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November 2022

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September 2023

Abstract

Using individual inflation and GDP growth forecasts by professional forecasters for a panel of emerging and advanced economies, we provide direct evidence that foreign forecasters update their forecasts less frequently than local forecasters (about 10% less frequently) and make larger errors in absolute value (up to 9% larger). The foreign forecasters' less accurate forecasts are not due to a more irrational expectation, but to less precise information. The asymmetry is stronger at shorter horizons and when forecasting inflation. In general, the asymmetry is not stronger when forecasting is more uncertain. Taken together, our results provide a basis for disciplining international finance and trade models with heterogeneous 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.

*We are thankful to Daron Acemoglu, Adrian Bruhin, Harald Hau, Lorenz Kueng, Evgenia Passari, Jean-Paul Renne, David Thesmar, Qingyuan Yang and seminar and conference participants at the University of Lausanne's Macro Workshop, the University of Lausanne's Department of Economics Research Days, the EEA annual meeting 2022, the RCEA 2022, the Webinar Series for Graduate Economic Students, T2M 2022, the University of Lyon 2, the KOF Institute, the 2022 Annual meeting of the CEPR International Macro and Finance group, the SFI annual meeting 2022, the Annual Congress of the Swiss Society of Economics and Statistics 2022, the Durham University Business School CEMAP Workshop 2022 and the University of Heidelberg for useful discussions. Navid Samadi provided outstanding research assistance. We acknowledge financial support by the SNSF grant number 100018_182195.

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1 Introduction

The informational advantage of locals over foreigners regarding macroeconomic fundamentals has far-reaching consequences. Information asymmetries are a primary explanation for the tendency of investors to prefer domestic assets in their investment portfolios, known as the home bias in asset holdings.[1] Information asymmetries are also a potential source of capital flow volatility, since disagreement between foreign and domestic investors can generate cross-border asset trade.[2] Beyond their impact on international asset markets, they also constitute a barrier to the international trade in goods, as highlighted by Anderson and van Wincoop (2004).[3] Finally, recent papers highlight their role in international business cycle comovement.[4] However, there remains a lack of direct evidence regarding the existence of information asymmetry regarding macroeconomic fundamentals and quantitative estimates of the extent of this asymmetry. Such evidence could be utilized to discipline international finance and trade models that incorporate heterogeneous information.

We fill this gap using a unique dataset of inflation and GDP growth forecasts for the current and the next year by local and foreign forecasters. Unlike previous studies, the forecaster and country dimensions of the panel allows us to control for a rich set of fixed effects. We first show that foreign forecasters update their forecasts about 10% less frequently than local forecasters. They also make more mistakes than local forecasters, as foreign forecasters' excess absolute error can be as high as 9%, depending on the horizon and on the forecasted variable.[5] The local advantage is especially large when predicting inflation as opposed to GDP and it is stronger for shorter forecasting horizons.

We then investigate the role of information frictions and behavioral biases in explaining

[1]The home bias in asset holdings was originally documented by French and Poterba (1991). 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).

[2]See Yuan (2005), Albuquerque et al. (2007), Albuquerque et al. (2009), Brennan and Cao (1997), Broner et al. (2013), Tille and van Wincoop (2010), Tille and van Wincoop (2014), Benhima and Cordonier (2022).

[3]See also Head and Mayer (2013), Allen (2014), Dasgupta and Mondria (2018), Eaton et al. (2021). Baley et al. (2020) show that cross-border uncertainty may sometimes increase trade.

[4]See Iliopulos et al. (2021) and Bui et al. (2021).

[5]Are these estimates economically significant? Take for instance the home bias in equity holdings. Van Nieuwerburgh and Veldkamp (2009) show that a difference in the variance of priors as small as 10% can generate empirically plausible levels of home bias when investors can choose what information to learn before they invest.

our results about errors. We do this in two steps. First, we rule out behavioral biases such as over-reaction to new information 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, 2022; Angeletos et al., 2021; Goldstein, 2021). In particular, we provide tests of asymmetric information that are robust to the presence of public signals. These tests show that foreign forecasters have less precise information.

Finally, we explore some determinants of the information asymmetry between local and foreign forecasters, and examine whether the asymmetry is related to factors that drive forecasting uncertainty. Interestingly, the asymmetry is not reduced when forecasting is less uncertain. If anything, it is increased. Indeed, the local advantage is higher for short horizons and for inflation (as opposed to GDP growth), but also for large countries. In all these situations, the forecasting uncertainty (measured by the average forecast error) happens to be *smaller*. However, we find no evidence that the difference in forecast errors between local and foreign forecasters is linked to the development status of the country, to institutional quality, or to the volatility of business cycles or financial markets, despite the fact that these variables do affect the average forecasting uncertainty.[6] These results should help further discipline the link between uncertainty and information asymmetry in models of international finance and trade.

This evidence suggests that when information becomes available, it flows to local forecasters, and sometimes, but not always, to foreign forecasters. These results would be consistent with better access to locally-produced information (by knowing when and where relevant information is released). We show that the information asymmetry is stronger for nowcasting, and that it increases in the course of a year (the asymmetry is higher in December than in January). This is consistent with the idea that local forecasters are exposed to the regular

[6]These findings echo the weak link between uncertainty and disagreement that has been documented in the literature (Lahiri and Sheng, 2010; Rich and Tracy, 2010).

releases of partial GDP growth and inflation figures and integrate this information faster. Interestingly, inflation figures are typically available at a higher frequency and with a shorter lag than GDP, making the access to that information an even greater advantage. This is consistent with our finding that the difference in updating frequency is larger for inflation forecasts than for GDP growth forecasts.

As we do not measure the incentives to acquire information at the forecaster level, we cannot document the extent to which the local advantage is determined by those incentives. However, we do find evidence that the forecasts issued by the financial industry are on average more precise than the forecasts issued by the non-financial industry. This is consistent with the idea that the finance industry has more incentives to produce accurate macroeconomic forecasts in order to better allocate portfolios between countries or between equity and bonds. However, there is no significant difference between the local advantage of the financial sector and that of the non-financial sector.

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) use 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 (2022) (BK henceforth) and Angeletos et al. (2021) (AHS henceforth), use the estimated coefficient in the individual pooled regression as an indicator of deviations from Rational Expectations (RE).[7] We borrow this test directly from the literature to assess whether domestic and foreign behavioral biases differ.

However, CG's Full Information (FI) test, which has been commonly used in the literature, is not adapted to our purpose. 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

[7]An earlier literature has previously identified deviations from rationality by studying the joint behavior of actual on predicted values, the auto-correlation of forecasts revisions and the predictability of errors. See, for example, Mincer and Zarnowitz (1969), Zarnowitz (1983), Nordhaus (1987), Clements (1997), Lahiri and Sheng (2008).

signals. Comparing the CG coefficient across local and foreign forecasters cannot indicate which group faces more frictions.[8] We thus provide two tests that are robust to the presence of public information. The first relies on individual regressions in the spirit of 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 local informational advantage. Many studies provide indirect evidence of asymmetric information between domestic and foreign investors by showing that location matters for portfolio composition and for portfolio returns.[9] However, based on investor choices and returns, some papers find that foreign investors perform better than local investors (e.g. Grinblatt and M. (2000)).[10] In contrast to these studies, we investigate whether location affects the quality of forecasters' information, thus providing direct evidence of information asymmetries. Closest to our study is the paper by Bae et al. (2008), which focuses on the performance of local and foreign analysts in forecasting earnings for firms. Our focus is different since we examine whether locals outperform foreigners in forecasting aggregate variables. Moreover, we not only document the foreign forecasters' excess errors, but we also investigate whether these excess mistakes come from information frictions or behavioral biases. Finally, other studies document foreigners' lack of attention to domestic information.[11]

The paper is structured as follows. Section 2 describes our dataset. Section 3 focuses on the updating frequency of forecasts. Section 4 documents the foreign forecasters' excess mistakes. Section 5 lays down a model of expectation formation and tests for the sources of the foreigners' excess mistakes. Section 6 investigates drivers of forecast errors and asymmetric

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

[9] See for instance 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).

[10] 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)).

[11] See for instance Leuz et al. (2009), Mondria et al. (2010) Huang (2015) and Cziraki et al. (2021).

information. Section 7 provides several robustness checks. Finally, section 8 concludes.

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 and we focus on observations between 1998 and 2021.[12] Each month, forecasters provide estimates of several macroeconomic indicators for the current and the following year. An advantage of this dataset is that it allows for meaningful comparisons across both countries and forecasters.[13] In this paper, we focus on two indicators, namely inflation and GDP growth. The dataset discloses the name of the individual forecasters. There are 748 unique forecasters from which 149 conduct forecasts for at least 2 distinct countries. For each forecaster-country pair, the average (median) number of observations is 80 (60), which corresponds to approximately 7 (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 inflation and real GDP growth 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

[12] For an overview of all advanced and emerging economies in our sample see table 12 in the appendix. Note that the survey provides forecasts as of 1989 for some countries. However, our sample period is limited by the GDP and inflation vintage series of actual outcomes provided by the IMF.

[13] Consensus Economics clearly defines each macroeconomic indicator surveyed.

IMF WEO published in September or in subsequent years.[14] 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, and 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, and those for future inflation and GDP by 10 and 7 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 in which the headquarters, the subsidiaries and the affiliates are located. 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 location information is not time-varying and corresponds to the information accessed in 2021. This amounts to a measurement error that could bias the magnitude of the location effect downward.

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

$$Error^{m}_{ijt,t} = x_{jt} - E^{m}_{ijt}(x_{jt})$$

[14]Using alternative vintage series ensures that differences in forecasting precisions are not solely due to individual forecasters that anticipate revisions in actual GDP or inflation and therefore have a different forecasting target.

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

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

Forecasters' Scope and Industry. Furthermore, we identify the scope of the forecasters. In more detail, we categorize forecasters with subsidiaries and headquarters all located in the same country as national forecasters. In contrast, we categorize forecasters with at least one subsidiary located in a country outside that of their headquarters as multinationals. Table 1 provides an overview of the distribution of observations across forecasters conditional on their location and scope.[15] Almost two thirds 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.[16]

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

3 Foreign Forecasters Update their Forecasts Less

Before considering forecast errors, it is informative to examine forecast updating. Here, we explore the hypothesis that local forecasters update their forecasts more often than foreign forecasters. To do so, we compute the number of published forecasts for each year-forecaster-country unit, which we denote N_{ijt}. The distribution of these numbers of yearly forecasts is provided in Figure 1. Most forecasters publish their forecasts 12 times a year, but some publish less often. A higher proportion of local forecasters publish a forecast at least 7 times

[15] As the scope variable is based on the location information, this variable is not time varying.

[16] We provide a similar distribution table for the number of country-forecaster pairs in Table 14 in the Appendix.

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

Location	**National**			**Multinational**			**Total**		
	N	Col %	Row %	N	Col %	Row %	N	Col %	Row %
Local	35,431	61.2	30.0	82,822	78.7	70.0	118,253	72.5	100.0
Foreign	22,452	38.8	50.0	22,446	21.3	50.0	44,898	27.5	100.0
Total	57,883	100.0	35.5	105,268	100.0	64.5	163,151	100.0	100.0

Notes: The table shows the distribution of the forecasters conditional on their location and scope. "N" refers to the number of observations, "Col %" to the column percentage, and "Row %" to the row percentages, respectively. Forecasters are either local or foreign. Local forecasters have the headquarter or subsidiary in the country they forecast for, otherwise they are considered as 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.

a year.

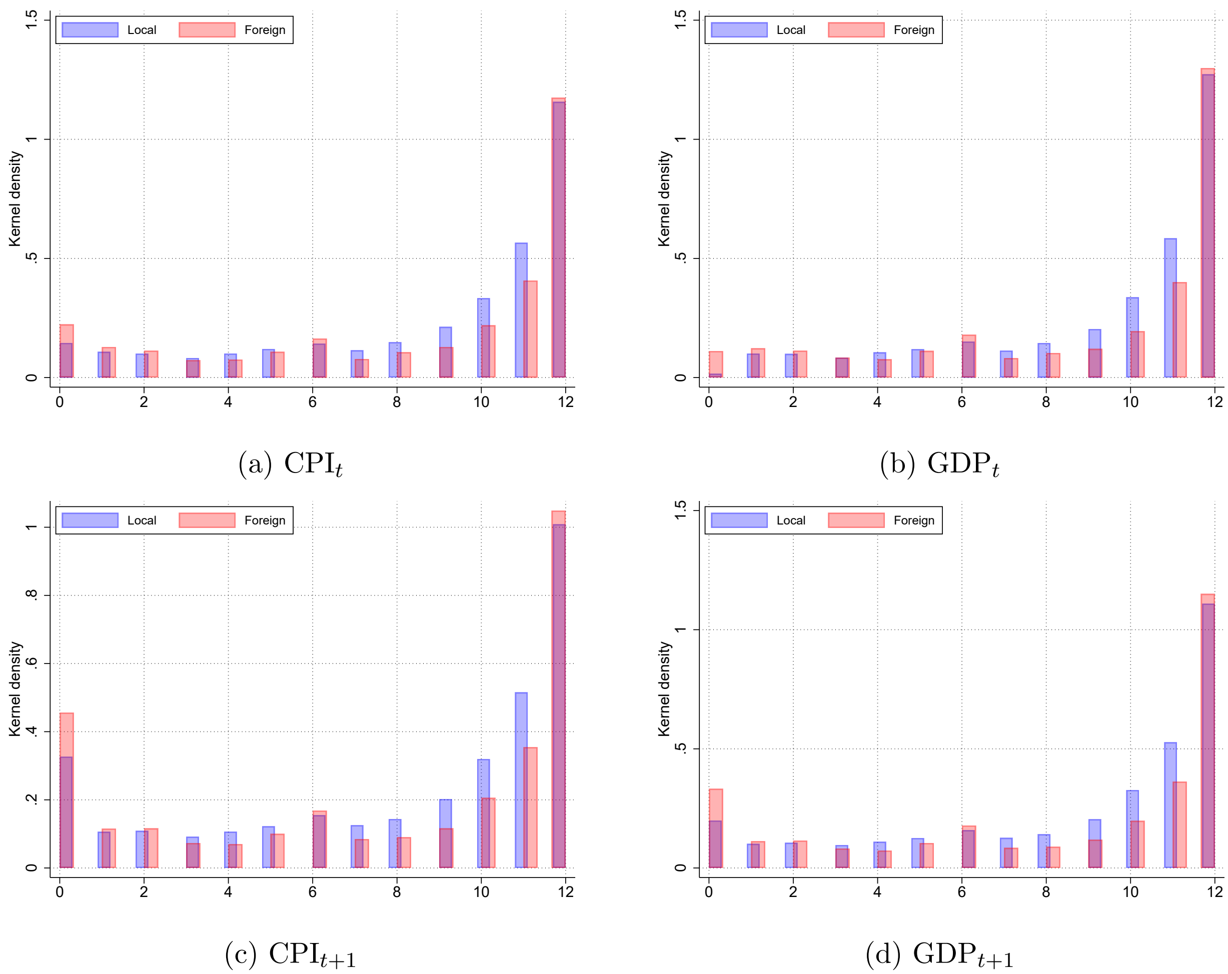
We test formally whether foreign forecasters publish forecasts less often by taking the log of N_{ijt} and estimating

$$\ln(N_{ijt}) = \tilde{\delta}_{it} + \bar{\delta}_{jt} + \beta \text{Foreign}_{ij} + \varepsilon_{ijt} \,, \tag{1}$$

where $\tilde{\delta}_{it}$ and $\bar{\delta}_{jt}$ are respectively forecaster-year and country-year fixed effects. Foreign$_{ij}$ is a dummy that takes the value of 1 if forecaster i is foreign to country j, and 0 otherwise.

The results are reported in Table 2. In the absence of fixed effects (column (2)), there is no significant difference in publication frequency between local and foreign forecasters. However, as soon as we include country and forecaster fixed effects (column (3)), it appears that foreign forecasters publish significantly less: they release 12% to 14% less forecasts depending on the forecasted variable. When including the country-year and the forecaster-year fixed effects (column (4)), the foreign forecasters still appear to publish their forecasts 10% to 12% less often than local forecasters. The difference in publication frequency between local and foreign forecasters is smaller when considering GDP growth (as opposed to inflation), and when forecasting (as opposed to nowcasting).

Note that forecasters may publish a forecast without necessarily updating it, so the publication frequency is an imperfect measure of the updating frequency. We thus compute



(a) CPI_t (b) GDP_t

(c) CPI_{t+1} (d) GDP_{t+1}

Figure 1: Distribution of the number of yearly updates

Notes: The figure displays the histograms of the number of updates by location. The population corresponds to all the country-forecaster-year units. We consider that any published forecast is an update.

the number of yearly forecasts when considering only "distinct" forecasts, that is, forecasts that differ from the previous release. This is also an imperfect measure of updating frequency, since an identical forecast does not necessarily reflect the absence of new information. It may simply reflect the fact that the new information is consistent with past information.[17]

Figure 4 in the Appendix provides the distribution of the number of yearly forecasts using only "distinct" forecasts. Foreign forecasters are more likely to provide the same forecast for a whole year. However, foreign forecasters are also slightly more likely to update their forecasts at a higher frequency of 11 to 12 times a year. We use this measure to estimate

[17]Note that the consistency of the new available information with past information can be assumed to be time and country specific and will thus be captured by the fixed effects. Then the relative ability of local and foreign forecasters to seize this new information is captured by the Foreign dummy.

Table 2: Forecast Error conditional on Location of the Forecaster

	(1)	(2)	(3)	(4)	(5)
Variable	Coefficient				
CPI_t	Foreign	–0.03	–0.14***	–0.12***	–0.12***
		(0.06)	(0.04)	(0.04)	(0.04)
	N	16,427	16,346	10,857	10,822
	R^2	0.00	0.23	0.53	0.50
GDP_t	Foreign	–0.04	–0.13***	–0.10***	–0.10***
		(0.06)	(0.04)	(0.03)	(0.03)
	N	17,091	17,008	11,240	11,238
	R^2	0.00	0.23	0.54	0.52
CPI_{t+1}	Foreign	–0.02	–0.14***	–0.11***	–0.10**
		(0.06)	(0.05)	(0.04)	(0.04)
	N	15,371	15,286	10,082	9,950
	R^2	0.00	0.25	0.53	0.50
GDP_{t+1}	Foreign	–0.02	–0.12***	–0.10**	–0.08**
		(0.06)	(0.04)	(0.04)	(0.03)
	N	16,048	15,961	10,464	10,342
	R^2	0.00	0.25	0.53	0.51
	Country and Forecaster FE	No	Yes	No	No
	Country × Year FE	No	No	Yes	Yes
	Forecaster × Year FE	No	No	Yes	Yes

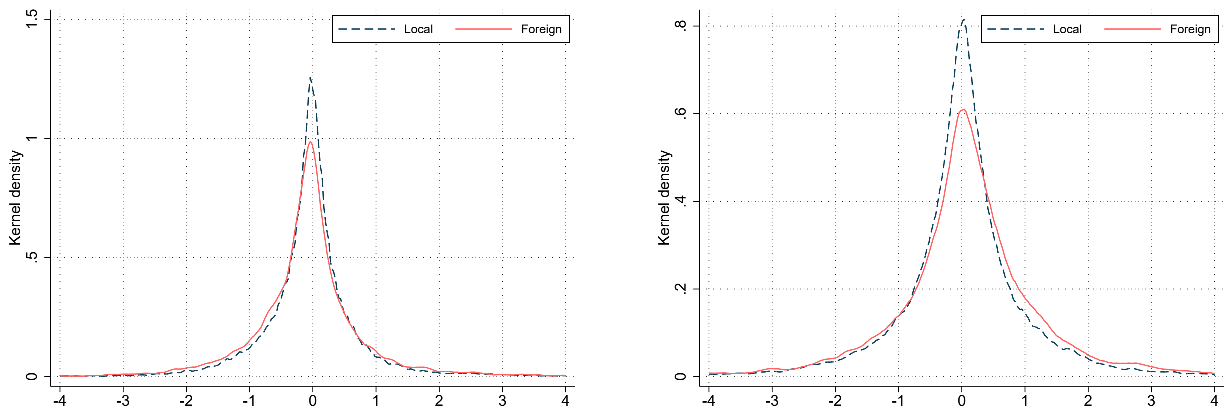
Notes: The table shows the results of regression of the number of forecast updates within a year on the location of the forecaster with different fixed-effects specifications. In columns (2) to (4), we consider that any available forecast is an update. In column (5), we only consider a forecast as an update if its value differs from the last available forecast. All standard errors are clustered at the country and forecaster level.

Equation (1) and report the results in column (5) of Table 2. The results, in fact, barely change. All in all, foreign forecasters publish their forecasts about 10% less frequently than local forecasters.

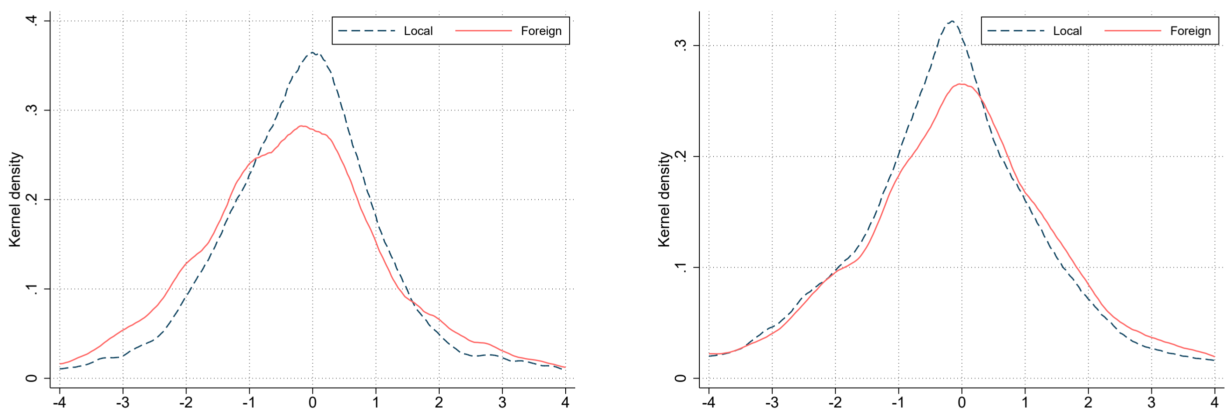
4 Foreign Forecasters Make More Errors

In this section, we analyze the forecasters' errors and find that foreign forecasters make more errors than local ones.

As preliminary descriptive evidence, Figure 2 shows the density of forecast errors for each group of forecasters. The forecast errors are distributed around 0 for both local and foreign forecasters. However, the distribution of forecast errors for foreign forecasters is wider than for local forecasters. A wider distribution of errors points towards less precise forecasts, as fewer errors are distributed close to zero. Formal tests of variance equality are performed in Appendix C.1 and show that the variance of foreign forecasters' errors is indeed significantly larger.



(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 forecaster.

Note, however, that this preliminary evidence does not control for country- and forecaster-specific characteristics. For instance, Table 1 shows that a higher proportion of forecasts by multinational forecasters is 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.[18] For this reason, we estimate different

[18]Similarly, even though Consensus Economics uses consistent definitions for macroeconomic indicators in their monthly survey for all forecasters, forecasters may employ divergent definitions that could bias the results.

fixed-effects model with alternative measures of the forecast error magnitude, and control for forecaster-, date- and country-specific characteristics by exploiting the panel structure of our data.

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 triplet (m, i, j) for current and future forecasts separately. We discard forecaster-country-month triplets with less than 10 observations. We take the log of $\sigma^m_{\mathrm{FE},i,j}$ and estimate

$$\ln(\sigma^m_{\mathrm{FE},i,j}) = \delta^m + \tilde{\delta}_i + \bar{\delta}_j + \beta \mathrm{Foreign}_{ij} + \varepsilon^m_{ij} \,, \tag{2}$$

where δ^m, $\tilde{\delta}_i$ and $\bar{\delta}_j$ are respectively month-of-year, forecaster and country fixed effects. $\mathrm{Foreign}_{ij}$ 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. The standard deviation of forecast errors is higher when the forecasts are produced by a foreign forecaster than when they are produced by a local one. This finding is robust across different fixed-effect specifications. In the most conservative specification (with country, forecaster and month-of-year fixed effects), foreign forecasts are 6% to 14% higher than local forecasts. The difference between local and foreign forecast precision is larger for inflation than for GDP growth, and is larger for the current year than for the following year.

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.[19] We use the logarithm of the absolute forecast error to give more weight to small differences

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

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

	(1)	(2)	(3)	(4)
Variable	Coefficient	$\ln(\sigma^m_{\mathrm{FE},i,j})$	$\ln(\sigma^m_{\mathrm{FE},i,j})$	$\ln(\sigma^m_{\mathrm{FE},i,j})$
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 and future 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.

around zero. The model we estimate is as follows.

$$\ln(|Error^m_{ijt,t}|) = \delta^m_{it} + \tilde{\delta}^m_{jt} + \beta \mathrm{Foreign}_{ij} + \varepsilon^m_{ij,t}\,, \tag{3}$$

δ^m_{it} are forecaster-date fixed effects and $\tilde{\delta}^m_{jt}$ are country-date fixed effects. These fixed effects enable us to control for country-specific trends in volatility and forecaster-specific trends in forecasting performance.

Table 4 displays the results for CPI and GDP. In all specifications, foreign forecast errors are significantly larger in absolute value than local forecasts. In the most conservative specification with country-date and forecaster-date fixed effects, the absolute value of foreign forecast errors is 9% larger for current inflation. The difference is smaller for current GDP growth (6%) and for future inflation (7%). For future GDP growth, there is no significant

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 $\times$ Date	No	No	Yes
	Forecaster $\times$ 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, forecaster and date level.

difference between local and foreign forecasts.

Are these excess errors due to the relatively less frequent updating of foreign forecasters documented in Section 3? To answer this question, we repeat the last exercise using only the forecasts that differ from their previous release. The results are reported in Table 16 in the Appendix. The results are very similar, except that the coefficient for current GDP growth and future inflation are slightly lower (5% instead of 6% and 7% in the last column). This implies that foreign forecasters also make more errors conditional on updating.

5 What Explains the Foreigner Error?

To account for foreigner error, 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 two tests that are robust to common behavioral biases and to public signals.

5.1 A Simple Noisy Information Model

We consider a set of N professional forecasters indexed by $i = 1, .., N$ who form expectations on J 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):

$$x_{jt} = \rho_j x_{jt-1} + \epsilon_{jt} \tag{4}$$

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

5.1.1 Information structure and behavioral biases

We consider an information structure and behavioral assumptions that are similar to Angeletos et al. (2021), except that we include public signals.

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

$$\phi^m_{jt} = x_{jt} + (\kappa^m_j)^{-1/2} u^m_{jt}$$

observed by all forecasters, where $u^m_{jt} \sim N(0, 1)$ is an i.i.d. aggregate noise shock and $\kappa^m_j > 0$ 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 $e_{ijt}^m \sim N(0,1)$ is an i.i.d. idiosyncratic noise shock, $\tau_{ij}^m > 0$ 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 $\frac{1}{N(j)} \sum_{i \in S(j)} \epsilon_{ijt}^m = 0$, $\frac{1}{N^l(j)} \sum_{i \in S^l(j)} \epsilon_{ijt}^m = 0$ and $\frac{1}{N^f(j)} \sum_{i \in S^f(j)} \epsilon_{ijt}^m = 0$. Local and foreign forecasters differ through the precision of their private information τ_{ij}^m: $\tau_{ij}^m = \tau_{jl}^m$ if $i \in S^l(j)$ and $\tau_{ij}^m = \tau_{jf}^m$ if $i \in S^f(j)$.

We assume that, for a given month m, ϵ_{ijt}^m and u_{jt}^m are mutually and serially independent. This means, for instance, that the noise shocks in the signals of month m from year t are not correlated with the noise shocks in the signals of month m from year $t-1$. But we do not impose that the noise shocks are serially uncorrelated within a given year.[20]

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 $\hat{\rho}_{ij} = \hat{\rho}_{jl}$ if $i \in S^l(j)$ and $\hat{\rho}_{ij} = \hat{\rho}_{jf}$ if $i \in S^f(j)$. Over-confidence (or under-confidence) consists in distorted beliefs about the precision of private signals τ_{jk}^m. We denote forecaster i's belief about her precision by $\hat{\tau}_{ij}^m$. Again, we assume that local and foreign forecasters may have different beliefs, so that $\hat{\tau}_{ij}^m = \hat{\tau}_{jl}^m$ if $i \in S^l(j)$ and $\hat{\tau}_{ij}^m = \hat{\tau}_{jf}^m$ 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:

$$\begin{aligned} s_{ijt}^m &= h_{ij}^m \phi_{jt}^m + (1 - h_{ij}^m) \varphi_{ijt}^m \\ &= x_{jt} + v_{ijt}^m \end{aligned} \tag{5}$$

[20] 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.

with

$$v_{ijt}^{m} = h_{ij}^{m}(\kappa_{j}^{m})^{-1/2}u_{jt}^{m} + (1-h_{ij}^{m})(\tau_{ij}^{m})^{-1/2}e_{ijt}^{m} \tag{6}$$

and $h_{ij}^{m} = \kappa_{j}^{m}/(\kappa_{j}^{m}+\hat{\tau}_{ij}^{m})$, so that $E_{ijt}^{m}(x_{jt}|\phi_{jt}^{m},\varphi_{ijt}^{m}) = (\kappa_{j}^{m}+\hat{\tau}_{ij}^{m})/(\gamma_j+\kappa_{j}^{m}+\hat{\tau}_{ij}^{m})s_{ijt}^{m}$.

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

$$E_{ijt}^{m}(x_{jt}) = (1-G_{ij}^{m})\hat{\rho}_{ij}E_{ijt-1}^{m}(x_{jt-1}) + G_{ij}^{m}s_{ijt}^{m} \tag{7}$$

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

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

$$Revision_{ijt}^{m} \quad = E_{ijt}^{m}(x_{jt}) - E_{ijt-1}^{m}(x_{jt}) \tag{8}$$

and the error as

$$Error_{ijt,t}^{m} \quad = x_{jt} - E_{ijt}^{m}(x_{jt}) \tag{9}$$

5.1.2 Error variance

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 G.1):

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

$$\begin{aligned} V(Error_{ijt,t-1}^{m}) &= V[x_{jt}-E_{ijt-1}^{m}(x_{jt})] &&= \tfrac{\gamma^{-1}}{1-\rho_j^2(1-G_{ij}^{m})} \\ V(Error_{ijt,t}^{m}) &= V[x_{jt}-E_{ijt}^{m}(x_{jt})] &&= \tfrac{\gamma^{-1}(1-G_{ij}^{m})}{1-\rho_j^2(1-G_{ij}^{m})} \end{aligned} \tag{10}$$

Both variances are decreasing in G_{jk}^m.

Since G_{ij}^m is increasing in τ_{ij}^m, then the variances are decreasing in τ_{ij}^m.

But asymmetric information is not the only potential source of difference in variance. 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 error variance as compared to the well-specified estimator. Therefore, the difference in variance 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.

5.2 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), 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 ($\hat{\tau}_{ij}^m \neq \tau_{ij}^m$). We rely on regressions popularized by Bordalo et al. (2020) and Kohlhas and Broer (2020) to assess the presence of such biases among forecasters:

$$Error_{ijt}^m = \beta_{ij}^{BGMSm} Revision_{ijt} + \delta_{ij}^m + \lambda_{ijt}^m \tag{11}$$

where β_{ij}^{BGMSm} is a country, month and forecaster specific coefficient, δ_{ij}^m are country-month-forecaster fixed effects and λ_{ijt}^m 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 G.2):

Proposition 2. *Estimating Equation* (11) *for each* $i = 1, ..N$, $j = 1, ..J$ *and* $m = 1, ..12$ *by OLS gives the following coefficients:*

$$\beta_{ij}^{BGMSm} = -(\hat{\rho}_{ij} - \rho_j)\beta_{1ij}^m - [(\tau_{ij}^m)^{-1} - (\hat{\tau}_{ij}^m)^{-1}]\beta_{2ij}^m$$

β^m_{1ij} *and* β^m_{2ij} *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 ($\hat{\tau}^m_{ij} - \tau^m_{ij} > 0$) or from over-extrapolation ($\hat{\rho}_{ij} - \rho_j > 0$).[21]

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 biases (see the proof in Appendix G.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 $\hat{\beta}^m_1$ *and* $\hat{\beta}^m_2$ *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 (11) using the mean-group methodology, under different assumptions about the homogeneity of the β^{BGMS} coefficient. We first assume that the coefficients only differ across countries and between local and foreign forecasters. We then allow the coefficients to differ across country-forecaster pairs. Finally, we allow the coefficients to differ across each month within a country-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

[21] In Bordalo et al. (2020), this over-reaction can be due to diagnostic expectations.

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.

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 (11) on different sub-groups of our sample. *Average Locals* corresponds to the constant term (or average fixed effect). *Foreign* 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).

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 most 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, 2022; Angeletos et al., 2021). 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 5 in the Appendix), and in particular, they are heterogeneous across countries (see Figure 6 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 with the existing evidence.

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:

$$E^m_{ijt}(x_{jt+1}) = \hat{\rho}_{ij} E^m_{ijt}(x_{jt}) \tag{12}$$

We estimate Equation (12) using the same mean-group methodology. As in our model, $\hat{\rho}_{ij}$ is specific to a country-forecaster pair and is independent of the month of the year, and we allow it to differ across months as well. In our model, all the innovations to inflation have the same persistence, whereas in reality, there could be 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 no longer significant.

In the Appendix, we additionally examine whether forecasters differ in the way they use public news, since Kohlhas and Broer (2022) and Gemmi and Valchev (2022) show that forecasters typically under-react to public news. In Tables 17 and 18, 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

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 (12) on different sub-groups of our sample. *Average Locals* corresponds to the constant term (or average fixed effect). *Foreign* 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).

of realized outcome. A negative (positive) coefficient implies that forecasters over-react (under-react) to public news. Again, we do not find any systematic difference in behavioral biases.[22]

All in all, foreign and local forecasters do not have significantly different biases. From now on, we thus 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 under this assumption.

5.3 Testing for Asymmetric Information

Consensus regressions that consist in regressing the consensus error (i.e., the average error) on the consensus revision (i.e., the average revision) as in Coibion and Gorodnichenko (2015) are commonly used to detect information frictions. A positive coefficient indicates

[22] Interestingly, in our most conservative specification (columns (5) and (6)), we find systematic under-reaction to the past consensus (in Table 17, we can see that forecasters under-react to the past consensus on both GDP growth and inflation, as both average coefficients are positive), but not systematic under-reaction to the last vintage (in Table 18, 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), which suggests that forecasters tend to differentiate their forecasts from those made by other forecasters.

deviations from full information. Can we use these regressions to identify differences in information frictions between local and foreign forecasters? We show here that the relation between the precision of information 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 are not a good indicator of the degree of information asymmetry. We propose two alternative tests that are robust to public signals.

5.3.1 Consensus regressions

Suppose that we perform the consensus regression as in Coibion and Gorodnichenko (2015) on both group of forecasters, that is, using the population of foreign forecasts on the one hand and the population of the local forecasts on the other, and then compare the coefficients. In this case, what would we be identifying?

In our setup, this regression can be written, for each $j = 1, ..J$, $m = 1, ..12$ and $k = l, f$, where l refers to the local forecasters' population by l and f refers to the foreign forecasters' population:

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

$Error^m_{jkt} = \frac{1}{N^k(j)} \sum_{i \in S^k(j)} Error^m_{ijt}$, $Revision^m_{jkt} = \frac{1}{N^k(j)} \sum_{i \in S^k(j)} Revision^m_{ijt}$, are the consensus error and the consensus revision in location $k = l, f$, 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^{CGm}_{jk} coefficient is positive on average, as is expected, there does not appear to be any significant difference between foreign and local coefficients.

This does not necessarily mean that there are no information asymmetries between local and foreign forecasters. Indeed, the following proposition shows that, in the presence of

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 (13) on different sub-groups of our sample. *Consensus* corresponds to the constant term (or average fixed effect). *Foreign* corresponds to the coefficient of the Foreign dummy. The observations are clustered at the country level.

public information, the relation between β^{CG} and the precision of private information is not monotonic (see the proof in Appendix G.4).

Proposition 3. *Suppose that there are no behavioral biases: $\hat{\rho}_{ij} = \rho_j$ and $\hat{\tau}_{ij}^m = \tau_j^m$, and that the precision parameters are identical among foreign forecasters and among local forecasters: $\tau_{ij}^m = \tau_{jl}^m$ if $i \in \mathcal{S}^l(j)$ and $\tau_{ij}^m = \tau_{jf}^m$ if $i \in \mathcal{S}^f(j)$, for all $j = 1, ..J$ and $m = 1, .., 12$. Estimating Equation (13) for each $j = 1, ..J$, $m = 1, .., 12$ and $k = l, f$ by OLS gives the following coefficients:*

$$\beta_{jk}^{CGm} = \frac{\frac{1-G_{jk}^m}{G_{jk}^m}\gamma^{-1} - [1 - \rho_j^2(1 - G_{jk}^m)]h_{jk}^2(\kappa_j^m)^{-1}}{\gamma^{-1} + [1 - \rho_j^2(1 - 2G_{jk}^m)](h_{jk}^m)^2(\kappa_j^m)^{-1}}$$

Note that $\beta_{jk}^{CGm} = (1-G_{jk}^m)/G_{jk}^m$ 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, $\beta_{jl}^{CGm} < \beta_{jf}^{CGm}$ would imply that foreigners have noisier information ($\tau_{jf}^m > \tau_{jl}^m$).

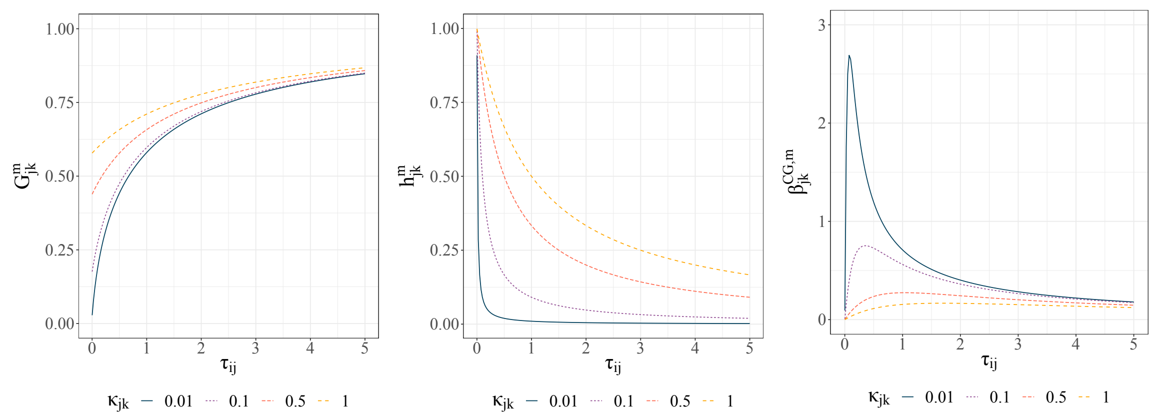
However, when $h_{jk}^m > 0$, β_{jk}^{CGm} depends on the variance of the fundamental shocks (γ^{-1}) and on the variance of the aggregate noise ($(\kappa_j^m)^{-1}$). β_{jk}^{CGm} is thus not a straightforward function of the information structure and it is not clear what to infer from $\beta_{jl}^{CGm} < \beta_{jf}^{CGm}$. 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_{jk}^m. 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 β_{jk}^{CGm} to be a monotonic function of τ_{jk}^m.

Figure 3 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. Beyond 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).

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

5.3.2 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 $j = 1, ..J$,



(a) G^m_{jk} (b) h^m_{jk} (c) $\beta^{CG,m}_{jk}$

Figure 3: The effect of τ^m_{jk} on β^{CGm}_{jk}

Notes: The figure shows how the precision of the private signal, τ_{jk}, affects the Kalman gain G^m_{jk}, the weight of public information h^m_{jk} and the coefficient β^{CGm}_{jk}. The different colors in each plot correspond to different levels of the public signal precision κ^m_j.

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

$$Error^m_{ijkt} = \beta^{FEm}_{jk} Revision^m_{ijkt} + \delta^m_{jkt} + \lambda^m_{ijkt} \tag{14}$$

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 depend only on differences in G^m_{jk} (see the proof in Appendix G.5).

Proposition 4. *Suppose that the parameters are homogeneous among foreign forecasters and among local forecasters: $\hat{\rho}_{ij} = \hat{\rho}_{jl}$, $\tau_{ij} = \tau_{jl}$ and $\hat{\tau}_{ij} = \hat{\tau}_j$, if $i \in \mathcal{S}^l(j)$, and $\hat{\rho}_{ij} = \hat{\rho}_{jf}$, $\tau_{ij} = \tau_{jf}$ and $\hat{\tau}_{ij} = \hat{\tau}_{jf}$, if $i \in \mathcal{S}^f(j)$. Estimating Equation (14) 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, that is, $\hat{\rho}_{jl} = \hat{\rho}_{jf} = \hat{\rho}_j$ *and* $(\hat{\tau}_{jl}^m)^{-1} - (\tau_{jl}^m)^{-1} = (\hat{\tau}_{jf}^m)^{-1} - (\tau_{jf}^m)^{-1}$*, and if* $0 < \hat{\rho}_j < 1$*, then* $\beta_{jf}^{FEm} < \beta_{jl}^{FEm}$ *if and only if* $\tau_{jl}^m > \tau_{jf}^m$*.*

If the foreign and local forecasters have similar behavioral biases and if forecasters believe that there is some persistence in the process, then $\beta_{jf}^{FEm} < \beta_{jl}^{FEm}$ 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_{jk}^m is lower). The lower G_{jk}^m, the more persistent is the forecast, as it incorporates new information in a slower fashion. This makes β_{jk}^{FEm} more negative because it increases the magnitude of the covariance between the revision and the forecast itself, which drives the error.[23][24]

We first estimate Equation (14) 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 differ 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. Second, 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 (the

[23]Note that the coefficient should be equal to β_{jk}^{BGMSm} 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. A negative coefficient therefore is not a sign of a deviation from rational expectations.

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

$$-\left(E_{ijkt}^m(x_{jt}) - E_{jkt}^m(x_{jt})\right) = \beta_{jk}^{FEm}(Revision_{ijkt}^m - Revision_{jkt}^m) + \lambda_{ijkt}^m$$

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:

$$\left(E_{ijkt}^m(x_{jt}) - E_{jkt}^m(x_{jt})\right) = \beta_{jk}^{Gm}\left(E_{ijkt-1}^m(x_{jt}) - E_{jkt-1}^m(x_{jt})\right) + \lambda_{ijkt}^m$$

$\beta_{jk}^{Gm} = 1 - G_{jk}^m$ is also directly and monotonically related to the degree of information frictions.

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 (14) on different sub-groups of our sample. *Average Locals* corresponds to the constant term (or average fixed effect). *Foreign* corresponds to the coefficient of the Foreign dummy. The observations are clustered at the country level in specifications (1) to (4).

p-value is higher than 10%). This is consistent with the preliminary evidence of Section 4 where we have shown that foreign forecasters made relatively more errors on inflation than on GDP growth.

5.3.3 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:

$$Disagreement^m_{jt} = E^m_{jlt}(x_{jt}) - E^m_{jft}(x_{jt}) \tag{15}$$

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

Consider now the following regression:

$$Disagreement^m_{jt} = \beta^{DISm}_j Revision^m_{jt} + \beta^{0m}_j x_{jt} + \beta^{1m}_j x_{jt-1} + \beta^{2m}_j E^m_{jlt-1}(x_{jt}) + \beta^{3m}_j E^m_{jft-1}(x_{jt}) + \delta^m_j + \lambda^m_{jt} \tag{16}$$

where $Revision^m_{jt} = \frac{1}{2}(Revision^m_{jlt} + Revision^m_{jft})$ 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 G.6).

Proposition 5. *Suppose that the parameters are homogeneous among foreign forecasters and among local forecasters:* $\hat{\rho}_{ij} = \hat{\rho}_{jl}$*,* $\tau_{ij} = \tau_{jl}$ *and* $\hat{\tau}_{ij} = \hat{\tau}_j$*, if* $i \in \mathcal{S}^l(j)$*, and* $\hat{\rho}_{ij} = \hat{\rho}_{jf}$*,* $\tau_{ij} = \tau_{jf}$ *and* $\hat{\tau}_{ij} = \hat{\tau}_{jf}$*, if* $i \in \mathcal{S}^f(j)$*. Estimating Equation* (16) *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, that is, $\hat{\rho}_{jl} = \hat{\rho}_{jf} = \hat{\rho}_j$ *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, β_j^{DISm} is negative if the foreign expectations are more sensitive to the public signal and hence to the public noise. This is the case if the foreign forecasters' private information is less informative than that of local forecasters.

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 (16) on different sub-groups of our sample. In specifications (1) and (2), we show robust standard errors in specifications (3) and (4), standard errors are clustered at the country level.

We first estimate Equation (16) 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 is smaller in magnitude for GDP growth, which is consistent with our previous results.

6 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.

6.1 Errors

We first stack observations of inflation and GDP growth errors and errors at different horizons. 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 it is inflation, 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 on the month, and a dummy equal to one if the country is an emerging market. We then examine the interaction between these variables and the Foreign dummy when including all the fixed effects.

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

Table 10: Forecast Error and Information Asymmetries - Drivers I

	(1)	(2)	(3)
Coefficient	$\ln(\lvert Error^{m}_{ijt,t}\rvert)$	$\ln(\lvert Error^{m}_{ijt,t}\rvert)$	$\ln(\lvert Error^{m}_{ijt,t}\rvert)$
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-effect specifications. All standard errors are clustered on the country, forecaster and date level.

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, somehow paradoxically, the foreign penalty is higher when there is less forecasting 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 or inflation rate standard deviation 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 deviation of the return within the month) and the VIX.[25]

Columns (1) to (5) show 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. This means that countries with improving institutions have also declining forecast errors. Better institutions lead to more transparency, which affects the precision of forecasts. Larger countries also have lower forecast errors. This effect is mainly driven by the cross-country dimension since it becomes insignificant when we add country fixed effects. Large countries may attract the attention of forecasters more or they may produce more information. Volatility also plays a role: countries with more volatile business cycles or with higher stock market volatility have higher forecast errors. Global volatility (the VIX) is also positively associated with higher forecast errors worldwide. Hence, uncertain environments are generally associated with poorer forecasting performance. 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. The effect of geography is negligible beyond the fact of being local or foreign. Finally, forecasters from the financial sector 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 local and foreign forecasters symmetrically. Similarly, financial forecasters are better at forecasting both local and foreign countries, but still perform better when forecasting locally. 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.[26]

[25]The data sources are the following: distance and country size (Conte and Mayer, 2022), quality of institutions (World Bank, 2022), business cycle volatility (IMF WEO), financial sector (Eikon), stock market volatility and VIX (Datastream).

[26]In the Appendix tables 20 and 21, we show that the results are unchanged when we interact the Foreign dummy with one variable at a time.

6.2 The β coefficients

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 22 and 23, are broadly consistent with the evidence on the errors.[27] First, according to Table 22, 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 23, 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.

6.3 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

[27] 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.

better at forecasting local firms' earnings, find that the protection of investors' rights does not influence the local advantage, nor does the development status of the country where the firms are located.[28]

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 local advantage. However, interestingly, that local advantage is typically greater in situations with less average forecasting uncertainty. It seems that when macroeconomic information is available, it flows to local forecasters.

These results are consistent with the locals' better access to locally-produced information (by knowing when and where relevant information is released). The fact that the information asymmetry is stronger for nowcasting (when forecasting the current year's GDP growth or inflation) and that it increases in the course of a year (the asymmetry is greater in December than in January) is consistent with the assumption that local forecasters are exposed to the regular releases of partial GDP growth and inflation figures and integrate this information faster. Interestingly, inflation is typically available at a higher frequency and with a shorter lag than GDP, making the access to that information an even greater advantage. This is consistent with Table 2 in Section 3, where we can see that the difference in updating frequency is 2% larger for inflation forecasts than for GDP growth forecasts.

7 Robustness Checks

Different Vintage Series. To calculate forecast errors, it is standard practice in the literature to use vintage series of actual outcomes for GDP and inflation. In the main text, we focus on the vintage series from the IMF that are published in April of the subsequent year. To show that our results do not depend on this specific vintage series, we provide a robustness check using two alternative series of the actual outcome of GDP and inflation.

As a first alternative, we use the vintage series published in September of the subsequent

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

year. For example, if a forecast for the year 2011 was submitted in October 2011, we take the vintage Series posted in September 2012 to calculate the forecast error. Similarly, if a forecast for the year 2012 was submitted in October 2011, we use the vintage Series posted in September 2013. As a second alternative, we take the data published in April two years after the forecast date. Therefore, for the same forecasts submitted in October 2011, we use the data published in April 2013 and in April 2014.

The results are displayed in columns (1) to (2) of Table 19 in the Appendix. We report the same regression results as in Tables 4, 5, 6, 8 and 9 using the vintage series published in September of the subsequent year. In columns (3) to (4), we replicate the same regressions using the vintage series published in April two years after the forecast date. Overall, the results are robust across vintage series.

Forecasters forecasting for both Local and Foreign Countries. The rich country and forecaster coverage in our dataset allows us to focus exclusively on forecasters that are both local and foreign with respect to the countries they forecast for. This allows for a more direct comparison of the forecast precision conditional on the location. With this restricted subsample, we re-estimate our main results from tables 4, 5, 6, 8 and 9. We report the results for the mean-group estimators with the most conservative fixed effects. Columns (5) and (6) of table 19 in the appendix report the results for inflation and GDP, respectively. Overall, the findings are very similar to the baseline results.

Alternative Trimming Strategy. In the main text, we trim observations removing forecasts that are more than 5 interquartile ranges away from the median. We re-estimate our main results with a slightly less conservative trimming method. We trim observations that are more than 6 interquartile ranges away from the median, resulting in a loss of observations for current inflation and GDP of 3 and 0.6 percent, and for future inflation and GDP of 9 and 7 percent, respectively. The results are displayed in columns (7) and (8) of table 19 in the appendix and are similar.

Alternative Definition of Foreign Forecaster. In the main text, a foreign forecaster is defined as a forecaster that has neither its headquarters nor any subsidiary located in the country it forecasts for. This definition suggests that there is an information flow even between subsidiaries and their headquarters, regardless of the size of these subsidiaries. In this robustness check, we use an alternative definition where we define a forecaster to be foreign if its headquarters are located in another country. Compared to the 28% of foreign forecasters in the baseline results, 64% of the forecasters are defined to be foreign according to the alternative definition. We re-estimate our main results, reported in columns (9) and (10) of table 19 in the appendix. Overall, our results remain robust to this alternative definition, even though they are slightly less pronounced and more imprecisely estimated. We conclude that the location of the headquarters seems to be relevant, but that there is some information flowing from local subsidiaries to foreign headquarters.

8 Conclusion

In this paper, we provide direct evidence of asymmetric information between domestic and foreign forecasters. Using professional forecaster expectation data, in which we determine the location of each forecaster-country pair, we show that foreign forecasters update their information less frequently compared to local forecasters and produce less precise forecasts, even conditional on updating their forecasts. These results hold across several different specifications of the forecast precision measure as well as when controlling for a rich set of fixed effects.

We analyze potential sources of the differences in forecasting precision using a model of expectation formation. We rule out over-confidence and over-extrapolation, and behavioral biases in general, as drivers of the foreigners' excess mistakes: these biases are not significantly different between local and foreign forecasters. We then identify differences in information asymmetries between foreign and local forecasters using two newly developed tests.

Finally, we explore some determinants of the information asymmetry between local and foreign forecasters. The asymmetry is stronger at shorter horizons and when forecasting inflation. In general, the asymmetry is not weaker when forecasting is less uncertain.

Our results have implications for the modeling and calibration of international trade and finance models with heterogeneous information. First, we provide estimates of the excess errors of foreign forecasters and their relative updating frequency. Second, we prove that the source of asymmetry between local and foreign forecasters is informational. Third, we provide evidence of an elusive link between forecasting uncertainty and information asymmetry.

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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 come 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

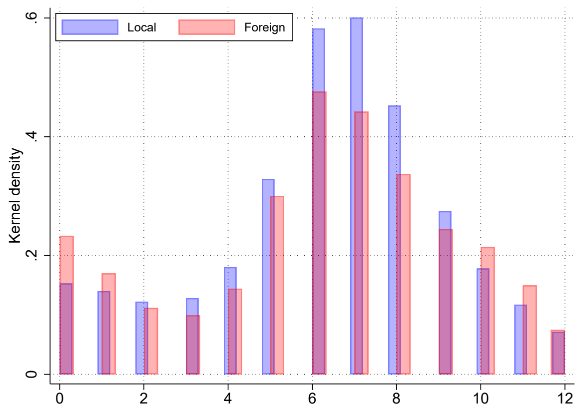
Notes: The table shows the development status of all countries in the sample.

Table 14: Distribution of Forecaster-Country Pairs by Location and Scope

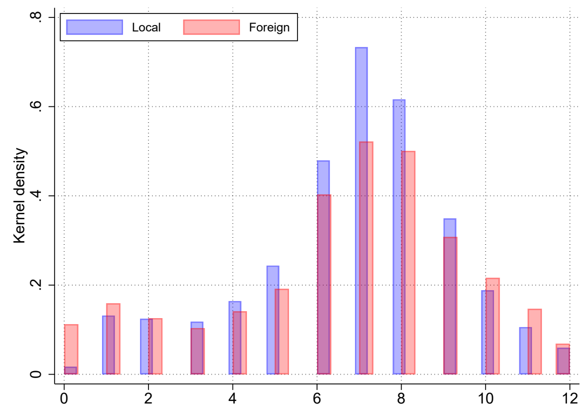
Location	**Scope**								
	National			**Multinational**			**Total**		
	N	Col %	Row %	N	Col %	Row %	N	Col %	Row %
Local	408	53.4	31.2	899	71.2	68.8	1,307	64.5	100.0
Foreign	356	46.6	49.5	363	28.8	50.5	719	35.5	100.0
Total	764	100.0	37.7	1,262	100.0	62.3	2,026	100.0	100.0

Notes: The table shows the distribution all forecaster-country pairs by location and scope. Among the 748 unique forecasters, we identify 2,026 forecaster-country pairs. Each forecaster-country pair is either foreign or local. Local forecasters have the headquarters or subsidiary in the country they forecast for, otherwise they are considered as a foreign forecaster. To identify forecaster scope, we define multinational forecasters to have subsidiaries in countries other than that in which the headquarters are located. National forecasters have only subsidiaries in the same country as the headquarter.

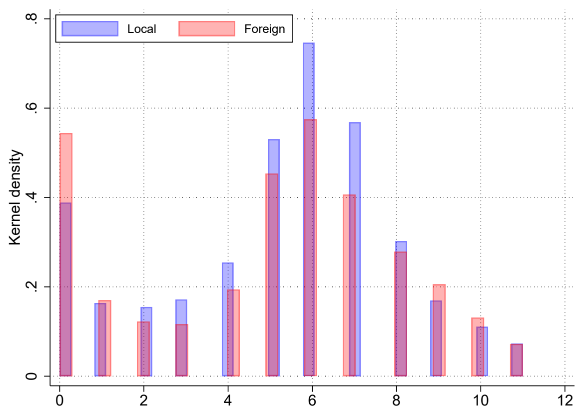
B Updating Appendix



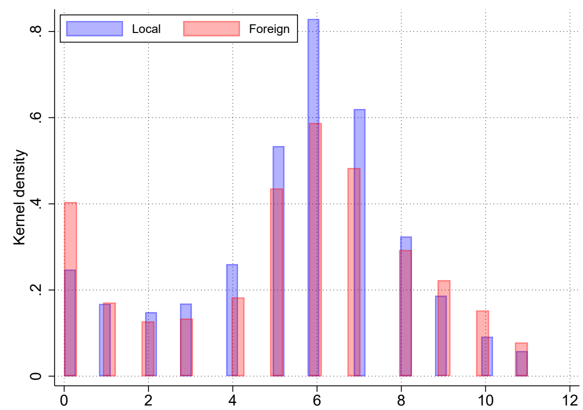
(a) CPI_t



(b) GDP_t



(c) CPI_{t+1}



(d) GDP_{t+1}

Figure 4: Distribution of the number of yearly updates - "Distinct" forecasts only

Notes: The figure displays the histograms of the number of updates by location. The population corresponds to all the country-forecaster-year units. We only consider a forecast as an update if its value differs from the last available forecast.

C Errors Appendix

C.1 Variance equality tests

In a more formal test, we investigate whether the variance of forecast errors is larger for foreign forecasters than the variance of local forecasters. To do this, we perform a simple variance equality test applied to the annual average of forecast errors across locations, defined as $\frac{1}{12}\sum_{m=1}^{12} Error_{ijt,t+h}^{m}$, for $h = 0, 1$. We use the annual average here to take into account a potential high correlation of the errors within a year, which could bias the test. We implement Levene's variance equality test (Levene, 1960). The null hypothesis, H_0, is that variances are equal $\sigma^2_{\mathrm{FE}_{\mathrm{Local}}} = \sigma^2_{\mathrm{FE}_{\mathrm{Foreign}}}$, versus the alternative hypothesis of unequal variances, H_A, $\sigma^2_{\mathrm{FE}_{\mathrm{Local}}} \neq \sigma^2_{\mathrm{FE}_{\mathrm{Foreign}}}$.[29]

[29] Note that there are different ways for calculating the test statistic for equal variances, namely using the mean, median or trimmed mean. We observe very little differences across these methods which is why we report the results of the test statistics calculating with the mean.

Table 15: 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	82.77	< 0.001
	Advanced Economies	5,655	1,278	0.42	0.49	29.39	< 0.001
	Emerging Economies	6,253	3,241	1.02	1.07	2.78	0.095
	Multinatonal firms	8,435	2,320	0.77	0.95	77.45	< 0.001
	National firms	3,473	2,199	0.86	0.93	12.74	< 0.001
	Financial Sector	8,005	1,274	0.78	1.04	69.99	< 0.001
	Non-Fincial Sector	1,828	2,158	0.74	0.83	19.10	< 0.001
GDP_t	All sample	12,390	4,701	1.15	1.44	131.49	< 0.001
	Advanced Economies	5,762	1,274	0.69	0.87	53.80	< 0.001
	Emerging Economies	6,628	3,427	1.44	1.60	15.36	< 0.001
	Multinatonal firms	8,690	2,424	1.11	1.51	148.38	< 0.001
	National firms	3,700	2,277	1.25	1.36	8.83	0.003
	Financial Sector	8,269	1,348	1.14	1.60	117.08	< 0.001
	Non-Fincial Sector	1,858	2,217	0.99	1.32	58.50	< 0.001
CPI_{t+1}	All sample	11,231	4,140	1.76	2.09	112.73	< 0.001
	Advanced Economies	5,382	1,171	0.91	1.04	22.85	< 0.001
	Emerging Economies	5,849	2,969	2.27	2.38	6.49	0.011
	Multinatonal firms	7,971	2,151	1.79	2.07	57.65	< 0.001
	National firms	3,260	1,989	1.68	2.10	60.22	< 0.001
	Financial Sector	7,582	1,192	1.81	2.17	44.28	< 0.001
	Non-Fincial Sector	1,711	1,964	1.66	2.00	45.50	< 0.001
GDP_{t+1}	All sample	11,707	4,341	2.45	3.10	109.10	< 0.001
	Advanced Economies	5,472	1,168	1.60	1.86	18.66	< 0.001
	Emerging Economies	6,235	3,173	3.00	3.45	15.99	< 0.001
	Multinatonal firms	8,206	2,275	2.36	3.24	123.84	< 0.001
	National firms	3,501	2,066	2.64	2.94	5.81	0.016
	Financial Sector	7,831	1,281	2.43	3.41	99.87	< 0.001
	Non-Fincial Sector	1,737	2,023	1.95	2.82	53.02	< 0.001

Notes: The table shows Levene's variance equality test applied to the forecast errors of local and foreign forecasters. The Null hypothesis posits that the variance of the forecast errors made by local forecasters is equal to the variance of the forecast errors made by foreign forecasters. The alternative hypothesis is that the variances are not equal. In the rows we report the test statistics for different subsamples.

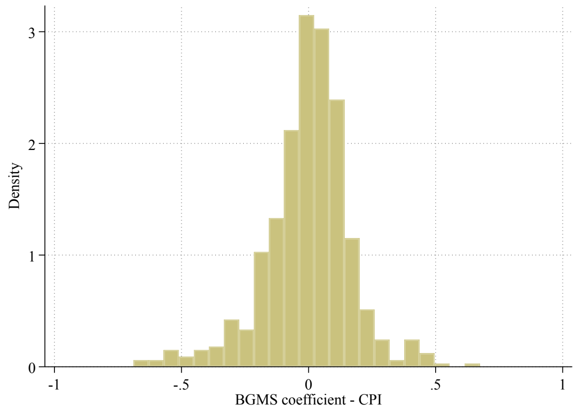
Table 15 reports the results. In column (1), we define different sub-samples. We split the sample into advanced and emerging countries, multinational and national forecasters, financial and non-financial forecasters. Column (2) and (3) show the number of observations for local and foreign forecasters, 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 16: Forecast Error conditional on Updating Forecasts

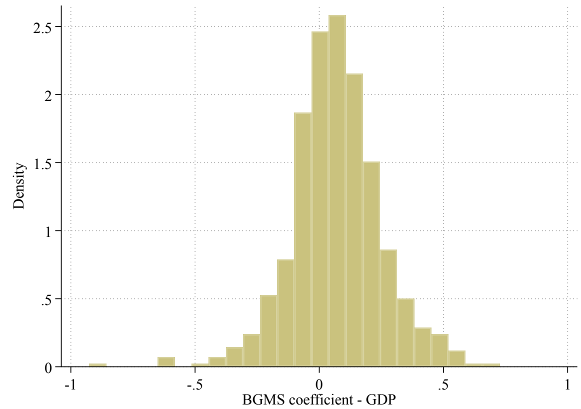
	(1)	(2)	(3)	(4)
Variable	Coefficient			
CPI_t	Foreign	0.25***	0.09***	0.09***
		(0.08)	(0.03)	(0.02)
	N	112,505	112,479	71,153
	R^2	0.01	0.14	0.65
GDP_t	Foreign	0.27***	0.11***	0.05*
		(0.09)	(0.02)	(0.02)
	N	116,080	116,054	73,067
	R^2	0.01	0.15	0.69
CPI_{t+1}	Foreign	0.26***	0.08**	0.05**
		(0.06)	(0.03)	(0.02)
	N	100,092	100,065	63,276
	R^2	0.01	0.14	0.69
GDP_{t+1}	Foreign	0.15*	0.09***	0.02
		(0.08)	(0.03)	(0.02)
	N	105,215	105,189	66,401
	R^2	0.00	0.16	0.74
	Country and Forecaster FE	No	Yes	Yes
	Country $\times$ Date	No	No	Yes
	Forecaster $\times$ 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-effect specifications, using only forecasts that are distinct from their last release. All standard errors are clustered on the country, forecaster and date level.

D Biases Appendix



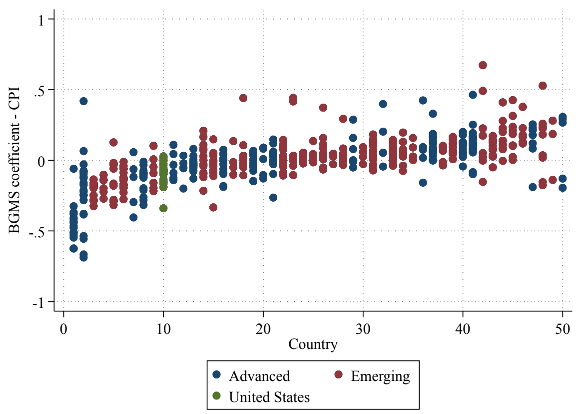
(a) CPI_t



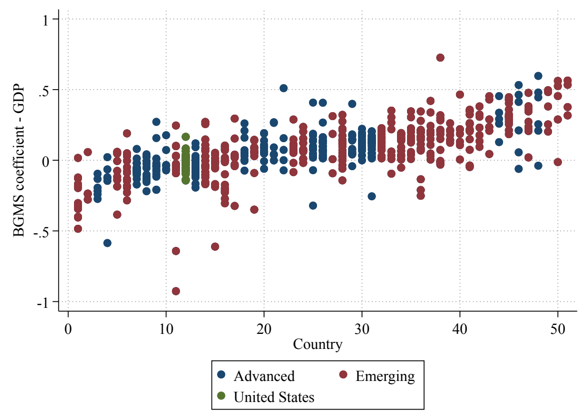
(b) GDP_t

Figure 5: 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 6: 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 17: 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 $m = 1$. *Average Locals* corresponds to the constant term (or average fixed effect). *Foreign* 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 18: 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 $Error^m_{ijt} = \beta^{LastVintage,m}_{ij} x_{jt-1} + \delta^m_{ij} + \lambda^m_{ijt}$. *Average Locals* corresponds to the constant term (or average fixed effect). *Foreign* 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).

F Determinants Appendix

Table 20: Forecast Error and Information Asymmetries - Drivers I, Separate Regressions

	(1)	(2)	(3)	(4)
Coefficient	$\ln(\lvert Error^m_{ijt,t}\rvert)$	$\ln(\lvert Error^m_{ijt,t}\rvert)$	$\ln(\lvert Error^m_{ijt,t}\rvert)$	$\ln(\lvert Error^m_{ijt,t}\rvert)$
Foreign	0.08***	0.07***	0.05**	0.02
	(0.02)	(0.02)	(0.02)	(0.02)
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	389,295	389,295	389,295	389,295
R^2	0.70	0.70	0.70	0.70
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-effect specifications. All standard errors are clustered on the country, forecaster and date level.

Table 21: Forecast Error and Information Asymmetries - Drivers II, Separate Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coefficient							
Foreign	0.09	0.06***	–0.26	0.07***	0.07***	0.05***	0.05*
	(0.10)	(0.02)	(0.17)	(0.02)	(0.02)	(0.02)	(0.02)
ln(Distance)	0.01						
	(0.01)						
Foreign × ln(Distance)	–0.00						
	(0.01)						
Foreign × Institutions		–0.00					
		(0.00)					
Foreign × ln(GDP)			0.02*				
			(0.01)				
Foreign × ln(sd(Fundamental))				–0.01			
				(0.02)			
Foreign × Finance					–0.01		
					(0.03)		
Foreign × ln(sd(Return))						0.02	
						(0.01)	
Foreign × VIX							0.00
							(0.00)
N	388,415	375,405	379,087	389,295	389,295	364,155	389,295
R^2	0.70	0.70	0.70	0.70	0.70	0.70	0.70
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-effect specifications. All standard errors are clustered on the country, forecaster and date level.

Table 22: Determinants of information asymmetries - I

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coefficient	β^{FE}	β^{FE}	β^{FE}	β^{Disag}	β^{Disag}	β^{Disag}	β^{Disag}
Foreign	–0.07***	–0.06**	0.00				
	(0.01)	(0.03)	(0.02)				
Month of year	0.03***	0.03***		–0.01*	–0.01**		
	(0.00)	(0.00)		(0.01)	(0.01)		
GDP	–0.03*	–0.02		0.02		0.02	
	(0.02)	(0.02)		(0.03)		(0.03)	
Emerging	–0.03	–0.04**		0.04			0.04
	(0.02)	(0.02)		(0.05)			(0.05)
Foreign × Month of year		–0.01***	–0.01***				
		(0.00)	(0.00)				
Foreign × GDP		–0.01	0.03				
		(0.02)	(0.02)				
Foreign × Emerging		0.06***	–0.00				
		(0.02)	(0.02)				
N	2,403	2,403	2,403	1,223	1,223	1,222	1,223
R^2	0.41	0.42	0.63	0.01	0.23	0.57	0.02
Country × Variable FE	No	No	Yes	No	Yes	No	No
Month-of-year × Variable FE	No	No	Yes	No	No	No	Yes
Country × Month-of-year FE	No	No	No	No	No	Yes	No

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

Table 23: Determinants of information asymmetries - II

	(1)	(2)	(3)	(4)
Coefficient	β^{FE}	β^{FE}	β^{FE}	β^{Disag}
Foreign	–0.04***	0.30	–0.17	
	(0.01)	(0.21)	(0.20)	
ln(sd(Fundamental))	0.01	0.00		0.04
	(0.02)	(0.02)		(0.05)
Institutions	0.01**	0.01**		–0.00
	(0.00)	(0.00)		(0.01)
ln(GDP)	0.03***	0.04***		–0.04**
	(0.01)	(0.01)		(0.02)
Foreign × ln(sd(Fundamental))		0.01	0.02	
		(0.03)	(0.03)	
Foreign × Institutions		–0.01	0.00	
		(0.01)	(0.01)	
Foreign × ln(GDP)		–0.02	0.01	
		(0.01)	(0.01)	
N	2,403	2,403	2,403	1,223
R^2	0.47	0.47	0.63	0.04
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-effect specifications. Fundamental is either CPI or GDP. All standard errors are clustered on the country level.

G Proofs

G.1 Proof of Proposition 1

The model can be written as follows:

$$\begin{aligned} x_{jt} &= \rho_j x_{jt-1} + \epsilon_{jt} \\ s^m_{ijt} &= x_{jt} + v^m_{ijt} \end{aligned} \tag{17}$$

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

$$\Phi^m_{ij} = \rho_j^2[\Phi^m_{ij} - \Phi^m_{ij}(\Phi^m_{ij} + (\lambda^m_{ij})^{-1})^{-1}\Phi^m_{ij}] + \gamma_j^{-1}.$$

Denote the gain of the Kalman filter with

$$G^m_{ij} = \Phi^m_{ij}(\Phi^m_{ij} + (\lambda^m_{ij})^{-1})^{-1}.$$

Substituting in the Riccati equation, we obtain

$$\Phi^m_{ij} = \rho_j^2(1 - G^m_{ij})\Phi^m_{ij} + \gamma_j^{-1},$$

hence the first result.

Now denote the nowcast error in the Kalman filter with $\Omega^m_{ij} = V(Error^m_{ijt,t}) = V[x_{jt} - E^m_{ijt}(x_{jt})]$ We can use recursions of the Kalman filter to relate Ω^m_{ij} and Φ^m_{ij}:

$$\Omega^m_{ij} = \Phi^m_{ij} - G^m_{ij}(\Phi^m_{ij} + (\lambda^m_{ij})^{-1})G^{m\prime}_{ij}$$

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:

$$\Phi_{ij}^m = \frac{1}{2}\left(\gamma_j^{-1} - (1-\rho_j^2)(\lambda_{ij}^m)^{-1} + \sqrt{(\gamma_j^{-1} - (1-\rho_j^2)(\lambda_{ij}^m)^{-1})^2 + 4\gamma_j^{-1}}\right) \tag{18}$$

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.

G.2 Proof of Proposition 2

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

$$E_{ijt}^m(x_{jt}) = \frac{G_{ij}^m}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}s_{ijt}^m \tag{19}$$

Forecast revision can then be written as

$$\begin{aligned}Revision_{ijt}^m &= E_{ijt}^m(x_{jt}) - E_{ijt-1}^m(x_{jt}) \\ &= E_{ijt}^m(x_{jt}) - \hat{\rho}_{ij}E_{ijt-1}^m(x_{jt-1}) \\ &= \tfrac{G_{ij}^m[1-\hat{\rho}_{ij}L]}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}s_{ijt}^m \\ &= \tfrac{G_{ij}^m[1-\hat{\rho}_{ij}L]}{1-(1-G_{ij}^m)\hat{\rho}_{ij}L}(x_{jt} + v_{ijt}^m)\end{aligned} \tag{20}$$

and the error as

$$
\begin{aligned}
Error^m_{ijt,t} &= x_{jt} - E^m_{ijt}(x_{jt}) \\
&= x_{jt} - \frac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L} s^m_{ijt} \\
&= \left(1 - \frac{G^m_{ij}}{1-(1-G^m_{ij})\rho_{ij}L}\right) x_{jt} - \frac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L} v^m_{ijt}
\end{aligned}
\tag{21}
$$

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:

$$
\tilde{E}rror^m_{ijt,t} = \left(1 - \frac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}\right)\tilde{x}_{ijt} - \frac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}\tilde{v}^m_{ijt} \tag{22}
$$

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:

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

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:

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

We used

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

We thus have

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

and

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

with

$$\begin{aligned} V(Revision_{ijt}^m) = & \frac{(G_{ij}^m)^2}{1-\frac{\hat{\rho}_{ij}}{\rho_j}(1-G_{ij}^m)} \left(\frac{G_{ij}^m \frac{\hat{\rho}_{ij}}{\rho_j}[1-\hat{\rho}_{ij}^2(1-G_{ij})]}{[1-\rho_j\hat{\rho}_{ij}(1-G_{ij})][1-\hat{\rho}_{ij}^2(1-G_{ij})^2]} - (\hat{\rho}_{ij}-\rho_j)\frac{1-\rho_j\hat{\rho}_{ij}}{[1-\rho_j\hat{\rho}_{ij}(1-G_{ij})](1-\rho_j^2)} \right) \\ & +(G_{ij}^m)^2 \left(1+\left(\frac{G_{ij}^m}{1-G_{ij}^m}\right)^2 \frac{\hat{\rho}_{ij}^2(1-G_{ij}^m)^2}{1-\hat{\rho}_{ij}^2(1-G_{ij}^m)^2}\right)[(h_{ij}^m)^2\kappa_j^{-1}+(1-h_{ij}^m)^2\tau_{ij}^{-1}] \end{aligned}$$

Here we used

$$\begin{aligned} Revision_{ijt}^m = & \frac{G_{ij}^m}{1-\frac{\hat{\rho}_{ij}}{\rho_j}(1-G_{ij}^m)} \left(\frac{\hat{\rho}_{ij}}{\rho_j} \sum_{s=0}^{+\infty}(1-G_{ij}^m)^s \hat{\rho}_{ij}^s L^s - \left(\frac{\hat{\rho}_{ij}}{\rho_j}-1\right) \sum_{s=0}^{+\infty} \rho_j^s L^s \right) \epsilon_{jt} \\ & +G_{ij}^m \left(1-\frac{G_{ij}^m}{1-G_{ij}^m} \sum_{s=1}^{+\infty}(1-G_{ij}^m)^s \hat{\rho}_{ij}^s L^s\right) v_{ijt}^m \end{aligned}$$

G.3 Proof of Corollary 1

We simply note here that β_{1ij}^m and β_{2ij}^m, evaluated at $(\hat{\tau}_{ij}^m)^{-1} = (\tau_{ij}^m)^{-1} = (\tau_j^m)^{-1}$ and $\hat{\rho}_{ij} = \rho_j$, are both strictly positive, while $\hat{\rho}_{ij} - \rho_j$ and $(\tau_{ij}^m)^{-1} - (\hat{\tau}_{ij}^m)^{-1}$ are both equal to zero for $\hat{\tau}_{ij}^m = \tau_{ij}^m = \tau_j^m$ and $\hat{\rho}_{ij} = \rho_j$.

More specifically, note that β_{1ij}^m and β_{2ij}^m are functions of the parameters, so we denote $\beta_{1ij}^m = g_1\left((\hat{\tau}_{ij}^m)^{-1}, (\tau_{ij}^m)^{-1}, \hat{\rho}_{ij}, \rho_j\right)$ and $\beta_{2ij}^m = g_2\left((\hat{\tau}_{ij}^m)^{-1}, (\tau_{ij}^m)^{-1}, \hat{\rho}_{ij}, \rho_j\right)$. The first-order Taylor expansion for β_{ij}^{BGMSm} around $(\hat{\tau}_{ij}^m)^{-1} = (\tau_{ij}^m)^{-1} = (\tau_j^m)^{-1}$ and $\hat{\rho}_{ij} = \rho_j$ is

$$\beta_{ij}^{BGMSm} \simeq -(\hat{\rho}_{ij}-\rho_j) g_1\left((\tau_j^m)^{-1}, (\tau_j^m)^{-1}, \rho_j, \rho_j\right) - [(\tau_{ij}^m)^{-1} - (\hat{\tau}_{ij}^m)^{-1}] g_2\left((\tau_j^m)^{-1}, (\tau_j^m)^{-1}, \rho_j, \rho_j\right)$$

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

G.4 Proof of Proposition 3

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

$$\beta_{jk}^{CGm} = \frac{Cov\left(Error_{jkt}^m, Revision_{jkt}^m\right)}{V\left(Revision_{jkt}^m\right)} \tag{23}$$

And we can write:

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

with $\tilde{E}rror^m_{jkt} = \frac{1}{N^k(j)} \sum_{i \in S^k(j)} \tilde{E}rror^m_{ijt}$ where $\tilde{E}rror^m_{ijt}$ is defined in (22).

We have

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

Here we used

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

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

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

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

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

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

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

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

G.5 Proof of Proposition 4

Consider Equations (20) and (21). We can rewrite them as follows:

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

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

$$\begin{aligned}
\beta_{jk}^{FEm} &= \frac{Cov\left(-\frac{G_{jk}^m}{1-(1-G_{jk}^m)\hat{\rho}_{jk}L}(1-h_{jk}^m)(\tau_{jk}^m)^{-1/2}e_{ijkt}^m, \frac{G_{jk}^m[1-\hat{\rho}_{jk}L]}{1-(1-G_{jk}^m)\hat{\rho}_{jk}L}(1-h_{jk}^m)(\tau_{jk}^m)^{-1/2}e_{ijkt}^m\right)}{V\left(\frac{G_{jk}^m[1-\hat{\rho}_{jk}L]}{1-(1-G_{jk}^m)\hat{\rho}_{jk}L}(1-h_{jk}^m)(\tau_{jk}^m)^{-1/2}e_{ijkt}^m\right)} \\
&= \frac{-(G_{jk}^m)^2\left(1-\frac{G_{jk}^m}{1-G_{jk}^m}\frac{\hat{\rho}_{jk}^2(1-G_{jk}^m)^2}{1-\hat{\rho}_{jk}^2(1-G_{jk}^m)^2}\right)(1-h_{jk}^m)^2(\tau_{jk}^m)^{-1}}{(G_{jk}^m)^2\left(1+\left(\frac{G_{jk}^m}{1-G_{jk}^m}\right)^2\frac{\hat{\rho}_{jk}^2(1-G_{jk}^m)^2}{1-\hat{\rho}_{jk}^2(1-G_{jk}^m)^2}\right)(1-h_{jk}^m)^2(\tau_{jk}^m)^{-1}}
\end{aligned}$$

Hence the result.

G.6 Proof of Proposition 5

We can write $Disagreement_{jt}$, $Revisionjt$ 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 (18) to compute this derivative:

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

$h_{jk}^m G_{jk}^m$ 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 $\hat{\tau}_{jk}^m$. As a consequence, $h_{jk}^m G_{jk}^m$ is decreasing in $\hat{\tau}_{jk}^m$. Therefore, for a given $(\hat{\tau}_{jk}^m)^{-1} - (\tau_{jk}^m)^{-1}$, $h_{jk}^m G_{jk}^m$ is decreasing in τ_{jk}^m. If the foreign and local forecasters have the same behavioral biases $\hat{\rho}_{jk}$ and $(\hat{\tau}_{jk}^m)^{-1} - (\tau_{jk}^m)^{-1}$, then differences in $h_{jk}^m G_{jk}^m$ reflect differences in τ_{jk}^m

Table 11: Forecast Error and Information Asymmetries - Drivers II

	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient						
Foreign	–0.05	–0.02	–0.00	0.08***	0.06***	–0.17
	(0.04)	(0.03)	(0.03)	(0.02)	(0.01)	(0.29)
ln(Distance)	0.03***	0.03**	0.03	0.01*	0.01	0.00
	(0.01)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)
Institutions	–0.02	–0.04*	–0.04**	–0.25***		
	(0.02)	(0.02)	(0.02)	(0.07)		
ln(GDP)	–0.11***	–0.10***	–0.09***	–0.46		
	(0.02)	(0.02)	(0.03)	(0.37)		
ln(sd(Fundamental))	0.55***	0.47***	0.46***			
	(0.10)	(0.10)	(0.11)			
Finance	–0.07***	–0.07***				
	(0.02)	(0.02)				
ln(sd(Return))	0.29***	0.16***	0.12**	0.06*		
	(0.05)	(0.06)	(0.05)	(0.04)		
VIX	0.01***					
	(0.00)					
Foreign × ln(Distance)						–0.01
						(0.01)
Foreign × Institutions						–0.00
						(0.01)
Foreign × ln(GDP)						0.02*
						(0.01)
Foreign × ln(sd(Fundamental))						–0.03
						(0.03)
Foreign × Finance						–0.02
						(0.02)
Foreign × ln(sd(Return))						0.02
						(0.02)
Foreign × VIX						0.00
						(0.00)
N	529,067	529,067	529,004	529,004	388,415	347,278
R^2	0.09	0.30	0.33	0.37	0.70	0.70
Date × Variable × Horizon FE	No	Yes	Yes	Yes	No	No
Forecaster × Variable × Horizon FE	No	No	Yes	Yes	No	No
Country × Variable × Horizon FE	No	No	No	Yes	No	No
Country × Date × Variable × Horizon FE	No	No	No	No	Yes	Yes
Forecaster × Date × Variable × Horizon FE	No	No	No	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, forecaster and date level.

E Robustness Appendix

Table 19: Robustness Checks - Summary Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
		Vintages September		**Vintages April**		**Local and Foreign**		**Trimming**		**Headquarter**	
$\ln(\lvert Error^m_{ijt,t}\rvert)$	Foreign	0.09***	0.05**	0.08***	0.05**	0.08***	0.06**	0.10***	0.06**	0.06	0.08**
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)
	N	99,228	103,722	91,844	95,826	70,885	74,550	99,791	104,645	99,228	103,866
BGMS Regression	Average Locals	0.04***	0.10***	0.03***	0.11***	0.03***	0.08***	0.03***	0.08***	0.04**	0.11***
		(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
	Foreign	0.00	0.05	0.00	0.02	0.02	0.01	0.00	0.04	–0.02	–0.02
		(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)
	N	4,979	5,357	4,457	4,772	1,875	2,056	5,012	5,431	4,979	5,373
Over-Extrapolation	Average Locals	0.39***	0.37***	0.39***	0.36***	0.39***	0.35***	0.39***	0.35***	0.38***	0.37***
		(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
	Foreign	0.03	0.03	0.03	0.05**	0.03	0.04	0.03	0.03	0.02	–0.02
		(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	N	3,808	4,006	3,359	3,562	6,097	6,535	6,137	6,584	6,097	6,535
Information Asymmetries	Average Locals	–0.29***	–0.32***	–0.29***	–0.32***	–0.29***	–0.32***	–0.29***	–0.32***	–0.29***	–0.34***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)
	Foreign	–0.05***	–0.02	–0.04***	–0.03	–0.05***	–0.02	–0.05***	–0.02	–0.02	0.03
		(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)
	N	1,196	1,207	1,187	1,198	1,196	1,207	1,200	1,207	1,028	1,038
Disagreement	Disagreement	–0.09***	–0.07**	–0.10***	–0.07***	–0.06**	–0.06**	–0.10***	–0.07**	–0.04	–0.07*
		(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
	N	611	612	611	612	592	597	611	612	548	550

Notes: This table shows the results of several robustness checks. In columns (2) and (3), we use alternative vintage series that were published in September of the year following the forecast. In columns (4) and (5), we use vintage series that were published in April two years after the forecast. In columns (6) and (7), we only use forecasters that forecast for both countries where they are foreign and local. In columns (8) and (9), we use a less conservative trimming strategy to remove outliers for inflation and GDP forecasts. In columns (10) and (11), we only use the headquarter of the forecaster to identify whether the forecaster is local or foreign. For each of these robustness checks, we reproduce the results of tables 4, 5, 6, 8 and 9.