Equity Flows in Uncertain Times: the Role of Heterogeneous Information

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Abstract

This paper investigates the role of information heterogeneity in driving equity flows throughout the global financial cycle. In periods of heightened uncertainty, investors retrench from most of foreign markets while maintaining investment in information-advantaged economies, particularly in the United States. We develop a multi-country model with endogenous information acquisition and heterogeneous learning costs, which generates three key predictions in uncertain times: (i) domestic investors become relatively better informed; (ii) aggregate foreign equity inflows fall where domestic agents hold an informational advantage; and (iii) investors reallocate toward markets they understand better. We validate these predictions using Consensus Economics forecasts and both aggregate and bilateral equity inflows. Higher uncertainty widens information asymmetries and leads to weaker foreign inflows where domestic precision improves, while capital shifts toward destinations that are easier to learn about.

JEL Codes: F32, F36, G11, D82
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1 Introduction

Equity flows are a fundamental component of the global financial system and a key channel through which uncertainty shocks spread across borders. This paper finds that, when uncertainty rises, foreign investors reduce their investments in countries with limited access to information, while maintaining their activity in markets with easier access such as the United States.

The recent literature on the global financial cycle, summarized in Coeurdacier and Rey (2013) and Miranda-Agrippino and Rey (2022), argues that episodes of global stress trigger a pronounced flight to safety and flight to quality, with equity investors reinforcing home bias and reallocating toward assets concentrated in the United States. Building on this evidence, Akinci and Kalemli-Ozcan (2024) shows that periods of heightened uncertainty are systematically associated with sharp reductions in foreign equity investment across most economies, whereas the United States remains a notable exception that continues to attract foreign capital. This asymmetric pattern points to open questions in the literature about which further channels might explain the observed cross-country differences.

The central question of this paper is whether information frictions can explain the heterogeneous response of equity inflows [1] to uncertainty. We argue that cross-country differences in the cost and precision of acquiring information about foreign assets play a central role in shaping these responses. When volatility increases, investors reduce exposure to destinations they understand less, while continuing to invest in those where learning is easier. As a result, most countries experience a broad retrenchment in foreign equity capital during turbulent periods, whereas a few information-advantaged markets remain resilient.

Understanding these flows is crucial because their magnitude and volatility make them a key source of financial fragility during global stress. Equity transactions account for nearly half of all cross-border capital movements, and gross inflows alone often exceed 10 % percent of GDP in many economies. During crises, declines in equity inflows have reached hundreds of billions of dollars, as shown in Caballero and Simsek (2020). They are also highly sensitive to uncertainty: a one-standard-deviation increase in global volatility lowers institutional equity inflows by about 2% per quarter, with even stronger effects in emerging markets

[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.

and at the investor-firm level, as shown in Kacperczyk et al. (2025). Even modest changes therefore involve very large portfolio reallocations [2], with important implications for asset prices, capital flow management, and disclosure regulation.

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 confirm these theoretical predictions 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

[2] The U.S. external liabilities position exceeds \$65 trillion in 2025. A one-percent reallocation of these holdings corresponds to more than \$650 billion in cross-border portfolio adjustments. Source: U.S. Bureau of Economic Analysis, International Investment Position of the United States, available at `https://www.bea.gov/data/intl-trade-investment/international-investment-position`.

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.

We document empirical evidence consistent with the three predictions of the model. First, uncertainty increases informational asymmetries: a one-standard-deviation rise in the VIX increases domestic relative forecast precision by about 3 % of its standard deviation on average, with substantially larger changes outside the United States, where foreign institutions sometimes outperform domestic forecasters. Second, these information gaps matter for aggregate flows: a one-standard-deviation improvement in informational advantage reduces foreign equity inflows by roughly 5 % of their standard deviation. Third, in the bilateral dimension, investors redirect portfolios toward destinations they understand better: a similar improvement in relative forecast precision about a partner economy increases bilateral inflows by about 20-25 % of their standard deviation. These results indicate that information frictions shape both the contraction and the reallocation of foreign equity investment when uncertainty rises.

Taken together, these findings show that information heterogeneity is a relevant channel in the global allocation of equity capital. By documenting the asymmetric response of inflows to uncertainty and linking it to observable variation in forecast precision, the paper offers a unified explanation for three central features of international finance: the sensitivity of capital flows to global volatility, the persistence of home bias, and the special role of the United States as an information haven.

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 remainder of the paper is structured as follows. Section 2 documents how foreign equity inflows respond to increases in uncertainty across countries, establishing the empirical patterns that motivate our analysis. Section 3 then introduces a simple multi-country portfolio choice framework with endogenous information acquisition to help interpret these patterns and clarify the mechanisms behind the heterogeneous flow responses. Section 4 takes the key implications of the model to the data, combining survey-based measures of forecast precision with both aggregate and bilateral equity flows. Section 5 concludes by summarizing the results and their implications for the international allocation of capital in periods of high uncertainty.

2 Motivating Evidence

In this section, we examine how foreign equity holdings respond to fluctuations in uncertainty, with a particular focus on how global shocks shape the cross-border allocation of financial capital. On average, periods of heightened uncertainty are associated with negative equity inflows across most countries, with the United States being the notable exception. This pattern reflects a broad flight-to-safety mechanism in investor behavior, consistent with Miranda-Agrippino and Rey (2015) and the role of uncertainty as a global pull factor documented by Choi et al. (2023). Even when global risk aversion rises, the United States continues to attract capital, reinforcing its position as a global financial safe haven.

We focus on cross-border portfolio equity holdings because informational frictions, such as asymmetric information, heterogeneous beliefs, and differences in monitoring capacity, are far more pronounced in equity markets. Equity investment requires forming expectations about firm-level performance and domestic economic conditions, both of which depend heavily on access to timely and accurate information. Bonds, by contrast, are typically less sensitive to such frictions, given their more predictable payoffs and institutional safeguards.

By studying portfolio equity inflows, we aim to understand how uncertainty affects the global reallocation of financial capital through informational and behavioral channels. This perspective isolates the decisions of global investors who adjust portfolios as information precision and perceived risk change, distinguishing between relatively opaque countries and those functioning as information havens. It therefore provides a more granular view of how uncertainty and information jointly shape the geography of equity flows.

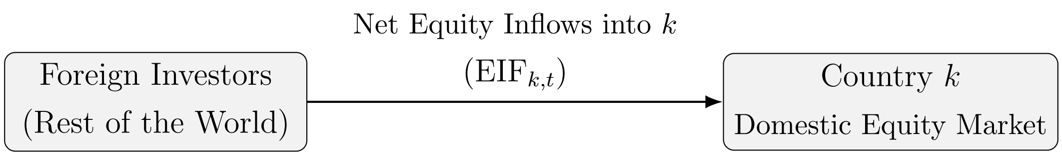
Equity inflows: Definition. We define equity inflows, following the balance of payments (BoP) convention, as the net transactions between nonresidents and residents of a given country that lead to changes in the ownership of domestic equities. Positive equity inflows indicate that foreign investors are, 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 [3].

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.

[3]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.

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.

Schematic Representation of Equity Inflows



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.

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 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:

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

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 B [4], 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 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.

[4] Appendix B 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.

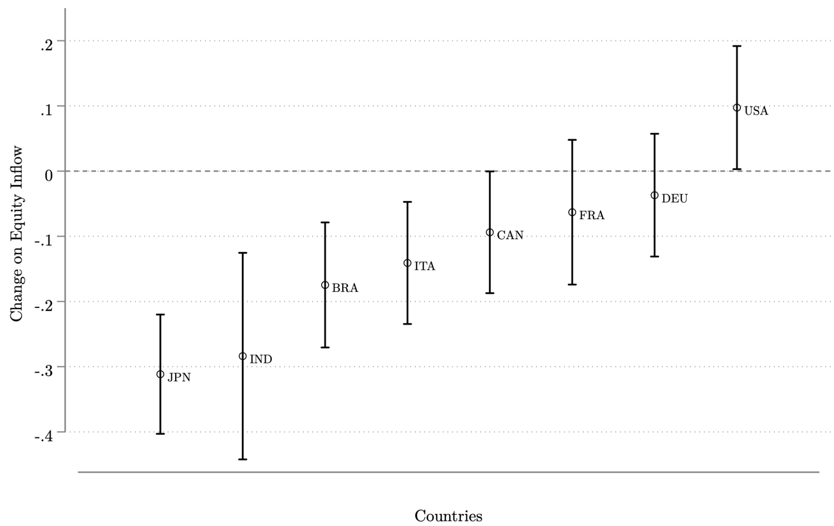
Second, the interaction term VIX $\times \mathbb{1}_{\{i=\text{US}\}}$ is positive and statistically significant, with estimated coefficients between 0.16 and 0.18. This result indicates that the response of equity inflows to global uncertainty differs systematically for the United States. Whereas most 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 [5].

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 negative 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 sensitivity of equity inflows to

[5] 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.

global uncertainty. Figure 1 reports these estimates for a set of major advanced economies alongside two large emerging markets [6]. The figure shows a clear ranking in the magnitude of the response: the United States exhibits a positive and statistically significant coefficient, indicating no retrenchment in foreign equity investment during uncertainty spikes; France and Germany display milder declines; while Canada, Italy, Brazil, India, and Japan experience progressively stronger contractions. This systematic ordering reflects greater vulnerability to uncertainty in countries where foreign participation is more sensitive to perceived informational frictions.

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 economies. Periods of high volatility coincide with weaker foreign participation, as global investors concentrate portfolios in markets where information is more readily available and reliable. The United States remains a notable exception, showing limited sensitivity of equity inflows to global shocks and, in some cases, continued capital attraction. This asymmetry highlights the importance of studying possible channels that might explain

[6]Results for the full country sample are reported in Appendix B.

how investments shape global equity flows and motivates our subsequent analysis of how informational frictions might drive investors' heterogeneous responses to uncertainty.

3 Model

In this section, we develop a multi-country portfolio choice model with endogenous information acquisition. Investors differ in their ability to learn: some are sophisticated and can pay to acquire private signals about domestic and foreign assets, while others rely only on prior beliefs. Sophisticated investors update their expectations using costly information, whereas unsophisticated investors never improve on the prior and therefore hold the same beliefs across markets and states of the world, regardless of prevailing conditions. Information costs vary across countries, so investors are not equally able to learn about every market. Before forming portfolios, sophisticated investors choose their research intensity, trading off precision against cost in a forward-looking manner. When uncertainty rises, the value of information increases, and investors shift learning effort and portfolio weight toward markets where information is cheaper to acquire and more effective.

The model delivers three main predictions. First, investors facing lower information costs for a given market acquire more precise signals and gain a relative informational advantage, and this advantage becomes stronger when uncertainty is high. Second, uncertainty affects foreign equity inflows at the aggregate level: when domestic investors have a clear informational edge over foreign investors, foreign inflows fall, whereas markets that are relatively easy for all investors to learn about continue to attract capital. Third, the model also characterizes bilateral inflows: whether investors from a particular source country increase or reduce their exposure to a destination depends on how their information cost for that market compares with the world average. Together, these predictions link changes in information precision to both the level and the geography of equity capital flows when uncertainty rises.

3.1 Setup

We now describe the economic environment that will guide the analysis, outlining the structure of countries, assets, investors, and information costs.

Countries and Assets. 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 $\{p_k\}_{k=1}^N$.

Investors. 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 share a common prior.

Timing. The model features three periods. In the first period, investors choose how much information to acquire about each asset, taking into account the cost of learning and the potential benefits from greater precision. In the second period, they observe the private signals generated by their research, update beliefs about future payoffs, and select their portfolios. In the final period, payoffs are realized, portfolios are liquidated, and investors consume their resulting wealth. This timing ensures that information acquisition is fully forward looking, since learning decisions shape beliefs and portfolio choices before uncertainty is resolved.

Information Acquisition. Unsophisticated investors cannot invest in research and rely fully on their prior. Sophisticated investors in country i can instead choose to acquire additional information about 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 $\theta_{ik}\tau_{ik,s}^2$, additive across assets. They receive the signals in the second period and use this information when making portfolio decisions. Uncertainty is then realized in the final period.

Heterogeneity in Information Costs. Heterogeneity among investors in different countries stems from differences in the cost of acquiring information, so that θ_{ik} can vary across all (i, k) pairs. We interpret this as capturing both cross-country differences in transparency and potential relative information advantage. While in principle this leads to a large number of parameters, in Section 3.3 we 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 investors. For illustrative purposes, we refer to *standard countries* as those with $\theta_{kk} < \theta_k$, exhibiting domestic information advantage, while if $\theta_{k'k'} \geq \theta_{k'}$ we call country k' an *information haven.*

Investor Problem. We now formally present the investor problem, proceeding backward through time. We begin with the standard investment decision in the second period, where portfolios are chosen after information has been acquired, and then move to the information choice problem in the first period, when investors decide what to learn about future payoffs. Details on the derivations are provided in Appendix C.

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, hence $\kappa \to 1$ [7], 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

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

[7] Appendix C.2 shows that the equilibrium of the generic economy with a measure κ of unsophisticated investors converges, as $\kappa \to 1$, to the equilibrium characterized in the main text. In particular, we establish continuity in κ of equilibrium prices, optimal portfolio allocations, and information acquisition choices. Therefore, taking the limit $\kappa \to 1$ is without loss of generality and simply eliminates posterior belief heterogeneity in the price system while preserving the economic content of the model.

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

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

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

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

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

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

3.3 Information Choice

In the first period, sophisticated investors in country i choose how much information to acquire about each asset. Specifically, they optimally select the precision of private signals $\{\tau_{ik,s}\}_{k=1}^{N}$ in order to maximize their ex ante expected utility over terminal wealth, taking into account that information will affect their posterior beliefs and therefore their future optimal portfolio holdings:

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

where τ denotes the vector collecting all signal precisions acquired by investor i. Information acquisition is costly, and the cost function is assumed to be quadratic and additively separable across assets:

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

This formulation captures the standard assumption that more precise private information is increasingly expensive to obtain, and that the learning technology for each asset is independent from the others.

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:

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

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

For 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 [8]*:*

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

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

In this subsection we characterize equity inflows in response to an increase in uncertainty about the asset of country k. For simplicity of exposition we present the result under a country specific uncertainty shock, but we can show that the same result holds under a global uncertainty shock as well.

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 [9]:

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

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

[8] 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.

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

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:

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

Aggregate Equity Inflows. The following proposition illustrates how aggregate equity inflows are related to the cost of information acquisition. Here we look at country specific uncertainty, but in Appendix C.3 we show that the expression for EIF_k is invariant to the nature of the uncertainty shock.

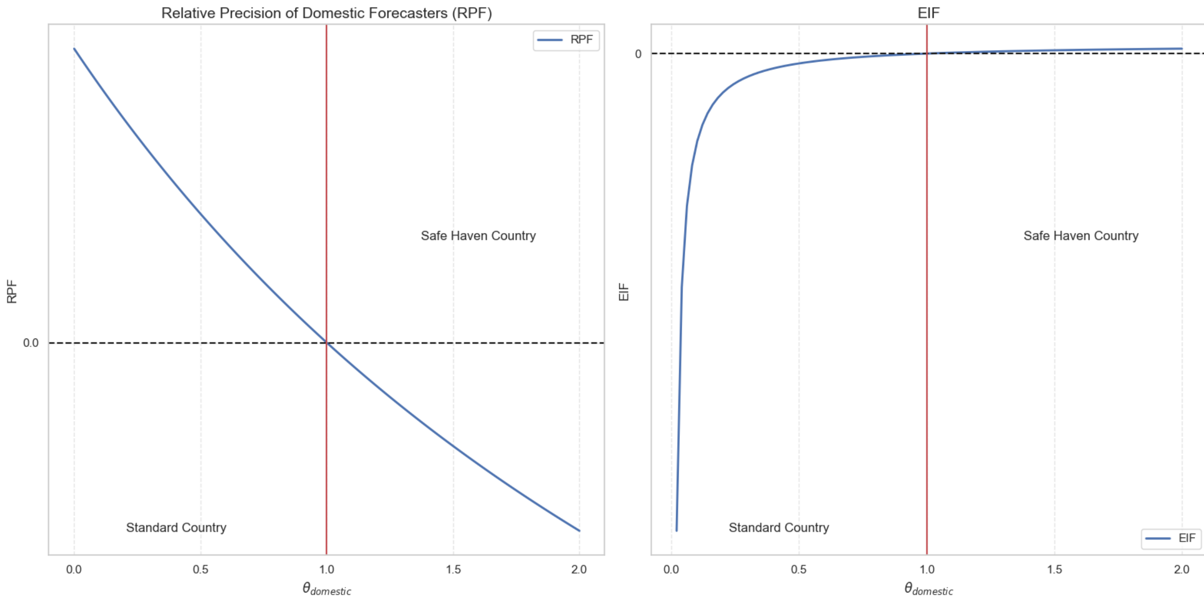
Proposition 2. *Denote EIF_k as the equity inflow for asset k when its uncertainty increases, then:*

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

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 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

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 $\theta_d \geq \theta_f$.

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 $\theta_d \geq \theta_f$ [10]. In the Appendix C.4 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

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

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.

Bilateral Equity Inflows. In analogy with the definition of aggregate inflows in Section 3.4, we define bilateral inflows as the change in 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 reveals not only whether foreign investors retrench from a country, but also *which* investors do so more strongly. It distinguishes between source countries that are relatively better or worse informed about a given destination, providing a more granular view of international equity reallocations directly linked to differences in information acquisition costs.

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 [11].

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

[11] Appendix C.3 shows that the expression for EIF_k is invariant to the nature of the uncertainty shock.

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 evaluate the three central predictions of our model. The theoretical analysis in Section 3 establishes that information frictions play a fundamental role in shaping international portfolio decisions when uncertainty rises. In particular, the model delivers three testable implications. First, when uncertainty increases, the value of acquiring information becomes higher, and investors with lower learning costs optimally increase their research effort. This behavior leads to a relative improvement in the precision of domestic investors' forecasts compared to foreign ones, thereby amplifying informational asymmetries in most countries. Second, these informational asymmetries translate directly into portfolio choices: when domestic agents possess a superior informational position, foreign investors become relatively disadvantaged and retrench, generating weaker aggregate equity inflows into that country. Third, as uncertainty grows, investors also reallocate equity across destinations based on where they enjoy a relative informational advantage, resulting in a systematic reshaping of the geography of bilateral flows. Thus, the model predicts both a contraction in foreign participation where domestic information advantages widen, and an expansion of positions toward destinations where investors are comparatively well informed.

In subsection 4.2, we examine the first prediction by studying how the informational advantage of domestic forecasters responds to changes in uncertainty. Using forecast performance data from Consensus Economics, we document that domestic investors indeed improve their relative forecast precision during uncertain periods, with the notable exception of the United States, which emerges as an information haven where informational frictions for foreigners are minimal. In subsection 4.3, we test the second and third predictions by linking relative forecast precision to observed portfolio flows. We study both aggregate equity inflows and bilateral reallocations, allowing us to measure how information shapes not only whether capital flows into a country but also where the flows originate. Consistent with the model's mechanism, we find that stronger domestic informational advantages are associated with weaker aggregate inflows, while investors redirect equity toward destinations in which they hold a relative informational edge. The combined evidence confirms that information frictions are key drivers of cross-border equity movements during periods of heightened global volatility, and validates the full set of mechanisms emphasized by the theoretical analysis.

4.1 Consensus Economics

To measure forecast precision and its variation with uncertainty, we use data from Consensus Economics [12], 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.

[12] 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.

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

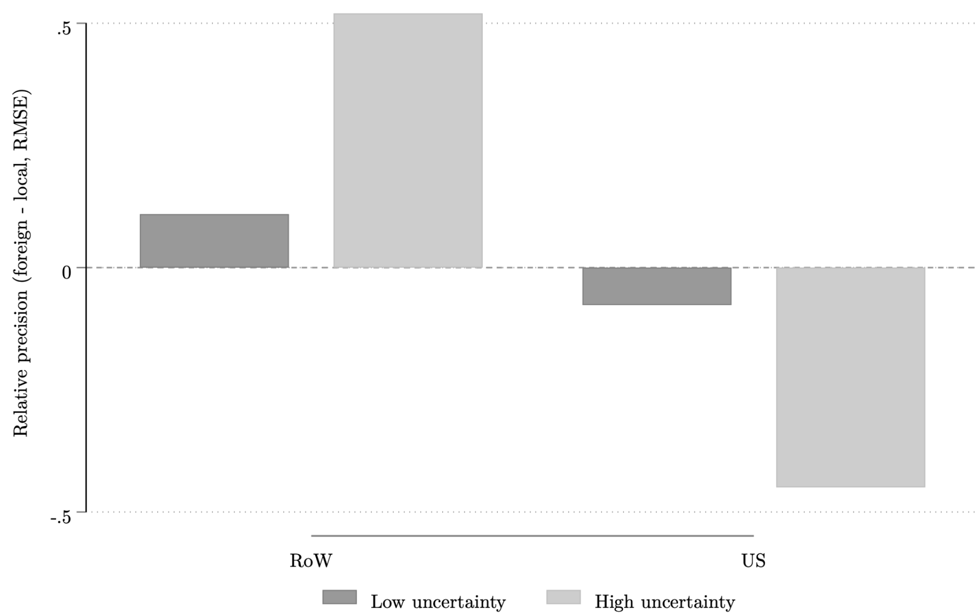
We now turn to the first empirical prediction of our model, which we test using the relationship between information advantage and uncertainty. Proposition 1 states that when the prior uncertainty about an asset (σ_k) is high, or when the cost of acquiring information (θ_{ik}) is relatively low, sophisticated 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

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.

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 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 [13]. 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.

For the United States, the pattern contrasts sharply with the rest of the world. We do not find a clear domestic information advantage; if anything, foreign institutions often forecast american macroeconomic conditions more accurately when uncertainty is high. This result is consistent with our interpretation of the United States as an information haven in the model, where information about domestic assets is relatively easy to acquire and process for all investors. As a consequence, informational gaps do not widen during volatile periods, helping explain why foreign equity inflows remain resilient there while they retrench elsewhere.

Empirical Specification and Forecaster Heterogeneity. A key identification concern is that the domestic information advantage documented above may reflect differences in forecasting skill rather than differences in information. Some institutions, such as large global banks or specialized research centers, systematically produce more accurate forecasts than others because they have deeper analytical capacity, access to proprietary data, or more sophisticated forecasting models. If these persistent differences in ability are correlated with whether a forecaster is domestic or foreign, the domestic advantage we observe could simply reflect who the forecasters are, not what they know about the country in question.

Our model rationalizes this distinct pattern by linking it to the openness and transparency of the american market, which eliminate a domestic learning advantage. Because information on its economy is widely produced and disseminated globally, foreign institutions devote substantial research resources to this destination, reflecting its central position in the international financial system. As a result, foreign analysts are not informationally disadvantaged during volatile periods, in line with the information haven interpretation and the observed resilience of equity inflows there when uncertainty rises.

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

To separate these effects, we turn to the micro-level panel of individual forecasts and explicitly control for heterogeneity across forecasters. We estimate a model in which forecast errors are regressed on global uncertainty and a domestic forecaster indicator, while including forecaster fixed effects that net out any time-invariant differences in forecasting ability. We also absorb country and variable-specific effects to account for recurring patterns in predictability across destinations and macroeconomic indicators. This specification isolates how uncertainty differentially affects the precision of domestic and foreign forecasts, ensuring that the patterns in Figure 3 reflect genuine informational frictions rather than selection or persistent skill advantages of certain types of institutions.

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. 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 3 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.

Table 3: Forecast Accuracy and Uncertainty

	Squared Forecast Error (1)	Squared Forecast Error (2)	Squared Forecast Error (3)
Domestic	0.009	0.028	-0.010
	(0.017)	(0.047)	(0.022)
VIX	0.299	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	0.083	0.008	0.096
	(0.017)	(0.073)	(0.031)
Domestic × VIX × US	0.079	0.042	0.034
	(0.013)	(0.014)	(0.013)
N	104656	104656	104656
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.

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 × 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 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.

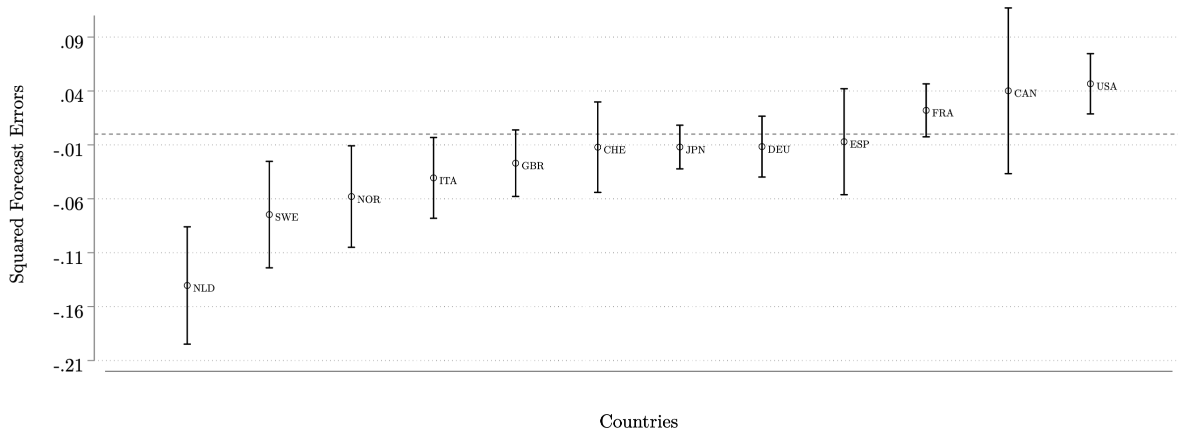
The triple interaction term, γ_{US}, associated with Domestic $\times$ Uncertainty $\times$ US, reverses this relationship for the United States. The coefficient is positive and significant in all columns, indicating that, when uncertainty rises, domestic U.S. forecasters lose precision relative to foreign 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 3, 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

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%.

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.

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 4, 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

Table 4: Aggregate Equity Inflows and Relative Precision of Domestic Forecasters

	Aggregate EIF (1)	Aggregate EIF (2)	Aggregate EIF (3)
RPF (ii)	-0.047	-0.047	-0.053
	(0.026)	(0.014)	(0.015)
Observations	879	879	879
FEs, Country	No	No	Yes
SEs, Robust	Yes	No	No
SEs, Country	No	Yes	Yes
RPF (p-value)	0.066	0.010	0.007

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.

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 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 5 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

Table 5: 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.

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

Summary of the Results. Across both the forecasting and equity inflow evidence, each of the three central predictions of the model finds support in the data. First, domestic agents become relatively better informed when uncertainty rises, except in information havens such as the United States. Second, this widening informational gap reduces aggregate foreign participation in markets where domestic investors enjoy a comparative advantage. Third, investors systematically redirect capital toward destinations they understand better, reinforcing the geography of information frictions.

Together, these results show that information heterogeneity is not only statistically significant but also economically meaningful: it governs both the contraction and the redistribution of international equity investment during episodes of global volatility.

5 Conclusion

This paper has examined how information heterogeneity shapes the dynamics of international equity flows during periods of 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 uncertainty 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 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 higher 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.

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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 6: 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 6 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

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

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 7 and the resulting of a 1.5% trimming from both left and right tails in Table 8 [14]. Moreover, in Figure 5 we show the distributions of the variables we included in our dataset.

Table 7: Descriptive Statistics: Data from Consensus Economics

	Mean	Median	Max	Min	N
Long-Term T-Bills ($\Delta\%$ $m, m+12$)	-0.62	-0.57	3.52	-3.76	21482
Short-Term T-Bills ($\Delta\%$ $m, m+12$)	-0.39	-0.19	2.35	-5.23	20868
GDP $\Delta\%$ ($\Delta\%$ $m, y+1$)	-0.43	-0.16	6.90	-8.60	30324
IP $\Delta\%$ ($\Delta\%$ $m, y+1$)	-2.48	-1.52	23.55	-31.11	20831
Unemployment Rate ($\Delta\%$ $y+1$)	-0.18	-0.27	5.43	-4.96	19055

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.

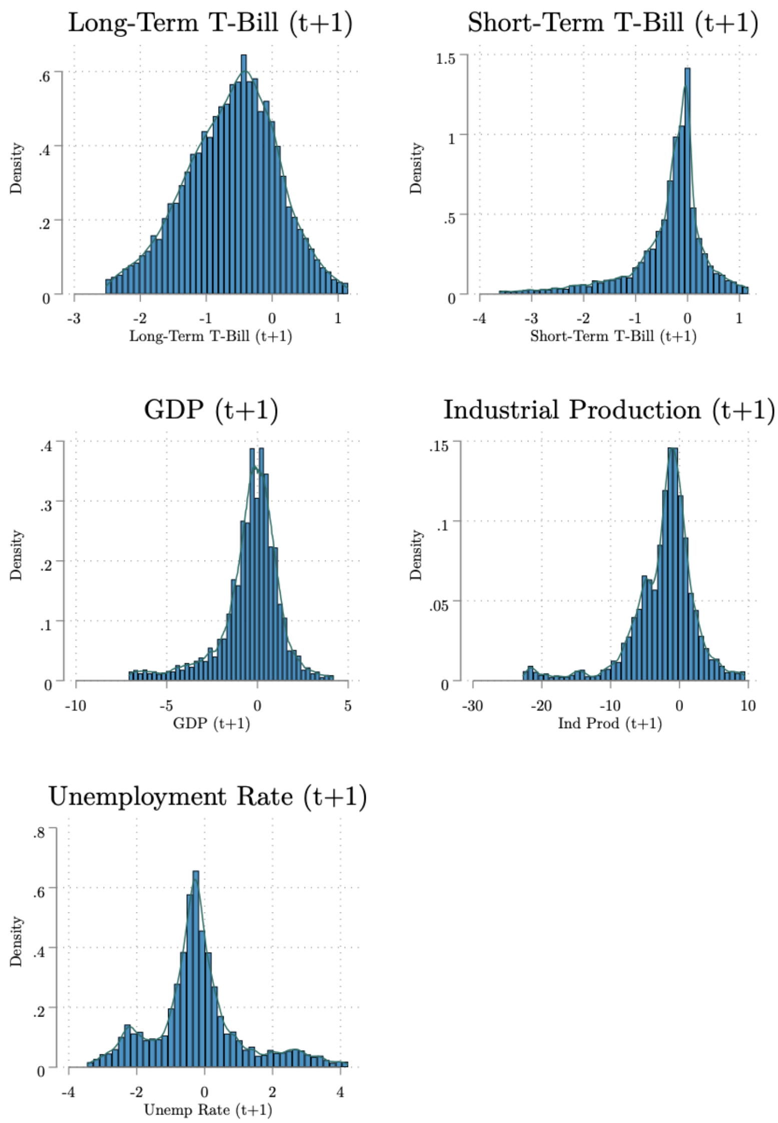
Table 8: Descriptive Statistics: Trimmed Data from Consensus Economics

	Mean	Median	Max	Min	N
Long-Term T-Bills ($\Delta\%$ $m, m+12$)	-0.62	-0.57	1.15	-2.53	21053
Short-Term T-Bills ($\Delta\%$ $m, m+12$)	-0.37	-0.19	1.17	-3.62	20446
GDP $\Delta\%$ ($\Delta\%$ $m, y+1$)	-0.41	-0.16	4.20	-7.10	29762
IP $\Delta\%$ ($\Delta\%$ $m, y+1$)	-2.39	-1.52	9.56	-22.76	20414
Unemployment Rate ($\Delta\%$ $y+1$)	-0.19	-0.27	4.22	-3.46	18677

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

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

Figure 5: Histogram of Squared Forecast Errors



Notes: Histograms of squared forecast errors, not standardized, for each variables we include in our dataset (Long-Term T-Bill, Short-Term T-Bill, Δ % GDP, Δ % IP, % Unemployment) . These data are trimmed both tail at 1%, to exclude potential outliers.

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) and the volatility of stock market returns at country level, a proxy for country-specific VIX. Table 9 shows how these measures are distributed.

Table 9: Descriptive of Uncertainty Measures

	Max	Min	N
VIX Index	5.21	-1.30	311
Financial Uncertainty JLN (2021)	3.26	-1.64	311
Country Uncertainty	6.12	-1.04	311

Notes: The Table reports the descriptive statistics of different measure of uncertainty. These measures are standardized to the mean. For country uncertainty, we average the index across all countries in the sample.

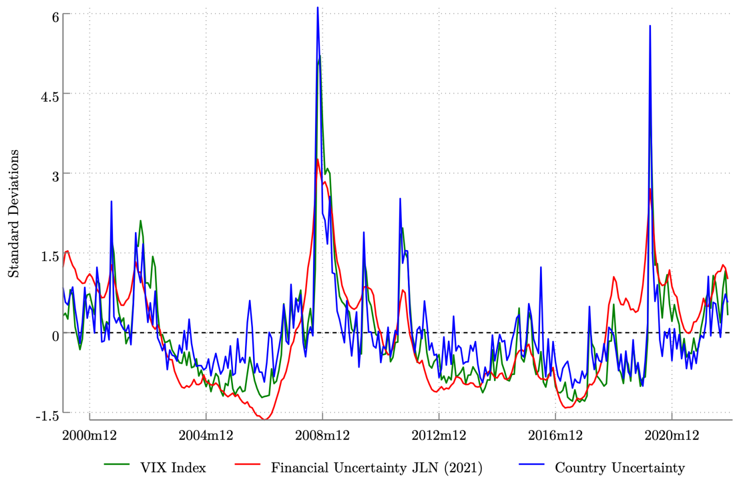
We also provide a table that shows how our main measure of uncertainty (VIX index) correlates with alternative measures.

Table 10: Correlation of VIX Index with Uncertainty Measures

	VIX Index
Financial Uncertainty JLN (2021)	0.80***
Country Uncertainty	0.88***

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 11: 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) $\times$ US	0.135	0.138	0.138
	(0.015)	(0.015)	(0.018)
GDP Δ%		0.012	0.010
		(0.004)	(0.005)
EER			0.036
			(0.017)
Bond Inflows			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 12: 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 13: Equity Inflows Excluding Extreme Uncertainty Episodes

	Aggregate EIF (1)	Aggregate EIF (2)	Aggregate EIF (3)
VIX	-0.133	-0.142	-0.148
	(0.019)	(0.019)	(0.023)
VIX $\times$ US	0.271	0.287	0.295
	(0.022)	(0.022)	(0.028)
GDP $\Delta\%$		0.013	0.011
		(0.004)	(0.005)
EER			0.027
			(0.018)
Bond Inflows			0.001
			(0.001)
Observations	6888	6761	5854
Country FEs	Yes	Yes	Yes

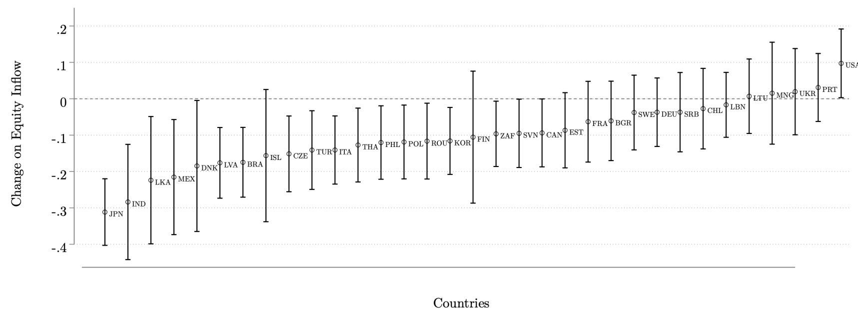
Notes: This table reports regressions of standardized equity inflows on uncertainty (measured by the VIX) after excluding periods of extreme volatility. Both dependent and independent variables are standardized. GDP % refers to yearly GDP growth.

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

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

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

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

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

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:

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

Therefore:

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

C.2 Proof of Convergence

In what follows we show formally that the generic economy with a measure κ of uninformed investors converges to the economy we describe when $\kappa = 1$. In particular, we establish continuity of equilibrium prices, continuity of optimal portfolio allocations, continuity of information acquisition choices, and finally continuity of capital flows. Therefore the case with $\kappa = 1$ is the well defined limit of the general model.

Step 1: Continuity of Equilibrium Price. The generic market clearing condition is:

$$
\begin{aligned}
\kappa \frac{1}{N} \sum_{i=1}^{N} \int_U x_{i,k}^U \, dU + (1-\kappa) \sum_{i=1}^{N} \int_S x_{i,k}^S \, dS &= 1 \\
\kappa \frac{1}{N} \sum_{i=1}^{N} \int_U \frac{\mu_k - r^f p_k}{\eta \sigma_k^2} \, dU + (1-\kappa) \sum_{i=1}^{N} \int_S \frac{\hat{r}_k - r^f p_k}{\eta \hat{\sigma}_k^2} \, dS &= 1 \\
\frac{\kappa}{\eta \sigma_k^2}(\mu_k - r^f p_k) + (1-\kappa) \sum_{i=1}^{N} \int_S \left(\frac{\hat{r}_k}{\eta \hat{\sigma}_k^2} - \frac{r^f}{\eta \hat{\sigma}_k^2} p_k \right) dS &= 1 \\
\frac{\kappa}{\eta \sigma_k^2} \mu_k - \frac{\kappa}{\eta \sigma_k^2} r^f p_k + (1-\kappa) \sum_{i=1}^{N} \int_S \frac{\hat{r}_k}{\eta \hat{\sigma}_k^2} \, dS - (1-\kappa) \sum_{i=1}^{N} \int_S \frac{r^f}{\eta \hat{\sigma}_k^2} \, dS \, p_k &= 1
\end{aligned}
$$

Therefore,

$$
p_k \left[\kappa \frac{r^f}{\eta \sigma_k^2} + (1-\kappa) \sum_{i=1}^{N} \int_S \frac{r^f}{\eta \hat{\sigma}_k^2} \, dS \right] = \kappa \frac{\mu_k}{\eta \sigma_k^2} + (1-\kappa) \sum_{i=1}^{N} \int_S \frac{\hat{r}_k}{\eta \hat{\sigma}_k^2} \, dS - 1 \tag{45}
$$

Rearranging, the price in a generic economy, given the posterior belief of sophisticated investors, is:

$$
p_k(\kappa) = \frac{\kappa \dfrac{\mu_k}{\eta \sigma_k^2} + (1-\kappa) \displaystyle\sum_{i=1}^{N} \int_S \frac{\hat{r}_k}{\eta \hat{\sigma}_k^2} \, dS - 1}{\kappa \dfrac{r^f}{\eta \sigma_k^2} + (1-\kappa) \displaystyle\sum_{i=1}^{N} \int_S \frac{r^f}{\eta \hat{\sigma}_k^2} \, dS}. \tag{46}
$$

The denominator has a finite nonzero limit as $\kappa \to 1$, so we can apply L'Hôpital rule. The expression does not depend on posterior beliefs of sophisticated investors in the limit:

$$\lim_{\kappa\to 1} p_k(\kappa) = \frac{\mu_k - \eta\sigma_k^2}{r^f}. \tag{47}$$

Thus equilibrium prices are continuous in κ at $\kappa = 1$.

Step 2: Continuity of Allocation Choice. Research choices are individual and exhibit no equilibrium feedback other than through prices. Let the investor objective be

$$U_i(x,p) = \sum_{k=1}^{N} \mathbb{E}_i\left[x_{ik}(r_k - r^f p_k)\right] - \frac{\eta}{2}\mathbb{V}_i\left[x_{ik}(r_k - r^f p_k)\right]. \tag{48}$$

This function is continuous in both x and p, and strictly concave in x. To satisfy these conditions, assume that short sales are ruled out and that the investor's portfolio is constrained by initial wealth W_0, so that $x_{ik} \in [0, W_0]$ for all k. Then $X(p)$ is compact and independent of p, and all conditions of Berge's Theorem are satisfied.
It follows that:

$$\lim_{p_k(k)\to p_k} x^*(p(k)) = x^*(p), \tag{49}$$

where the convergence is understood element-wise, i.e., $p(k) = (p_1(k), \ldots, p_N(k)) \to p = (p_1, \ldots, p_N)$ with $p_k = \frac{\mu_k - \eta\sigma_k^2}{r^f}$.
If short sales are allowed, the feasible set $X = \mathbb{R}^N$ is unbounded and Berge's Maximum Theorem does not apply directly. However, the objective function remains strictly concave in x and satisfies a coercivity condition:

$$\|x\| \to \infty \quad \Rightarrow \quad U_i(x,p) \to -\infty. \tag{50}$$

This ensures the existence of a unique finite maximizer, even on an unbounded domain. As a result, the optimization problem may equivalently be solved over a sufficiently large compact subset of $\mathbb{R}^N$ that contains the maximizer. On such a compact set, the conditions of Berge's Maximum Theorem are restored, and the argmax correspondence remains continuous in p.

Thus,

$$\lim_{p_k(k)\to p_k} x^*(p(k)) = x^*(p), \tag{51}$$

remains valid even without short-sale constraints.

Step 3: Continuity of Research Choices. In the first step investors choose signal precision $\tau_{ik,s}$ to maximize expected wealth net of information costs:

$$\max_{\tau \geq 0} \left\{ \mathbb{E}\left[\mathbb{E}_i(W_i) - \frac{\eta}{2} \mathbb{V}_i(W_i) \right] - C_i(\tau) \right\}, \tag{52}$$

with

$$C_i(\tau) = \sum_{k=1}^{N} \frac{\theta_{ik}}{2} \tau_{ik,s}^2. \tag{53}$$

Let the indirect utility from research be

$$V_i(\tau, p) = \mathbb{E}\left[\mathbb{E}_i(W_i) - \frac{\eta}{2} \mathbb{V}_i(W_i) \right] - C_i(\tau), \tag{54}$$

which is continuous in (τ, p) and strictly concave in τ. Since optimal portfolios $x^*(p)$ were shown continuous in p, posterior beliefs and therefore V_i inherit continuity in p. By Berge maximum theorem:

$$\lim_{\kappa \to 1} \tau^*(p(\kappa)) = \tau^*(p). \tag{55}$$

Hence optimal research choices are continuous in the limit.

Conclusion. All equilibrium objects depend continuously on κ at $\kappa = 1$: equilibrium prices, portfolio allocations and information acquisition. Therefore the equilibrium of the economy with only uninformed investors is the well defined limit of the generic economy as κ approaches one.

C.3 Global uncertainty

In this section we consider the special case in which all countries have the same initial level of uncertainty τ_i. In this case the term ν_i does not vary across countries and therefore it factors out of all summations. We denote this common level by ν_{global}. This simplification allows us to isolate the role of country transparency in determining the response of equity inflows to a global increase in uncertainty.

To capture informational differences across destinations, we define the average cost for foreign investors to learn about the assets issued in country k by

$$\theta_{-k} = \frac{N-1}{\sum_{i \neq k} \frac{1}{\theta_{ik}}}. \tag{56}$$

Equivalently,

$$\frac{1}{\theta_{-k}} = \frac{1}{N-1} \sum_{i \neq k} \frac{1}{\theta_{ik}}. \tag{57}$$

Under this assumption, a global increase in uncertainty leads to equity inflows into country k that are proportional to

$$EIF_k = \nu_{global} \left[\frac{1}{\theta_{kk}} - \frac{1}{N} \sum_{j=1}^{N} \frac{1}{\theta_{-j}} \right]. \tag{58}$$

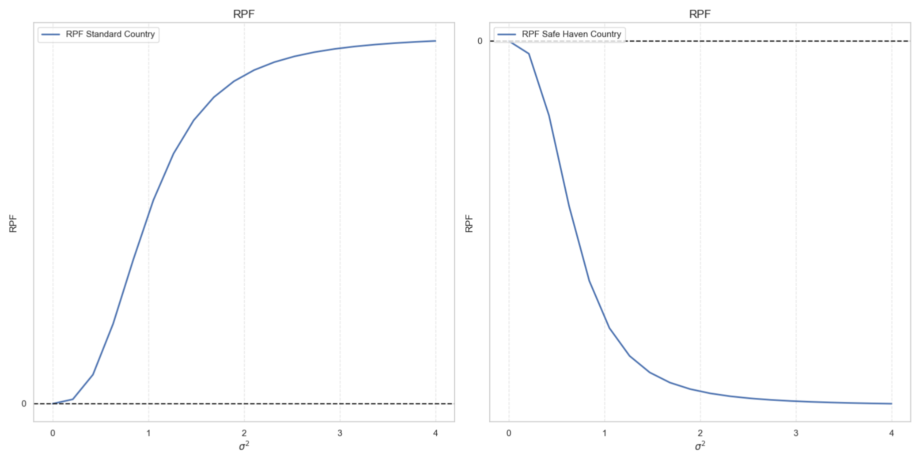
The sign and magnitude of EIF_k depends entirely on the transparency of country k relative to the world average. If foreign investors can acquire information about assets in country k at a comparatively low cost, then equity inflows into that country increase when global uncertainty rises. Conversely, if the information cost in country k is high relative to other destinations, then uncertainty growth results in lower equity inflows.

In summary, the sensitivity of equity inflows to uncertainty is governed by country transparency. This transparency is measured by the relative ease with which foreign investors can acquire information about domestic assets, as captured by the comparison between the learning cost θ_{kk} and the average learning cost faced by investors across other countries.

C.4 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.

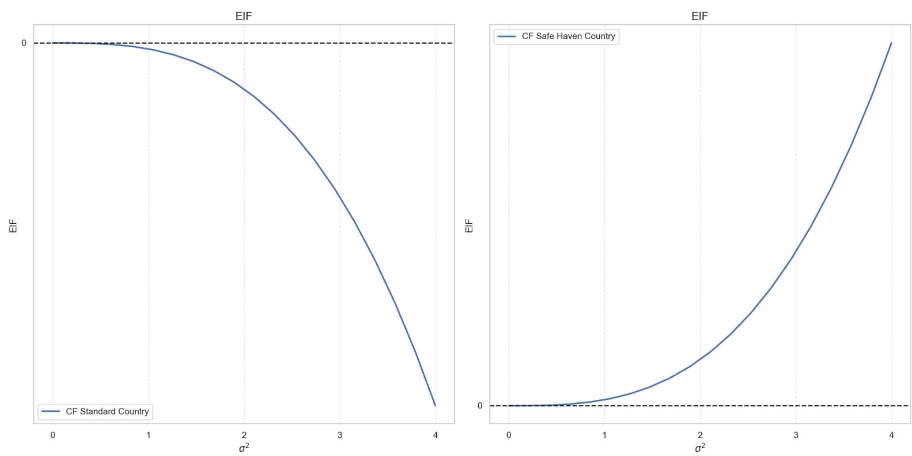
Figure 8: RPF_{ii} and EIF changing σ^2



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:

$$\begin{aligned}\mathrm{FE}^2_{i,j,c,t} &= \alpha + \zeta_j + \tau \mathbb{1}_{\{c=\mathrm{US}\}} \\ &+ \left(\beta + \beta_{\mathrm{US}} \mathbb{1}_{\{c=\mathrm{US}\}}\right) \mathbb{1}_{\{i=d\}} \\ &+ \left(\gamma + \gamma_{\mathrm{US}} \mathbb{1}_{\{c=\mathrm{US}\}}\right) \mathbb{1}_{\{i=d\}} \times \mathrm{V}_t + \varepsilon_{i,j,c,t},\end{aligned} \tag{59}$$

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 14 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 14: Forecast Precision and Alternative Measures of Uncertainty

	Squared Forecast Error VIX (1)	Squared Forecast Error JLN (2)	Squared Forecast Error Country (3)
Domestic	-0.010	-0.014	0.009
	(0.022)	(0.022)	(0.041)
Uncertainty	0.272	0.315	0.249
	(0.028)	(0.034)	(0.038)
Domestic × Uncertainty	-0.023	-0.037	-0.028
	(0.013)	(0.016)	(0.015)
US	0.000	0.000	0.000
	(.)	(.)	(.)
Domestic × US	0.096	0.108	0.081
	(0.031)	(0.033)	(0.045)
Domestic × Uncertainty × US	0.034	0.047	0.017
	(0.013)	(0.016)	(0.015)
N	104656	104656	83835
R^2	0.117	0.133	0.110
adj. R^2	0.115	0.131	0.108
FEs, Forecasters	Yes	Yes	Yes
FEs, Variable	Yes	Yes	Yes
FEs, Country	Yes	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, Column (2) replaces it with the Financial Uncertainty index of Jurado (2015) (JLN) and Column (3) collects monthly volatility of ETF at country level, as a proxy of local uncertainty. 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:

$$\text{Dispersion}_{i,j,c,t} = \left\{ \mathbb{E}_t[\mathbf{x}_{i,j,c,t}] - \mathbb{E}_t[\bar{\mathbf{x}}_t] \right\}^2, \tag{60}$$

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:

$$\begin{aligned} \text{Dispersion}_{i,j,c,t} = {} & \alpha + \zeta_j + \tau \mathbb{1}_{\{c=\text{US}\}} \\ & + \left(\beta + \beta_{\text{US}} \mathbb{1}_{\{c=\text{US}\}}\right) \mathbb{1}_{\{i=d\}} \\ & + \left(\gamma + \gamma_{\text{US}} \mathbb{1}_{\{c=\text{US}\}}\right) \mathbb{1}_{\{i=d\}} \times \mathbf{V}_t + \varepsilon_{i,j,c,t}, \end{aligned} \tag{61}$$

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 15: Forecast Dispersion and Uncertainty

	Dispersion (1)	Dispersion (2)	Dispersion (3)
Domestic	-0.481	-0.191	-0.191
	(0.344)	(0.217)	(0.217)
VIX	0.951	0.902	0.902
	(0.203)	(0.215)	(0.215)
Domestic $\times$ VIX	-0.295	-0.262	-0.262
	(0.156)	(0.174)	(0.174)
US	-0.822	0.000	0.000
	(0.486)	(.)	(.)
Domestic $\times$ US	0.412	-0.234	-0.234
	(0.825)	(0.543)	(0.543)
Domestic $\times$ VIX $\times$ US	0.410	0.386	0.386
	(0.160)	(0.181)	(0.181)
N	106590	106590	106590
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 (61), 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 15 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.