu (2010), Dziuda and Mondria (2012), Valchev (2017), Kacperczyk et al. (2019), De Marco et al. (2022), Veldkamp (2023). Existing work has studied the role of information choices and advantages in explaining the seemingly under-diversified and differentially concentrated portfolio holdings across investors. Our work contributes to the literature by demonstrating that heterogeneity in investors' learning technology, and thus beliefs, can also help explain the observed heterogeneous international equity flow patterns. Kacperczyk et al. (2025) investigates the equity flows of institutional investors in periods of high global uncertainty, when foreign and domestic institutional investors differ in their size and information processing capacities. Our model allows investors to acquire information for multiple assets in equilibrium, allowing for a different behavior of investors, which may vary across countries. Our information mechanism is also related to Malmendier et al. (2020), which studies the role of past investor experiences in explaining capital flows. We instead emphasize the role of endogenous information acquisition and, most importantly, we test in the data the predictions of the model on heterogeneous forecast precision. Third, we contribute to a literature that studies empirically the existence of local information advantage, as in Batchelor (2007), Ager et al. (2009), Mehrotra and Yetman (2014), Coibion and Gorodnichenko (2015), Bordalo et al. (2020), Gemmi and Valchev (2025), and Benhima and Bolliger (2025). We contribute to this literature by providing evidence that not only there is a local information advantage, but that this becomes more marked in times of uncertainty. We also show that the United States does not display a local information advantage, behaving consistently with our theoretical notion of information haven.

Outline. The paper is organized as follows. Section 2 is our motivating evidence, showing how equity inflows react to uncertainty shocks, across countries. In section 3 we develop our theoretical framework. Section 4 tests the theory using Consensus Economics forecasts and equity flows data. Section 5 concludes.

2 Motivating Evidence

In this section, we examine how foreign equity holdings respond to fluctuations in uncertainty, with a particular emphasis on how global shocks shape the cross-border allocation of financial capital. Our results show that, on average, periods of heightened uncertainty are associated with negative equity inflows, with the notable exception of the United States. This pattern reflects a broad flight-to-safety mechanism in investor behavior, consistent with the evidence documented by Miranda-Agrippino and Rey (2015) and with the role of uncertainty as a global pull factor for capital discussed in Choi et al. (2023). During uncertain times, investors tend to reduce exposure to riskier or less familiar markets and reallocate funds toward economies perceived as safer, more transparent, or more liquid. The United States stands out in this respect, as it continues to attract capital even when global risk aversion rises, underscoring its unique position as a global financial safe haven.

While these empirical regularities are well established in the literature, our analysis focuses specifically on cross-border portfolio equity holdings to shed light on the informational foundations of these capital movements. We concentrate on equity, rather than bonds, because informational frictions, such as asymmetric information, heterogeneous investor beliefs, and differences in monitoring capacity, are far more pronounced in equity markets. Equity investments require forming expectations about firm-level performance and local economic conditions, both of which depend heavily on access to timely and accurate information. Bonds, by contrast, are typically less sensitive to informational asymmetries, as their payoffs are more predictable and often supported by institutional guarantees.

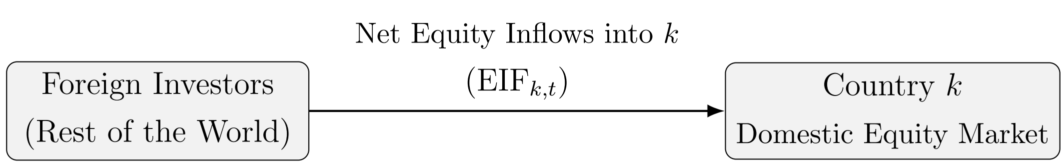
By examining portfolio equity inflows, we aim to uncover how uncertainty influences the reallocation of financial capital across countries through informational and behavioral channels, rather than through the broader movement of real investment. This approach allows us to focus on the decisions of global investors who continuously rebalance portfolios in response to perceived changes in information precision and risk. In doing so, we can isolate the mechanisms through which uncertainty reshapes international portfolio choices, distinguishing between countries that are relatively opaque and those that function as information havens. Overall, this perspective provides a more granular understanding of how uncertainty interacts with information to drive the global geography of equity flows.

Equity inflows: Definition. We define equity inflows, following the balance of payments (BoP) convention, as the net transactions between nonresidents and residents of a given country that lead to changes in the ownership of domestic equities. Positive equity inflows indicate that foreign investors are, on net, purchasing domestic equities from residents, thereby increasing their exposure to that country's equity market. In contrast, negative equity inflows reflect net sales of domestic equities by nonresidents, implying a withdrawal or retrenchment of foreign capital.[2]

This definition captures one side of the cross-border portfolio adjustment process, focusing on how much foreign investors increase or reduce their holdings of a country's equity. Conceptually, equity inflows measure how the rest of the world reallocates its financial capital toward or away from a given destination in response to shifts in uncertainty or risk perception. This measure provides a direct and intuitive indicator of international capital movements, and it serves as the key variable in our empirical analysis of how uncertainty shapes global equity allocations. In what follows, we use this measure to quantify how global shocks and informational frictions jointly drive the dynamics of cross-border equity flows.

Beyond this baseline definition, it is useful to distinguish between aggregate and bilateral equity inflows. Aggregate equity inflows refer to the net flow of foreign equity investment into a given country from all other countries combined. They capture whether, on balance, foreign investors as a whole are expanding or reducing their exposure to that market, and thus provide a macro-level indicator of a country's ability to attract foreign capital. By contrast, bilateral equity inflows focus on the net equity investment between a specific investor country and a specific destination country. The bilateral measure isolates how one country reallocates its equity holdings toward or away from another, allowing us to study the geography of capital flows and identify which countries adjust more strongly when uncertainty or informational frictions change. This distinction is central for our empirical strategy: aggregate inflows speak to whether a country gains or loses foreign capital overall, while bilateral inflows reveal who is driving these changes and how information asymmetries shape the cross-country reallocation of portfolios.

Schematic Representation of Equity Inflows



Empirical specification. To study how equity inflows respond to global uncertainty, we use monthly portfolio equity inflow data from De Crescenzio and Lepers (2025), covering 49

[2] This definition of equity inflows as the net flow of foreign holdings of equity in a given country follows the official definition provided by the TIC US system.

countries over the period 1997-2025. The data follow the IMF balance of payments definition of portfolio equity and measure the net acquisition of domestic equity by foreign investors. In other words, they capture the change in foreign holdings of each country's equity over time, expressed as:

$$\mathrm{IF}_{k,t} = \Delta\Big(\text{foreign holdings of } k\text{'s equity}\Big)_t.$$

This variable measures how much new foreign capital enters the domestic equity market of country k at time t. Positive values indicate that foreign investors are increasing their exposure to that country's equity market, while negative values correspond to retrenchment or net sales by nonresidents.

Our main measure of uncertainty is the VIX index, which captures global financial market volatility and serves as a widely used proxy for risk perception. The analysis focuses on global uncertainty as a common driver of cross-border portfolio movements. Nevertheless, in Appendix **??**[3], we show that the results are robust to alternative measures of uncertainty and to extreme market events.

We estimate the following specification:

$$\begin{aligned} \mathrm{EIF}_{i,t} = {} & \alpha_i + (\beta + \beta_{\mathrm{US}} \mathbb{1}_{\{i=\mathrm{US}\}})\, \mathrm{VIX}_t \\ & + \delta_1\, \mathrm{GDP}_{i,t} + \delta_2\, \mathrm{EER}_{i,t} + \delta_3\, \mathrm{BIF}_{i,t} + \gamma \sum_{z=1}^{4} \mathrm{EIF}_{i,t-z} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where $\mathrm{EIF}_{i,t}$ denotes standardized net equity inflows for country i at time t, and α_i captures country fixed effects. The coefficient β measures the average response of equity inflows to global uncertainty, while β_{US} captures the differential sensitivity of the United States relative to other economies. The control variables include annual GDP growth ($\mathrm{GDP}_{i,t}$), the change in the effective exchange rate ($\mathrm{EER}_{i,t}$), and net bond inflows ($\mathrm{BIF}_{i,t}$), which help account for macroeconomic conditions and potential liquidity reallocations across asset classes.

Results. Three main findings emerge from Table 1. First, the coefficient on the VIX is negative and highly significant across all specifications, ranging between -0.10 and -0.11. This result indicates that a one standard deviation increase in global uncertainty, relative to the mean of the sample, is associated with a decline in equity inflows of about ten percent

[3] Appendix **??** presents robustness checks using the Jurado, Ludvigson, and Ng (JLN) macroeconomic uncertainty index, as well as local measures of uncertainty based on country-level ETF volatility. We also verify that the results are unaffected when excluding months in which the standardized VIX exceeds two standard deviations above its mean.

Table 1: Uncertainty and Aggregate Equity Inflows

	Aggregate EIF (1)	Aggregate EIF (2)	Aggregate EIF (3)
VIX	-0.099	-0.108	-0.113
	(0.014)	(0.014)	(0.016)
VIX × US	0.161	0.172	0.176
	(0.017)	(0.017)	(0.020)
GDP Δ%		0.014	0.012
		(0.004)	(0.005)
EER			0.034
			(0.017)
Bond Inflows			0.001
			(0.001)
Observations	7484	7349	6375
Country FEs	Yes	Yes	Yes

Notes: This table reports OLS estimates of Equation (1). The dependent variable is standardized net equity inflows. Column (1) includes only the VIX and its U.S. interaction term. Column (2) adds GDP growth as a control, while Column (3) further introduces the effective exchange rate and net bond inflows (BIF) to capture liquidity and portfolio reallocation effects. Standard errors, clustered at the country level, are reported in parentheses.

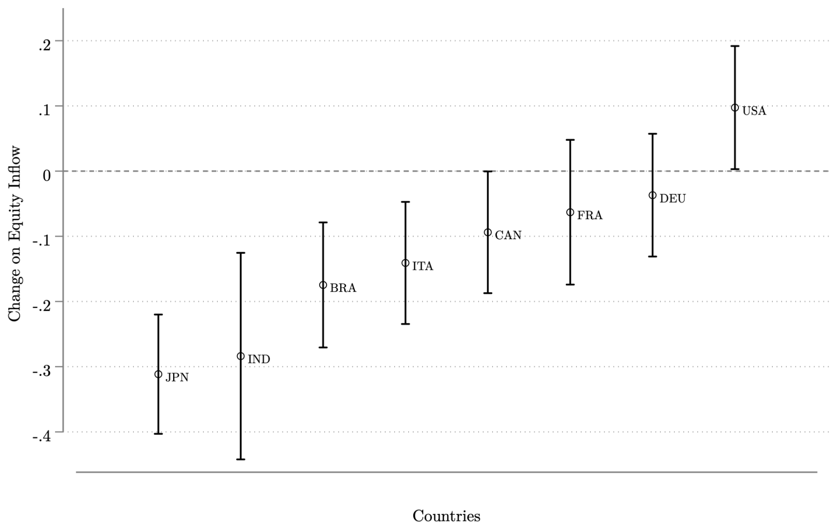
on average. In other words, when global volatility rises, foreign investors reduce their net purchases of domestic equities, leading to a fall in the foreign holdings of equity assets in each country. This evidence points to a generalized contraction in cross-border equity investment during uncertain periods, consistent with the view that heightened uncertainty discourages international risk-taking and portfolio rebalancing.

Second, the interaction term VIX $\times \mathbb{1}_{\{i=\text{US}\}}$ is positive and statistically significant, with estimated coefficients between 0.16 and 0.18. This result indicates that the response of equity inflows to global uncertainty differs systematically for the United States. Whereas most countries experience a reduction in foreign equity investment when uncertainty rises, the decline is significantly smaller for the United States. In relative terms, this suggests that U.S. equity markets retain or attract a larger share of foreign investment compared with other destinations during volatile periods.[4]

Third, the inclusion of additional control variables, such as GDP growth, exchange rate changes, and bond inflows, does not materially affect the size or significance of these key coefficients. The persistence of the main results across specifications confirms that the nega-

[4] A similar asymmetry is documented by Akinci and Kalemli-Ozcan (2024) using banking data.

Figure 1: Uncertainty and Equity Inflows by Country (G7)



Notes: This figure shows the country-specific sensitivity of equity inflows to global uncertainty for each G7 country. Both variables are standardized to have mean zero and unit variance. The shaded areas represent 95 percent confidence intervals.

tive global effect of uncertainty and the relative resilience of the U.S. pattern are both robust and economically meaningful.

To ensure that these findings are not driven by a small subset of economies or by outliers, we re-estimate Equation (1) separately for each country in our sample. In this country-level analysis, we focus on the coefficient β, which captures the specific response of each economy's equity inflows to global uncertainty. Figure 1 reports these coefficients for the G7 economies. The results show that equity inflows decline with uncertainty in all major economies, indicating a broad-based reduction in the foreign holdings of domestic equity assets. Once again, the United States stands out as the only country where this reduction is not observed, suggesting a relative resilience of U.S. equity markets in the face of global shocks.

Overall, the evidence shows that global uncertainty is associated with a broad contraction in cross-border equity investment and a decline in foreign purchases of domestic assets across most countries. Periods of high volatility coincide with weaker foreign participation, as investors concentrate portfolios where information is more reliable. The United States stands out as an exception, showing limited sensitivity of equity inflows to global shocks and, at times, continued capital attraction. This asymmetry points to the central role of information quality and transparency in shaping global equity flows and motivates our analysis of how informational frictions and differences in information precision explain investors' heterogeneous responses to uncertainty.

3 Model

In this section, we develop a multi-country portfolio choice model with endogenous information acquisition. A fraction of investors are sophisticated and can pay to acquire information about domestic and foreign assets, while the rest do not make research, choosing their optimal portfolio based on the prior distribution of asset returns. The key distinction is that sophisticated investors update their beliefs using costly private signals, whereas unsophisticated investors never improve upon the prior and therefore hold the same expectation of payoffs regardless of market conditions. Information costs differ across countries, so investors are not equally able to learn about foreign markets. Sophisticated investors choose how much information to acquire before forming portfolios, trading off precision against cost. When uncertainty rises, the value of information increases, leading them to concentrate both learning and portfolios on markets they can research more cheaply.

The model delivers three results. First, investors with lower information costs for a given market achieve higher forecast precision, and this informational advantage becomes stronger when uncertainty increases. Second, uncertainty affects foreign equity inflows at the aggregate level, defined as the net change in total foreign holdings of a country's assets: countries where domestic investors have lower information costs experience a fall in aggregate foreign inflows, while countries that are cheaper to learn about for all investors attract inflows. Third, the model also characterizes bilateral inflows: whether investors from a specific foreign country increase or reduce their holdings depends on whether their information cost for that market is below or above the world average.

3.1 Setup

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

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

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

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

We now formally present the investor problem proceeding backward. We will start with the standard investment decision in the second period, and then move to the information choice problem in the first period [5].

3.2 Portfolio Choice

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

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

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:

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

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

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

and yields the equilibrium asset price p_k as

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

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

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

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

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

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

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

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

3.3 Information Choice

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

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

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

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

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

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

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

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

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

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

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

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

The relative forecast precision for asset k's payoff between investors in country i and j reacts to uncertainty as follows[6] *:*

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

- When $\theta_{ik} < \theta_{jk}$, investors in country i have better forecast on r_k than investors in country j, i.e. $\frac{\widehat{\tau}_{ik}}{\widehat{\tau}_{jk}} > 1$.

[6] We provide the full derivation of this result in Appendix C.1.3. The key step is to differentiate the ratio of posterior precisions with respect to the asset's uncertainty, which reveals that the sign of the response depends only on the relative information costs..

- When $\theta_{ik} < \theta_{jk}$, $\frac{\widehat{\tau}_{ik}}{\widehat{\tau}_{jk}}$ is increasing in the prior variance σ_k^2.

3.4 Equity Inflows

Before analyzing equity inflows, 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 [7]:

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

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

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

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

The following proposition illustrates how equity inflows are related to the cost of information acquisition.

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

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

where $\nu_k = \frac{1}{2}\left(\frac{3\eta}{\tau_k^4} + \frac{2}{\eta\tau_k^3}\right)$. Country k experiences negative equity inflows, when its domestic

[7] We provide the full derivation of this result in Appendix C.1.4.

investors face lower-than-average cost in learning about the domestic risky asset than foreign investors.

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

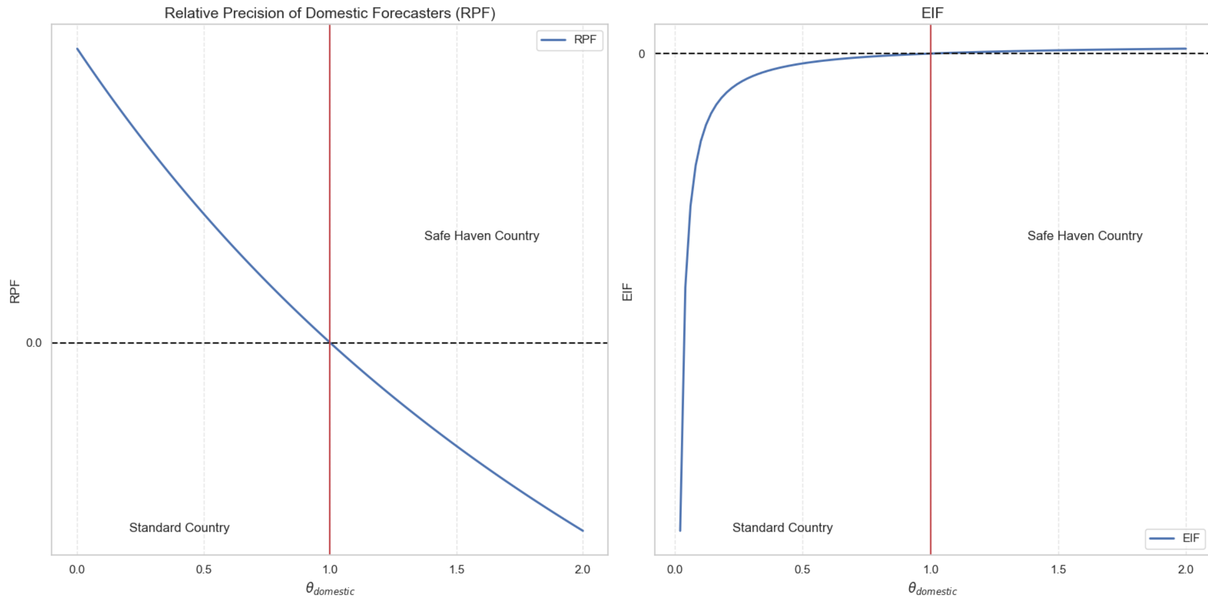
Figure 2 shows how relative precision of domestic forecasters and equity inflows change in sign as we move from a standard country environment, which is characterized by $\theta_d < \theta_f$, into an information haven country environment, which is characterized by $\theta_d \geq \theta_f$ [8]. In the Appendix C.2 we also show the dynamics of RPF_{ii} and IF for different values of σ^2.

We next extend our analysis from aggregate to bilateral equity inflows. While aggregate inflows capture the aggregate difference between domestic and foreign investors' responses to higher uncertainty, they do not reveal which countries adjust their positions relative to one another. In other words, aggregate inflows provide a net measure of how much foreign investment as a whole moves in or out of a country, but they abstract from the identity of the investors driving these inflows. Different countries may vary substantially in their sensitivity to changes in uncertainty, depending on how costly it is for their investors to acquire information about a given market. To better understand the cross-country reallocation of portfolios and the heterogeneity in investor responses, we characterize bilateral inflows between a specific investor country i and destination country k.

In analogy with the definition of aggregate inflows in Section 3.4, we define bilateral inflows as the change in the portfolio holdings of investors from country i in asset k, relative to the global average, when the uncertainty of asset k increases. This bilateral perspective highlights how information asymmetries shape not only whether foreign investors as a whole retrench from a country, but also *which* foreign investors do so more strongly. It allows us to distinguish between countries that are relatively better informed about the destination market and those that are less informed, thereby providing a more granular view of inter-

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

Figure 2: RPF_{ii} and IF changing θ_d



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

national equity reallocations. Moreover, it links the direction and magnitude of bilateral portfolio adjustments directly to differences in information acquisition costs, rather than to aggregate averages alone.

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

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

where ν_k is the same scaling factor as in Proposition 2.

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

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

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

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

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

4 Empirical Validation

In this section, we present novel empirical evidence to test the two central predictions of our model. In subsection 4.2, we first examine how the forecast accuracy of local investors relative to foreign forecasters varies with the level of uncertainty, highlighting the distinctive case of the United States, which emerges as an information haven. Then, in subsection 4.3, we test the information channel by assessing whether equity inflows empirically respond to relative forecast precision. Consistent with the model, we find that countries with a stronger domestic informational advantage experience weaker equity inflows, as foreign investors withdraw when they are informationally disadvantaged. This relationship also holds in the bilateral dimension, where investors with a relative informational advantage allocate more capital toward countries where their informational edge is greater.

Our empirical findings are consistent with the theoretical model developed in Section 3, which formalizes how heterogeneous learning between local and foreign investors affects both forecast precision and equity flows during periods of heightened uncertainty. The results confirm the information channel, showing that investors with a relative informational advantage expand their exposure, while those at an informational disadvantage retrench. This pattern holds for both aggregate and bilateral equity inflows, reinforcing the conclusion that informational advantages systematically shape the international allocation of capital. Together, these results show that information frictions are not only statistically significant drivers of capital flows, but also economically meaningful, with clear implications for how global shocks redistribute international investment.

4.1 Consensus Economics

To measure forecast precision and its variation with uncertainty, we use data from Consensus Economics [9], as in De Marco et al. (2022) and Benhima and Bolliger (2025).

A distinctive feature of this dataset is the classification of forecasters according to their origin, distinguishing between domestic and foreign analysts. Following Benhima and Bolliger (2025), this categorization is based on the location of the forecasting institution headquarters, while also accounting for international subsidiaries. This approach allows us to separate local and foreign forecasting behavior within each country and to compare their respective performance. By doing so, we are able to quantify informational advantages and to assess how they relate to the degree of uncertainty in the global environment. Our main objective is to compute forecast errors and forecast precision for both domestic and foreign groups across a set of key macroeconomic variables.

The dataset includes forecasts for five major macroeconomic indicators: long-term treasury bill yields with a 10-year maturity, short-term treasury bill yields with a 3-month maturity, GDP growth, industrial production growth, and the unemployment rate. For each of these variables, we focus exclusively on one-year-ahead forecasts, discarding shorter-term horizons such as four-month-ahead predictions. This restriction ensures that the informational horizon is consistent across variables and comparable across countries, avoiding biases that could arise from different forecast frequencies or time horizons.

Formally, for each country k and forecast horizon h, we define the forecast error as

$$\mathrm{FE}^2_{i,j,c,t} = \left\{ \mathbf{x}_{j,c,t} - \mathbb{E}_{t-1}[\mathbf{x}_{i,j,c,t}] \right\}^2 \tag{17}$$

where i denotes the forecaster, j the variable, c the country, and t the monthly observation date. Forecast errors are squared and then trimmed symmetrically at the 1% tails of their distribution in order to remove outliers and prevent extreme values from distorting the results. We then standardize each variable with respect to its country-specific and variable of forecast mean, allowing for meaningful cross-country comparisons of forecast precision.

Our sample initially includes forecasts from 20 countries: Austria, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece,

[9] Consensus Economics compiles forecasts of macroeconomic variables from analysts across a wide range of countries, originating from diverse professional backgrounds such as banks, universities, research centers, and private institutions. The dataset covers the period from 2006 to 2018 and is structured as a monthly panel. More details on the data construction are provided in Appendix A.3.

Ireland, Israel, Italy, Japan, the Netherlands, Norway, Portugal, Sweden, and the United States. We exclude from the sample countries with fewer than two years of available observations, specifically Israel and Portugal, yielding a final balanced panel of 18 countries. This cross-country structure provides a comprehensive basis for analyzing how forecast precision, and therefore informational advantages, evolve across countries and over time in response to changes in uncertainty.

4.2 Information Advantage and Uncertainty

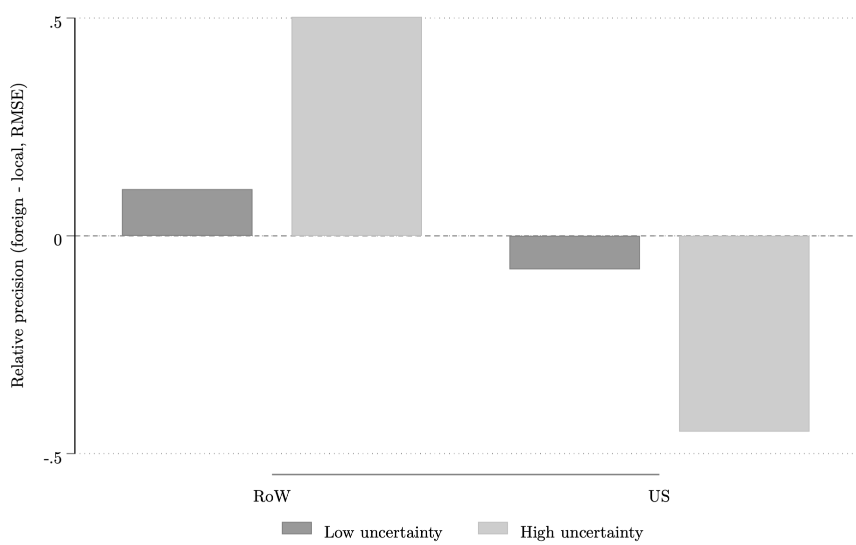
We now turn to the first empirical prediction of our model, which we test using the relationship between information advantage and uncertainty. Proposition 1 states that when the prior uncertainty about an asset (σ_k) is high, or when the cost of acquiring information (θ_{ik}) is relatively low, sophisticated investors optimally choose more precise signals about that asset. Although investors share a common prior, differences in information costs across countries imply that investors may learn with different precision. As a result, when uncertainty rises, investors with lower information costs (typically domestic agents) should experience a stronger improvement in forecast precision relative to foreign investors. Our empirical analysis in this subsection is designed to test this prediction by examining how the relative forecast precision of domestic versus foreign forecasters changes under different levels of uncertainty. In particular, we expect that during periods of high uncertainty, domestic forecasters will display a larger informational advantage, while in information havens such as the United States this advantage may weaken or even reverse.

Relative Precision of Domestic Forecasters. We compute the average forecast error for domestic and foreign forecasters in each country k, denoted by $\overline{\mathrm{FE}_k^{2,d}}$ and $\overline{\mathrm{FE}_k^{2,f}}$, where the superscripts d and f refer to domestic and foreign forecasters, respectively. We then define the Relative Precision of Domestic Forecasters (RPDF) as the difference in root mean squared forecast errors between foreign and domestic forecasters:

$$\mathrm{RPDF}_k = \sqrt{\overline{\mathrm{FE}_k^{2,f}}} - \sqrt{\overline{\mathrm{FE}_k^{2,d}}}. \tag{18}$$

A positive value of RPDF_k means that domestic forecasters make smaller forecast errors than foreign forecasters, indicating that domestic analysts are relatively more accurate and hold a stronger informational advantage in predicting country k's economic outcomes. In contrast, a negative value of RPDF_k implies that foreign forecasters make smaller errors on

Figure 3: Uncertainty and RPDF



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

average, suggesting that they possess more precise or timelier information about country k, possibly because they allocate greater attention or resources to tracking its economic conditions.

To study how uncertainty shapes this informational advantage, we compute RPDF_k separately for episodes of high and low uncertainty, defining high uncertainty as months when the VIX is more than two standard deviations above its average value. This comparison allows us to examine whether the informational advantage of domestic forecasters strengthens or weakens as global uncertainty rises. By contrasting forecast precision across high and low uncertainty regimes, we can assess how shifts in global volatility influence the relative learning capacity of domestic and foreign investors.

Figure 3 illustrates this relationship by showing the relative precision of domestic forecasters across countries during low- and high-uncertainty environments. For countries other than the United States (RoW), domestic forecasters display a clear informational advantage even when uncertainty is low, and this advantage becomes more pronounced as uncertainty increases, indicating that domestic forecast accuracy improves in relative terms during volatile times. This pattern is consistent with the model prediction that the cost of acquiring information rises more steeply for foreign than for domestic agents, as outlined in Proposition 1 of Section 3 [10]. While a domestic informational advantage has been documented in previous studies, our results extend this evidence by showing that information home bias systematically intensifies during periods of heightened uncertainty.

Turning to the results for the United States, we find that there is no clear domestic information advantage. Indeed, foreign forecasters often outperform domestic analysts in predicting key macroeconomic variables during periods of high uncertainty. This distinctive behavior is consistent with our definition of the United States as an information haven in the model.

Empirical Specification and Forecaster Heterogeneity. A potential concern with the interpretation of the patterns described above is that some institutions may systematically produce more accurate forecasts than others, regardless of whether they are domestic or foreign. Large international banks or specialized research centers, for example, may outperform smaller local forecasters simply because they have greater analytical capacity, more data, or better forecasting tools. If such differences in forecaster ability are not accounted for, the observed domestic advantage could reflect disparities in forecasting skill rather than genuine informational advantages.

To address this concern, we turn to the micro-level data on individual forecasts and estimate a regression model that controls for heterogeneity across forecasters. This allows us to isolate informational effects from persistent differences in forecasting skill. Using the full microdata, we examine how uncertainty affects forecast accuracy and the domestic information advantage documented in Figure 3. The inclusion of forecaster fixed effects ensures that our results capture the informational mechanism, rather than time-invariant differences in forecasting ability across institutions, while additional controls account for country- and variable-specific factors.

Formally, we estimate the following OLS specification:

$$
\begin{aligned}
\mathrm{FE}^2_{i,j,c,t} = \alpha &+ \zeta_i + \tau \mathbb{1}_{\{c=\mathrm{US}\}} \\
&+ \left(\beta + \beta_{\mathrm{US}} \mathbb{1}_{\{c=\mathrm{US}\}}\right) \mathbb{1}_{\{i=d\}} \\
&+ \left(\gamma + \gamma_{\mathrm{US}} \mathbb{1}_{\{c=\mathrm{US}\}}\right) \mathbb{1}_{\{i=d\}} \times \mathrm{VIX}_t + \varepsilon_{i,j,c,t},
\end{aligned}
\tag{19}
$$

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

[10] This result is also supported by Benhima and Bolliger (2025), where they show that there exist an information home bias on average.

The indicator $\mathbb{1}_{\{i=c\}}$ equals one if forecaster i is domestic, and $\mathbb{1}_{\{c=\mathrm{US}\}}$ equals one when the destination country c is the United States.

The coefficient β captures the unconditional domestic information advantage, while γ measures how this advantage varies with uncertainty. The interaction terms β_{US} and γ_{US} allow these effects to differ for the United States, capturing its role as an information haven. The coefficient τ accounts for a U.S. specific intercept shift, and ζ_i denotes foreaster fixed effects, ensuring that our estimates reflect informational mechanisms rather than systematic differences in accuracy. Indeed, this is the main purpose of this analysis, compared to the previous case, when considering RPDF on average.

In alternative specifications, we include variable and country fixed effects to control for persistent differences which might bias our estimates. Robustness to alternative measures of uncertainty is discussed in Appendix D.1, and additional data construction details are provided in Appendix A.3.

Table 2 summarizes the results from equation (19). What clearly emerges from the table is the presence of a domestic informational advantage that becomes stronger as uncertainty increases. Across all specifications, domestic forecasters tend to perform relatively better when uncertainty rises, in line with the model's prediction that higher uncertainty amplifies information home bias.

Column (1) presents the baseline specification without fixed effects. Column (2) introduces forecaster fixed effects to control for persistent differences in forecasting skill across institutions, while Column (3) adds forecast variable and country fixed effects to account for systematic differences in forecast difficulty across macroeconomic indicators and national environments. This stepwise inclusion of controls ensures that our findings are not driven by compositional differences in either forecaster type or forecasted variables.

The first coefficient, β, captures the unconditional domestic effect. In the baseline specification, it is small and statistically indistinguishable from zero, indicating no meaningful difference in forecast accuracy between domestic and foreign forecasters once uncertainty is excluded. When forecaster fixed effects are added in Column (2), β turns slightly negative (around -0.01), suggesting that after controlling for consistently superior global institutions, domestic forecasters may even perform marginally better on average.

The main coefficient of interest, γ, corresponding to Domestic $\times$ Uncertainty, is negative and statistically significant across all specifications, ranging from roughly -0.03 to -0.02. Quantitatively, this implies that a one-standard-deviation increase in the VIX improves the relative precision of domestic forecasters by approximately 0.03 standard deviations. The

Table 2: Forecast Accuracy and Uncertainty

	Squared Forecast Error (1)	Squared Forecast Error (2)	Squared Forecast Error (3)
Domestic	0.009	0.029	-0.010
	(0.017)	(0.047)	(0.023)
VIX	0.298	0.281	0.272
	(0.028)	(0.028)	(0.028)
Domestic × VIX	-0.032	-0.032	-0.023
	(0.013)	(0.014)	(0.013)
US	-0.126	-0.103	0.000
	(0.067)	(0.065)	(.)
Domestic × US	0.084	0.007	0.095
	(0.017)	(0.073)	(0.032)
Domestic × VIX × US	0.079	0.042	0.034
	(0.013)	(0.014)	(0.013)
N	104661	104661	104661
R^2	0.072	0.106	0.117
adj. R^2	0.071	0.104	0.115
FEs, Forecasters	No	Yes	Yes
FEs, Variable	No	No	Yes
FEs, Country	No	No	Yes

Notes: The table reports the results of the specification described in this section. The dependent variable is the normalized squared forecast error. Column (1) presents results without bank fixed effects; Column (2) includes forecasters fixed effects; Column (3) adds variable and country fixed effects. Standard errors, clustered at the time level, are reported in parentheses.

coefficient remains significant at the 5% level or better in every column, providing strong evidence that rising uncertainty strengthens the informational advantage of domestic agents.

The triple interaction term, γ_{US}, associated with Domestic × Uncertainty × US, reverses this relationship for the United States. The coefficient is positive and significant in all columns, indicating that, when uncertainty rises, domestic U.S. forecasters lose precision relative to foreign ones. Importantly, the inclusion of forecaster fixed effects substantially reduces the magnitude of this coefficient, from around 0.08 in the baseline to roughly 0.04 once forecaster heterogeneity is accounted for. This attenuation supports the concern that part of the initial positive effect for the United States may stem from systematically superior global institutions rather than a genuine informational difference. Overall, the result remains consistent with our interpretation of the United States as an information haven, where information is more evenly distributed and local agents do not enjoy a comparative advantage.

Overall, the stability of both γ and γ_{US} across specifications confirms that the results are robust to increasingly rich sets of fixed effects. As reported at the bottom of Table 2, the R^2 rises from 0.07 in the baseline to 0.12 when all fixed effects are included, indicating improved explanatory power without altering the main coefficients of interest. These results support the prediction that uncertainty amplifies informational asymmetries in most countries, whereas in the United States, foreign analysts retain or even gain an informational edge.

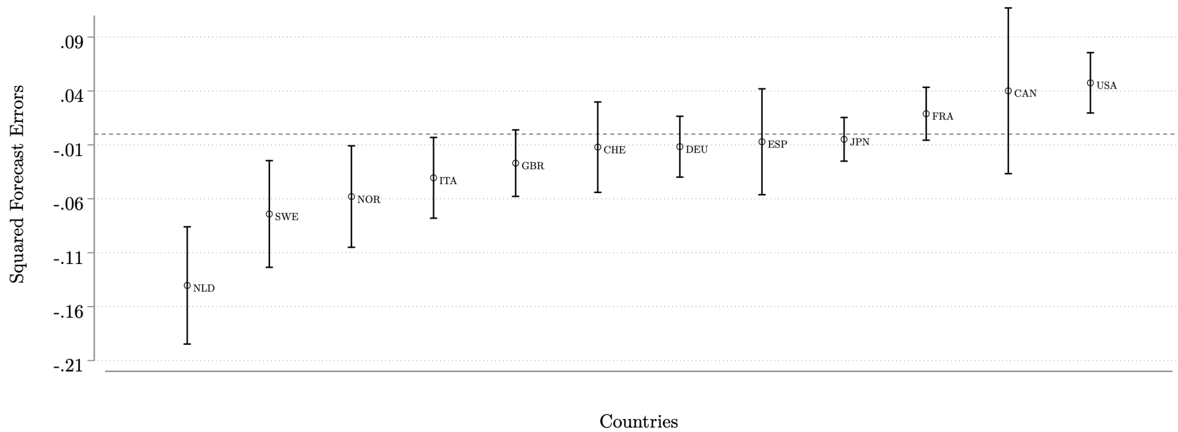
Similarly to our motivation in Section 2, we also verify whether our findings are robust across different countries and not driven by outliers. To do so, we re-estimate the same OLS specification separately for each country in the sample, focusing on the coefficient γ, which captures the effect of uncertainty on the relative accuracy of domestic forecasters. The goal is to examine how this relationship varies across countries.

Figure 4 shows that, in most countries, domestic investors experience a smaller increase in forecast errors when uncertainty rises. In other words, the domestic informational advantage becomes stronger in more uncertain times. The United States again stands out as the country with the largest foreign advantage, as foreign forecasters become more precise than domestic ones when uncertainty increases. The only other exception to this pattern is Canada, which, as shown in Figure 1, exhibits a sensitivity of capital inflows to uncertainty similar to that of the United States.

Overall, we provide evidence that, on average, forecasters tend to be more precise in predicting their domestic economies than foreign ones during periods of heightened uncertainty. This implies that domestic economies experience a relatively higher increase in research effort during uncertain times compared to foreign economies, with the United States being the key exception, as predicted by Proposition 1 in Section 3.

Our model explains this exceptional behavior of the United States through its greater openness and transparency, which translate into the absence of a domestic learning advantage. Such transparency may stem from institutional quality, but it also reflects the broader centrality of the United States in the global financial system. Major international institutions and banks headquartered outside the United States typically allocate substantial resources to research on the U.S. economy, reinforcing its role as an information hub. This pattern is consistent with the notions of flight to safety and flight to home discussed by Miranda-Agrippino and Rey (2015). In most countries, analysts focus their research on domestic conditions and on perceived safe regions, notably the United States. This helps explain the

Figure 4: Country-Specific Analysis



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

distinct forecasting dynamics observed for the United States relative to the rest of the world.

As a robustness check, we show in Appendix D that our results are unchanged when using alternative measures of uncertainty. We also confirm that the findings remain consistent when forecast precision is measured through the dispersion across forecasters rather than ex-post forecast errors. These checks confirm that our main results are not driven by the specific choice of uncertainty or precision measure.

4.3 Testing the Information Channel

In the theoretical framework we show that investors' portfolio decisions respond systematically to differences in information precision. When some investors possess superior information about a particular country or asset, they allocate a larger share of their portfolio toward it, while those at an informational disadvantage reduce their exposure. This mechanism implies that information asymmetries directly shape the direction and magnitude of cross-border capital flows. Moreover, the model predicts that these asymmetries become more salient during periods of heightened uncertainty, as the value of accurate information rises and investors reoptimize their portfolios accordingly. In such episodes, countries where domestic investors enjoy a relative informational advantage should experience weaker foreign inflows, while destinations that are more transparent or better understood abroad should continue to attract capital.

Formally, the model links the cost of acquiring information to both aggregate and bilateral equity inflows. When domestic investors face lower learning costs than foreign ones, they can process local signals more efficiently, which strengthens their informational advantage as uncertainty increases. This widening gap in information precision discourages foreign participation and results in a decline in foreign equity inflows. Conversely, when foreign investors enjoy relatively low learning costs about a particular destination, their informational edge leads to stronger inflows into that market. In both cases, changes in uncertainty amplify reallocations along informational lines, providing a clear testable channel through which information shapes global capital movements.

We test whether information operates as a channel through which uncertainty affects cross-border equity flows. Our empirical strategy proceeds in two complementary parts. First, we examine how domestic informational advantages influence aggregate equity inflows (RPF_{ii}), asking whether countries in which domestic forecasters are relatively more precise than foreign ones experience weaker foreign inflows during uncertain periods. This test captures the aggregate effect of informational frictions on foreign participation. Second, we turn to the bilateral dimension (RPF_{ik}), investigating whether investors from origin i allocate more equity toward destination countries k they understand better relative to other global investors. This exercise allows us to trace how information advantages shape the geography of capital reallocation in response to global uncertainty. Taken together, these two approaches provide a comprehensive empirical counterpart to the model's mechanism, allowing us to evaluate how cross-country differences in information precision govern the dynamics of equity inflows during periods of heightened volatility.

Aggregate Equity Inflows. We begin by examining the aggregate relationship between domestic informational advantage and foreign equity inflows. The key variable of interest, RPF_{ii}, measures the relative precision of domestic forecasters i about their own country i in a given month. Intuitively, this variable captures the informational gap between domestic and foreign agents: when domestic institutions forecast their own macroeconomic conditions more accurately than foreign ones, they possess an informational advantage that foreign investors lack. From an economic perspective, such informational asymmetries can deter cross-border investment, as foreign investors may perceive themselves to be at a disadvantage in evaluating local fundamentals and therefore scale back their holdings.

Formally, RPF_{ii} is constructed as the difference between the average squared forecast error of foreign institutions and that of domestic institutions for the same macroeconomic variable, winsorized at the 1st and 99th percentiles and standardized to have mean zero and unit variance. Positive values of RPF_{ii} therefore indicate that domestic forecasters outperform their foreign counterparts, signaling greater informational precision at home relative to abroad.

This empirical setup provides a direct counterpart to Proposition 2, which links equity inflows to the relative cost of information acquisition between domestic and foreign investors. In the model, when domestic investors face lower learning costs than foreign ones, they obtain a relative informational advantage that becomes more valuable as uncertainty increases. This advantage leads domestic agents to hold a larger share of domestic assets, while foreign investors, recognizing their informational disadvantage, reduce their exposure. As a result, the model predicts that equity inflows decline when the informational gap between domestic and foreign investors widens. In our empirical framework, RPF_{ii} serves as an observable proxy for this gap in information precision, and the estimated coefficient ξ in the regression below captures how such informational asymmetries translate into aggregate changes in equity inflows.

We estimate the following specification to assess how domestic informational advantage affects the volume of capital inflows:

$$EIF_{i,t} = \alpha + \xi \text{RPF}_{ii,t} + \gamma EIF_{i,t-1} + \varepsilon_{i,t}, \tag{20}$$

where $EIF_{i,t}$ denotes standardized monthly equity inflows into country i. The coefficient ξ quantifies the effect of changes in domestic relative precision on foreign equity inflows, while the lagged term $EIF_{i,t-1}$ controls for persistence in capital flows over time.

In column (1) of Table 3, we estimate this relationship using ordinary least squares (OLS) without fixed effects and employ heteroskedasticity-robust standard errors. In column (2), we introduce country fixed effects to absorb time-invariant differences across countries, such as institutional quality or market depth, and we cluster standard errors at the country level to allow for serial correlation within each country.

Across both specifications, the coefficient on RPF_{ii} is consistently negative, around -0.05, and statistically significant at the 5 percent level. Because both equity inflows and RPF_{ii} are standardized, this magnitude is directly interpretable: a one-standard-deviation increase in domestic informational advantage is associated with roughly a 5 percent standard-deviation

Table 3: Aggregate Equity Inflows and Relative Precision of Domestic Forecasters

	Aggregate EIF (1)	Aggregate EIF (2)	Aggregate EIF (3)
RPF (ii)	-0.051	-0.051	-0.054
	(0.026)	(0.014)	(0.015)
Observations	861	861	861
FEs, Country	No	No	Yes
SEs, Robust	Yes	No	No
SEs, Country	No	Yes	Yes
RPF (p-value)	0.051	0.007	0.008

Notes: This table reports regressions of standardized equity inflows on the relative precision of domestic forecasters (RPF_{ii}). Column (1) reports OLS estimates without fixed effects and uses heteroskedasticity-robust standard errors. Column (2) includes country fixed effects and clusters standard errors at the country level. RPF_{ii} is computed as the difference between the average squared forecast error of foreign and domestic forecasters within each country-month, winsorized at the 1st and 99th percentiles, and standardized across the panel.

decline in equity inflows. In line with Proposition 2, this negative coefficient indicates that when domestic agents become relatively better informed about local conditions, foreign investors withdraw, reducing their net purchases of domestic equities. The pattern is precisely what the theoretical model predicts: higher uncertainty amplifies informational asymmetries, and investors with higher learning costs, typically foreigners, choose to retrench rather than compete in markets where their informational position is weaker.

Moreover, the robustness of this relationship to the inclusion of fixed effects and clustered standard errors confirms that the effect is not driven by persistent cross-country differences, but by within-country variation in information precision over time. Taken together, these results provide strong empirical support for the mechanism formalized in Proposition 2, showing that informational frictions play a central role in shaping the dynamics of international portfolio adjustments during periods of uncertainty.

Bilateral Equity Inflows. We now turn to the bilateral dimension to test whether informational advantages affect where investors reallocate their equity during uncertainty. We use bilateral investment data from the JRC-ECFIN Finflows database by Nardo et al. (2017). This dataset provides yearly bilateral positions and flows of cross-border investment up to

2020, covering both private and official transactions. It reports financial stocks (the gross bilateral international investment position) as well as financial flows (gross bilateral financial account transactions) between reporting and partner countries. The database includes more than 80 reporting and partner countries, allowing us to map the cross-country patterns of capital reallocation in response to changes in uncertainty and relative forecast precision. The model predicts that, when uncertainty rises, equity should flow toward destinations about which investors have superior information. To capture this, we construct a bilateral measure of relative forecast precision, RPF_{ik}, for each origin i and destination k. This variable compares the forecasting performance of institutions located in country i regarding country k to the global benchmark for k, defined as the average forecast error across all origins. Thus, positive values of RPF_{ik} indicate that forecasters in i are more accurate about k than the average global forecaster, an informational edge for investors from i.

We estimate the following specification:

$$EIF_{ik,t} = \alpha_i + \xi \mathrm{RPF}_{ik,t} + \gamma EIF_{ik,t-1} + \varepsilon_{ik,t}, \tag{21}$$

where $EIF_{ik,t}$ are standardized annual bilateral equity inflows from origin i into destination k, scaled by the destination's trend GDP and standardized within each origin. Column (1) of Table 4 reports a baseline specification including lagged inflows and robust standard errors. Column (2) adds country-pair fixed effects (for origin-destination pairs) and clusters standard errors at the country-year level to allow for correlation across bilateral links involving the same country-year.

The coefficient on RPF_{ik} is positive and economically meaningful, around 0.23 across specifications, and statistically significant at conventional levels (p around 0.10). The interpretation is straightforward: a one-standard-deviation increase in an origin's relative forecast precision about a given destination is associated with roughly a 20–25 percent standard-deviation increase in bilateral equity inflows from that origin into that destination. In other words, when investors in i gain an informational advantage about k, they allocate more equity there relative to other destinations.

Taken together, the aggregate and bilateral results present a coherent picture. When domestic forecasters gain precision, aggregate equity inflows decline because foreigners retreat (RPF_{ii} regressions). At the same time, investors redirect equity toward destinations where they hold a relative informational edge (RPF_{ik} regressions). These findings confirm that information heterogeneity is not merely a microfoundation for home bias, it is also a key

Table 4: Bilateral Equity Inflows and Relative Precision of i over k

	Bilateral EIF (1)	Bilateral EIF (2)	Bilateral EIF (3)
RPF (ik)	0.268	0.268	0.254
	(0.138)	(0.139)	(0.149)
Observations	154	154	153
FEs, Report Country	No	No	Yes
FEs, Partner Country	No	No	Yes
SEs, Robust	Yes	No	No
SEs, Country × Year	No	Yes	Yes
RPF (p-value)	0.053	0.057	0.093

Notes: The table reports regressions of standardized bilateral equity inflows on standardized bilateral relative forecast precision (RPF_{ik}). Column (1) includes controls for GDP growth and lagged inflows with robust standard errors. Column (2) adds country-pair fixed effects and clusters standard errors at the country-year level. RPF_{ik} measures the difference between the average squared forecast error of forecasters from origin i about destination k and the global benchmark forecast error for k, standardized to zero mean and unit variance.

driver of the dynamics of international equity flows in periods of uncertainty.

5 Conclusion

This paper has examined how information heterogeneity shapes the dynamics of international equity flows during periods of global uncertainty. We began by documenting the stylized facts of the global financial cycle, showing that when uncertainty rises, investors reduce their equity holdings abroad, moving back toward their home markets and toward the United States. These patterns suggest that differences in information precision across countries play a central role in explaining the asymmetric response of equity inflows to global shocks.

To rationalize these facts, we developed a multi country model of portfolio choice with endogenous information acquisition. In the model, investors face different costs of learning about domestic and foreign assets, and these costs vary across countries. When global uncertainty increases, the value of information rises, leading investors to reallocate both attention and portfolios toward assets they understand best. The model predicts that countries where domestic agents have a strong information advantage experience a decline in foreign equity inflows, while transparent economies without a home information edge, such as the United States, behave as information havens that continue to attract capital.

We tested these predictions using data from Consensus Economics combined with aggregate and bilateral equity flow data. The evidence confirms that domestic forecasters are more accurate in predicting their own country's outcomes and that this informational advantage strengthens in times of global volatility. For the United States, however, no such domestic advantage exists, consistent with its interpretation as an information haven.

Finally, we linked relative forecast precision directly to capital flows. At the aggregate level, we found that greater domestic informational advantage is associated with lower foreign equity inflows, consistent with the idea that informational disadvantage discourages foreign participation. At the bilateral level, investors allocate more equity toward destinations about which they hold a relative informational edge, validating the model's bilateral predictions.

Taken together, our theoretical and empirical results provide a unified explanation for three key features of global equity dynamics: the retrenchment of foreign capital during uncertainty, the persistence of home bias, and the resilience of information haven countries such as the United States. By highlighting the role of information heterogeneity in shaping international capital flows, our analysis contributes to a deeper understanding of how global uncertainty interacts with knowledge and transparency to drive the geography of financial capital.

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Appendix

A Dataset Construction

A.1 Aggregate Flows

We use aggregate portfolio equity flow data from Koepke and Paetzold (2022), which cover 47 countries over the period 1997 to 2023. The dataset provides monthly information on cross-border equity transactions, consistent with the IMF Balance of Payments (BoP) definition of portfolio equity. Data are expressed in nominal values (USD) and measure the net acquisition of domestic equity by nonresidents, corresponding to equity inflows (EIF). These data allow us to analyze how global financial uncertainty affects the reallocation of foreign capital across countries.

Sample construction and coverage. The sample includes both advanced and emerging economies, spanning all major geographic regions. The list of countries in our baseline dataset is as follows: Belgium, Bulgaria, Brazil, Canada, Chile, China, Colombia, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Greece, Croatia, Hungary, Indonesia, India, Iceland, Italy, Japan, Korea, Lebanon, Sri Lanka, Lithuania, Latvia, Mexico, Mongolia, Malaysia, Netherlands, Pakistan, Philippines, Poland, Portugal, Romania, Serbia, Slovenia, Sweden, Thailand, Turkey, Ukraine, United States, and South Africa. The dataset combines data from national balance-of-payments statistics harmonized by the IMF and updated by the authors. Missing monthly observations are filled using documented linear interpolation procedures.

Transformations and normalization. To improve comparability across countries and reduce the influence of extreme observations, we winsorize the raw series of equity inflows at the 1st and 99th percentiles. We then standardize each series within country according to

$$Z_{it} = \frac{X_{it} - \mathbb{E}[X_i]}{\sigma_{X_i}}, \tag{22}$$

where X_{it} denotes equity inflows for country i at time t, $\mathbb{E}[X_i]$ is the country-specific mean, and σ_{X_i} is the corresponding standard deviation. This transformation yields standardized inflows with mean zero and unit variance, allowing for cross-country comparisons and a direct

Table 5: Descriptive Statistics: Equity and Capital Inflows

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

Notes: Descriptive statistics for monthly portfolio inflows (in billions of USD), 1997 to 2023. Equity, bond, and total capital inflows are reported separately. The sample includes 47 countries.

interpretation of regression coefficients in standard-deviation units.

Descriptive statistics. Table 5 presents descriptive statistics for monthly portfolio inflows. All values are expressed in billions of U.S. dollars. We report the mean, standard deviation, median, maximum, minimum, and number of observations for equity, bond, and total capital (equity plus bonds) inflows.

Equity inflows (EIF) exhibit a mean of approximately 1.0 billion USD and a standard deviation of 12.9, while bond inflows (BIF) average 2.4 billion USD with a standard deviation of 14.4. These figures underscore the strong cyclicality and volatility of cross-border portfolio movements. Total capital inflows, defined as equity plus bond inflows, average about 3.3 billion USD with a standard deviation near 19, highlighting the amplitude of international portfolio reallocation.

To evaluate the relative importance of equity within total portfolio inflows, we define the equity inflow share as:

$$S = \frac{\text{EIF}}{\text{EIF} + \text{BIF}}. \tag{23}$$

Aggregating across all observations, the average value of S is approximately 0.47, indicating that equity accounts for nearly half of total cross-border portfolio inflows. Moreover, equity inflows explain more than half of the total variance in aggregate capital movements, emphasizing their central role in the dynamics of global financial adjustment.

These properties justify focusing on equity inflows in the empirical analysis. Equity investments respond more directly to information, expectations, and shifts in perceived risk, whereas bond flows are mainly driven by interest rate differentials and liquidity conditions.

As such, EIF provides a sharper lens through which to study how uncertainty and information heterogeneity drive international capital allocation.

A.2 Bilateral Flows

We use bilateral cross-border investment positions and flows from the JRC–ECFIN *Finflows* database from Nardo et al. (2017). The Finflows dataset consolidates bilateral financial linkages from multiple official sources and provides yearly data from 2000 onward for more than 80 countries. It covers both private and official cross–border transactions and distinguishes among foreign direct investment, portfolio equity, portfolio debt, and other investment, following BPM6 standards. The database harmonizes stocks and flows, resolves bilateral asymmetries, and imputes missing observations using documented procedures. Detailed methodological information is provided in the official manual. Our empirical analysis focuses on portfolio equity flows and positions. The dependent variable in the bilateral regressions is gross portfolio equity inflows from origin i to destination k, drawn directly from Finflows and matched by ISO reporter and partner codes to our forecast dataset. This structure allows us to link bilateral financial reallocations to relative information precision between countries.

Sample construction and exclusions. To ensure that observed capital reallocations reflect genuine information channels rather than financial conduit or booking activities, we exclude jurisdictions commonly used as offshore or intermediary financial centers. This follows the rationale in Coppola et al. (2021), who show that tax havens and special-purpose entities obscure the geography of global capital flows. Accordingly, we remove observations where either the reporter or the partner belongs to the following set: Bermuda (BMU), Cayman Islands (CYM), Curacao (CUW), Hong Kong SAR (HKG), Ireland (IRL), Jersey (JEY), Luxembourg (LUX), Panama (PAN), British Virgin Islands (VGB), Singapore (SGP), South Korea (KOR), and the Netherlands (NLD). These filters are applied symmetrically to both reporting and partner countries.

Transformations and normalization. To limit the influence of outliers, we winsorize gross bilateral portfolio equity inflows at the 1st and 99th percentiles. We then scale inflows by trend GDP in the destination country to account for country size, defining

$$\mathrm{IEF}_w = 1000 \times \frac{\mathrm{IEF}}{\mathrm{GDP}_{\mathrm{trend}}}. \tag{24}$$

Next, we standardize the resulting variable within each reporter country to obtain a normalized bilateral inflow measure. The baseline dynamic specification includes the lag of normalized inflows to absorb persistence in bilateral activity. Standard errors are either robust or clustered at the reporter–year level, as reported in each table.

Coverage and definitions. Finflows provides annual bilateral external assets and liabilities and corresponding bilateral financial account transactions for EU, OECD, large emerging, and selected offshore economies. Data are expressed in millions of euros. The database integrates IMF, OECD, BIS, Eurostat, and national sources, enforcing bilateral consistency between assets and liabilities. After filtering and harmonization, our final sample spans roughly 18 reporting countries and more than 1,000 bilateral country pairs, covering the period from 2006 to 2020.

A.3 Consensus Economics

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. 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 (2025). This categorization is determined by the location of the forecasting institution's headquarters, while also accounting for their subsidiaries. Our primary objective is to calculate the forecast error and dispersion for both groups of forecasters. The macroeconomic variables analyzed include long-term treasury bills (10 years), short-term treasury bills (3 months), GDP growth, industrial production growth and unemployment rate. We include only forecasts made for periods longer than two years. The resulting data forms a comprehensive panel encompassing forecasts from 12 different countries, allowing for a comparative analysis over the decade in question. Below a description of the variables we use in our dataset and in parenthesis the corresponding name of the variable you find in the code:

- $\mathbb{E}_t[\%\mathbf{B}_{t+12,t}]$ (10 yrs Long Term Treasury Bills), where t is monthly date.
- $\mathbb{E}_t[\%\mathbf{b}_{t+12,t}]$ (3 months Short Term Treasury Bills), where t is monthly date.
- $\mathbb{E}_t[\Delta\%\mathbf{GDP}_{y+1,y}]$ (Gross Domestic Product), where t is monthly date and y yearly date.
- $\mathbb{E}_t[\Delta\%\mathbf{IP}_{y+1,y}]$ (Industrial Production), where t is monthly date and y yearly date.
- $\mathbb{E}_t[\Delta\mathbf{UNEMP}_{y+1,y}]$ (Unemployment Rate), where t is monthly date and y yearly date.

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

Descriptive Statistics. We report descriptive statistics of the data in Table 6 and the resulting of a 1.5% trimming from both left and right tails in Table 7 [11]. Moreover, in Figure 5 we show the distributions of the variables we included in our dataset.

Table 6: Descriptive Statistics: Data from Consensus Economics

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

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

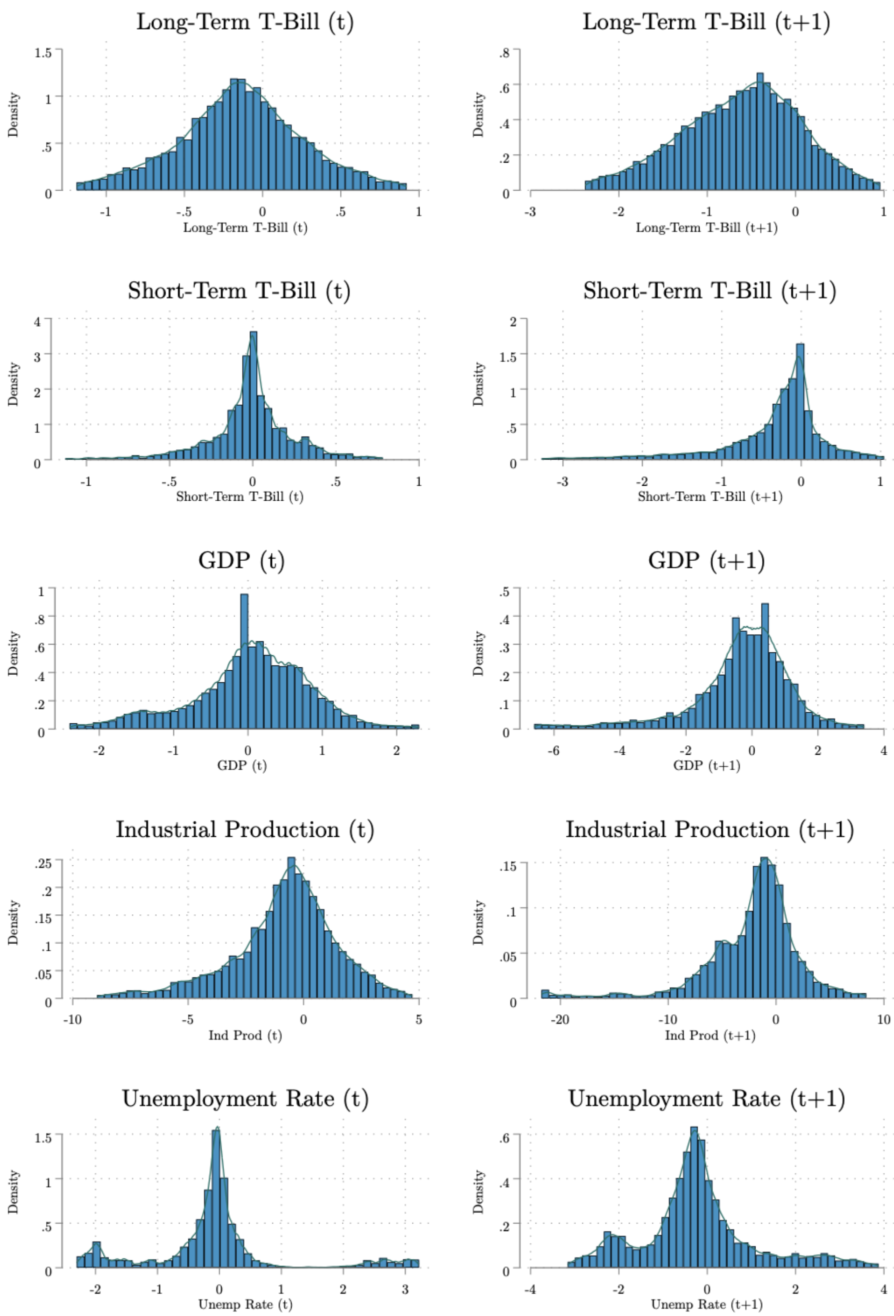
Table 7: Descriptive Statistics: Trimmed Data from Consensus Economics

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

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

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

Figure 5: Histogram of Forecast Variables



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

A.4 Measures of Uncertainty.

We collect several measures of uncertainty at monthly level: the VIX index, the Jurado et al. (2015) measure of financial uncertainty (updated in 2021), the VSTOXX index, the volatility of the ACWI index and also country level uncertainty measures, such as the one from Ozturk and Sheng (2017) and the volatility of stock market returns at country level. Table 8 shows how these measures are distributed.

Table 8: Descriptive of Uncertainty Measures

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

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

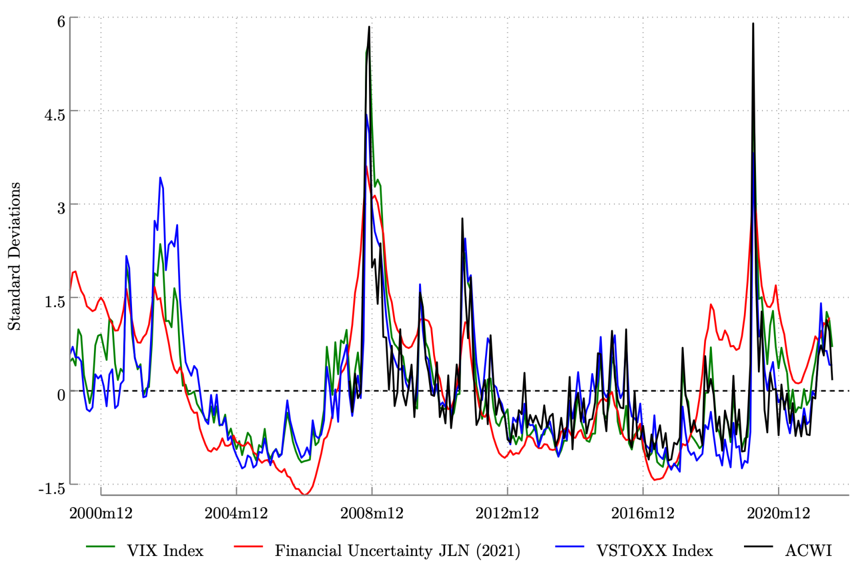
We also provide a table that shows how our main measure of uncertainty (VIX index) correlates with alternative measures.

Table 9: Correlation of VIX Index with Uncertainty Measures

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

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

Figure 6: Time Series of Uncertainty Measures



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

B Motivating Evidence

This section provides several robustness checks for the motivating evidence presented in Section 2. We confirm that the main results are not sensitive to the measure of uncertainty, to the set of countries included, or to the exclusion of extreme events.

Alternative Measures of Uncertainty We first verify that the negative association between uncertainty and equity inflows is not specific to the VIX index used in the main analysis. To this end, we replicate the baseline specification using an alternative measures of global financial uncertainty: the financial uncertainty index of Jurado et al. (2015) (updated in 2021). Each regression maintains the same set of controls and estimation strategy as in the main specification.

Table 10: Equity Inflows and Financial Uncertainty (JLN Index)

	Aggregate EIF (1)	Aggregate EIF (2)	Aggregate EIF (3)
Financial JLN (2021)	-0.080	-0.083	-0.085
	(0.013)	(0.014)	(0.015)
Financial JLN (2021) × US	0.135	0.138	0.138
	(0.015)	(0.015)	(0.018)
L.gdp_growth		0.012	0.010
		(0.004)	(0.005)
der			0.036
			(0.017)
inflow_bonds_norm			0.001
			(0.001)
Observations	7484	7349	6375
Country FEs	Yes	Yes	Yes

Notes: This table reports regressions of standardized equity inflows on the financial uncertainty index of Jurado et al. (2015). The specification followsthe baseline in Section 2. Both dependent and independent variables are standardized. GDP % refers to yearly GDP growth. Standard errors are clustered at the country level.

Country-Specific Uncertainty. Next, we explore whether the same relationship holds when uncertainty is measured locally rather than globally. We construct a country-specific uncertainty indicator based on the volatility of domestic stock returns, using data from Global Financial Data. This measure captures the degree of local market turbulence that investors may face when allocating capital across borders.

Table 11: Equity Inflows and Country-Specific Uncertainty (Volatility of Stock Returns)

	Aggregate EIF (1)	Aggregate EIF (2)	Aggregate EIF (3)
Local Uncertainty	-0.134	-0.134	-0.130
	(0.023)	(0.023)	(0.023)
Local Uncertainty × US	0.215	0.215	0.205
	(0.024)	(0.024)	(0.029)
GDP Δ%			0.012
			(0.007)
EER			0.030
			(0.018)
Bond Inflows			-0.000
			(0.008)
Observations	3756	3756	3638
Country FEs	Yes	Yes	Yes

Notes: This table reports regressions of standardized equity inflows on country-specific uncertainty, measured as the volatility of stock returns. Both dependent and independent variables are standardized. GDP % refers to yearly GDP growth. Standard errors are clustered at the country level.

Extreme Events. Finally, we test whether our results are driven by episodes of extreme global volatility. If equity inflows respond only during such events, the observed patterns could reflect short-lived flight-to-quality episodes rather than systematic responses to uncertainty.

Table 12: Equity Inflows Excluding Extreme Uncertainty Episodes

	Inflows (1)	Inflows (2)	Inflows (3)	Outflows (4)
VIX	-0.10^{***}	-0.10^{***}	-0.06^{*}	-0.06^{**}
	(0.02)	(0.02)	(0.03)	(0.03)
VIX × US	0.37^{***}	0.37^{***}	-0.07^{**}	-0.07^{*}
	(0.03)	(0.03)	(0.03)	(0.03)
GDP Δ%		0.01^{***}		-0.00
		(0.00)		(0.01)
N	7578	7494	6144	6072
Country FEs	Yes	Yes	Yes	Yes

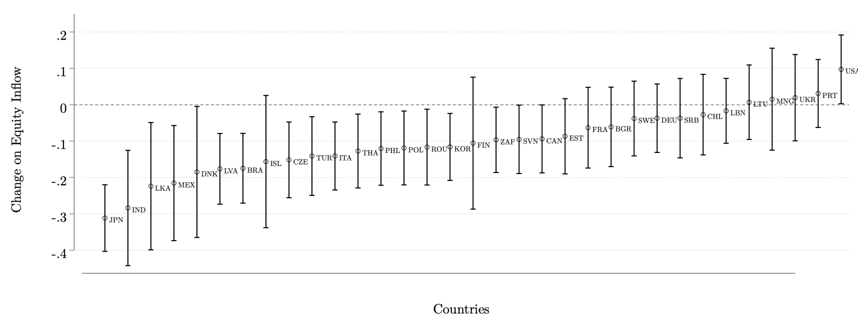
Notes: This table reports regressions of standardized equity inflows on uncertainty (measured by the VIX) after excluding periods of extreme volatility. Both dependent and independent variables are standardized. GDP % refers to yearly GDP growth.

To examine this, we re-estimate the baseline regression after excluding periods of exceptionally high uncertainty, defined as months when the VIX exceeds two standard deviations above its historical mean.

We also test alternative thresholds to ensure robustness. Overall, the results across all robustness checks confirm the stability of our main findings: periods of elevated uncertainty are systematically associated with lower equity inflows, and the United States remains the only major economy experiencing positive inflows during such periods.

Full Country Sample. We next extend the analysis presented in Figure 1, which focused on the G7 economies, to the full set of 47 countries in our sample. We exclude only those with fewer than two years of observations and re-estimate the specification in Section 2. The results confirm that the United States remains the only country with a significant positive association between uncertainty and equity inflows.

Figure 7: Uncertainty and Equity Inflows: Full Country Sample



Notes: This figure plots the estimated sensitivity of equity inflows to changes in uncertainty (measured by the VIX index) for all countries in the sample. The y-axis reports the coefficient on uncertainty from country-level regressions. The confidence intervals correspond to 95%.

C Theoretical Analysis

C.1 Derivations

C.1.1 Objective in the first period

In the first period, the objective function for the sophisticated investor i is:

$$U_i \equiv \mathbb{E}\left[\mathbb{E}_i\left(W_i\right) - \frac{\eta}{2}\mathbb{V}_i\left(W_i\right)\right] \tag{25}$$

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

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

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

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

Take expectation in the first period, we obtain

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

Under the assumption that risky asset payoffs are independently distributed, we can write the objective function 25 as:

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

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

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

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

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

$$\max\ \frac{1}{2}\sum_{k=1}^{N}\left(\eta\frac{\tau_k + \tau_{ik,s}}{\tau_k^2} + \frac{1}{\eta}\frac{\tau_{ik,s}}{\tau_k}\right) - \sum_{k=1}^{N}\frac{\theta_{ik}}{2}\tau_{ik,s}^2 \tag{26}$$

C.1.2 Information choice

Solve for optimal $\tau_{ik,s}$ from 26, we get:

$$\tau_{ik,s} = \frac{1}{2\theta_{ik}}\left(\frac{\eta}{\tau_k^2} + \frac{1}{\eta\tau_k}\right) \tag{27}$$

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

C.1.3 Relative Precision and Uncertainty

We start with the expression:

$$\frac{\hat{\tau}_{ik}}{\hat{\tau}_{jk}} = \frac{1 + \frac{1}{2\theta_{ik}}\sigma_k^4\left(\frac{1}{\eta} + \eta\sigma_k^2\right)}{1 + \frac{1}{2\theta_{jk}}\sigma_k^4\left(\frac{1}{\eta} + \eta\sigma_k^2\right)} \tag{28}$$

Let $x = \sigma_k^2$ and define:

$$A = \frac{1}{\eta} + \eta x \tag{29}$$

Then:

$$N(x) = 1 + \frac{1}{2\theta_{ik}}x^2 A, \qquad D(x) = 1 + \frac{1}{2\theta_{jk}}x^2 A \tag{30}$$

We want to compute the derivative:

$$\frac{d}{dx}\left(\frac{N(x)}{D(x)}\right) = \frac{N'(x)D(x) - N(x)D'(x)}{D(x)^2} \tag{31}$$

We compute:

$$A' = \eta \tag{32}$$

$$N'(x) = \frac{1}{2\theta_{ik}}\left(2xA + x^2A'\right) = \frac{1}{2\theta_{ik}}\left(2x\left(\frac{1}{\eta} + \eta x\right) + x^2\eta\right) \tag{33}$$

$$D'(x) = \frac{1}{2\theta_{jk}}\left(2xA + x^2A'\right) = \frac{1}{2\theta_{jk}}\left(2x\left(\frac{1}{\eta} + \eta x\right) + x^2\eta\right) \tag{34}$$

Therefore:

$$\frac{d}{dx}\left(\frac{\hat{\tau}_{ik}}{\hat{\tau}_{jk}}\right) = \frac{(2xA + x^2\eta)\left[\frac{1}{2\theta_{ik}}D(x) - \frac{1}{2\theta_{jk}}N(x)\right]}{D(x)^2} \tag{35}$$

Using:

$$D(x) = 1 + \frac{1}{2\theta_{jk}}x^2A, \qquad N(x) = 1 + \frac{1}{2\theta_{ik}}x^2A \tag{36}$$

we expand:

$$\begin{aligned}\frac{1}{2\theta_{ik}}D(x) - \frac{1}{2\theta_{jk}}N(x) &= \frac{1}{2\theta_{ik}}\left(1 + \frac{1}{2\theta_{jk}}x^2A\right) - \frac{1}{2\theta_{jk}}\left(1 + \frac{1}{2\theta_{ik}}x^2A\right) \\ &= \frac{1}{2\theta_{ik}} - \frac{1}{2\theta_{jk}}\end{aligned} \tag{37}$$

So the full derivative is:

$$\frac{d}{d\sigma_k^2}\left(\frac{\hat{\tau}_{ik}}{\hat{\tau}_{jk}}\right) = \frac{\left(2\sigma_k^2\left(\frac{1}{\eta} + \eta\sigma_k^2\right) + \sigma_k^4\eta\right)\left(\frac{1}{2\theta_{ik}} - \frac{1}{2\theta_{jk}}\right)}{\left(1 + \frac{1}{2\theta_{jk}}\sigma_k^4\left(\frac{1}{\eta} + \eta\sigma_k^2\right)\right)^2} \tag{38}$$

C.1.4 Optimal Portfolio

With the optimal information allocation, in the second period,

$$\widehat{r}_{ik} = \kappa_i s_{ik} + (1 - \kappa_i)\mu_k \tag{39}$$

$$\widehat{\sigma}_{ik}^2 = 1/\widehat{\tau}_{ik} = \frac{\sigma_k^2}{1 + \frac{1}{2\theta_{ik}}\sigma_k^4\left(\frac{1}{\eta} + \eta\sigma_k^2\right)} \tag{40}$$

Substitute 39 and 40 into the portfolio holdings in the second period 6, we get the aggregate demand for asset k of sophisticated investors in country i is:

$$\mathbb{E}\int_S x_{i,k}^S dS = \mathbb{E}\int_S \frac{\widehat{r}_{ik} - \mu_k + \eta\sigma_k^2}{\eta\widehat{\sigma}_{ik}^2} dS = 1 + \frac{1}{2\theta_{ik}}\left(\frac{\eta}{\tau_k^3} + \frac{1}{\eta\tau_k^2}\right) \tag{41}$$

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

C.1.5 Equity Inflows

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

$$\frac{\partial}{\partial \sigma_k^2}\left(-x_{kk}^S + \frac{1}{N}\sum_{i=1}^{N} x_{ik}^S\right) = \frac{1}{2}\left(\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\theta_{ik}} - \frac{1}{\theta_{kk}}\right)\left(\frac{3\eta}{\tau_k^4} + \frac{2}{\eta\tau_k^3}\right) \tag{42}$$

Hence,

$$\frac{\partial}{\partial \sigma_k^2}\left(-x_{kk}^S + \frac{1}{N}\sum_{i=1}^{N} x_{ik}^S\right) \propto \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\theta_{ik}} - \frac{1}{\theta_{kk}} \tag{43}$$

All terms outside the difference $\frac{1}{2\theta_{ik}} - \frac{1}{2\theta_{jk}}$ are positive (since $\sigma_k^2 > 0$, $\eta > 0$, etc.). Hence, the sign of the derivative is:

$$\operatorname{sign}\left(\frac{1}{\theta_{ik}} - \frac{1}{\theta_{jk}}\right) \tag{44}$$

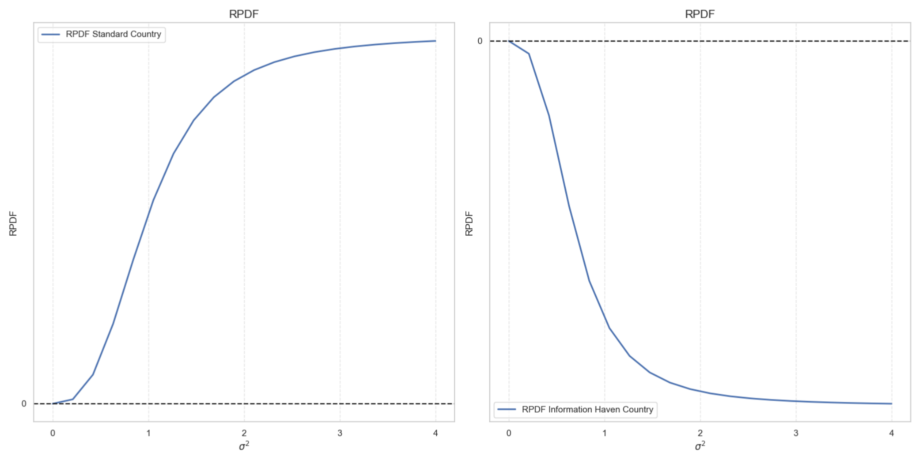
Therefore:

- If $\theta_{ik} < \theta_{jk}$, the derivative is positive.
- If $\theta_{ik} > \theta_{jk}$, the derivative is negative.

C.2 Comparative Statics of the Model

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

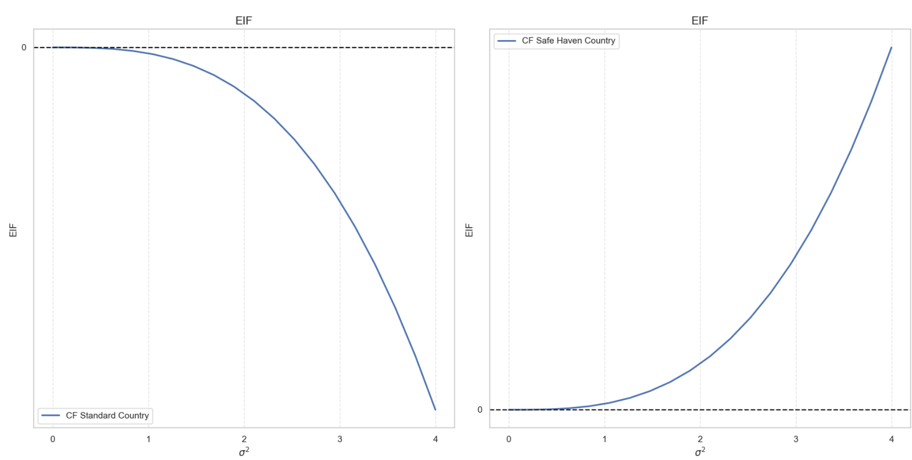
Figure 8: RPF_{ii} and *EIF* changing σ^2



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

Equity Inflows. We show how *EIF* changes in both a standard country and information haven country when uncertainty, σ^2, ranges from 0 to 4.

Figure 9: RPF_{ii} and *EIF* changing σ^2



Notes: This plot shows how equity inflows change in sign as σ^2 increases.

D Empirical Validation

D.1 Alternative Measures of Uncertainty

As an additional robustness check, we replicate our baseline analysis using alternative measures of uncertainty. While our main specification relies on the VIX index, which captures global financial market volatility, other indices may better reflect macroeconomic or broader financial uncertainty. To this end, we consider the Financial Uncertainty index proposed by Jurado (2015) (JLN), which measures the latent component of macroeconomic and financial volatility extracted from a large panel of U.S. time series.

Empirical specification. We estimate the same model as in Section 4, replacing the VIX with the JLN Financial Uncertainty index as the key regressor. The specification is:

$$\begin{aligned}\mathrm{FE}^2_{i,j,c,t} = {} & \alpha + \zeta_j + \tau \mathbb{1}_{\{c=\mathrm{US}\}} \\ & + \left(\beta + \beta_{\mathrm{US}} \mathbb{1}_{\{c=\mathrm{US}\}}\right) \mathbb{1}_{\{i=d\}} \\ & + \left(\gamma + \gamma_{\mathrm{US}} \mathbb{1}_{\{c=\mathrm{US}\}}\right) \mathbb{1}_{\{i=d\}} \times \mathrm{V}_t + \varepsilon_{i,j,c,t},\end{aligned} \tag{45}$$

where V_t represents either the VIX or the JLN uncertainty index. All specifications include forecaster, variable, and country fixed effects, and standard errors are clustered at the time level.

Comparison of results. Table 13 compares the estimates obtained using the VIX (Column 1) and the JLN index (Column 2). The coefficient γ, which captures the effect of global uncertainty on forecast errors, is positive and highly significant in both cases (0.27 with the VIX and 0.32 with the JLN index). This confirms that higher uncertainty reduces forecast precision on average.

The coefficient β, associated with the domestic indicator, remains negative and stable across specifications (around -0.02 with the VIX and -0.04 with the JLN index), indicating that domestic forecasters retain a relative informational advantage when uncertainty rises.

Finally, the U.S.-specific term γ_{US} is positive and significant (0.03–0.05), suggesting that this relationship reverses in the United States: when uncertainty increases, domestic U.S. forecasters lose precision relative to foreign ones.

Overall, the results demonstrate that the main findings are robust to the choice of uncertainty measure. Both financial market and macroeconomic uncertainty indices yield consis-

Table 13: Forecast Precision and Alternative Measures of Uncertainty

	Squared Forecast Error VIX (1)	Squared Forecast Error JLN (2)
Domestic	-0.010	-0.013
	(0.023)	(0.023)
Uncertainty	0.272	0.315
	(0.028)	(0.033)
Domestic × Uncertainty	-0.023	-0.036
	(0.013)	(0.017)
US	0.000	0.000
	(.)	(.)
Domestic × US	0.095	0.108
	(0.032)	(0.033)
Domestic × Uncertainty × US	0.034	0.048
	(0.013)	(0.017)
N	104661	104661
R^2	0.117	0.133
adj. R^2	0.115	0.131
FEs, Forecasters	Yes	Yes
FEs, Variable	Yes	Yes
FEs, Country	Yes	Yes

Notes: The table reports OLS estimates from the specification described above. Column (1) uses the VIX index as a measure of global financial uncertainty, while Column (2) replaces it with the Financial Uncertainty index of Jurado (2015) (JLN). The dependent variable is the squared forecast error, standardized to have mean zero and unit variance. All specifications include forecaster, variable, and country fixed effects. Standard errors, clustered at the time level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $* * * = 1\%$ level.

tent and economically meaningful patterns, reinforcing the view that uncertainty amplifies informational asymmetries across countries but flattens them within the United States.

D.2 Alternative Measure of Forecast Precision: Dispersion

As a robustness exercise, we re-estimate the main specification using an alternative measure of information heterogeneity based on forecast dispersion rather than squared forecast errors. While the benchmark analysis captures the precision of each forecaster relative to realized outcomes, dispersion reflects the degree of disagreement among forecasters at the time of prediction. This distinction allows us to verify that the main results are not driven by the ex-post definition of precision, but rather hold more generally for ex-ante perceptions of uncertainty and information heterogeneity.

A measure of dispersion. To verify that our main results are not driven by the specific construction of the forecast precision measure, we reproduce the analysis using an alternative proxy based on the cross-sectional dispersion of forecasts. Dispersion captures the extent of disagreement across institutions in their expectations for a given macroeconomic variable and country at each point in time. Larger dispersion reflects greater heterogeneity in beliefs and, consequently, lower perceived information precision.

Formally, we define dispersion as:

$$\text{Dispersion}_{i,j,c,t} = \left\{ \mathbb{E}_t[\mathbf{x}_{i,j,c,t}] - \mathbb{E}_t[\bar{\mathbf{x}}_t] \right\}^2, \tag{46}$$

where i denotes the forecaster, j the macroeconomic variable, c the country, and t the month. The term $\bar{\mathbf{x}}_t$ represents the average forecast across all forecasters, variables, and countries at time t. A higher value of $\text{Dispersion}_{i,j,c,t}$ therefore indicates greater forecast disagreement among institutions.

Empirical specification. We estimate an OLS model that parallels our main regression for forecast precision, replacing the squared forecast error with the dispersion measure as the dependent variable. The empirical specification is:

$$\begin{aligned} \text{Dispersion}_{i,j,c,t} = {} & \alpha + \zeta_j + \tau \mathbb{1}_{\{c=\text{US}\}} \\ & + \left(\beta + \beta_{\text{US}} \mathbb{1}_{\{c=\text{US}\}}\right) \mathbb{1}_{\{i=d\}} \\ & + \left(\gamma + \gamma_{\text{US}} \mathbb{1}_{\{c=\text{US}\}}\right) \mathbb{1}_{\{i=d\}} \times \mathbf{V}_t + \varepsilon_{i,j,c,t}, \end{aligned} \tag{47}$$

where $\mathbb{1}_{\{i=d\}}$ is an indicator for domestic forecasters, $\mathbb{1}_{\{c=\text{US}\}}$ identifies the United States, and $\mathbf{V}_t$ is the level of global uncertainty, proxied by the VIX index. The coefficients γ

and γ_{US} capture the differential sensitivity of forecast dispersion to uncertainty for domestic forecasters overall and for those located in the United States. All specifications include variable fixed effects ζ_j, and standard errors are clustered at the time level.

Table 14: Forecast Dispersion and Uncertainty

	Dispersion (1)	Dispersion (2)	Dispersion (3)
Domestic	-0.451	-0.166	-0.166
	(0.325)	(0.197)	(0.197)
VIX	0.938	0.889	0.889
	(0.196)	(0.208)	(0.208)
Domestic × VIX	-0.314	-0.282	-0.282
	(0.162)	(0.179)	(0.179)
US	-0.816	0.000	0.000
	(0.483)	(.)	(.)
Domestic × US	0.377	-0.255	-0.255
	(0.802)	(0.528)	(0.528)
Domestic × VIX × US	0.374	0.352	0.352
	(0.165)	(0.186)	(0.186)
N	106597	106597	106597
R^2	0.017	0.059	0.059
adj. R^2	0.015	0.057	0.057
FEs, Forecasters	No	Yes	Yes
FEs, Variable	No	No	Yes
FEs, Country	No	No	Yes

Notes: This table reports OLS estimates from Equation (47), where the dependent variable is the dispersion of forecasts across institutions for each country, variable, and time period. Dispersion is computed as the squared deviation of each forecaster's expectation from the global cross-sectional mean. The main regressor is the VIX index, interacted with indicators for domestic forecasters and for the United States. Standard errors, clustered at the time level, are reported in parentheses. $*$ = 10% level, $**$ = 5% level, and $***$ = 1% level.

Across specifications, the results in Columns (1)–(3) of Table 14 confirm the robustness of our findings. The coefficient on the VIX is positive and highly significant (ranging from 0.89 to 0.94), indicating that higher global uncertainty increases forecast dispersion among institutions. This suggests that during volatile periods, disagreement across forecasters widens, consistent with a fall in overall information precision.

The interaction term Domestic $\times$ VIX is negative and significant (approximately -0.28 to -0.31), showing that domestic forecasters are less affected by increases in global uncertainty. In other words, local agents tend to maintain more similar expectations when volatility rises, reflecting a relative informational advantage.

Finally, the triple interaction Domestic $\times$ VIX $\times$ US is positive and significant (about 0.35 to 0.37), reversing this pattern for the United States. This indicates that, unlike in other countries, U.S. forecasters exhibit greater dispersion when uncertainty increases. This finding is consistent with the interpretation of the United States as an information haven, where information is more symmetrically distributed and domestic agents do not enjoy the same comparative advantage as elsewhere.

Overall, the results corroborate the mechanism documented in the main analysis: global uncertainty raises forecast disagreement, but domestic forecasters outside the United States remain relatively insulated, while in the United States, the informational structure appears flatter and less segmented between local and foreign institutions.