Do Local Forecasters Have Better Information?*

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Abstract

Do local forecasters outperform foreign ones when forecasting macroeconomic fundamentals? If so, is this local advantage due to behavioral biases or to information asymmetries? In this paper, we provide direct evidence of both a better performance of local forecasters and of the informational origin of this local advantage by looking at survey expectations. Using individual GDP growth and inflation forecasts by professional forecasters for a panel of emerging and advanced economies, we show that foreign forecasters make more mistakes than local forecasters. The local forecasters' more accurate expectations is not due to a more irrational expectation formation by foreigners, but to local forecasters' more precise information. On the methodological side, we provide tests that identify differences in information frictions across groups.

Keywords: Information asymmetries, Expectation formation.

JEL codes: E3, E7, D82.

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1 Introduction

Do local forecasters have better information than foreign ones? We answer this question by providing direct evidence of information asymmetries between local and foreign professional forecasters using a unique dataset of GDP growth and inflation forecasts by individual professional forecasters for a panel of emerging and advanced economies. We first show that foreign forecasters make more mistakes on inflation and output growth than local forecasters. We do this using the forecaster and country dimensions of our panel, which allows us to control for a rich set of fixed effects. Controlling for both time-specific country and forecaster unobservables, we show that local forecasters make less mistakes than foreign ones, and that the difference is statistically and economically significant. The local advantage is especially large when nowcasting as opposed to forecasting and when predicting inflation as opposed to GDP. In general, we show that the local advantage is stronger for shorter horizons.

We then investigate the role of information versus behavioral biases in explaining our results. We do this in two steps. First, we rule out behavioral biases such as over-reaction to new information and over-extrapolation as explanations of the foreigners' excess mistakes, by showing that the local and foreign behavioral biases do not differ systematically. Second, we test for the relative precision of local and foreign forecasters' private information, and find that local forecasters have more precise private information. To do so, we build on and extend the fast-growing literature that uses model-based tests to identify frictions in the expectation formation of survey respondents (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020; Kohlhas and Broer, 2019; Angeletos et al., 2020; Goldstein, 2021). In particular, we provide tests of asymmetric information that are robust to the presence of public signals (more on that below). These tests show that foreign forecasters have less precise information.

Finally, we explore some determinants of this information asymmetry. Interestingly, the local advantage is not weaker when forecasting is less uncertain. If anything, it is stronger. Indeed, while inflation, shorter horizons and large countries are typically characterized by smaller errors and less information frictions on average, the local advantage is stronger for shorter horizons (it is especially strong when nowcasting as opposed to forecasting and it increases over the year), when predicting inflation as opposed to GDP growth, and when predicting large countries' fundamentals. While the performance of forecasters for advanced economies and economies with better institutions is stronger on average, there is no significantly different local advantage for these countries as opposed to emerging economies and economies with poorer institutions. Similarly, financial forecasters perform better than non-financial forecasters on average, but the local financial forecasters outperform the foreign financial ones as much as the local non-financial forecasters outperform the foreign non-financial ones. This evidence suggests that when information becomes available, it always flows to local forecasters, but not always to foreign forecasters.

This paper contributes to the recent literature that uses professional forecasters' expectations to identify information frictions and behavioral biases. This literature has used reduced-form estimations as indicators of deviations from Full-Information Rational Expectations (FIRE). Coibion and Gorodnichenko (2015) (CG henceforth) uses the estimated coefficient in the regression of the consensus error on the consensus revision as an indicator of deviations from Full Information (FI). Bordalo et al. (2020), (BGMS henceforth) Kohlhas and Broer (2019) (BK henceforth) and Angeletos et al. (2020) (AHS henceforth) use the estimated coefficient in the individual pooled regression as an indicator of deviations from Rational Expectations (RE). We borrow this test directly from this literature to assess whether domestic and foreign behavioral biases differ.

However, the Full Information (FI) test that has been commonly used in the literature is not adapted to our purpose. Indeed, in the presence of public information, the CG coefficient, which is a common measure of information frictions, is biased. Importantly, the bias depends on the precision of the public signal and is not a monotonic function of the precision of private signals. Comparing the CG coefficient across local and foreign forecasters cannot indicate which group faces more frictions.[1] We thus provide two tests that are robust to the presence of public information. The first one relies on individual regressions à la BGMS but with country-time fixed effects to capture aggregate shocks and the public signals. This test is similar in spirit to Goldstein (2021), who proposes to use forecasters' deviations from the mean to measure information frictions robustly. The second test infers the relative precision of private information from the relative reaction of expectations to public signals.

This paper also belongs to the empirical literature documenting the home bias in information. Kang and Stulz (1997), Grinblatt and Keloharju (2001), Dvořák (2003), Portes and Rey (2005), Ahearne et al. (2004), Hamao and J. (2001), Hau (2001), Choe et al. (2005), Baik et al. (2010) and Sialm et al. (2020) provide indirect evidence of asymmetric information between domestic and foreign investors by showing that location matters for portfolio composition and for portfolio returns. However, based on investor choices and returns, some papers find that foreign investors perform better than local investors (e.g. Grinblatt and M. (2000)).[2] In contrast to these studies, we investigate whether location affects the quality of information possessed by forecasters, thus providing direct evidence of a home bias in information. Closest to our study is the paper by Bae et al. (2008), which studies the performance of local and foreign analysts in forecasting earnings for firms. Our focus is different since we examine whether local forecasters outperform foreign ones regarding aggregate forecasts.

[1]Both CG and Goldstein (2021) have emphasized that the CG coefficient is biased, but have not highlighted the implied non-monotonicity.

[2]This could be explained by the specialization of some investors in some specific markets where they have an initial informational advantage. This informational advantage can be due to location, but not only. Therefore, information heterogeneity can also lead to specialization in non-domestic assets (see Van Nieuwerburgh and Veldkamp (2010) and De Marco et al. (2021)).

Besides, we not only document the foreign forecasters excess errors, but we also investigate whether these excess mistakes come from information frictions or behavioral biases. Also, different from them, we use our panel structure to systematically control for both forecasters and country fixed effects. Finally, Leuz et al. (2009), Mondria et al. (2010) Huang (2015) and Cziraki et al. (2021) document foreigners' lack of attention to domestic information.

Our findings have important implications for international macroeconomics and finance. The informational advantage of local agents over foreigners regarding macroeconomic fundamentals is one of the main explanations for the home bias in asset holdings. The home bias in asset holdings, originally documented by French and Poterba (1991), refers to the fact that domestic assets constitute a disproportionate share of portfolios.[3] Indeed, if domestic investors have an informational advantage, then the conditional risk associated with foreign asset holding is higher than the conditional risk associated with domestic asset holding, which may explain why portfolios are tilted towards domestic assets.

Besides, information asymmetries between domestic and foreign investors can explain why we observe large, volatile and positively correlated capital inflows and outflows. This phenomenon is particularly hard to explain (Broner et al., 2013). But if information is asymmetric, then foreign and domestic agents may have a different assessment of the domestic economic development, and foreign investors may become more (or less) optimistic than the domestic investors. In that case, foreigners would buy (sell) domestic assets from domestic agents at the same time as they would sell (buy) foreign assets, which represents respectively a capital inflow and an outflow from the perspective of the domestic economy (Tille and van Wincoop, 2014; Benhima and Cordonier, 2022).

The paper is structured as follows. Section 2 describes our dataset. Section 3 documents the foreign forecasters' excess mistakes. Section 4 lays down a model of expectation formation and tests for the sources of the foreigners' excess mistakes.

2 The Data

Forecasts. – We use data from Consensus Economics. Consensus Economics is a survey firm polling individual economic forecasters on a monthly frequency. The survey covers 51 advanced and emerging countries for a maximum time span between 1989 and 2021.[4] Each month, forecasters provide estimates of several macroeconomic indicators for the current and the following year. In this paper, we focus on two indicators, namely GDP and inflation. The dataset discloses the name of the individual forecasters. There are 748 unique forecasters

[3]See also Ahearne et al. (2004), Portes and Rey (2005) and Coeurdacier and Rey (2013). Work on asymmetric information and the home bias includes Pàstor (2000), Brennan and Cao (1997), Portes et al. (2001), Van Nieuwerburgh and Veldkamp (2009), Mondria (2010), De Marco et al. (2021).

[4]For an overview of all advanced and emerging economies in our sample see table 12 in the appendix.

from which 149 conduct forecasts for at least 2 distinct countries. For each forecaster-country pair, the average (median) number of observations is 76 (54), which corresponds to approximately 6 (5) years . This leads to an unbalanced panel dataset.

Realized Outcomes. – Following the literature, we use first release data to compare forecast precision across forecasters. For each survey year, we use the realized outcome for yearly real GDP growth and inflation from the International Monetary Fund World Economic Outlook (IMF WEO) published in April of the subsequent year. This allows us to match the information set of the agents as closely as possible and avoids forecast errors that are due to data revisions. For example, to assess the accuracy of the 2013 real GDP growth forecast for Brazil from the January 2013 survey, we use the yearly GDP growth reported in the April 2014 IMF WEO as realized outcome. To assess the accuracy of the 2014 real GDP growth forecast for Brazil from the same January 2013 survey, we use the yearly GDP growth reported in April 2015. We conduct robustness checks with alternative vintages using IMF WEO published in September or in subsequent years. Archived IMF WEO vintage data are available from 1998 onwards. Table 12 presents the list of variables and countries we study as well as the time range for which both forecast and realized data are available.

As is common in the literature, we trim observations, removing forecasts that are more than 5 interquartile ranges away from the median. The quantiles are calculated in two different ways. First, on the whole sample, but separately for emerging and advanced countries. Second, conditional on each country and date. This trimming ensures that our results are not driven by extreme outcomes, such as periods of hyperinflation, or by typos. It reduces the number of forecasts for current inflation and GDP by 4 and 1 percent, respectively. We conduct robustness checks with alternative trimming strategies.

Location. – Consensus Economics discloses the name of the forecasting institution. We use this name to match the Consensus Economics data to information about the location of the forecaster from Eikon (Refinitiv). Eikon provides the company tree structure of most forecasters in our dataset. The tree structure includes information about the countries of the headquarter as well as the subsidiaries and affiliates. If the forecaster was not listed in the Eikon database, we manually searched for this information on the internet. In the main analysis, we consider a forecaster to be foreign if neither its headquarter nor any of its subsidiaries are located in the country of the forecast. However, the information on the location is not time-varying and corresponds to the information accessed in 2021. This amounts to a measurement error that could bias downward the magnitude of the effect of location.

Table 1: Distribution of Observations across Forecasters conditional on Location and Scope

				Scope					
Location	**National**			**Multinational**			**Total**		
	No.	%	%	No.	%	%	No.	%	%
Local	46,275	62.5	31.8	99,330	79.6	68.2	145,605	73.2	100.0
Foreign	27,801	37.5	52.3	25,380	20.4	47.7	53,181	26.8	100.0
Total	74,076	100.0	37.3	124,710	100.0	62.7	198,786	100.0	100.0

Notes: The table shows the distribution of the forecasters conditional on their scope and location. Forecasters are either local or foreign. Local forecasters have the headquarter or subsidiary in the country they forecast for, otherwise they are considered as being a foreign forecaster. Multinational forecasters have subsidiaries in different countries than their headquarter is located in. National forecasters have only subsidiaries in the same country as the headquarter.

Forecast errors. – We use this information to construct forecast errors. The forecast errors with respect to the current year are defined as

$$Error^{m}_{ijkt,t} = x_{jt} - E_{ijkt}(x_{jt})$$

where t refers to the year, i is the forecaster, j is the country, $m = 1, .., 12$ is the month of the year when the forecast is produced, and x is either inflation of GDP growth. And the forecast errors with respect to the next year are defined as

$$Error^{m}_{ijt,t+1} = x_{jt+1} - E_{ijt}(x_{jt+1}).$$

Forecasters' Scope and Industry. Furthermore, we characterize the scope of the forecasters. In more detail, we categorize forecasters with subsidiaries and headquarter all located in the same country as national forecasters. In contrast, we categorize forecasters with at least one subsidiary located in a country different from their headquarters as multinationals. Table 1 provides an overview of the distribution of observations across forecasters conditional on their location and scope. Almost two third of the forecasts come from multinational forecasters, and almost three quarters are made by local forecasters. A higher proportion of forecasts by multinational forecasters is local, because multinationals are more likely to have a branch in the countries for which they produce forecasts.

Besides data on location, Eikon provides information about the industry of the forecaster which we manually verified. We use industry information of the headquarter to distinguish non-financial from financial forecasters.

3 Foreign Forecasters Make More Mistakes

In this section, we analyse the forecast error of the forecasters conditional on their location. We find that foreign forecasters make more mistakes than local ones.

As preliminary evidence, we examine the distribution of forecast errors for local and foreign forecasters. In Figure 2 in the Appendix, we plot the density of the forecast error conditional on the location of the forecaster. A wider distribution of the forecast error provides evidence of a more imprecise forecast. We observe a larger variance for foreign forecasters compared to local ones. These differences are more pronounced for the current than for the future forecast horizon.

To formally test for differences in variance, we perform a simple test of equality of the variances of forecast error across location. We compute the ratio of the standard deviation of the errors of local forecasters to that of foreign ones. We conduct a one-sided test with the null hypothesis, H_0, of equal variance, i.e. $\frac{\sigma_{\text{FE}_{\text{Local}}}}{\sigma_{\text{FE}_{\text{Foreign}}}} = 1$ versus the alternative hypothesis, H_A, that the ratio is < 1. $\sigma_{\text{FE}_{\text{Local}}}$ and $\sigma_{\text{FE}_{\text{Foreign}}}$ are respectively the standard errors of the forecast errors $Error^m_{ijt,t}$ (or $Error^m_{ijt,t+1}$, depending on the horizon) when forecaster i is located in country j and when it is not.

Table 2 reports the results. In column (1), we define different sub-samples. We split the sample into advanced and emerging countries, multinational and national forecasters, financial and non-financial forecasters. Column (2) and (3) show the number of observations for local and foreign forecasters, respectively. Column (4) and (5) show the standard deviation of the forecast error conditional on the location. Column (6) reports the F-statistics and column (7) the corresponding p-value.

Table 2: Test for differences in Variance of Forecast Error

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	Sample	N Local	N Foreign	σ_{Local}	σ_{Foreign}	F-test	p-value
CPI_t	All sample	11,908	4,519	0.79	0.94	0.71	< 0.001
	Advanced Economies	5,655	1,278	0.42	0.49	0.74	< 0.001
	Emerging Economies	6,253	3,241	1.02	1.07	0.91	0.001
	Multinatonal firms	8,435	2,320	0.77	0.95	0.65	< 0.001
	National firms	3,473	2,199	0.86	0.93	0.84	< 0.001
	Financial Sector	8,005	1,274	0.78	1.04	0.57	< 0.001
	Non-Fincial Sector	1,828	2,158	0.74	0.83	0.79	< 0.001
GDP_t	All sample	12,390	4,701	1.15	1.44	0.64	< 0.001
	Advanced Economies	5,762	1,274	0.69	0.87	0.62	< 0.001
	Emerging Economies	6,628	3,427	1.44	1.60	0.80	< 0.001
	Multinatonal firms	8,690	2,424	1.11	1.51	0.54	< 0.001
	National firms	3,700	2,277	1.25	1.36	0.83	< 0.001
	Financial Sector	8,269	1,348	1.14	1.60	0.51	< 0.001
	Non-Fincial Sector	1,858	2,217	0.99	1.32	0.56	< 0.001
CPI_{t+1}	All sample	11,231	4,140	1.76	2.09	0.71	< 0.001
	Advanced Economies	5,382	1,171	0.91	1.04	0.78	< 0.001
	Emerging Economies	5,849	2,969	2.27	2.38	0.91	0.002
	Multinatonal firms	7,971	2,151	1.79	2.07	0.75	< 0.001
	National firms	3,260	1,989	1.68	2.10	0.64	< 0.001
	Financial Sector	7,582	1,192	1.81	2.17	0.69	< 0.001
	Non-Fincial Sector	1,711	1,964	1.66	2.00	0.69	< 0.001
GDP_{t+1}	All sample	11,707	4,341	2.45	3.10	0.62	< 0.001
	Advanced Economies	5,472	1,168	1.60	1.86	0.74	< 0.001
	Emerging Economies	6,235	3,173	3.00	3.45	0.76	< 0.001
	Multinatonal firms	8,206	2,275	2.36	3.24	0.53	< 0.001
	National firms	3,501	2,066	2.64	2.94	0.80	< 0.001
	Financial Sector	7,831	1,281	2.43	3.41	0.51	< 0.001
	Non-Fincial Sector	1,737	2,023	1.95	2.82	0.48	< 0.001

Notes: The table shows a test for differences in the standard deviation between local and foreign forecasters. The Null hypothesis posits that the ratio of the standard deviation of the errors across local forecasters to the standard deviation across foreign forecasters is equal to 1. The alternative hypothesis is that this ratio is smaller than 1. In the rows we report the test statistics for different subsamples.

For current CPI and GDP, the null hypothesis of equal variances of the forecast error between local and foreign forecasters can be rejected at the 1% significance level. This result holds over the entire sample as well as all subsamples. The results for the next year forecast horizon are similar. Note, however, that the test for equal variance does not allow to control for country- and forecaster-specific characteristics. For this reason, we estimate different fixed-effects model with alternative measures of the forecast error magnitude. They exploit the panel structure of our data and control for forecaster-, date- and country-specific characteristics. For instance, we have seen that a higher proportion of forecasts by multinational forecasters are local. Given that multinationals are also more likely to have well-endowed forecasting departments, local forecasts could artificially appear more accurate if we do not control for forecasters' characteristics.

As a first measure of the forecast error distribution, we estimate the standard deviation $\sigma^m_{\mathrm{FE},i,j}$ of the forecast error for every forecaster-country-month triple (m, i, j) for current and future forecasts separately. We discard forecaster-country-month triples with less than 10 observations per month. We take the log of $\sigma^m_{\mathrm{FE},i,j}$ and estimate

$$\ln(\sigma^m_{\mathrm{FE},i,j}) = \delta^m + \tilde{\delta}_i + \bar{\delta}_j + \beta \mathrm{Foreign}_{ij} + \varepsilon^m_{ij} \,, \tag{1}$$

with δ^m being month fixed effects, $\tilde{\delta}_i$ controlling for forecaster fixed effects and $\bar{\delta}_j$ for country-specific characteristics. $\mathrm{Foreign}_{ij}$ is a dummy that takes the value of 1 if forecaster i is foreign to country j, and 0 otherwise.

Table 3 reports the coefficient β for different specifications of the model. Estimated over the entire sample, foreign forecasters have a higher forecast standard error than local forecasters. This finding is robust across different fixed effects specifications. In the most conservative specification (with country, forecaster and month-of-year fixed effects), being a foreign forecaster increases the standard error by 6% to 14%. The difference between local and foreign forecasters' performance is larger for inflation than for GDP growth, and for the current than for the future year, confirming the visual evidence shown in Figure 2.

Table 3: Standard Deviation of the Forecast Error conditional on Location of the Forecaster

	(1)	(2)	(3)	(4)
Variable	Coefficient			
CPI_t	Foreign	0.12***	0.13**	0.14***
		(0.04)	(0.05)	(0.05)
	N	6,107	6,097	6,097
	R^2	0.47	0.50	0.81
GDP_t	Foreign	0.06***	0.12**	0.11***
		(0.02)	(0.05)	(0.03)
	N	6,544	6,535	6,535
	R^2	0.49	0.51	0.89
CPI_{t+1}	Foreign	0.07***	0.06	0.06*
		(0.02)	(0.04)	(0.04)
	N	6,107	6,097	6,097
	R^2	0.79	0.83	0.86
GDP_{t+1}	Foreign	0.07***	0.06**	0.06**
		(0.02)	(0.03)	(0.03)
	N	6,544	6,535	6,535
	R^2	0.77	0.81	0.86
	Country FE	Yes	Yes	Yes
	Forecaster FE	No	Yes	Yes
	Month FE	No	No	Yes

Notes: The table shows the regression of the log standard deviation of current CPI and GDP on the location of the forecaster with different fixed-effects specifications. The standard deviation is calculated by forecaster-country pair for each month. We neglect forecasters that have less than 10 observations for a given month. All standard errors are clustered on the country and forecaster level.

In this specification, we control for country, forecaster and month-of-year characteristics, but not for the time period. Ignoring time-specific characteristics could bias our results if, for instance, more foreign forecasts are produced in times of turmoil and uncertainty, where all forecasters will make more mistakes. Therefore, as a second measure of the forecast error distribution, we calculate the log absolute value of the forecast error, which is time-varying.[5] We use the logarithm of the absolute forecast error as a large mass of errors are distributed closely around zero. The model we estimate is as follows.

$$\ln(|Error^m_{ijt,t}| = \delta^m_{it} + \tilde{\delta}^m_{jt} + \beta \text{Foreign}_{ij} + \varepsilon^m_{ij,t}\,, \tag{2}$$

δ^m_{it} are forecaster-date fixed effects and $\tilde{\delta}^m_{jt}$ are country-date fixed effects. These fixed effects

[5]For absolute forecast errors smaller than 0.001, we assign the value of ln(0.001) to keep all observations in the sample. The results are robust for different thresholds.

enables us to control for country-specific trends in volatility and forecaster-specific trends in forecasting performance.

Table 4: Forecast Error conditional on Location of the Forecaster

	(1)	(2)	(3)	(4)
Variable	Coefficient			
CPI_t	Foreign	0.26***	0.10***	0.09***
		(0.08)	(0.03)	(0.02)
	N	153,089	153,066	99,228
	R^2	0.01	0.14	0.62
GDP_t	Foreign	0.27***	0.11***	0.06**
		(0.08)	(0.03)	(0.02)
	N	160,971	160,947	103,866
	R^2	0.01	0.15	0.66
CPI_{t+1}	Foreign	0.27***	0.09***	0.07***
		(0.06)	(0.03)	(0.02)
	N	140,177	140,152	90,693
	R^2	0.01	0.14	0.67
GDP_{t+1}	Foreign	0.15*	0.08**	0.01
		(0.08)	(0.03)	(0.02)
	N	147,885	147,860	95,508
	R^2	0.00	0.16	0.72
	Country and Forecaster FE	No	Yes	Yes
	Country × Date	No	No	Yes
	Forecaster × Date FE	No	No	Yes

Notes: The table shows the regression of the log absolute forecast error of current CPI and GDP on the location of the forecaster with different fixed-effects specifications. All standard errors are clustered on the country, year × country, forecaster and date level.

Table 4 displays the results for CPI and GDP. In all specifications, foreign forecasters have a significantly larger log absolute forecast error than local forecasters. In the most conservative specification with country-date and forecaster-date fixed effects, being a foreign forecaster increases the absolute forecast error by 9% for current inflation. The difference in absolute forecast error is smaller for current GDP growth (6%) and for future inflation (6% as well). For future GDP growth, there is no significant difference between local and foreign forecasters. Presumably, as uncertainty is higher when forecasting at a longer time horizon, the informational advantage is lower for local forecasters.

4 What Explains the Foreigners' Errors?

To explore what explains the foreigners' errors, we lay down a simple noisy information model. We explore two potential sources of heterogeneity between local and foreign forecasters: behavioral biases and information asymmetry. We rule out differences in behavioral biases using rational expectation tests that are now common in the literature. We then establish the presence of asymmetric information by using a test that is robust to common behavioral biases and to public signals. Finally, we test an implication of our noisy-information model: foreigners react more to public signals.

4.1 A Simple Noisy Information Model

We consider a set of professional forecasters indexed by $i = 1, .., N$ who form expectations on K countries indexed by $j = 1, .., J$. We denote by x_{jt} the variable that is forecasted. Denote by S_j the set of forecasters who form expectations on country j. Forecaster $i \in S(j)$ can belong either to the group of local forecasters $S^l(j)$ or to the group of foreign forecasters $S^f(j)$. We denote by $N(j)$, $N^l(j)$ and $N^f(j)$ the number of elements in $S(j)$, $S^l(j)$ and $S^f(j)$ respectively.

We assume that x_{jt}, the yearly realization of x_j, follows an AR(1):

$$x_{jt} = \rho_j x_{jt-1} + \epsilon_{jt} \tag{3}$$

with $\epsilon_{jt} \sim N(0, \gamma^{-1/2})$.

4.1.1 Information structure and behavioral biases

We consider an information structure and behavioral assumptions that are similar to Angeletos, Huo and Sastry (2020), except that we include public signals.

Information structure We assume that the information structure is country, month, and group-specific. Between month m of year $t-1$ and month m of year t, forecasters receive two types of signals: a public signal

$$\phi_{jt}^m = x_{jt} + (\kappa_j^m)^{-1/2} u_{jt}^m$$

observed by all forecasters, where $u_{jt}^m \sim N(0, 1)$ is an i.i.d. aggregate noise shock and $\kappa_j^m > 0$ is the precision of the public signal, which is specific to country j and to month m, and a private signal

$$\varphi_{ijt}^m = x_{jt} + (\tau_{ij}^m)^{-1/2} e_{ijt}^m$$

that is observed only by forecaster i, where $e^m_{ijt} \sim N(0,1)$ is an i.i.d. idiosyncratic noise $\tau^m_{ij} > 0$ is the precision of the private signal, which is specific to country j, to month m, but also to forecaster i. Through the law of large numbers we have $\frac{1}{N(j)} \sum_{i \in S(j)} \epsilon^m_{ijt} = 0$, $\frac{1}{N^l(j)} \sum_{i \in S^l(j)} \epsilon^m_{ijt} = 0$ and $\frac{1}{N^f(j)} \sum_{i \in S^f(j)} \epsilon^m_{ijt} = 0$. Local and foreign forecasters differ through the precision of their private information τ^m_{ij}: $\tau^m_{ij} = \tau_{jl}$ if $i \in S^l(j)$ and $\tau^m_{ij} = \tau_{jf}$ if $i \in S^f(j)$.

We assume that, for a given month m, ϵ^m_{ijt} and u^m_{jt} are independent from each other and are not serially correlated. This means for instance that the noises in the signals of month m from year t are not correlated with the noises in the signals of month m from year $t-1$. But we do not impose that the noises are serially uncorrelated within a given year.[6]

Behavioral biases We consider two behavioral biases: over-extrapolation and over-confidence. Over-extrapolation (or under-extrapolation) consists in distorted beliefs about the persistence of shocks ρ_j. We denote forecaster i's belief about the persistence of x_{jt} by $\hat{\rho}_{ij}$. We assume that local and foreign forecasters may have different beliefs, so that $\hat{\rho}^m_{ij} = \hat{\rho}_{jl}$ if $i \in S^l(j)$ and $\hat{\rho}^m_{ij} = \hat{\rho}_{jf}$ if $i \in S^f(j)$. Over-confidence (or under-confidence) consists in distorted beliefs about the precision of private signals τ^m_{jk}. We denote forecaster i's belief about her precision by $\hat{\tau}_{ij}$. Again, we assume that local and foreign forecasters may have different beliefs, so that $\hat{\tau}^m_{ij} = \hat{\tau}_{jl}$ if $i \in S^l(j)$ and $\hat{\tau}^m_{ij} = \hat{\tau}_{jf}$ if $i \in S^f(j)$.

Expectations In month m of year t, forecasters build a "synthetic" signal out of the public and private signals:

$$\begin{aligned} s^m_{ijt} &= h^m_{ij}\phi^m_{jt} + (1 - h^m_{ij})\varphi^m_{ijt} \\ &= x_{jt} + v^m_{ijt} \end{aligned} \tag{4}$$

with

$$v^m_{ijt} = h^m_{ij}(\kappa^m_j)^{-1/2}u^m_{jt} + (1 - h^m_{ij})(\tau^m_{ij})^{-1/2}e^m_{ijt} \tag{5}$$

and $h^m_{ij} = \kappa^m_j/(\kappa^m_j + \hat{\tau}^m_{ij})$, so that $E^m_{ijt}(x_{jt}|\phi^m_{jt}, \varphi^m_{ijt}) = (\kappa^m_j + \hat{\tau}^m_{ij})/(\gamma_j + \kappa^m_j + \hat{\tau}^m_{ij})s^m_{ijt}$.

Between month m of year $t-1$ and month m of year t, the forecasters update their expectations in the following way:

$$E^m_{ijt}(x_{jt}) = (1 - G^m_{ij})\hat{\rho}^m_{ij}E^m_{ijt-1}(x_{jt-1}) + G^m_{ij}s^m_{ijt} \tag{6}$$

where G^m_{ij} is the Kalman gain that is consistent with forecaster i' beliefs about the persistence of x_{jt} and about the precision of their signal.

[6] This type of information structure would arise if forecasters were receiving independent signals every month. In that case, the information received between month m of year $t-1$ and month m of year t would be represented by a 12-month moving average of the monthly signals, which is serially correlated on a month-on-month basis, but not on a year-on-year basis.

We define the forecast revisions between month m of year $t-1$ and month m of year t as

$$Revision^m_{ijt} \quad = E^m_{ijt}(x_{jt}) - E^m_{ijt-1}(x_{jt}) \tag{7}$$

and the error as

$$Error^m_{ijt,t} \quad = x_{jt} - E^m_{ijt}(x_{jt}) \tag{8}$$

4.1.2 The variance of errors

Consider the case with no behavioral biases. Forecasters with less precise information make more errors on average. This derives from the forecasters' optimal use of information. In fact, the variance of errors can be related to the Kalman gain, as stated in the following proposition (see the proof in Appendix F.1):

Proposition 1. *In the absence of behavioral biases ($\hat{\rho}_{ij} = \rho_j$ and $\hat{\tau}^m_{ij} = \tau^m_{ij}$), the variance of errors is given by:*

$$\begin{array}{llll} V(Error^m_{ijt,t-1}) & = V[x_{jt} - E^m_{ijt-1}(x_{jt})] & = \frac{\gamma^{-1}}{1-\rho_j^2(1-G^m_{ij})} \\ V(Error^m_{ijt,t}) & = V[x_{jt} - E^m_{ijt}(x_{jt})] & = \frac{\gamma^{-1}(1-G^m_{ij})}{1-\rho_j^2(1-G^m_{ij})} \end{array} \tag{9}$$

Both variances are decreasing in G^m_{jk}.

Since G^m_{ij} is increasing in τ^m_{ij}, then the variances are decreasing in τ^m_{ij}.[7]

But asymmetric information is not the only potential source of differences in variances. Consider now the case with behavioral biases. The Kalman filter is a minimum mean-square error estimator. Therefore, mis-specified statistical and parametric inputs to the estimator will increase the variance of errors as compared to the well-specified estimator. Therefore, the difference in variances may be due to differences in behavioral biases. In the remainder of the section, we use model-based tests to detect differences in behavioral biases and differences in information.

4.2 Testing for Differences in Behavioral Biases

BGMS regressions Here we examine whether local and foreign forecasters differ systematically in the way they form expectations. Following Angeletos, Huo and Sastry (2020),

[7] Note that, contrary to the variance of the error, disagreement is not a good measure of noisy information. To understand, notice that the idiosyncratic component of the forecast is proportional to $(1-h^m_{ij})(\tau^m_{ij})^{-1/2}e^m_{ijt}$. The variance of this term is $(1-h^m_{ij})^2(\tau^m_{ij})^{-1} = \tau^m_{ij}(\kappa^m_j + \tau^m_{ij})^{-2}$. This term is equal to zero when the private signal is not informative ($\tau^m_{ij} = 0$). It goes to zero when, on the opposite, the signal becomes perfect (τ^m_{ij} goes to infinity). Disagreement disappears when either the private signal is not used because it is of poor quality or when the signal is so good that it is closely distributed around the fundamental.

we consider two behavioral biases that go a long way in explaining survey forecasts: over-extrapolation ($\hat{\rho}_{jk} \neq \rho_j$) and over-confidence ($\hat{\tau}_{ij} \neq \tau_{ij}$). We rely on regressions popularized by Bordalo et al. (2020) and Kohlhas and Broer (2020) to assess the presence of such biases among forecasters:

$$Error^m_{ijt} = \beta^{BGMSm}_{ij} Revision_{ijt} + \delta^m_{ij} + \lambda^m_{ijt} \tag{10}$$

where β^{BGMSm}_{ij} is a country, month and forecaster specific coefficient, δ^m_{jk} are country-month-forecaster fixed effects and λ^m_{ijt} is an error term.

Following Angeletos, Huo and Sastry (2020), we can show that these coefficients are related to the deviations of the beliefs $\hat{\rho}_{ij}$ and $\hat{\tau}_{ij}$ from their true counterparts (see the proof in Appendix F.2):

Proposition 2. *Estimating Equation* (10) *for each $j = 1, ..K$ and $k = l, f$ by OLS gives the following coefficients:*

$$\beta^{BGMSm}_{ij} = -(\hat{\rho}_{ij} - \rho_j)\beta_1 - [(\tau^m_{ij})^{-1} - (\hat{\tau}^m_{ij})^{-1}]\beta_2$$

β_1 and β_2 are described in the Appendix. They depend on the country-invariant parameters κ^m_j and ρ_j but also on the forecaster-specific beliefs $\hat{\tau}^m_{ij}$ and $\hat{\rho}_{ij}$.

A negative coefficient reflects an over-reaction of forecasters to their information. This over-reaction can arise from over-confidence ($\hat{\tau}^m_{ij} - \tau^m_{jk} > 0$) or from over-extrapolation ($\hat{\rho}_{ij} - \rho_j > 0$). In Bordalo et al. (2020), this over-reaction can be due to diagnostic expectations.

While a non-zero coefficient can help detect the presence of behavioral biases, it suffers from one drawback in our context: the coefficient is a non-linear and potentially non-monotonic function of $\hat{\tau}_{ij} - \tau_{ij}$, $\hat{\rho}_{ij} - \rho_j$, the biases, but also of τ_{ij}, the precision of private signals. Interpreting differences in coefficients is therefore not easy.

To help our interpretation of the results, we consider a first-order expansion of the BGMS coefficient around close-to-zero and symmetric parameters (see the proof in Appendix F.3):

Corollary 1. *The coefficient β^{BGMSm}_{ij} can be approximated at the first-order around $(\hat{\tau}^m_{ij})^{-1} = (\tau^m_{ij})^{-1} = (\tau^m_j)^{-1}$, where τ^m_j is the average level of precision and $\hat{\rho}_{ij} = \hat{\rho}_j = \rho_j$ as follows:*

$$\beta^{BGMSm}_{ij} \simeq -(\hat{\rho}_{ij} - \rho_j)\hat{\beta}^m_1 - [(\tau^m_{ij})^{-1} - (\hat{\tau}^m_{ij})^{-1}]\hat{\beta}^m_2$$

where $\hat{\beta}_1$ and $\hat{\beta}_2$ are strictly positive and independent of $\hat{\rho}_{ij}$, τ^m_{ij} and $\hat{\tau}^m_{ij}$.

Therefore, a more negative BGMS coefficient will be interpreted as reflecting differences in either over-confidence or over-extrapolation.

We estimate Equation (10) using the mean-group methodology, under different assumptions about the homogeneity of the β^{BGMS} coefficient. We first assume that the coefficients differ only across countries and are homogeneous across foreign forecasters and local forecasters. We then allow the coefficients to differ across individual forecasters within a country. Finally, we allow the coefficients to differ across month within a country and forecaster pair. In each of these specifications, we collect the β^{BGMS} coefficients and test for significant differences between local and foreign forecasters by regressing the coefficient on the Foreign dummy, controlling for country, forecaster and month fixed effects when possible. A significant coefficient for the Foreign dummy would indicate that there are systematic differences in behavioral biases. When allowing the coefficients to differ across country-forecaster pairs, we restrict the sample to the pairs providing forecasts for at least 10 years.

The results are displayed in Table 5. In all specifications, there is no systematic difference between local and foreign forecasters. Interestingly, the average coefficient is positive for both inflation and GDP growth in our more conservative specification (columns (5) and (6)), suggesting that forecasters under-react to news on average. This might seem in contradiction with previous evidence, which has found over-reaction, especially for inflation (Bordalo et al., 2020; Kohlhas and Broer, 2019; Angeletos et al., 2020). However, note that previous evidence has focused on the Survey of Professional Forecasters, which provides forecasts for the US. Our estimated parameters are in fact highly heterogeneous (see Figure 3 in the Appendix), and in particular, they are heterogeneous across countries (see Figure 4 in the Appendix). Focusing on the US, we find that the inflation forecasts feature over-reaction on average, which is consistent with previous evidence. GDP growth forecasts do not feature systematic over- or under-reaction, which is also consistent.

All in all, foreign forecasters do not have significantly different behavioral biases as compared to local forecasters. From now on, we therefore assume common behavioral parameters $\hat{\rho}_{jl} = \hat{\rho}_{jf} = \hat{\rho}_j$ and $\hat{\tau}^m_{jl} = \hat{\tau}^m_{jf} = \hat{\tau}^m_j$. In the next sub-section, we examine differences in information frictions.

Table 5: Behavioral Biases - BGMS regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t
Average Locals	–0.01**	0.06***	0.01	0.04***	0.03***	0.09***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Foreign	0.00	–0.02	0.00	0.03	0.00	0.04
	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)
N	102	102	364	393	4,979	5,373
R^2	0.96	0.94	0.71	0.76	0.43	0.46
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Forecaster FE	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	No	Yes	Yes
Mean-group by country and location	Yes	Yes	No	No	No	No
Mean-group by country and forecaster	No	No	Yes	Yes	No	No
Mean-group by cty, forc. and month	No	No	No	No	Yes	Yes

Notes: The table shows the results of a regression of the β^{BGMS} coefficients on the Foreign dummy, where the β^{BGMS} are estimated using Equation (10) on different sub-groups of our sample. corresponds to the constant term (or average fixed effect). corresponds to the coefficient of the Foreign dummy. The observations are clustered at the country level in specifications (1) and (2), and at the country and forecaster levels in specifications (3) to (6).

Perceived persistence A non-negative BGMS coefficient can arise both from distorted beliefs on the precision of private signals and from distorted beliefs on the persistence of the shocks. We have shown that these BGMS coefficients do not differ systematically between local and foreign forecasters. However, this does not imply that foreign forecasters have similar over-/under-confidence and over-/under-extrapolation. A similar result would arise if the relative over-/under-confidence of foreign forecasters compensates their relative over- /under-extrapolation. We examine more directly whether the beliefs on persistence are similar.

To do this, we use the relation between the forecasts on current and future variables implied by our model:

$$E^m_{ijt}(x_{jt+1}) = \hat{\rho}_{ij} E^m_{ijt}(x_{jt}) \tag{11}$$

We estimate Equation (11) using the same mean-group methodology. While in our model $\hat{\rho}_{ij}$ is specific to a country-forecaster pair and is independent of the month of the year, we allow it to differ across months as well. Indeed, while in our model, all the innovations to inflation have the same persistence, in reality, there could some components of inflation that are purely transitory. We cannot exclude that forecasters learn about the transitory component over the year. That would affect the month-specific correlation between the nowcast and the forecast.

The results are reported in Table 6. In all specifications but one, the estimated perceived persistence is not significantly different for foreign forecasters. In column (6), where we allow the perceived persistence to vary across forecaster-country pairs, the foreign perceived persistence of GDP growth is significantly higher than the local one. However, when we allow the perceived persistence to vary across months as well, the difference is not significant anymore.

Table 6: Behavioral Biases - Over-extrapolation regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t
Average Locals	0.41***	0.35***	0.41***	0.35***	0.39***	0.35***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Foreign	–0.00	0.01	0.02	0.04*	0.03	0.04
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
N	102	102	404	428	6,097	6,535
R^2	0.96	0.97	0.65	0.78	0.54	0.66
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Forecaster FE	No	No	Yes	Yes	Yes	Yes
Month-of-year FE	No	No	No	No	Yes	Yes
Mean-group by country and location	Yes	Yes	No	No	No	No
Mean-group by country and forecaster	No	No	Yes	Yes	No	No
Mean-group by country, forecaster and month	No	No	No	No	Yes	Yes

Notes: The table shows the results of a regression of the perceived autocorrelation coefficients $\hat{\rho}$ on the Foreign dummy, where the $\hat{\rho}$ is estimated using Equation (11) on different sub-groups of our sample. corresponds to the constant term (or average fixed effect). corresponds to the coefficient of the Foreign dummy. The obervations are clustered at the country level in specifications (1) and (2), and at the country and forecaster levels in specifications (3) to (6).

All in all, foreign and local forecasters do not differ systematically in terms of behavioral biases. In the Appendix, we examine whether forecasters differ in the way they use public news, since Kohlhas and Broer (2019) and Gemmi and Valchev (2022) show that forecasters typically under-react to public news. In Tables 14 and 15, we examine over-/under-reaction to public news, by examining regressions of forecast errors on public news, using two different measures of public news: the past consensus and the last vintage of realized outcome. A positive (negative) coefficient implies that forecasters over-react (under-react) to public news. Again, we do not find any systematic difference in behavioral biases.[8]

[8]Interestingly, in our most conservative specification (columns (5) and (6)), we find systematic under-reaction to the past consensus (in 14, we can see that forecasters under-react to the past consensus on both

4.3 Testing for Asymmetric Information

Consensus regression as in Coibion and Gorodnichenko (2015) are commonly used to detect information frictions. Can we use these regressions to identify differences in information frictions between local and foreign forecasters? We show here that the relation between noise in the private signal and the coefficient of the consensus regression is non-monotonic in the presence of public signals. Therefore, even in the absence of behavioral biases, differences in the coefficient of the consensus regression is not a good indicator of the degree of information asymmetry. We propose two alternative tests that are robust to public signals.

4.3.1 Consensus regressions

Consensus regression as in Coibion and Gorodnichenko (2015) are commonly used to detect information frictions. Can we use these regressions to identify differences in information frictions between local and foreign forecasters? Suppose that we performed the consensus regression as in Coibion and Gorodnichenko (2015) on both group of forecasters, what would we be identifying?

In our setup, this regression can be written, for each $j = 1, ..J$ and $k = l, f$:

$$Error^m_{jkt} = \beta^{CGm}_{jk} Revision^m_{jkt} + \delta^m_{jk} + \lambda^m_{jkt} \tag{12}$$

where $Error^m_{jkt} = \frac{1}{N^k(j)} \sum_{i \in S^k(j)} Error^m_{ijt}$, $Revision^m_{jkt} = \frac{1}{N^k(j)} \sum_{i \in S^k(j)} Revision^m_{ijt}$, δ^m_{jk} are country-month-location fixed effects and λ^m_{jkt} is an error term. The estimated parameter β^{CGm}_{jk} is a function of the deep parameters.

Table 7 displays the results of the estimation of β^{CGm}_{jk} using the mean-group estimator, under different assumptions on the heterogeneity of β^{CGm}_{jk}. In columns (1) and (2), we assume that β^{CGm}_{jk} differs across countries and locations. In columns (3) and (4), we assume that β^{CGm}_{jk} can also differ across months. While the β coefficient is positive on average, as is expected, there does not appear to be any significant difference between foreign and local coefficients.

GDP growth and inflation, as both average coefficients are positive), but not systematic under-reaction to the last vintage (in 15, we can see that forecasters only under-react to the last vintage of inflation and over-react to the last vintage of GDP growth, as only the average coefficient is positive for inflation and negative for GDP growth). This is consistent with the evidence provided by Gemmi and Valchev (2022).

Table 7: Information Asymmetries - Consensus regressions

	(1)	(2)	(3)	(4)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t
Consensus	0.07***	0.12***	0.11***	0.16***
	(0.01)	(0.01)	(0.01)	(0.01)
Foreign	–0.01	–0.02	–0.00	–0.01
	(0.01)	(0.01)	(0.02)	(0.02)
N	102	102	1,223	1,224
R^2	0.93	0.94	0.50	0.53
Mean-group by country and location	Yes	Yes	Yes	Yes
Mean-group by country and month	No	No	No	No

Notes: The table shows the results of a regression of the β^{CG} coefficients on the Foreign dummy, where the β^{CG} are estimated using equation (12) on different sub-groups of our sample. corresponds to the constant term (or average fixed effect). corresponds to the coefficient of the Foreign dummy. The obervations are clustered at the country level.

This does not necessarily mean that there are not information asymmetries between local and foreign forecasters. Indeed, the following proposition shows that, in the presence of public information, the relation between β^{CG} and the precision of private information is not monotonic (see the proof in Appendix F.4).

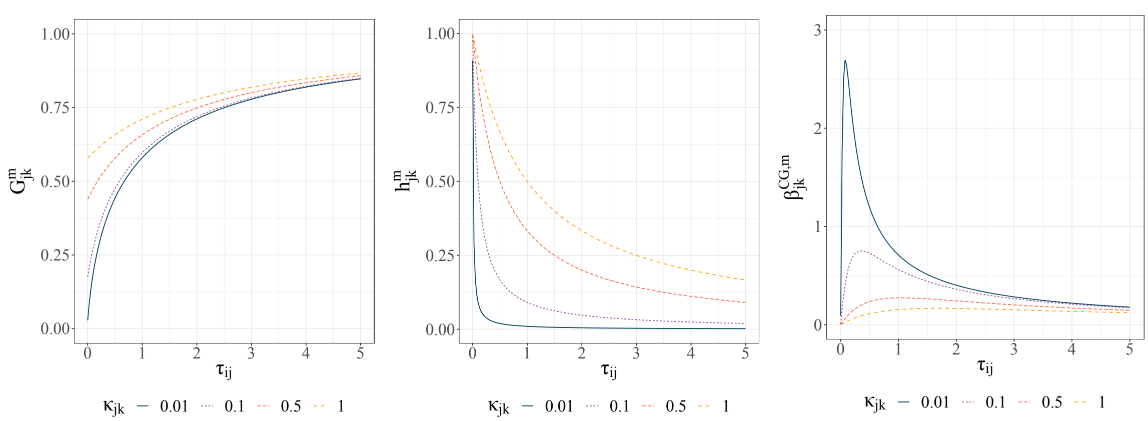
Proposition 3. *Suppose that there are no behavioral biases: $\hat{\rho}_{ij} = \rho_j$ and $\hat{\tau}^m_{ij} = \tau^m_{ij}$, and that the precision parameters are identical within foreign forecasters and within local forecasters: $\tau^m_{ij} = \tau^m_{jk(i,j)}$ for all $j = 1, ..J$, $m = 1, .., 12$, where $k(i, j) = l$ if i is local to j and $k(i, j) = f$ if i is foreign. Estimating Equation* (12) *for each $j = 1, ..J$, $m = 1, .., 12$ and $k = l, f$ by OLS gives the following coefficients:*

$$\beta^{CGm}_{jk} = \frac{\frac{1-G^m_{jk}}{G^m_{jk}}\gamma^{-1} - [1-\rho^2_j(1-G^m_{jk})]h^2_{jk}(\kappa^m_j)^{-1}}{\gamma^{-1} + [1-\rho^2_j(1-2G^m_{jk})](h^m_{jk})^2(\kappa^m_j)^{-1}}$$

Note that $\beta^{CGm}_{jk} = (1-G^m_{jk})/G^m_{jk}$ when there is no public signal, which corresponds to the case studied by Coibion and Gorodnichenko (2015). The coefficient is directly related to the Kalman gain. A large coefficient implies a small Kalman gain and hence noisier information. Therefore, $\beta^{CGm}_{jl} < \beta^{CGm}_{jf}$ would imply that foreigners have noisier information.

However, when $h^m_{jk} > 0$, β^{CGm}_{jk} depends on the variance of the fundamental shocks (γ^{-1}) and on the variance of the aggregate noise ($(\kappa^m_j)^{-1}$). β^{CGm}_{jk} is thus not a straightforward function of the information structure and it is not clear what to infer from $\beta^{CGm}_{jl} < \beta^{CGm}_{jf}$. This is due to the presence of aggregate noise. This aggregate noise, as discussed in Coibion and Gorodnichenko (2015) , introduces a negative bias in the estimation of G^m_{jk}. Indeed, while the correlation between the error and the revision driven by the fundamental x_{jt} is positive, the public noise introduces a negative correlation. CG argue that because the bias is negative, a positive coefficient is still a sign of noisy information. However, in order to test for *differences* in the quality of private information by comparing β_{jl}^{CGm} and β_{jf}^{CGm}, we need that β_{jk}^{CGm} is a monotonic function of τ_{jk}^{m}.

Figure 1 shows that this is not the case. The figure describes how the precision of the private signal, τ_{jk}, affects the Kalman gain G_{jk}^{m}, the weight of public information h_{jk}^{m} and the coefficient β_{jk}^{CGm}. While the Kalman gain is increasing in the precision of private information, the weight of the public signal is decreasing. As a result, when the precision of the private signal goes to zero, forecasters put the highest possible weight on the public signal, and the coefficient is equal to zero. In this case, the public signal is the only valid source of information, so the individual forecasts correspond to the aggregate one. Rational expectations then imply a zero covariance between the aggregate revision and the aggregate error. When the precision of the private signal increases, the weight put on the public signal decreases, so the coefficient increases and becomes positive. Passed a certain threshold, the contribution of the public noise to the coefficient becomes negligible and the coefficient starts decreasing in τ_{jk}^{m}, driven by the increase in the Kalman gain, as in Coibion and Gorodnichenko (2015).



(a) G_{jk}^{m} (b) h_{jk}^{m} (c) $\beta_{jk}^{CG,m}$

Figure 1: The effect of τ_{jk}^{m} on β_{jk}^{CGm}

We thus need tests that map to the degree of information frictions and that are robust to public information. We propose two such tests.

4.3.2 Fixed-effect regressions

For our first test of asymmetric information, we use an extension of the BGMS regression that controls for public noise. We use the following pooled regression, for each $j = 1, ..J$,

$m = 1, .., 12$ and $k = l, f$:

$$Error^m_{ijkt} = \beta^{FEm}_{jk} Revision^m_{ijkt} + \delta^m_{jkt} + \lambda^m_{ijkt} \tag{13}$$

where δ^m_{jkt} are country-location-time fixed effects and λ^m_{ijkt} is an error term. The estimated parameter β^{FEm}_{jk} is a function of the deep parameters. We can show that, if $\hat{\rho}_{jk} = \hat{\rho}_j$ is homogeneous across groups, then differences in the estimated parameter $\beta^{FE^m}_{jk}$ across locations depends only on differences in G^m_{jk}.

Proposition 4. *Suppose that the parameters are homogeneous within foreign forecasters and within local forecasters $\hat{\rho}_{ij} = \hat{\rho}_{jk}$, $\tau_{ij} = \tau_{jk}$ and $\hat{\tau}_{ij} = \hat{\tau}_{jk}$, where $k(i, j) = l, f$. Estimating Equation (13) for each $j = 1, ..J$, $m = 1, .., 12$ and $k = l, f$ by OLS gives the following coefficients:*

$$\beta^{FEm}_{jk} = -\frac{1 - \hat{\rho}_{jk}(1 - G^m_{jk})}{1 - \hat{\rho}_{jk}(1 - 2G^m_{jk})}$$

If forecasters have identical behavioral biases, i.e. $\hat{\rho}_{jl} = \hat{\rho}_{jf} = \hat{\rho}_j$ and $(\hat{\tau}^m_{jl})^{-1} - (\tau^m_{jl})^{-1} = (\hat{\tau}^m_{jf})^{-1} - (\tau^m_{jf})^{-1}$, then $\beta^{FEm}_{jf} < \beta^{FEm}_{jl}$ if and only if $\tau^m_{jl} > \tau^m_{jf}$.

see the proof in Appendix F.5. If the foreign and local forecasters have similar behavioral biases, then $\beta^{FEm}_{jf} < \beta^{FEm}_{jl}$ reflects an informational advantage for locals.

The estimated coefficient depends on the covariance between the error and the revision that is driven by idiosyncratic shocks. This covariance is necessarily negative: optimistic forecasters make a more negative error than pessimistic forecasters. As long as $\hat{\rho}_j$ is positive, this coefficient is more negative when information frictions are stronger (when the Kalman gain G^m_{jk} is lower). The lower G^m_{jk}, the more persistent is the forecast, as it incorporates new information slower. This makes β^{FEm}_{jk} more negative because it increases the magnitude of the covariance between the revision and the forecast itself, which drives the error.[9][10]

In columns (1) and (2), we assume that β^{CGm}_{jk} differs across countries and locations. In

[9] Note that the coefficient should be equal to β^{BGMSm}_{jk} in the absence of fixed effects. Why is it that adding fixed effects in the pooled regression results in a negative coefficient? It is because the fixed effects control for aggregate shocks (ϵ_{jt} and u_{jt}), which are not observed by forecasters at the time they revise their forecasts.

[10] Note also that adding time fixed effects to the regression is equivalent to subtracting the cross-forecaster average from each side of the equation:

$$-\left(E^m_{ijkt}(x_{jt}) - E^m_{jkt}(x_{jt})\right) = \beta^{FEm}_{jk}(Revision^m_{ijkt} - Revision^m_{jkt}) + \lambda^m_{ijkt}$$

In that sense, this test is similar in spirit to Goldstein (2021), who proposes to measure information frictions by estimating the persistence of a forecaster's deviation from the mean:

$$\left(E^m_{ijkt}(x_{jt}) - E^m_{jkt}(x_{jt})\right) = \beta^{Gm}_{jk}\left(E^m_{ijkt-1}(x_{jt}) - E^m_{jkt-1}(x_{jt})\right) + \lambda^m_{ijkt}$$

$\beta^{Gm}_{jk} = 1 - G^m_{jk}$ is also directly and monotonically related to the degree of information frictions.

columns (3) and (4), we assume that β_{jk}^{CGm} can also differ across months. There does not appear to be any significant difference between foreign and local coefficients.

We first estimate Equation (13) under the assumption that the β^{FE} coefficients differ across countries and locations, but not across months. We then regress these coefficients on the Foreign dummy and report the results in columns (1) and (2). We then estimate the equation under the assumption that the β^{FE} coefficients differs across countries, locations, and months. Similarly, we regress these coefficients on the Foreign dummy and report the results in columns (3) and (4). Note first that the estimated coefficients are negative on average, as predicted. Secoond, the coefficient for Foreign dummy is significantly negative for inflation. For GDP growth, it is negative as well, but smaller in magnitude and less significant. This is consistent with the preliminary evidence of Section 3 where we have shown that foreign forecasters made relatively more errors on inflation than on GDP growth.

Table 8: Information Asymmetries - Fixed-effect regressions

	(1)	(2)	(3)	(4)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t
Average Locals	–0.31***	–0.35***	–0.29***	–0.32***
	(0.00)	(0.00)	(0.00)	(0.00)
Foreign	–0.05***	–0.02	–0.05***	–0.02
	(0.01)	(0.01)	(0.01)	(0.01)
N	100	100	1,196	1,207
R^2	0.87	0.88	0.64	0.61
Country FE	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	Yes
Mean-group by country and location	Yes	Yes	No	No
Mean-group by country, location and month	No	No	Yes	Yes

Notes: The table shows the results of a regression of the β^{FE} coefficients on the Foreign dummy, where the β^{FE} are estimated using Equation (13) on different sub-groups of our sample. corresponds to the constant term (or average fixed effect). corresponds to the coefficient of the Foreign dummy. The observations are clustered at the country level in specifications (1) and (2), and at the country and forecaster levels in specifications (3) to (6).

4.3.3 Foreign-local disagreement

Our second test of asymmetric information is based on disagreement between local and foreign forecasters. We define the disagreement between the local and foreign forecasters as follows:

$$Disagreement_{jt}^{m} = E_{jlt}^{m}(x_{jt}) - E_{jft}^{m}(x_{jt}) \tag{14}$$

where $E_{jkt}^{m}(x_{jt}) = \frac{1}{N(j)^k} \sum_{i \in S^k(j)} E_{ijkt}(x_{jt})$ is the location-specific average revision.

Consider now the following regression:

$$Disagreement_{jt}^{m} = \beta_j^{DISm} Revision_{jt}^{m} + \beta_j^{0m} x_{jt} + \beta_j^{1m} x_{jt-1} + \beta_j^{2m} E_{jlt-1}^{m}(x_{jt}) + \beta_j^{3m} E_{jft-1}^{m}(x_{jt}) + \delta_j^{m} + \lambda_{jt}^{m} \quad (15)$$

where $Revision_{jt}^{m} = \frac{1}{2}(Revision_{jlt}^{m} + Revision_{jft}^{m})$ is the average revision across locations for country j in year t and month m.

We can show that the sign of β_j^{DISm} depends on the relative precision of local forecasters versus foreign forecasters when the behavioral biases are homogeneous across locations (see the proof in Appendix F.6).

Proposition 5. *Suppose that the parameters are homogeneous within foreign forecasters and within local forecasters $\hat{\rho}_{ij} = \hat{\rho}_{jk}$, $\tau_{ij} = \tau_{jk}$ and $\hat{\tau}_{ij} = \hat{\tau}_{jk}$, where $k(i,j) = l, f$. Estimating Equation* (15) *for each $j = 1, ..J$ and $m = 1, .., 12$ by OLS gives the following coefficients:*

$$\beta_j^{DISm} = \left(\frac{G_{jl}^{m} h_{jl}^{m} - G_{jf}^{m} h_{jf}^{m}}{G_j^{m} h_j^{m}} \right)$$

where $G_j^{m} h_j^{m} = \frac{1}{2}(G_{jl} h_{jl} + G_{jl} h_{jl})$.

If forecasters have identical behavioral biases, i.e. $\hat{\rho}_{jl} = \hat{\rho}_{jf} = \hat{\rho}_j$ and $(\hat{\tau}_{jl}^{m})^{-1} - (\tau_{jl}^{m})^{-1} = (\hat{\tau}_{jf}^{m})^{-1} - (\tau_{jf}^{m})^{-1}$, then $\beta_j^{DISm} < 0$ if and only if $\tau_{jl}^{m} > \tau_{jf}^{m}$.

Intuitively, $\beta_j^{DISm} > 0$ if the foreign expectations are more sensitive to the public signal and hence to the public noise. This would be the case if the foreign forecasters' private information is less informative than the local one.

We first estimate Equation (15) under the assumption that the β^{Dis} coefficients differ across countries, but not across months. We then test whether the coefficients are different from zero on average and report the results in columns (1) and (2). We then estimate the equation under the assumption that the coefficients differ across countries and months. Similarly, columns (3) and (4) report the significance tests. The disagreement coefficients are significantly negative on average for both inflation and GDP growth and in both specifications. Notably, the coefficient of GDP is smaller in magnitude, which is consistent with our previous results.

Table 9: Information Asymmetries - Disagreement regressions

	(1)	(2)	(3)	(4)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t
Disagreement	–0.09***	–0.07***	–0.09***	–0.07**
	(0.02)	(0.02)	(0.03)	(0.03)
N	51	51	611	612
R^2	0	0	–0.00	0
Mean-group by country	Yes	Yes	No	No
Mean-group by country and month	No	No	Yes	Yes

Notes: The table shows the results of a regression of the β^{Dis} coefficients on the constant, where the β^{Dis} are estimated using Equation (15) on different sub-groups of our sample. corresponds to the constant term. In specifications (1) and (2), we show robust standard errors in specifications (3) to (6), standard errors are clustered at the country level.

5 What drives Asymmetric Information?

We have shown that foreign forecasters make more mistakes than local forecasters, and that their relative under-performance is explained by information asymmetries. In this subsection, we use our multi-country, multi-forecaster panel to explore the determinants of these asymmetries.

We first stack observations of inflation and GDP growth errors and errors at different horizon. We then regress the log of the absolute value of the error on the Foreign dummy and other variables, without fixed effects: a dummy that is equal to 1 if GDP growth is the forecasted variable and to 0 if inflation is, a dummy that is equal to 1 if the horizon is the next year and 0 if the horizon is the current year, and a variable that goes from 1 to 12 depending of the month of year. We then examine the interaction between these variables and the Foreign dummy when including all the fixed effects.

Table 10: Forecast Error conditional on Location of the Forecaster

	(1)	(2)	(3)
Coefficient			
Foreign	0.11**	0.06***	0.05**
	(0.04)	(0.02)	(0.03)
GDP	0.33***		
	(0.07)		
future	0.96***		
	(0.05)		
Emerging	0.61***		
	(0.09)		
Month-of-year	–0.08***		
	(0.01)		
Foreign × GDP			–0.04**
			(0.02)
Foreign × future			–0.03**
			(0.01)
Foreign × Emerging			0.01
			(0.02)
Foreign × Month-of-year			0.01**
			(0.00)
N	602,122	389,295	389,295
R^2	0.18	0.70	0.70
Country × Date × Variable × Horizon FE	No	Yes	Yes
Forecaster × Date × Variable × Horizon FE	No	Yes	Yes

Notes: The table shows the regression of the log absolute forecast error of current and future CPI and GDP on regressors with different fixed-effects specifications. All standard errors are clustered on the country, year × country, forecaster and date level.

The results are reported in Table 10. Column (1), which does not include any fixed effect, shows that forecast errors are higher for GDP growth, for the future year and for Emerging economies. Noticeably, the forecast errors diminish over time within a given year, which suggests that information flows continuously during the year. Columns (2) and (3) include variable- and horizon-specific country-time fixed effects. Foreigners have a 6% penalty on average across all variables and horizons, as column (2) shows. Column (3) shows that this penalty is significantly lower for GDP growth and for the future year. Interestingly, the penalty increases over time within a given year.This evidence shows that, paradoxically, the foreign penalty is higher when there is less uncertainty. Finally, the foreign penalty does not depend on the development status of a country. This last result is consistent with the evidence in Bae et al. (2008) on the local advantage of foreign analysts.

Table 11 further explores the role of country-specific, forecaster-specific and time-specific variables: log of distance, quality of institutions (from the World Development Indicators), country size (log of GDP evaluated at purchasing power parity), business cycle volatility (log of the yearly GDP growth rate standard error over the whole period), financial sector dummy (equal to one if the forecaster belongs to the financial sector), stock market volatility (log of the standard error of the return within the month) and the VIX.[11] Columns (1) to (5) shows how these variables affect the log of the absolute value of the forecast error with different fixed-effect specifications. Better institutions are negatively associated with the size of forecast errors, even when we control for country fixed effects, which means that countries with improving institutions have also declining forecast errors. better institutions leads to more transparency, which affects the precision of forecasts. Larger countries have also lower forecast errors. This effect is mainly driven by the cross-country dimension since it becomes insignificant when we add country fixed effects. Indeed, large countries may attract more the attention of forecasters, or they may be producing more information. Volatility plays a role too: countries with more volatile business cycles or with higher market volatility have higher forecast errors. Global volatility (the VIX) is also positively associated with higher forecast errors worldwide. Hence, more uncertainty is generally associated with more errors by forecasters. The effect of distance, which is positive in some specifications, is completely absorbed by the Foreign dummy in Column (5), where we include all fixed effects. There is no effect of geography beyond the fact of being local or foreign. Finally, financial forecasters produce better forecasts, probably because they devote more resources to forecasting.

In Column (6), these variables are interacted with the Foreign dummy. While most of these variables have a significant effect on the precision of forecasts, they do not influence the foreign penalty. Better institutions and lower business cycle or market volatility benefit symmetrically to local and foreign forecasters. Similarly, financial forecasters are better at forecasting both local and foreign countries. Only the country size has an influence: the foreign penalty is larger for larger countries. In this case, as for the evidence in Table 10, lower uncertainty is associated with a larger foreign penalty.[12]

[11] The data sources are the following: ???

[12] In the Appendix tables 16 and 17, we show that the results are unchanged when we interact the Foreign dummy with one variable at a time.

Table 11: Forecast Error conditional on Location of the Forecaster

	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient						
Foreign	-.052	-.017	–4.4e-03	.075***	.056***	-.17
	(.036)	(.033)	(.035)	(.018)	(.014)	(.29)
log(distance)	.034***	.029**	.029	6.5e-03*	5.8e-03	1.5e-03
	(.011)	(.011)	(.021)	(3.5e-03)	(7.7e-03)	(8.0e-03)
Institutions	-.021	-.043*	-.043**	-.25***		
	(.021)	(.022)	(.021)	(.071)		
log(GDP)	-.11***	-.098***	-.091***	-.46		
	(.022)	(.022)	(.026)	(.37)		
log(sd(variable))	.55***	.47***	.46***			
	(.1)	(.1)	(.11)			
Finance	-.074***	-.072***				
	(.02)	(.02)				
log(sd(return))	.29***	.16***	.12**	.064*		
	(.049)	(.061)	(.05)	(.037)		
VIX	.011***					
	(3.5e-03)					
Foreign × log(distance)						-.011
						(.014)
Foreign × Institutions						–3.7e-03
						(7.2e-03)
Foreign × log(GDP)						.017*
						(9.9e-03)
Foreign × log(sd(variable))						-.029
						(.029)
Foreign × Finance						-.016
						(.024)
Foreign × log(sd(return))						.017
						(.022)
Foreign × VIX						2.8e-04
						(1.3e-03)
N	529,067	529,067	529,004	529,004	388,415	347,278
R^2	.087	.3	.33	.37	.7	.7
Date × Variable × Horizon FE	No	Yes	Yes	Yes	No	No
Institution × Variable × Horizon FE	No	No	Yes	Yes	No	No
Country × Variable × Horizon FE	No	No	No	Yes	No	No

In the Appendix, we conduct a similar analysis, using the estimated coefficients from our asymmetric information tests, β^{FE} and β^{Dis}. The results, which are shown in Tables 18 and 19, are broadly consistent with the evidence on the errors.[13] First, according to Table 18, β^{FE} is more negative for GDP growth and emerging economies, and less negative in later months of the year, which implies that information frictions are more prevalent for the former, and less so for the latter. Consistently, we also find that the foreign penalty is lower for GDP growth (the interaction between the GDP growth dummy and the Foreign dummy has a positive coefficient) and stronger for later months (the interaction between the month variable and the Foreign dummy has a negative coefficient), but here, this penalty is only significant for the month variable. There is still no significant extra foreign penalty for Emerging economies. Consistently, the β^{Dis} coefficient, which directly measures the foreign penalty (a more negative coefficient implies a stronger foreign penalty), only depends significantly (and negatively) on the month variable.

In Table 19, β^{FE} is significantly less negative for countries with better institutions and for larger countries, but is not more negative in more volatile countries. The foreign penalty is still stronger in large countries, but not significantly so (the interaction between country size and the Foreign dummy has a negative coefficient). However, country size does make β^{Dis} significantly more negative, which means that it matters for the foreign penalty. All in all, our results are in line with the evidence on errors, except that they are less precisely estimated.

Discussion The asymmetry of information between local and foreign forecasters regarding aggregate variables is a robust findings. It is not affected by the development status of the economy that is being forecasted, or by the quality of institutions. This is not surprising with regards to existing evidence. Indeed, Bae et al. (2008), who examine whether local analysts are better at forecasting local firms' earnings, find that the protection of investors' rights does not influence the locals' advantage, nor does the development status of the country where the firms are located.[14] We do find that a few variables, like country size, the nature of the variable that is being forecasted, and the forecast horizon, do influence the locals' advantage. However, interestingly, that local advantage is typically higher in situations with less uncertainty. It seems that when aggregate information is available, it flows to local forecasters.

[13] Note that, because these coefficients are estimated at the country level and do not vary across forecasters, we cannot estimate the effect of forecaster-specific variables like distance from the forecasted country or sector.

[14] In their paper, Bae et al. (2008) show that variables that improve the functioning of the local stock market do lower the local advantage (for instance, business disclosure). But these variables are not relevant when it comes to forecast aggregate outcomes.

6 Conclusion

In this paper, we provide direct evidence of asymmetric information between domestic and foreign forecasters. We use professional forecasters' expectations data and determine the location of each forecaster-country pair. Using this unique panel data, we find that local forecasters make less mistakes than foreign forecasters regarding both inflation and output growth. This result is robust across emerging and advanced countries, different time periods and sectors (financial versus non-financial).

We then analyse potential sources of the differences in forecasting precision using a model of expectation formation. This model allows for two deviations from rational expectations, namely over-confidence and over-extrapolation. Consistent with other studies (BGMS and AHS), we find evidence of over-confidence and over-extrapolation of forecasters in our data. However, we rule them out in explaining the foreigners' exess mistakes - using both pooled panel and individual country-location regressions, we find that the biases are not significantly different between local and foreign forecasters.

In our methodological contribution, we develop two tests to identify differences in information asymmetries between two groups. First, we compare the relative precision of local and foreign forecasters' private information. We find evidence that local institutions have more precise information than foreign institutions. Second, we analyse the disagreement between local and foreign forecasters. We show that foreign institutions react more to public signals than local institutions.

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A Data Appendix

Table 12: Range of Observation Periods for each Country

	Country	GDP	CPI
1	Argentina	1998m2– 2019m12	1998m2– 2013m12
2	Austria	2005m1– 2019m12	2005m1– 2019m12
3	Belgium	2005m1– 2019m12	2005m1– 2019m12
4	Brazil	1998m2– 2019m12	1998m2– 2019m12
5	Bulgaria	2007m5– 2019m12	2007m5– 2019m12
6	Canada	1998m1– 2019m12	1998m1– 2019m12
7	Chile	1998m2– 2019m12	1998m2– 2019m12
8	China	1998m1– 2019m12	1998m1– 2019m12
9	Colombia	1998m2– 2019m12	1998m2– 2019m12
10	Croatia	2007m5– 2019m12	2007m5– 2019m12
11	Czech Republic	2002m1– 2019m12	2002m1– 2019m12
12	Denmark	2005m1– 2019m12	2005m1– 2019m12
13	Estonia	2007m5– 2019m12	2007m5– 2019m12
14	Finland	2005m1– 2019m12	2005m1– 2019m12
15	France	1998m1– 2019m12	1998m1– 2019m12
16	Germany	1998m1– 2019m12	1998m1– 2019m12
17	Greece	2005m1– 2019m12	2005m1– 2019m12
18	Hungary	2002m1– 2019m12	2002m1– 2019m12
19	India	1998m1– 2019m12	1998m1– 2019m12
20	Indonesia	1998m1– 2019m12	1999m1– 2019m12
21	Ireland	2005m1– 2019m12	2005m1– 2019m12
22	Israel	2005m1– 2019m12	2005m1– 2019m12
23	Italy	1998m1– 2019m12	1998m1– 2019m12
24	Japan	1998m1– 2019m12	1998m1– 2019m12
25	Latvia	2007m5– 2019m12	2007m5– 2019m12
26	Lithuania	2007m5– 2019m12	2007m5– 2019m12
27	Malaysia	1998m1– 2019m12	1998m1– 2019m12
28	Mexico	1998m2– 2019m12	1998m2– 2019m12
29	Netherlands	1998m1– 2019m12	1998m1– 2019m12
30	New Zealand	1998m1– 2019m12	1998m1– 2019m12
31	Nigeria	2005m1– 2019m12	2005m1– 2019m12
32	Norway	1998m6– 2019m12	1998m6– 2019m12
33	Peru	1998m2– 2019m12	1998m2– 2019m12
34	Philippines	1998m1– 2019m12	1998m1– 2019m12
35	Poland	2002m1– 2019m12	2002m1– 2019m12
36	Portugal	2005m1– 2019m12	2005m1– 2019m12
37	Romania	2002m1– 2019m12	2002m9– 2019m12
38	Russia	2002m1– 2019m12	2002m1– 2019m12
39	Saudi Arabia	2005m1– 2019m12	2005m1– 2019m12
40	Slovakia	2002m1– 2019m12	2002m1– 2019m12
41	Slovenia	2007m5– 2019m12	2007m5– 2019m12
42	South Africa	2005m1– 2019m12	2005m1– 2019m12
43	South Korea	1998m1– 2019m12	1998m1– 2019m12
44	Spain	1998m1– 2019m12	1998m1– 2019m12
45	Sweden	1998m1– 2019m12	1998m1– 2019m12
46	Switzerland	1998m6– 2019m12	1998m6– 2019m12
47	Thailand	1998m1– 2019m12	1998m1– 2019m12
48	Turkey	2002m1– 2019m12	2003m1– 2019m12
49	United Kingdom	1998m1– 2019m12	1998m1– 2019m12
50	United States	1998m1– 2019m12	1998m1– 2019m12
51	Venezuela	1998m2– 2017m12	1999m6– 2012m12

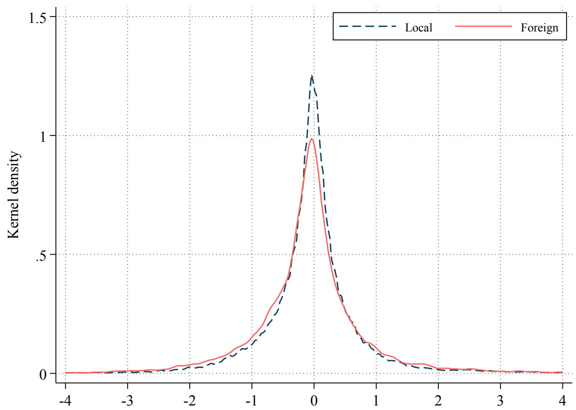
Notes: The table shows the first and last observation date for GDP and CPI for which forecasts and vintages are available. The data for forecasts comes from Consensus Economics, while actual outcomes are from the International Monetary Fund World Economic Outlook (IMF WEO).

Table 13: Development Status of all Countries

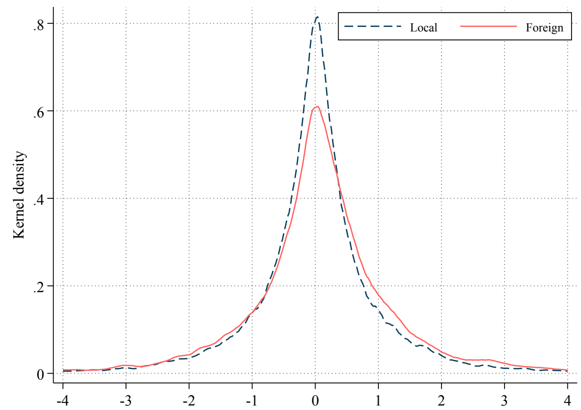
	Country	DS*		Country	DS*		Country	DS*
1	Argentina	Emerging	18	Hungary	Emerging	35	Poland	Emerging
2	Austria	Advanced	19	India	Emerging	36	Portugal	Advanced
3	Belgium	Advanced	20	Indonesia	Emerging	37	Romania	Emerging
4	Brazil	Emerging	21	Ireland	Advanced	38	Russia	Emerging
5	Bulgaria	Emerging	22	Israel	Emerging	39	Saudi Arabia	Emerging
6	Canada	Advanced	23	Italy	Advanced	40	Slovakia	Emerging
7	Chile	Emerging	24	Japan	Advanced	41	Slovenia	Emerging
8	China	Emerging	25	Latvia	Emerging	42	South Africa	Emerging
9	Colombia	Emerging	26	Lithuania	Emerging	43	South Korea	Emerging
10	Croatia	Emerging	27	Malaysia	Emerging	44	Spain	Advanced
11	Czech Republic	Emerging	28	Mexico	Emerging	45	Sweden	Advanced
12	Denmark	Advanced	29	Netherlands	Advanced	46	Switzerland	Advanced
13	Estonia	Emerging	30	New Zealand	Advanced	47	Thailand	Emerging
14	Finland	Advanced	31	Nigeria	Emerging	48	Turkey	Emerging
15	France	Advanced	32	Norway	Advanced	49	United Kingdom	Advanced
16	Germany	Advanced	33	Peru	Emerging	50	United States	Advanced
17	Greece	Advanced	34	Philippines	Emerging	51	Venezuela	Emerging

* Development Status

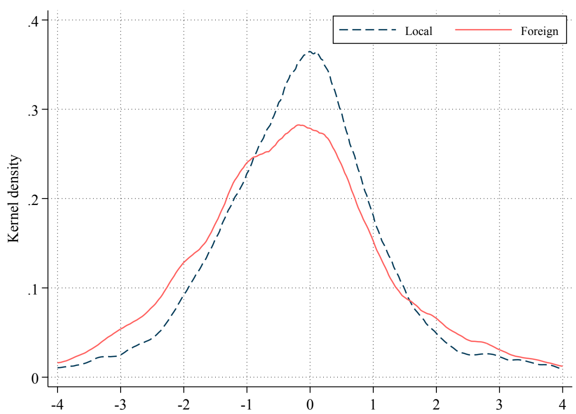
B Errors Appendix



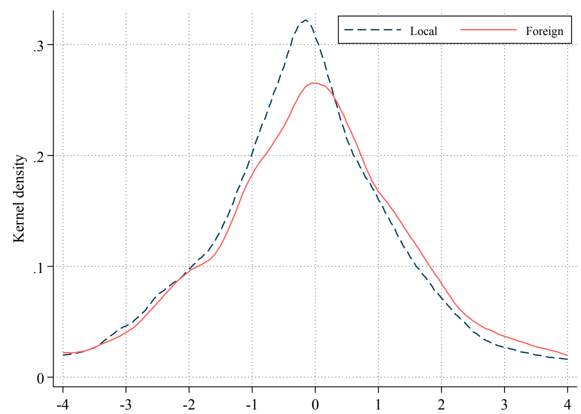
(a) CPI_t



(b) GDP_t



(c) CPI_{t+1}

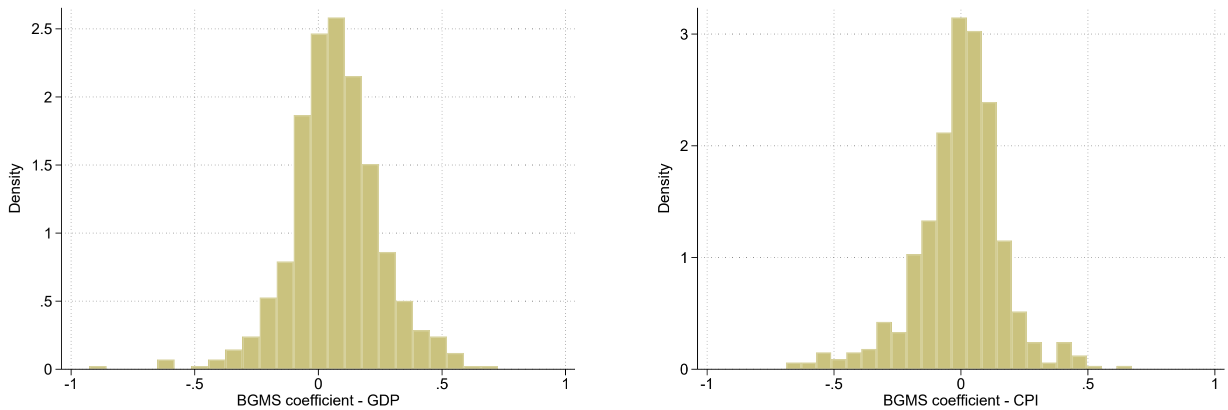


(d) GDP_{t+1}

Figure 2: Density plot of $Error^{m}_{ijt,t}$

Notes: The figure displays the density of the forecast error $Error^{m}_{ijt,t}$ conditional on the location of the institution.

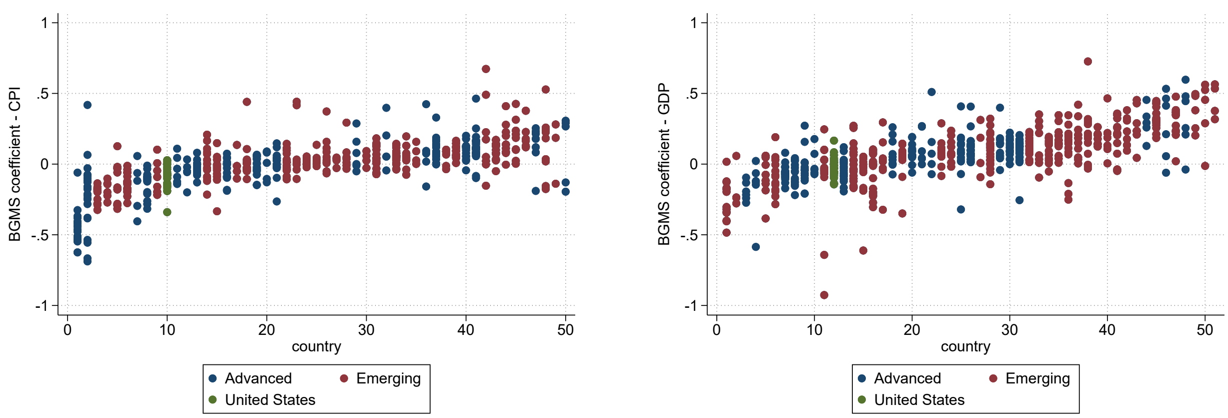
C Biases Appendix



(a) CPI_t (b) GDP_t

Figure 3: Distribution of β^{BGMS} coefficients

Notes: The figure displays the distribution of the β^{BGMS} coefficients estimated for each country-forecaster pair.



(a) CPI_t (b) GDP_t

Figure 4: β^{BGMS} coefficients by country

Notes: The figure displays the β^{BGMS} coefficients estimated for each country-forecaster pair, by country, where countries are ranked by their median value.

Table 14: Behavioral Biases - Past consensus regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t
Average Locals	0.01***	0.02***	0.02***	–0.01**	0.05***	0.02***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
Foreign	0.02	–0.02	–0.02	–0.01	–0.01	–0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)
N	102	102	390	411	6,213	6,655
R^2	0.95	0.91	0.71	0.73	0.36	0.34
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Forecaster FE	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	No	Yes	Yes
Mean-group by cty and loc.	Yes	Yes	No	No	No	No
Mean-group by cty and for.	No	No	Yes	Yes	No	No
Mean-group by cty, for. and month	No	No	No	No	Yes	Yes

Notes: The table shows the results of a regression of the $\beta^{PastConsensus}$ coefficients on the Foreign dummy, where the $\beta^{PastConsensus}$ are estimated on different sub-groups of our sample using $Error^m_{ijt} = \beta^{PastConsensus,m}_{ij} E^{m-1}_{jt}(x_{jt}) + \delta^m_{ij} + \lambda^m_{ijt}$, with $E^m_{jt}(x_{jt}) = \frac{1}{N(j)} \sum_{i \in S^j} E_{ijt}(x_{jt})$ is the average expectation across all forecasters and $E^{m-1}_{jt}(x_{jt}) = E^{12}_{jt-1}(x_{jt})$ if $m = 1$. corresponds to the constant term (or average fixed effect). corresponds to the coefficient of the Foreign dummy. The observations are clustered at the country level in specifications (1) and (2), and at the country and forecaster levels in specifications (3) to (6).

Table 15: Behavioral Biases - Vintage regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t
Average Locals	0.01***	–0.09***	0.02***	–0.09***	0.03***	–0.08***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Foreign	–0.00	–0.01*	–0.01	–0.01	–0.01	–0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	102	102	425	448	6,662	7,131
R^2	0.95	0.95	0.72	0.74	0.45	0.49
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Forecaster FE	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	No	Yes	Yes
Mean-group by cty and loc.	Yes	Yes	No	No	No	No
Mean-group by country and for.	No	No	Yes	Yes	No	No
Mean-group by cty, for. and month	No	No	No	No	Yes	Yes

Notes: The table shows the results of a regression of the $\beta^{LastVintage}$ coefficients on the Foreign dummy, where $\beta^{LastVintage}$ are estimated on different sub-groups of our sample using $Error^m_{ijt} = \beta^{LastVintage,m}_{ij} x_{jt-1} + \delta^m_{ij} + \lambda^m_{ijt}$. corresponds to the constant term (or average fixed effect). corresponds to the coefficient of the Foreign dummy. The observations are clustered at the country level in specifications (1) and (2), and at the country and forecaster levels in specifications (3) to (6).

D Robustness Appendix

E Determinants Appendix

Table 16: Forecast Error conditional on Location of the Forecaster

	(1)	(2)	(3)	(4)
Coefficient				
Foreign	.081***	.073***	.051**	.022
	(.019)	(.018)	(.023)	(.021)
Foreign × GDP	-.045**			
	(.022)			
Foreign × future		-.033**		
		(.013)		
Foreign × Emerging			9.9e-03	
			(.023)	
Foreign × Month-of-year				5.5e-03**
				(2.2e-03)
N	389,295	389,295	389,295	389,295
R^2	.7	.7	.7	.7
Country × Date × Variable × Horizon FE	Yes	Yes	Yes	Yes
Forecaster × Date × Variable × Horizon FE	Yes	Yes	Yes	Yes

Notes: The table shows the regression of the log absolute forecast error of current and future CPI and GDP on regressors with different fixed-effects specifications. All standard errors are clustered on the country, year × country, forecaster and date level.

Table 17: Forecast Error conditional on Location of the Institution

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coefficient	All sample	All sample	All sample	All sample	All sample	All sample	All sample
Foreign	.09	.056***	-.26	.069***	.066***	.053***	.047*
	(.097)	(.016)	(.17)	(.024)	(.02)	(.017)	(.024)
log(distance)	6.6e-03						
	(7.4e-03)						
Foreign × log(distance)	−4.0e-03						
	(.012)						
Foreign × Institutions		−1.4e-03					
		(4.9e-03)					
Foreign × log(GDP)			.016*				
			(8.4e-03)				
Foreign × log(sd(variable))				-.014			
				(.019)			
Foreign × Finance					-.014		
					(.025)		
Foreign × log(sd(return))						.02	
						(.014)	
Foreign × VIX							5.9e-04
							(1.1e-03)
N	388,415	375,405	379,087	389,295	389,295	364,155	389,295
R^2	.7	.7	.7	.7	.7	.7	.7
Cty × Date × Var. × Hor. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inst. × Date × Var. × Hor. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows the regression of the log absolute forecast error of current and future CPI and GDP on regressors with different fixed-effects specifications. All standard errors are clustered on the country, year × country, institution and date level.

Table 18: Determinants of information asymmetries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coefficient	β^{FE}	β^{FE}	β^{FE}	β^{Disag}	β^{Disag}	β^{Disag}	β^{Disag}
Foreign	-.066***	-.059**	3.4e-03				
	(.011)	(.026)	(.024)				
Month of year	.032***	.034***		–9.9e-03*	-.01**		
	(1.6e-03)	(1.9e-03)		(5.0e-03)	(5.0e-03)		
GDP	-.026*	-.024		.024		.021	
	(.016)	(.019)		(.032)		(.032)	
Emerging	-.031	-.045**		.045			.045
	(.02)	(.021)		(.053)			(.053)
Foreign × Month of year		–7.1e-03***	–7.0e-03***				
		(2.2e-03)	(2.2e-03)				
Foreign × GDP		–7.5e-03	.029				
		(.024)	(.018)				
Foreign × Emerging		.064***	–3.1e-03				
		(.022)	(.021)				
N	2,403	2,403	2,403	1,223	1,223	1,222	1,223
R^2	.41	.42	.63	8.2e-03	.23	.57	.019
Country × Variable FE	No	No	No	No	Yes	No	No
Month-of-year × Variable FE	No	No	No	No	No	No	Yes
Country × Month-of-year FE	No	No	Yes	No	No	Yes	No

Notes: The table shows the regression of β^{FE} and β^{Disag} on regressors with different fixed-effects specifications. All standard errors are clustered on the country level.

Table 19: Determinants of information asymmetries

	(1)	(2)	(3)	(4)
Coefficient	β^{FE}	β^{FE}	β^{FE}	β^{Disag}
Foreign	-.036***	.3	-.17	
	(8.6e-03)	(.21)	(.2)	
log(sd(variable))	.01	4.9e-03		.044
	(.019)	(.021)		(.051)
Institutions	8.4e-03**	9.0e-03**		–1.6e-03
	(4.1e-03)	(4.2e-03)		(.011)
log(GDP)	.033***	.036***		-.043**
	(6.2e-03)	(6.0e-03)		(.018)
Foreign × log(sd(variable))		.011	.025	
		(.028)	(.025)	
Foreign × Institutions		–7.8e-03	1.2e-03	
		(6.9e-03)	(7.3e-03)	
Foreign × log(GDP)		-.017	6.2e-03	
		(.01)	(9.6e-03)	
N	2,403	2,403	2,403	1,223
R^2	.47	.47	.63	.035
Month-of-year × Variable FE	Yes	Yes	Yes	Yes
Country × Variable FE	No	No	Yes	No

Notes: The table shows the regression of β^{FE} and β^{Disag} on regressors with different fixed-effects specifications. All standard errors are clustered on the country level.

F Proofs

F.1 Proof of Proposition 1

The model can be written as follows:

$$\begin{aligned} x_{jt} &= \rho_j x_{jt-1} + \epsilon_{jt} \\ s^m_{ijt} &= x_{jt} + v^m_{ijt} \end{aligned} \tag{16}$$

with $v^m_{ijt} \sim N(0, (\kappa^m_j + \tau^m_{ij})^{-1/2})$. We denote $\lambda^m_{ij} = \kappa^m_j + \tau^m_{ij}$

Denote the one step-ahead forecast error for the forecast in the Kalman filter with $\Phi^m_{ij} = V(Error^m_{ijt,t-1}) = V[x_{jt} - E^m_{ijt-1}(x_{jt})]$. We can find Φ^m_{ij} from the Riccati equation

$$\Phi^m_{ij} = \rho^2_j[\Phi^m_{ij} - \Phi^m_{ij}(\Phi^m_{ij} + (\lambda^m_{ij})^{-1})^{-1}\Phi^m_{ij}] + \gamma^{-1}_j.$$

Denote the gain of the Kalman filter with

$$G_{ij}^m = \Phi_{ij}^m(\Phi_{ij}^m + (\lambda_{ij}^m)^{-1})^{-1}.$$

Substituting in the Riccati equation, we obtain

$$\Phi_{ij}^m = \rho_j^2(1 - G_{ij}^m)\Phi_{ij}^m + \gamma_j^{-1},$$

hence the first result.

Now denote the nowcast error in the Kalman filter with $\Omega_{ij}^m = V(Error_{ijt,t}^m) = V[x_{jt} - E_{ijt}^m(x_{jt})]$ We can use recursions of the Kalman filter to relate Ω_{ij}^m and Φ_{ij}^m:

$$\Omega_{ij}^m = \Phi_{ij}^m - G_{ij}^m(\Phi_{ij}^m + (\lambda_{ij}^m)^{-1})G_{ij}^{m\prime}$$

Replacing $G_{jk}^{m\prime}$, we obtain

$$\begin{aligned}\Omega_{ij}^m &= \Phi_{ij}^m - G_{ij}^m(\Phi_{ij}^m + (\lambda_{ij}^m)^{-1})[\Phi_{ij}^m(\Phi_{ij}^m + (\lambda_{ij}^m)^{-1})^{-1}]' \\ &= \Phi_{ij}^m - G_{ij}^m\Phi_{ij}^m \\ &= (1 - G_{ij}^m)\Phi_{ij}^m\end{aligned}$$

Hence the second result.

Note that solving the Riccati equation gives us an expression for Φ_{ij}^m:

$$\Phi_{ij}^m = \frac{1}{2}\left(\gamma_j^{-1} - (1-\rho_j^2)(\lambda_{ij}^m)^{-1} + \sqrt{(\gamma_j^{-1} - (1-\rho_j^2)(\lambda_{ij}^m)^{-1})^2 + 4\gamma_j^{-1}}\right) \tag{17}$$

and for G_{ij}:

$$G_{ij}^m = 1 - \frac{2}{\lambda_{ij}^m/\gamma_j + 1 + \rho_j^2 + \sqrt{(\lambda_{ij}^m/\gamma_j - (1-\rho_j^2))^2 + 4\lambda_{ij}^m/\gamma_j}}$$

which is an increasing function of λ_{ij}^m and hence of τ_{ij}^m.

F.2 Proof of Proposition 2

Notice that $E_{ijt}^m(x_{jt})$ can be rewritten in its moving-average form as follows:

$$E_{ijt}^m(x_{jt}) = \frac{G_{ij}^m}{1 - (1 - G_{ij}^m)\hat{\rho}_{ij}L}s_{ijt}^m \tag{18}$$

Forecast revision can then be written as

$$
\begin{aligned}
Revision^m_{ijt} &= E^m_{ijt}(x_{jt}) - E^m_{ijt-1}(x_{jt}) \\
&= E^m_{ijt}(x_{jt}) - \hat{\rho}_{ij} E^m_{ijt-1}(x_{jt-1}) \\
&= \frac{G^m_{ij}[1-\hat{\rho}_{ij}L]}{1-(1-G^m_{ij})\hat{\rho}_{ij}L} s^m_{ijt} \\
&= \frac{G^m_{ij}[1-\hat{\rho}_{ij}L]}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}(x_{jt} + vijt^m)
\end{aligned}
\tag{19}
$$

and the error as

$$
\begin{aligned}
Error^m_{ijt,t} &= x_{jt} - E^m_{ijt}(x_{jt}) \\
&= x_{jt} - \frac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L} s^m_{ijt} \\
&= \left(1 - \frac{G^m_{ij}}{1-(1-G^m_{ij})\rho_{ij}L}\right) x_{jt} - \frac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L} v^m_{ijt}
\end{aligned}
\tag{20}
$$

with $v^m_{ijt} = h^m_{ij}(\kappa^m_j)^{-1/2}u^m_{jt} + (1-h^m_{ij})(\tau^m_{ij})^{-1/2}e^m_{ijt}$ is the total noise.

The estimated OLS coefficient β^{BGMSm}_{ij} is given by

$$
\beta^{BGMSm}_{ij} = \frac{Cov\left(Error^m_{ijt}, Revision^m_{ijt}\right)}{V\left(Revision^m_{ijt}\right)}
$$

We define $\tilde{E}rror^m_{ijt,t}$ as the error if the persistence and private signal precisions were the ones corresponding to the forecaster's beliefs:

$$
\tilde{E}rror^m_{ijt,t} = \left(1 - \frac{G^m_{ij}}{1-(1-G^m_{ij})\rho_{ij}L}\right)\tilde{x}_{ijt} - \frac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}\tilde{v}^m_{ijt} \tag{21}
$$

with $\tilde{x}_{ijt} = \epsilon_{jt}/(1-\hat{\rho}_{ij}L)$ and $\tilde{v}^m_{ijt} = h^m_{ij}(\kappa^m_j)^{-1/2}u^m_{jt} + (1-h^m_{ij})(\hat{\tau}^m_{ij})^{-1/2}e^m_{ijt}$. We define $\tilde{R}evision^m_{ijt,t}$ similarly:

$$
Revision^m_{ijt} = \frac{G^m_{ij}[1-\hat{\rho}_{ij}L]}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}(\tilde{x}_{ijt} + \tilde{v}ijt^m)
$$

We then use the fact that the forecaster's expectations are rational conditional on their beliefs: $Cov(\tilde{E}rror^m_{ijt,t}, \tilde{R}evision^m_{ijt}) = 0$ to determine the covariance of the actual errors and revisions:

$$\begin{aligned}
Cov\left(Error_{ijt}^m, Revision_{ijt}^m\right) = \;& Cov\left(Error_{ijt}^m - \tilde{E}rror_{ijt}^m, \tilde{R}evision_{ijt}^m\right)\\
&+Cov\left(\tilde{E}rror_{ijt}^m, Revision_{ijt}^m - \tilde{R}evision_{ijt}^m\right)\\
&+Cov\left(Error_{ijt}^m - \tilde{E}rror_{ijt}^m,, Revision_{ijt}^m - \tilde{R}evision_{ijt}^m\right)\\
= \;& Cov\left(\left(1-\tfrac{G_{ij}^m}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}\right)(x_{jt}-\tilde{x}_{ijt}), \tfrac{G_{ij}^m(1-\hat{\rho}_{ij}L)}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}\tilde{x}_{ijt}\right)\\
&+Cov\left(\left(1-\tfrac{G_{ij}^m}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}\right)\tilde{x}_{ijt}, \tfrac{G_{ij}^m(1-\hat{\rho}_{ij}L)}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}(x_{jt}-\tilde{x}_{ijt})\right)\\
&+Cov\left(\left(1-\tfrac{G_{ij}^m}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}\right)(x_{jt}-\tilde{x}_{ijt}), \tfrac{G_{ij}^m(1-\hat{\rho}_{ij}L)}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}(x_{jt}-\tilde{x}_{ijt})\right)\\
&-Cov\left(\tfrac{G_{ij}^m}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}\tilde{v}_{ijt}^m, \tfrac{G_{ij}^m(1-\hat{\rho}_{ij}L)}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}(v_{ijt}^m-\tilde{v}_{ijt}^m)\right)\\
&-Cov\left(\tfrac{G_{ij}^m}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}(v_{ijt}^m-\tilde{v}_{ijt}^m), \tfrac{G_{ij}^m(1-\hat{\rho}_{ij}L)}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}\tilde{v}_{ijt}^m\right)\\
&-Cov\left(\tfrac{G_{ij}^m}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}(v_{ijt}^m-\tilde{v}_{ijt}^m), \tfrac{G_{ij}^m(1-\hat{\rho}_{ij}L)}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}(v_{ijt}^m-\tilde{v}_{ijt}^m)\right)\\
= \;& -(\hat{\rho}_{ij}-\rho_j)G_{ij}^m(1-G_{ij}^m)\tfrac{2\hat{\rho}_{ij}(1-G_{ij}^m)(1-\rho_j^2)-(\hat{\rho}_{ij}-\rho_j)[1+\rho_j\hat{\rho}_{ij}(1-G_{ij}^m)]}{[1-\rho_j\hat{\rho}_{ij}(1-G_{ij}^m)][1-\rho_j^2][1-\hat{\rho}_{ij}^2(1-G_{ij}^m)^2]}\\
&-[(\tau_{ij}^m)^{-1}-(\hat{\tau}_{ij}^m)^{-1}](h_{ij}^m G_{ij}^m)^2\tfrac{1-\hat{\rho}_{ij}^2(1-G_{ij}^m)}{1-\hat{\rho}_{ij}^2(1-G_{ij}^m)^2}
\end{aligned}$$

We used

$$\begin{aligned}
\tilde{E}rror_{ijt}^m \;& = (1-G_{ij}^m)\textstyle\sum_{s=0}^{+\infty}(1-G_{ij}^m)^s\hat{\rho}_{ij}^s L^s\epsilon_{jt}\\
& -G_{ij}^m\textstyle\sum_{s=0}^{+\infty}(1-G_{ij}^m)^s\hat{\rho}_{ij}^s L^s h_{ij}^m(\hat{\tau}_{ij}^m)^{-1/2}e_{ijt}^m\\
\tilde{R}evision_{ijt}^m \;& = G_{ij}^m\textstyle\sum_{s=0}^{+\infty}(1-G_{ij}^m)^s\hat{\rho}_{ij}^s L^s\epsilon_{jt}\\
& -G_{ij}^m\left(1-\tfrac{G_{ij}^m}{1-G_{ij}^m}\textstyle\sum_{s=1}^{+\infty}(1-G_{ij}^m)^s\hat{\rho}_{ij}^s L^s\right)h_{ij}^m(\hat{\tau}_{ij}^m)^{-1/2}e_{ijt}^m\\
Error_{ijt}^m - \tilde{E}rror_{ijt}^m \;& = \tfrac{-\left(\frac{\hat{\rho}_{ij}}{\rho_j}-1\right)(1-G_{ij}^m)}{1-(1-G_{ij}^m)\frac{\hat{\rho}_{ij}}{\rho_j}}\left(\textstyle\sum_{s=0}^{+\infty}\rho_{ij}^s L^s - \sum_{s=0}^{+\infty}(1-G_{ij}^m)^s\hat{\rho}_{ij}^s L^s\right)\epsilon_{jt}\\
& -G_{ij}^m\textstyle\sum_{s=0}^{+\infty}(1-G_{ij}^m)^s\hat{\rho}_{ij}^s L^s h_{ij}^m[(\tau_{ij}^m)^{-1/2}-(\hat{\tau}_{ij}^m)^{-1/2}]e_{ijt}^m\\
Revision_{ijt}^m - \tilde{R}evision_{ijt}^m \;& = \tfrac{-\left(\frac{\hat{\rho}_{ij}}{\rho_j}-1\right)G_{ij}^m}{1-(1-G_{ij}^m)\frac{\hat{\rho}_{ij}}{\rho_j}}\left(\textstyle\sum_{s=0}^{+\infty}\rho_{ij}^s L^s - \sum_{s=0}^{+\infty}(1-G_{ij}^m)^s\hat{\rho}_{ij}^s L^s\right)\epsilon_{jt}\\
& -G_{ij}^m\left(1-\tfrac{G_{ij}^m}{1-G_{ij}^m}\textstyle\sum_{s=1}^{+\infty}(1-G_{ij}^m)^s\hat{\rho}_{ij}^s L^s\right)h_{ij}^m[(\tau_{ij}^m)^{-1/2}-(\hat{\tau}_{ij}^m)^{-1/2}]e_{ijt}^m
\end{aligned}$$

We thus have

$$\beta_1 = \frac{G_{ij}^m(1-G_{ij}^m)\frac{2\hat{\rho}_{ij}(1-G_{ij}^m)(1-\rho_j^2)-(\hat{\rho}_{ij}-\rho_j)[1+\rho_j\hat{\rho}_{ij}(1-G_{ij}^m)]}{[1-\rho_j\hat{\rho}_{ij}(1-G_{ij}^m)][1-\rho_j^2][1-\hat{\rho}_{ij}^2(1-G_{ij}^m)^2]}}{V\left(Revision_{ijt}^m\right)}$$

and

$$\beta_2 = \frac{(h_{ij}^m G_{ij}^m)^2\frac{1-\hat{\rho}_{ij}^2(1-G_{ij}^m)}{1-\hat{\rho}_{ij}^2(1-G_{ij}^m)^2}}{V\left(Revision_{ijt}^m\right)}$$

with

$$V(Revision^m_{ijt}) = \frac{(G^m_{ij})^2}{1-\frac{\hat{\rho}_{ij}}{\rho_j}(1-G^m_{ij})}\left(\frac{G^m_{ij}\frac{\hat{\rho}_{ij}}{\rho_j}[1-\hat{\rho}^2_{ij}(1-G_{ij})]}{[1-\rho_j\hat{\rho}_{ij}(1-G_{ij})][1-\hat{\rho}^2_{ij}(1-G_{ij})^2]} - (\hat{\rho}_{ij}-\rho_j)\frac{1-\rho_j\hat{\rho}_{ij}}{[1-\rho_j\hat{\rho}_{ij}(1-G_{ij})](1-\rho_j^2)}\right)$$
$$+(G^m_{ij})^2\left(1+\left(\frac{G^m_{ij}}{1-G^m_{ij}}\right)^2\frac{\hat{\rho}^2_{ij}(1-G^m_{ij})^2}{1-\hat{\rho}^2_{ij}(1-G^m_{ij})^2}\right)[(h^m_{ij})^2\kappa_j^{-1}+(1-h^m_{ij})^2\tau_{ij}^{-1}]$$

Here we used

$$Revision^m_{ijt} = \frac{G^m_{ij}}{1-\frac{\hat{\rho}_{ij}}{\rho_j}(1-G^m_{ij})}\left(\frac{\hat{\rho}_{ij}}{\rho_j}\sum_{s=0}^{+\infty}(1-G^m_{ij})^s\hat{\rho}^s_{ij}L^s - \left(\frac{\hat{\rho}_{ij}}{\rho_j}-1\right)\sum_{s=0}^{+\infty}\rho_j^s L^s\right)\epsilon_{jt}$$
$$+G^m_{ij}\left(1-\frac{G^m_{ij}}{1-G^m_{ij}}\sum_{s=1}^{+\infty}(1-G^m_{ij})^s\hat{\rho}^s_{ij}L^s\right)v^m_{ijt}$$

F.3 Proof of Corollary 1

We simply note here that β_1 and β_2, evaluated at $(\hat{\tau}^m_{ij})^{-1} = (\tau^m_{ij})^{-1} = (\tau^m_j)^{-1}$ and $\hat{\rho}_{ij} = \rho_j$, are both strictly positive, while $\hat{\rho}_{ij} - \rho_j$ and $(\tau^m_{ij})^{-1} - (\hat{\tau}^m_{ij})^{-1}$ are both equal to zero for $\hat{\tau}^m_{ij} = \tau^m_{ij} = \tau^m_j$ and $\hat{\rho}_{ij} = \rho_j$.

More specifically, note that β_1 and β_2 are functions of the parameters, so we denote $\beta_1 = g_1\left((\hat{\tau}^m_{ij})^{-1}, (\tau^m_{ij})^{-1}, \hat{\rho}_{ij}, \rho_j\right)$ and $\beta_2 = g_2\left((\hat{\tau}^m_{ij})^{-1}, (\tau^m_{ij})^{-1}, \hat{\rho}_{ij}, \rho_j\right)$. The first-order Taylor expansion for β^{BGMSm}_{ij} around $(\hat{\tau}^m_{ij})^{-1} = (\tau^m_{ij})^{-1} = (\tau^m_j)^{-1}$ and $\hat{\rho}_{ij} = \rho_j$ is

$$\beta^{BGMSm}_{ij} \simeq -(\hat{\rho}_{ij}-\rho_j)g_1\left((\tau^m_j)^{-1}, (\tau^m_j)^{-1}, \rho_j, \rho_j\right) - [(\tau^m_{ij})^{-1} - (\hat{\tau}^m_{ij})^{-1}]g_2\left((\tau^m_j)^{-1}, (\tau^m_j)^{-1}, \rho_j, \rho_j\right)$$

We can show that $\hat{\beta}^m_{1j} = g_1\left((\tau^m_j)^{-1}, (\tau^m_j)^{-1}, \rho_j, \rho_j\right)$ and $\hat{\beta}^m_{2j} = g_2\left((\tau^m_j)^{-1}, (\tau^m_j)^{-1}, \rho_j, \rho_j\right)$ are both strictly positive, hence the result.

F.4 Proof of Proposition 3

The estimated OLS coefficient β^{CGm}_{jk}, for $k = l, f$, $m = 1, .., 12$ and $j = 1, .., J$, is given by

$$\beta^{CGm}_{jk} = \frac{Cov\left(Error^m_{jkt}, Revision^m_{jkt}\right)}{V\left(Revision^m_{jkt}\right)} \tag{22}$$

And we can write:

$$Cov\left(Error^m_{jkt}, Revision^m_{jkt}\right) = Cov\left(\tilde{E}rror^m_{jkt}, \tilde{R}evision^m_{jkt}\right)$$
$$+Cov\left(Error^m_{jkt} - \tilde{E}rror^m_{jkt}, \tilde{R}evision^m_{jkt}\right)$$
$$+Cov\left(\tilde{E}rror^m_{jkt}, Revision^m_{jkt} - \tilde{R}evision^m_{jkt}\right)$$
$$+Cov\left(Error^m_{jkt} - \tilde{E}rror^m_{jkt}, Revision^m_{jkt} - \tilde{R}evision^m_{jkt}\right)$$

with $\tilde{Error}^m_{jkt} = \frac{1}{N^k(j)} \sum_{i \in S^k(j)} \tilde{Error}^m_{ijt}$ where $\tilde{Error}^m_{ijt}$ is defined in (21).

We have

$$\begin{aligned} Cov\left(\tilde{Error}^m_{jkt}, \tilde{Revision}^m_{jkt}\right) &= Cov\left(\left(1 - \frac{G^m_{jk}}{1-(1-G^m_{jk})\hat{\rho}_{jk}L}\right)\frac{1}{1-\hat{\rho}_{jk}L}\epsilon_{jt}, \frac{G^m_{jk}}{1-(1-G^m_{jk})\hat{\rho}_{jk}L}\epsilon_{jt}\right) \\ &+ Cov\left(-\frac{G^m_{jk}}{1-(1-G^m_{jk})\hat{\rho}_{jk}L}h^m_{jk}(\kappa^m_j)^{-1/2}u^m_{jt}, \frac{G^m_{jk}[1-\hat{\rho}_{jk}L]}{1-(1-G^m_{jk})\hat{\rho}_{jk}L}h^m_{jk}(\kappa^m_j)^{-1/2}u^m_{jt}\right) \\ &= \frac{G^m_{jk}(1-G^m_{jk})}{1-\hat{\rho}^2_{jk}(1-G^m_{jk})^2}\gamma^{-1} - (G^m_{jk})^2\left(1 - \frac{G^m_{jk}}{1-G^m_{jk}}\frac{\hat{\rho}^2_{jk}(1-G^m_{jk})^2}{1-\hat{\rho}^2_{jk}(1-G^m_{jk})^2}\right)(h^m_{jk})^2(\kappa^m_j)^{-1} \end{aligned}$$

Here we used

$$\begin{aligned} \tilde{Error}^m_{jkt} &= \left(1 - \frac{G^m_{jk}}{1-(1-G^m_{jk})\hat{\rho}_{jk}L}\right)\frac{1}{1-\hat{\rho}_{jk}L}\epsilon_{jt} \\ &- \frac{G^m_{jk}}{1-(1-G^m_{jk})\hat{\rho}_{jk}L}h^m_{jk}(\kappa^m_j)^{-1/2}u^m_{jt} \\ &= \left(\sum_{s=0}^{+\infty}\hat{\rho}^s_{jk}\left[1 - G^m_{jk}\left(\sum_{i=0}^{s}(1-G^m_{jk})^i\right)\right]L^s\right)\epsilon_{jt} \\ &- G^m_{jk}\sum_{s=0}^{+\infty}\hat{\rho}^s_{jk}(1-G^m_{jk})^s L^s h^m_{jk}(\kappa^m_j)^{-1/2}u^m_{jt} \\ \tilde{Revision}^m_{jkt} &= \frac{G^m_{jk}}{1-(1-G^m_{jk})\hat{\rho}_{jk}L}\epsilon_{jt} \\ &+ \frac{G^m_{jk}[1-\hat{\rho}_{jk}L]}{1-(1-G^m_{jk})\hat{\rho}_{jk}L}h_{jk}(\kappa^m_j)^{-1/2}u^m_{jt} \\ &= G^m_{jk}\sum_{s=0}^{+\infty}\hat{\rho}^s_{jk}(1-G^m_{jk})^s L^s\epsilon_{jt} \\ &+ G^m_{jk}\left(1 - \frac{G^m_{jk}}{1-G^m_{jk}}\sum_{s=1}^{+\infty}\hat{\rho}^s_{jk}(1-G^m_{jk})^s L^s\right)h^m_{jk}(\kappa^m_j)^{-1/2}u^m_{jt} \end{aligned}$$

Therefore,

$$\begin{aligned} Cov\left(Error^m_{jkt}, Revision^m_{jkt}\right) = &\frac{G^m_{jk}(1-G^m_{jk})}{1-\hat{\rho}^2_{jk}(1-G^m_{jk})^2}\gamma^{-1} - (G^m_{jk})^2\left(1 - \frac{G^m_{jk}}{1-G^m_{jk}}\frac{\hat{\rho}^2_{jk}(1-G^m_{jk})^2}{1-\hat{\rho}^2_{jk}(1-G^m_{jk})^2}\right)(h^m_{jk})^2(\kappa^m_j)^{-1} \\ &-(\hat{\rho}_{jk}-\rho_j)G^m_{jk}(1-G^m_{jk})\frac{2\hat{\rho}_{jk}(1-G^m_{jk})(1-\rho^2_j)-(\hat{\rho}_{jk}-\rho_j)[1+\rho_j\hat{\rho}_{jk}(1-G^m_{jk})]}{[1-\rho_j\hat{\rho}_{jk}(1-G^m_{jk})][1-\rho^2_j][1-\hat{\rho}^2_{jk}(1-G^m_{jk})^2]}\gamma^{-1} \end{aligned}$$

and

$$\begin{aligned} V(Revision^m_{jkt}) = &\frac{(G^m_{jk})^2}{1-\frac{\hat{\rho}_{jk}}{\rho_j}(1-G^m_{jk})}\left(\frac{G^m_{jk}\frac{\hat{\rho}_{jk}}{\rho_j}[1-\hat{\rho}^2_{jk}(1-G_{jk})]}{[1-\rho_j\hat{\rho}_{jk}(1-G_{jk})][1-\hat{\rho}^2_{jk}(1-G_{jk})^2]} - (\hat{\rho}_{jk}-\rho_j)\frac{1-\rho_j\hat{\rho}_{jk}}{[1-\rho_j\hat{\rho}_{jk}(1-G_{jk})](1-\rho^2_j)}\right) \\ &+(G^m_{jk})^2\left(1+\left(\frac{G^m_{jk}}{1-G^m_{jk}}\right)^2\frac{\hat{\rho}^2_{jk}(1-G^m_{jk})^2}{1-\hat{\rho}^2_{jk}(1-G^m_{jk})^2}\right)(h^m_{jk})^2\kappa^{-1}_j \\ &= (G^m_{jk})^2\frac{1}{1-\hat{\rho}^2_{jk}(1-G^m_{jk})^2}\gamma^{-1} + (G^m_{jk})^2\left(1+\left(\frac{G^m_{jk}}{1-G^m_{jk}}\right)^2\frac{\hat{\rho}^2_{jk}(1-G^m_{jk})^2}{1-\hat{\rho}^2_{jk}(1-G^m_{jk})^2}\right)(h^m_{jk})^2(\kappa^m_j)^{-1} \\ &-(\hat{\rho}_{jk}-\rho_j)(G^m_{jk})^2\frac{2\hat{\rho}_{jk}(1-G^m_{jk})(1-\rho^2_j)-(\hat{\rho}_{jk}-\rho_j)[1+\rho_j\hat{\rho}_{jk}(1-G^m_{jk})]}{[1-\rho_j\hat{\rho}_{jk}(1-G^m_{jk})][1-\rho^2_j][1-\hat{\rho}^2_{jk}(1-G^m_{jk})^2]}\gamma^{-1} \end{aligned}$$

Therefore, if $\hat{\rho}_{jk} = \rho_j$, then

$$\begin{aligned} \beta^{CGm}_{jk} = \beta^{CG}(\rho_j) &= \frac{\frac{G^m_{jk}(1-G^m_{jk})}{1-\rho^2_j(1-G^m_{jk})^2}\gamma^{-1} - (G^m_{jk})^2\left(1-\frac{G^m_{jk}}{1-G^m_{jk}}\frac{\rho^2_j(1-G^m_{jk})^2}{1-\rho^2_j(1-G^m_{jk})^2}\right)(h^m_{jk})^2(\kappa^m_j)^{-1}}{(G^m_{jk})^2\frac{1}{1-\rho^2_j(1-G^m_{jk})^2}\gamma^{-1}+(G^m_{jk})^2\left(1+\left(\frac{G^m_{jk}}{1-G^m_{jk}}\right)^2\frac{\rho^2_j(1-G^m_{jk})^2}{1-\rho^2_j(1-G^m_{jk})^2}\right)(h^m_{jk})^2(\kappa^m_j)^{-1}} \\ &= \frac{\frac{1-G^m_{jk}}{G^m_{jk}}\gamma^{-1} - [1-\rho^2_j(1-G^m_{jk})](h^m_{jk})^2(\kappa^m_j)^{-1}}{\gamma^{-1}+[1-\rho^2_j(1-2G^m_{jk})](h^m_{jk})^2(\kappa^m_j)^{-1}} \end{aligned}$$

If $\hat{\rho}_{jk} \neq \rho_j$, then

$$\beta^{CGm}_{jk} = \beta^{CG}(\hat{\rho}_{jk}) - \frac{(\hat{\rho}_{jk}-\rho_j)\chi}{V(\tilde{R}evision^m_{jkt})-(\hat{\rho}_{jk}-\rho_j)\chi}[1-\beta^{CG}(\hat{\rho}_{jk})]$$

with $\chi = (G^m_{jk})^2 \frac{2\hat{\rho}_{jk}(1-G^m_{jk})(1-\rho_j^2)-(\hat{\rho}_{jk}-\rho_j)[1+\rho_j\hat{\rho}_{jk}(1-G^m_{jk})]}{[1-\rho_j\hat{\rho}_{jk}(1-G^m_{jk})][1-\rho_j^2][1-\hat{\rho}^2_{jk}(1-G^m_{jk})^2]}\gamma^{-1}$.

F.5 Proof of Proposition 4

Consider Equations (19) and (20). We can rewrite them as follows:

$$\begin{aligned}
Revision^m_{ijkt} &= E^m_{ijkt}(x_{jt}) - E^m_{ijkt-1}(x_{jt-1}) \\
&= \frac{G^m_{jk}[1-\hat{\rho}_{jk}L]}{1-(1-G^m_{jk})\hat{\rho}_{jk}L}(1-h^m_{jk})(\tau^m_{jk})^{-1/2}e^m_{ijkt} + \text{terms specific to } \{j,k,m,t\} \\
Error^m_{ijkt} &= x_{jt} - E^m_{ijkt}(x_{jt}) \\
&= -\frac{G^m_{jk}}{1-(1-G^m_{jk})\hat{\rho}_{jk}L}(1-h^m_{jk})(\tau^m_{jk})^{-1/2}e^m_{ijkt} + \text{terms specific to } \{j,k,m,t\}
\end{aligned}$$

The estimated coefficient is then equal to the covariance between the error and the revision conditional on all the terms that are country-location-time specific, divided by the variance of the revision conditional on all the terms that are country-location-time specific

$$\begin{aligned}
\beta^{FEm}_{jk} &= \frac{Cov\left(-\frac{G^m_{jk}}{1-(1-G^m_{jk})\hat{\rho}_{jk}L}(1-h^m_{jk})(\tau^m_{jk})^{-1/2}e^m_{ijkt}, \frac{G^m_{jk}[1-\hat{\rho}_{jk}L]}{1-(1-G^m_{jk})\hat{\rho}_{jk}L}(1-h^m_{jk})(\tau^m_{jk})^{-1/2}e^m_{ijkt}\right)}{V\left(\frac{G^m_{jk}[1-\hat{\rho}_{jk}L]}{1-(1-G^m_{jk})\hat{\rho}_{jk}L}(1-h^m_{jk})(\tau^m_{jk})^{-1/2}e^m_{ijkt}\right)} \\
&= \frac{-(G^m_{jk})^2\left(1-\frac{G^m_{jk}}{1-G^m_{jk}}\frac{\hat{\rho}^2_{jk}(1-G^m_{jk})^2}{1-\hat{\rho}^2_{jk}(1-G^m_{jk})^2}\right)(1-h^m_{jk})^2(\tau^m_{jk})^{-1}}{(G^m_{jk})^2\left(1+\left(\frac{G^m_{jk}}{1-G^m_{jk}}\right)^2\frac{\hat{\rho}^2_{jk}(1-G^m_{jk})^2}{1-\hat{\rho}^2_{jk}(1-G^m_{jk})^2}\right)(1-h^m_{jk})^2(\tau^m_{jk})^{-1}}
\end{aligned}$$

Hence the result.

F.6 Proof of Proposition 5

We can write $Disagreement_{jt}$, $Revision jt$ and x_{jt} as a function of the current shocks and past variables:

$$\begin{aligned}
Disagreement_{jt}^m = \; & G_{jl}^m(x_{jt} + h_{jl}^m(\kappa_j^m)^{-1/2}u_{jt}^m) + (1-G_{jl}^m)E_{jlt-1}^m(x_t) \\
& -G_{jf}^m(x_{jt} + h_{jf}^m(\kappa_j^m)^{-1/2}u_{jt}^m) - (1-G_{jf}^m)E_{jft-1}^m(x_t) \\
= \; & G_{jl}^m(\epsilon_{jt} + \rho_j x_{jt-1} + h_{jl}^m(\kappa_j^m)^{-1/2}u_{jt}^m) + (1-G_{jl}^m)E_{jlt-1}^m(x_t) \\
& -G_{jf}^m(\epsilon_{jt} + \rho_j x_{jt-1} + h_{jf}^m(\kappa_j^m)^{-1/2}u_{jt}) - (1-G_{jf}^m)E_{jft-1}^m(x_t) \\
= \; & (G_{jl}^m - G_{jf}^m)\epsilon_{jt} + (G_{jl}^m h_{jl}^m - G_{jf}^m h_{jk}^m)(\kappa_j^m)^{-1/2}u_{jt}^m \\
& +\rho_j(G_{jl}^m - G_{jf}^m)x_{jt-1} + (1-G_{jl}^m)E_{jlt-1}^m(x_t) - (1-G_{jf}^m)E_{jft-1}^m(x_t) \\
Revision_{jt}^m = \; & G_j^m[(x_{jt} + h_j^m(\kappa_j^m)^{-1/2}u_{jt}^m) - E_{jt-1}^m(x_t)] \\
= \; & G_j^m[\epsilon_{jt} + \rho_j x_{jt-1} + h_j^m(\kappa_j^m)^{-1/2}u_{jt}^m) - E_{jt-1}^m(x_t)] \\
= \; & G_j^m\epsilon_{jt} + G_j^m h_j^m(\kappa_j^m)^{-1/2}u_{jt} + \rho_j G_j^m x_{jt-1} - G_j^m E_{jt-1}^m(x_t) \\
x_{jt} = \; & \epsilon_{jt} + \rho_j x_{t-1}
\end{aligned}$$

The estimated coefficient is given by

$$\begin{aligned}
\beta_j^{DISm} &= \frac{Cov\left(h_j^m G_j^m(\kappa_j^m)^{-1/2}u_{jt}^m, (h_{jl}^m G_{jl}^m - h_{jf}^m G_{jf}^m)(\kappa_j^m)^{-1/2}u_{jt}^m\right)}{V\left(h_j^m G_j^m(\kappa_j^m)^{-1/2}u_{jt}^m\right)} \\
&= \frac{h_{jl}^m G_{jl}^m - h_{jf}^m G_{jf}^m}{h_j^m G_j^m}
\end{aligned}$$

Hence the result.

Consider the rational expectations case. The Kalman filter is given by: $G_{jk}^m = \Phi_{jk}(\Phi_{jk} + (\lambda_{jk}^m)^{-1})^{-1}$ and $h_{jk}^m = \kappa_j^m/\lambda_{jk}^m$. We can thus rewrite:

$$h_{jk}^m G_{jk}^m = \frac{\kappa_j^m}{\lambda_{jk}^m + \Phi_{jk}^{-1}}$$

For $h_{jk}^m G_{jk}^m$ to be decreasing in τ_{jk}^m, it is enough that $\lambda_{jk}^m + \Phi_{jk}^{-1}$ is increasing in λ_{jk}^m. We use the definition of Φ_{jk} in (17) to compute this derivative:

$$\begin{aligned}
\frac{\partial(\lambda_{jk}^m + \Phi_{jk}^{-1})}{\partial\lambda_{jk}^m} &= 1 + \frac{1}{2}(1-\rho_j^2)\frac{1}{(\lambda_{jk}^m)^2}\left(1 - \frac{(1-\rho_j^2)(\lambda_{jk}^m)^{-1} - \gamma_j^{-1}}{\sqrt{(\gamma_j^{-1} - (1-\rho_j^2)(\lambda_{jk}^m)^{-1})^2 + 4\gamma_j^{-1}}}\right) \\
&= 1 + \frac{1}{2}(1-\rho_j^2)\frac{1}{(\lambda_{jk}^m)^2}\left(\underbrace{\frac{\sqrt{(\gamma_j^{-1} - (1-\rho_j^2)(\lambda_{jk}^m)^{-1})^2 + 4\gamma_j^{-1}} + \gamma_j^{-1} - (1-\rho_j^2)(\lambda_{jk}^m)^{-1}}{\sqrt{(\gamma_j^{-1} - (1-\rho_j^2)(\lambda_{jk}^m)^{-1})^2 + 4\gamma_j^{-1}}}}_{>0}\right)
\end{aligned}$$

$h_{jk}^m G_{jk}^m$ is therefore decreasing in τ_{jk}^m.

Consider the case with behavioral biases. h_{jk} and G_{jk} are identical except that they reflect the forecasters' perceived parameters $\hat{\rho}_{jk}$ and $\hat{\tau}^m_{jk}$. As a consequence, $h^m_{jk}G^m_{jk}$ is decreasing in $\hat{\tau}^m_{jk}$. Therefore, for a given $(\hat{\tau}^m_{jk})^{-1} - (\tau^m_{jk})^{-1}$, $h^m_{jk}G^m_{jk}$ is decreasing in τ^m_{jk}. If the foreign and local forecasters have the same behavioral biases $\hat{\rho}_{jk}$ and $(\hat{\tau}^m_{jk})^{-1} - (\tau^m_{jk})^{-1}$, then differences in $h^m_{jk}G^m_{jk}$ reflect differences in τ^m_{jk}