Do Local Forecasters Have Better Information? Online Appendix

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A 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, $\sigma^2_{\mathrm{FE}_{\mathrm{Local}}} \neq \sigma^2_{\mathrm{FE}_{\mathrm{Foreign}}}$.[1]

[1] 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 A.1: 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 A.1 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.

B Robustness analysis

We perform robustness tests where (i) we use alternative vintage series to compute the forecast errors, (ii) we include only forecasters who produce forecasts for both local and foreign forecasts, (iii) we use alternative trimming strategies, (iv) we exclude forecasts that are identical to their previous release and (vi) use an alternative definition of Foreign forecasters. We replicate the results of Table **??** and Table **??** under these different specifications. The results are very stable across these different exercises.

In addition, in Table B.2 we provide an additional robustness check for our results of the panel regression **??** using Driscoll and Kraay (1998) standard errors.

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 an alternative series of the actual outcome of GDP and inflation.

We use the data published in April two years after the forecast date. For a forecast submitted in October 2011 for the year 2011 (t) and for 2012 ($t+1$), we use the data published in April 2013 and in April 2014 to calculate the forecast error for 2011 (t) and 2012 ($t+1$).

The results are displayed in Columns (2) to (3) of Table B.1, for inflation and GDP. Overall, the results are robust across this 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 and report them in Columns (4) and (5) of Table B.1. Overall, the findings are very similar to the baseline results.

Alternative Trimming Strategy. In the main text, we remove 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 (6) and (7) of table B.1 and are similar.

Distinct Forecasts. In columns (8) and (9), we re-estimate our main results using only those forecasts that differ from the previous forecast. Forecasters may publish a forecast without necessarily updating it. Conditioning on those forecasts that differ from the last publication, we are assure that the forecasts reveal new information. The results using this subsample remain very similar to the results from the main text.

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 (10) and (11) of table B.1. 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.

Alternative Clustering. For our main panel regression of equation **??**, we report alternative standard errors in Table B.2. We use Driscoll and Kraay (1998) with various bandwidths, including the rule-of-thumb $\mathbf{BW} = 4(T/100)^{2/9} = 5$. These standard errors are robust to disturbances that are common to the forecasters and that are autocorrelated. The results are very similar to our baseline specification with clustered standard errors.

Table B.1: Robustness Checks - Summary Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
		Vintages April		**Local and Foreign**		**Trimming**		**Distinct Forecasts**		**Headquarter**	
		CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t
$\ln(\lvert Error^m_{ijt,t}\rvert)$	Foreign	0.08***	0.05**	0.09***	0.05**	0.10***	0.06**	0.08***	0.06**	0.06	0.08**
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.04)	(0.04)
	N	91,844	95,826	88,098	92,454	99,791	104,645	54,654	58,157	99,228	103,866
β^{BGMS}	Average Locals	0.01	0.07***	0.01*	0.03***	0.01**	0.04***	0.01**	0.04***	0.02	0.06***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
	Foreign	–0.01	0.02	–0.00	0.03	–0.00	0.04*	–0.01	0.03	–0.01	–0.01
		(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	N	2,613	2,813	2,858	3,093	3,090	3,380	3,067	3,333	3,067	3,333
$\hat{\rho}$	Average Locals	0.40***	0.37***	0.40***	0.37***	0.41***	0.37***	0.40***	0.38***	0.39***	0.41***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
	Foreign	0.03	0.05**	0.03	0.03	0.03	0.03*	0.03	0.04	0.02	–0.02
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	N	3,423	3,628	3,635	3,880	3,967	4,227	3,937	4,196	3,937	4,196
β^{CG}	Average Locals	0.04***	0.12***	0.05***	0.08***	0.04***	0.10***	0.04***	0.10***	0.04***	0.10***
		(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
	Foreign	–0.00	–0.01	0.00	0.00	–0.01	–0.01	–0.00	–0.01	0.01	–0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	N	1,214	1,224	1,164	1,180	1,220	1,224	1,214	1,224	1,004	1,022
β^{FE}	Average Locals	–0.25***	–0.31***	–0.60***	–0.30***	–0.60***	–0.31***	–0.60***	–0.32***	–0.24***	–0.29***
		(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
	Foreign	–0.04***	–0.02	–0.04***	–0.03*	–0.05***	–0.03*	–0.04***	–0.02*	–0.02	0.00
		(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	N	1,104	1,124	1,030	1,066	1,150	1,162	1,138	1,160	792	812
β^{Dis}	Average	–0.09***	–0.05***	–0.09***	–0.08***	–0.07***	–0.07***	–0.08***	–0.07***	–0.01	–0.09*
		(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.05)
	N	579	591	556	566	593	604	592	604	484	493

Notes: This table shows the results of several robustness checks. In columns (2) and (3), we use an alternative vintage series to calculate the forecast error that was published in April of the subsequent year of the forecast. In columns (4) and (5), we restrict the sample to forecasters that forecast for both countries where they are foreign and local. In columns (6) and (7) we use a less conservative trimming strategy to remove outliers for inflation and GDP forecasts. In columns (8) and (9) we restrict the sample to distinct forecasts only. 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 **??** column (2) and all the regressions displayed in table **??**.

Table B.2: Forecast Errors $\ln(|Error^{m}_{ijt,t}|)$ using Driscoll-Kraay Standard Errors with different Bandwidths

		Entire Sample				Distinct Updates			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Coefficient	BW 4	BW 5	BW 6	BW 7	BW 4	BW 5	BW 6	BW 7
CPI_t	Foreign	0.09***	0.09***	0.09***	0.09***	0.08***	0.08***	0.08***	0.08***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
	N	99,228	99,228	99,228	99,228	54,654	54,654	54,654	54,654
GDP_t	Foreign	0.06**	0.06**	0.06**	0.06**	0.06**	0.06**	0.06**	0.06**
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	N	103,866	103,866	103,866	103,866	103,866	103,866	103,866	103,866
CPI_{t+1}	Foreign	0.07***	0.07***	0.07***	0.07***	0.07***	0.07***	0.07***	0.07***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	N	90,693	90,693	90,693	90,693	90,693	90,693	90,693	90,693
GDP_{t+1}	Foreign	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	N	95,508	95,508	95,508	95,508	95,508	95,508	95,508	95,508
	Country × Date FE	✓	✓	✓	✓	✓	✓	✓	✓
	Forecaster × Date FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Columns (1) to (4) show the regression of the log absolute forecast error on the location of the forecaster using different bandwidths. Columns (5) to (6) show the same regression using the subsample of the published forecasts that are distinct from the last published one, again for different bandwidths.

C Tables

Table C.1: 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 C.2: Development Status of all Countries

	Country	DS*		Country	DS*		Country	DS*
1	Argentina	Emerging	18	Hungary	Emerging	35	Poland	Emerging
2	Austria	Developed	19	India	Emerging	36	Portugal	Developed
3	Belgium	Developed	20	Indonesia	Emerging	37	Romania	Emerging
4	Brazil	Emerging	21	Ireland	Developed	38	Russia	Emerging
5	Bulgaria	Emerging	22	Israel	Emerging	39	Saudi Arabia	Emerging
6	Canada	Developed	23	Italy	Developed	40	Slovakia	Emerging
7	Chile	Emerging	24	Japan	Developed	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	Developed
11	Czech Republic	Emerging	28	Mexico	Emerging	45	Sweden	Developed
12	Denmark	Developed	29	Netherlands	Developed	46	Switzerland	Developed
13	Estonia	Emerging	30	New Zealand	Developed	47	Thailand	Emerging
14	Finland	Developed	31	Nigeria	Emerging	48	Turkey	Emerging
15	France	Developed	32	Norway	Developed	49	United Kingdom	Developed
16	Germany	Developed	33	Peru	Emerging	50	United States	Developed
17	Greece	Developed	34	Philippines	Emerging	51	Venezuela	Emerging

* Development Status

Table C.3: Standard Deviation of Forecast Errors and the Location of the Forecaster - Alternative fixed effects

		$\ln(\sigma^m_{\mathrm{FE},i,j})$			
					Baseline
Variable	Coefficient	(1)	(2)	(3)	(4)
CPI_t	Foreign	0.22**	0.10***	0.12**	0.12**
		(0.09)	(0.03)	(0.05)	(0.05)
	N	6,671	6,671	6,662	6,662
	R^2	0.01	0.46	0.50	0.80
GDP_t	Foreign	0.25***	0.04*	0.10**	0.09**
		(0.08)	(0.02)	(0.05)	(0.04)
	N	7,139	7,139	7,131	7,131
	R^2	0.02	0.49	0.52	0.88
	Country FE		✓	✓	✓
	Forecaster FE			✓	✓
	Month FE				✓

Notes: Columns (1) to (4) show the regression of the log standard deviation of the errors on the location of the forecaster with different fixed-effect specifications. Standard errors are clustered at the country and forecaster levels.

Table C.4: Absolute Forecast Errors and the Location of the Forecaster - Alternative fixed effects

		$\ln(\lvert Error^m_{ijt,t}\rvert)$				
						Baseline
Variable	Coefficient	(1)	(2)	(3)	(4)	(5)
CPI_t	Foreign	0.26***	0.09***	0.10***	0.10***	0.09***
		(0.08)	(0.03)	(0.03)	(0.02)	(0.02)
	N	153,089	153,089	153,066	152,886	99,228
	R^2	0.01	0.11	0.14	0.55	0.62
GDP_t	Foreign	0.27***	0.02	0.11***	0.06**	0.06**
		(0.08)	(0.03)	(0.03)	(0.02)	(0.02)
	N	160,971	160,971	160,947	160,765	103,866
	R^2	0.01	0.13	0.15	0.60	0.66
	Country FE		✓	✓		
	Forecaster FE			✓	✓	
	Country × Date FE				✓	✓
	Forecaster × Date FE					✓

Notes: Columns (1) to (5) show the regression of the log absolute forecast error on the location of the forecaster with different fixed-effect specifications. Standard errors are clustered at the country, forecaster and date level.

Table C.5: Updating and the Location of the Forecaster - Alternative fixed effects

		$\ln(N_{ijt})$				
						Baseline
Variable	Coefficient	(1)	(2)	(3)	(4)	(5)
	Foreign	–0.03	0.01	–0.14***	–0.14***	–0.12***
		(0.06)	(0.05)	(0.04)	(0.04)	(0.04)
	N	16,427	16,427	16,346	16,334	10,857
	R^2	0.00	0.05	0.23	0.36	0.53
	Foreign	–0.04	0.01	–0.13***	–0.12***	–0.10***
		(0.06)	(0.05)	(0.04)	(0.04)	(0.03)
	N	17,091	17,091	17,008	16,997	11,240
	R^2	0.00	0.04	0.23	0.36	0.54
	Country FE		✓	✓		
	Forecaster FE			✓	✓	
	Country × Year FE				✓	✓
	Forecaster × Year FE					✓

Notes: Columns (1) to (5) show the regression of the number of forecast updates within a year on the location of the forecaster with different fixed-effect specifications. Standard errors are clustered at the country and forecaster levels.

Table C.6: Forecast Errors, Updating, and the Location of the Forecaster - Forecasts on the Future Year

		$\ln(\sigma^m_{\mathrm{FE},i,j})$	$\ln(\lvert Error^m_{ijt,t}\rvert)$		$\ln(N_{ijt})$	
Variable	Coefficient	(1)	(2)	(3) Distinct updates	(4)	(5) Distinct updates
CPI_{t+1}	Foreign	0.07*	0.07***	0.05**	–0.11***	–0.12***
		(0.04)	(0.02)	(0.02)	(0.04)	(0.04)
	N	6,134	90,693	48,937	10,082	10,082
	R^2	0.86	0.67	0.71	0.53	0.51
GDP_{t+1}	Foreign	0.06**	0.01	0.01	–0.10**	–0.10***
		(0.03)	(0.02)	(0.02)	(0.04)	(0.03)
	N	6,565	95,508	51,379	10,464	10,464
	R^2	0.86	0.72	0.76	0.53	0.52
	Country, For., Month FE	✓				
	Country × Year FE				✓	✓
	Forecaster × Year FE				✓	✓
	Country × Date FE		✓	✓		
	Forecaster × Date FE		✓	✓		

Notes: Column (1) shows the regression of the log standard deviation of the errors on the location of the forecaster. Columns (2) and (3) show the regression of the log absolute forecast error on the location of the forecaster. Columns (4) and (5)) show the results of regression of the number of forecast updates within a year on the location of the forecaster. Standard errors are clustered at the country and forecaster level in columns (1), (4) and (5), and at the country, forecaster and date level in Columns (2) and (3). In Columns (3) and (5), the sample is restricted to the published forecasts that are distinct from the last published one.

Table C.7: Over-reaction - Aternative MG and Fixed Effects

	β^{BGMS}							
							Baseline	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t
Average Locals	0.00	0.06***	0.01	0.03***	0.01*	0.05***	0.01**	0.04***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Foreign	–0.00	–0.02	–0.00	0.03	–0.00	0.03	–0.01	0.03
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	102	102	364	393	4,979	5,373	3,067	3,333
R^2	0.94	0.92	0.66	0.73	0.45	0.43	0.65	0.72
Country FE	✓	✓	✓	✓	✓	✓		
Forecaster FE			✓	✓	✓	✓		
Month FE					✓	✓		
Ctry × month FE							✓	✓
For. × month FE							✓	✓
MG by ctry and loc.	✓	✓						
MG by ctry and for.			✓	✓				
MG by ctry, for., and month					✓	✓	✓	✓

Notes: Columns (1) to (8) show the results of a regression of the β^{BGMS} coefficients on the Foreign dummy, where the β^{BGMS} are estimated using Equation (**??**) with different fixed effects and mean-groups. The observations are clustered at the country level in Columns (1) and (2), and at the country and forecaster levels in Columns (3) to (8). All observations are weighted by the inverse of the estimated standard error of the β^{BGMS} coefficient.

Table C.8: Overextrapolation - Aternative MG and Fixed Effects

	$\hat{\rho}$							
							Baseline	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t
Average Locals	0.42***	0.37***	0.41***	0.36***	0.38***	0.36***	0.40***	0.38***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Foreign	0.00	0.01	0.04	0.03	0.04*	0.03	0.03	0.04
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	102	102	404	428	6,095	6,535	3,937	4,196
R^2	0.95	0.93	0.67	0.76	0.57	0.69	0.63	0.72
Country FE	✓	✓	✓	✓	✓	✓		
Forecaster FE			✓	✓	✓	✓		
Month FE					✓	✓		
Ctry $\times$ month FE							✓	✓
For. $\times$ month FE							✓	✓
MG by ctry and loc.	✓	✓						
MG by ctry and for.			✓	✓				
MG by ctry, for., and month					✓	✓	✓	✓

Notes: Columns (1) to (8) show the results of a regression of the perceived autocorrelation coefficients $\hat{\rho}$ on the Foreign dummy, where the $\hat{\rho}$ is estimated using Equation (**??**) with different fixed effects and mean-groups. The observations are clustered at the country level in Columns (1)) and (2), and at the country and forecaster levels in Columns (3) to (8). All observations are weighted by the inverse of the estimated standard error of the $\hat{\rho}$ coefficient.

Table C.9: Past consensus - Aternative MG and Fixed Effects

	$\beta^{PastConsensus}$							
							Baseline	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t
Average Locals	0.03***	0.01**	0.03***	–0.01***	0.02***	0.00	0.02***	–0.01***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Foreign	0.01	–0.01	–0.02	0.01	–0.00	0.02	–0.00	0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
N	102	102	376	397	5,852	6,247	3,750	3,947
R^2	0.93	0.89	0.69	0.71	0.43	0.31	0.66	0.68
Country FE	✓	✓	✓	✓	✓	✓		
Forecaster FE			✓	✓	✓	✓		
Month FE					✓	✓		
Ctry × month FE							✓	✓
For. × month FE							✓	✓
MG by ctry and loc.	✓	✓						
MG by ctry and for.			✓	✓				
MG by ctry, for., and month					✓	✓	✓	✓

Notes: Columns (1) to (8) show the results of a regression of the $\beta^{PastConsensus}$ coefficients on the Foreign dummy, where the $\beta^{PastConsensus}$ are estimated using $Error^m_{ijt} = \beta^{PastConsensus,m}_{ij} E^{m-1}_{jt}(x_{jt}) + \delta^m_{ij} + \lambda^m_{ijt}$, with different fixed effects and mean-groups. The observations are clustered at the country level in Columns (1) and (2), and at the country and forecaster levels in Columns (3) to (8). All observations are weighted by the inverse of the estimated standard error of the $\beta^{PastConsensus}$ coefficient.

Table C.10: Last Vintage - Aternative MG and Fixed Effects

	$\beta^{LastVintage}$							
							Baseline	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t
Average Locals	–0.00	–0.09***	0.01**	–0.08***	0.01***	–0.06***	0.00**	–0.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Foreign	–0.00	–0.01*	0.00	–0.01	0.00	–0.01	–0.00	–0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
N	102	102	378	396	5,312	5,607	3,299	3,428
R^2	0.91	0.94	0.67	0.72	0.45	0.54	0.66	0.73
Country FE	✓	✓	✓	✓	✓	✓		
Forecaster FE			✓	✓	✓	✓		
Month FE					✓	✓		
Ctry × month FE							✓	✓
For. × month FE							✓	✓
MG by ctry and loc.	✓	✓						
MG by ctry and for.			✓	✓				
MG by ctry, for., and month					✓	✓	✓	✓

Notes: Columns (1) to (8) show the results of a regression of the $\beta^{LastVintage}$ coefficients on the Foreign dummy, where the $\beta^{LastVintage}$ are estimated using $Error^m_{ijt} = \beta^{LastVintage,m}_{ij} x_{jt-1} + \delta^m_{ij} + \lambda^m_{ijt}$, where $\frac{1}{N(j)} \sum_{i \in S(j)} E^m_{ijt}(x_{jt})$ is the average expectation across all forecasters, with different fixed effects and mean-groups. The obervations are clustered at the country level in Columns (1) and (2), and at the country and forecaster levels in Columns (3) to (8). All observations are weighted by the inverse of the estimated standard error of the $\beta^{LastVintage}$ coefficient.

Table C.11: Systematic error - Aternative MG and Fixed Effects

	$\beta^{Systematic}$							
							Baseline	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coefficient	CPI$_t$	GDP$_t$	CPI$_t$	GDP$_t$	CPI$_t$	GDP$_t$	CPI$_t$	GDP$_t$
Average Locals	–0.03***	–0.01	–0.02***	0.03***	–0.02***	0.02***	–0.02***	0.04***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Foreign	–0.01	0.02	–0.02	–0.02	–0.02*	–0.02	–0.02	–0.02
	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
N	102	102	425	448	6,662	7,131	4,332	4,568
R^2	0.96	0.94	0.76	0.74	0.57	0.61	0.73	0.72
Country FE	✓	✓	✓	✓	✓	✓		
Forecaster FE			✓	✓	✓	✓		
Month FE					✓	✓		
Ctry × month FE							✓	✓
For. × month FE							✓	✓
MG by ctry and loc.	✓	✓						
MG by ctry and for.			✓	✓				
MG by ctry, for., and month					✓	✓	✓	✓

Notes: Columns (1) to (8) show the results of a regression of the $\beta^{Systematic}$ coefficients on the Foreign dummy, where the $\beta^{Systematic}$ are estimated using $Error^m_{ijt} = \beta^{Systematic,m}_{ij} + \lambda^m_{ijt}$, with different fixed effects and mean-groups. The obervations are clustered at the country level in Columns (1) and (2), and at the country and forecaster levels in Columns (3) to (8). All observations are weighted by the inverse of the estimated standard error of the $\beta^{Systematic}$ coefficient.

Table C.12: Consensus regressions - Aternative MG and Fixed Effects

	β^{CG}					
					Baseline	
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t
Average Locals	0.06***	0.11***	0.04***	0.10***	0.04***	0.10***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Foreign	–0.01	–0.01	–0.00	–0.01	–0.00	–0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	102	102	1,218	1,224	1,214	1,224
R^2	0.92	0.93	0.54	0.54	0.87	0.90
Country FE	✓	✓	✓	✓		
Month FE			✓	✓		
Ctry × month FE					✓	✓
MG by ctry and loc.	✓	✓				
MG by ctry, loc., and month			✓	✓	✓	✓

Notes: Columns (1) to (6) show the results of a regression of the β^{CG} coefficients on the Foreign dummy, where the β^{CG} are estimated using equation (**??**) with different fixed effects and mean-groups. The obervations are clustered at the country level. All observations are weighted by the inverse of the estimated standard error of the β^{CG} coefficient.

Table C.13: Fixed-effect regressions - Aternative MG and Fixed Effects

	β^{FE}					
					Baseline	
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t	CPI_t	GDP_t
Average Locals	–0.32***	–0.36***	–0.25***	–0.31***	–0.26***	–0.32***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Foreign	–0.06***	–0.02*	–0.05***	–0.03*	–0.04***	–0.02*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
N	100	100	1,173	1,192	1,136	1,160
R^2	0.77	0.81	0.73	0.56	0.85	0.76
Country FE	✓	✓	✓	✓		
Month FE			✓	✓		
Ctry × month FE					✓	✓
MG by ctry and loc.	✓	✓				
MG by ctry, loc., and month			✓	✓	✓	✓

Notes: Columns (1) to (6) show the regression of the β^{FE} coefficients on the Foreign dummy, where the β^{FE} are estimated using Equation (**??**) with different fixed effects and mean-groups. The obervations are clustered at the country level. All observations are weighted by the inverse of the estimated standard error of the β^{FE} coefficient.

Table C.14: Disagreement regressions - Aternative MG and Fixed Effects

	β^{Dis}			
			Baseline	
	(1)	(2)	(3)	(4)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t
Average	–0.06***	–0.05***	–0.08***	–0.07***
	(0.02)	(0.02)	(0.03)	(0.02)
N	51	51	592	604
R^2	0.00	0	0.00	0
MG by ctry	✓	✓		
MG by ctry and month			✓	✓

Notes: Columns (1) to (4) show the regression of the β^{Dis} coefficients on the constant, where the β^{Dis} are estimated using Equation (**??**) with different fixed effects and mean-groups. The obervations are clustered at the country level. All observations are weighted by the inverse of the estimated standard error of the β^{Dis} coefficient.

Table C.15: Information Asymmetries - Non-multinationals only

	β^{FE}		β^{Dis}	
	(1)	(2)	(3)	(4)
Coefficient	CPI_t	GDP_t	CPI_t	GDP_t
Average			–0.13***	–0.07***
			(0.04)	(0.02)
Average Locals	–0.25***	–0.32***		
	(0.01)	(0.01)		
Foreign	–0.08**	–0.04		
	(0.03)	(0.03)		
N	470	506	412	426
R^2	0.60	0.70	0.00	0
Country × month FE	✓	✓		
Forecaster × month FE				
MG by ctry and month			✓	✓
MG by ctry, loc., and month	✓	✓		
MG by ctry, for., and month				

Notes: Columns (1) and (2) show the results of a regression of the β^{FE} coefficients on the Foreign dummy, where the β^{FE} are estimated using Equation (**??**) 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. Columns (3) and (4) show the results of a regression of the β^{Dis} coefficients on the constant, where the β^{Dis} are estimated using Equation (**??**) on different sub-groups of our sample. *Average* corresponds to the constant term. Standard errors are clustered at the country and forecaster levels in Columns (1) to (4). All observations are weighted by the inverse of the estimated standard error of the corresponding β. The sample is restricted to forecasts produced by non-multinational firms

Table C.16: Variable, Horizon, Time and Country Dependence - Separate Regressions

	$\ln(\lvert Error^{m}_{ijt,t}\rvert)$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coefficient								
Foreign	0.08***	0.07***	0.02	0.05*	0.06***	0.05**	0.06***	–0.26
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.17)
Foreign × GDP	–0.04**							
	(0.02)							
Foreign × Future		–0.03**						
		(0.01)						
Foreign × Month-of-year			0.01**					
			(0.00)					
Foreign × VIX				0.00				
				(0.00)				
Foreign × Recession					0.02			
					(0.02)			
Foreign × Emerging						0.01		
						(0.02)		
Foreign × Institutions							–0.00	
							(0.00)	
Foreign × ln(GDP)								0.02*
								(0.01)
N	389,295	389,295	389,295	389,295	389,218	389,295	375,405	379,087
R^2	0.70	0.70	0.70	0.70	0.70	0.70	0.70	0.70
Cty × Date × Var. × Hor. FE	✓	✓	✓	✓	✓	✓	✓	✓
For. × Date × Var. × Hor. FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table shows the regression of the log absolute forecast error of current and future CPI and GDP on different regressors. All standard errors are clustered at the country, forecaster and date levels.

Table C.17: Variable, Horizon, and Country Dependence - β coefficients

	β^{FE}					β^{Dis}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coefficient								
Foreign	–0.49***	–0.10***	–0.08**	–0.54	–0.54			
	(0.02)	(0.02)	(0.03)	(0.44)	(0.41)			
GDP	–0.47***					0.02		
	(0.02)					(0.03)		
Month of year	0.04***					–0.00	–0.00	
	(0.00)					(0.00)	(0.00)	
Institutions		0.01						0.00
		(0.01)						(0.01)
Emerging		–0.01						–0.00
		(0.04)						(0.06)
ln(GDP)		0.01						–0.01
		(0.01)						(0.01)
Foreign × GDP			0.04		0.09			
			(0.04)		(0.06)			
Foreign × Month of year			–0.01***		–0.01*			
			(0.00)		(0.00)			
Foreign × Institutions				–0.04**	–0.03**			
				(0.01)	(0.01)			
Foreign × Emerging				–0.02	–0.01			
				(0.07)	(0.07)			
Foreign × ln(GDP)				0.02	0.02			
				(0.02)	(0.02)			
N	1,705	1,705	1,705	1,705	1,705	1,006	1,006	1,006
R^2	0.67	0.91	0.91	0.95	0.95	0.21	0.45	0.02
Country × Variable FE			✓	✓	✓		✓	
Month-of-year × Variable FE		✓	✓	✓	✓			✓

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

Table C.18: Variable Description for Barriers to Information

Variable	Descrption	Source
Physical Distance	Calculates the shortest path, or geodesic distance, between two countries by averaging the distances between their capital cities, with each distance weighted according to the population distribution.	CEPII's GeoDist dataset (Mayer and Zignago, 2011)
Cultural Distance	The Cultural Distance measure reflects differences in current values and beliefs as initially conceptualized by Spolaore and Wacziarg (2016). It is based on responses to 98 selected questions from the World Values Survey, spanning the years 1981–2010. These questions cover areas such as personal views on life, the environment, work, family, politics, religion, and national identity. This subset, drawn from an original pool of 740 questions, was specifically chosen to ensure comparability across country pairs. To calculate cultural distance, Euclidean distances are determined for each question's responses between countries, and these distances are then averaged to create a comprehensive index.	Spolaore and Wacziarg (2016)
Linguistic Distance	Measures the distance in spoken languages between countries. It quantifies how closely related contemporary languages are based on their historical lineage. For instance, Italian and French, both derived from Latin, are more closely related than German, which comes from a different branch of the Indo-European family. This measure is calculated by counting the linguistic nodes between languages as classified by Ethnologue. It reflects potential communication challenges and information frictions that arise from language differences, impacting cross-cultural interactions.	Fearon (2003), Spolaore and Wacziarg (2016)
Business Cycle Comovement	Squared correlation of GDP growth or inflation rates between the forecaster's country and the target country, capturing cyclical alignment.	Constructed using the IMF WEO vintage data information for GDP and inflation
Migration	Share of the forecaster country's population born in the target country in 2000, measuring population links. Based on the Global Bilateral Migration Database	Özden et al. (2011)
Trade Linkages	Exports from the forecaster's headquarters country to the target country, normalized by the forecaster's country GDP, reflecting trade ties.	Trade data from CEPII's GeoDist dataset (Mayer and Zignago, 2011), national accounts
Institutions	Measures the quality of institutions in the target country performing a principal component analysis on 6 indicators from the Worldbank Worldwide Governance Indicators. Namely, we used control of corruption, government effectiveness, political stability and absence of violence/terrorism, regulatory quality, rule of law, and voice and accountability.	(Kaufmann and Kraay, 2023)
Low Cap. Controls	Indicator variable for countries with low capital controls, representing financial openness. It is calculated as the sum of the two indicators on inflow and outflow control in Fernández et al. (2016). We define having low capital controls as a dummy when this indicator is equal or below 0.1, which represents the first quartile of openness.	Fernández et al. (2016)

Notes: The table describes the additional data used for regressions in Table **??**.

D Figures

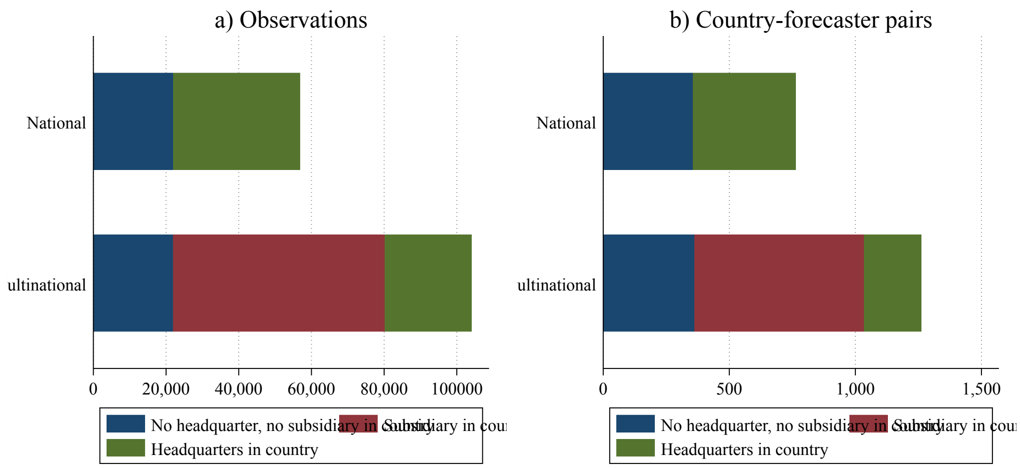


Figure D.1: Distribution of forecasts and country-forecaster pairs conditional on Location and Scope of Forecaster

Notes: The figure shows the distribution of the forecasts and country-forecaster pairs conditional on the location and scope of the forecaster. A forecast is either provided by a forecaster with headquarters located in the country, or by a forecaster with no headquarters but with at least a subsidiary located in the country, or by a forecaster with neither headquarters or subsidiaries located in the country. Multinational forecasters have subsidiaries in countries other than the one where their headquarters are located. National forecasters have only subsidiaries in the same country as their headquarters.

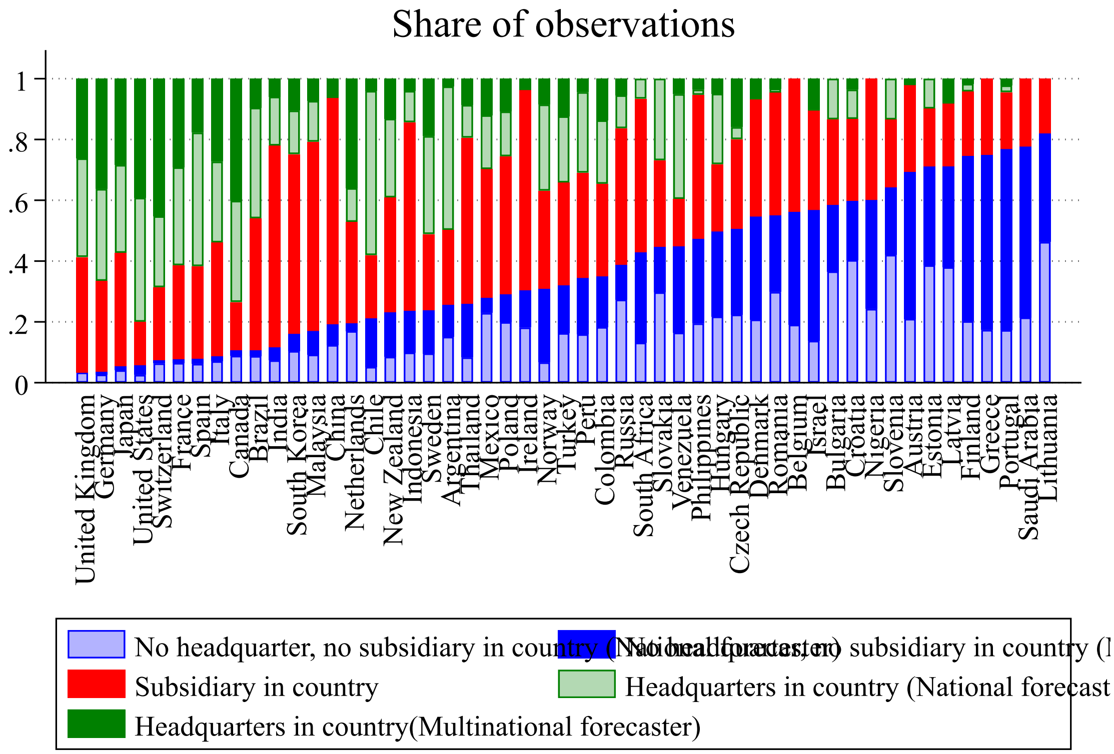


Figure D.2: Proportion of forecasts conditional on Location and Scope of Forecaster, by country

Notes: The figure shows the distribution of the forecasts conditional on the location and scope of the forecaster. A forecast is either provided by a forecaster with headquarters located in the country, or by a forecaster with no headquarters but with at least a subsidiary located in the country, or by a forecaster with neither headquarters or subsidiaries located in the country. Multinational forecasters have subsidiaries in countries other than the one where their headquarters are located. National forecasters have only subsidiaries in the same country as their headquarters.

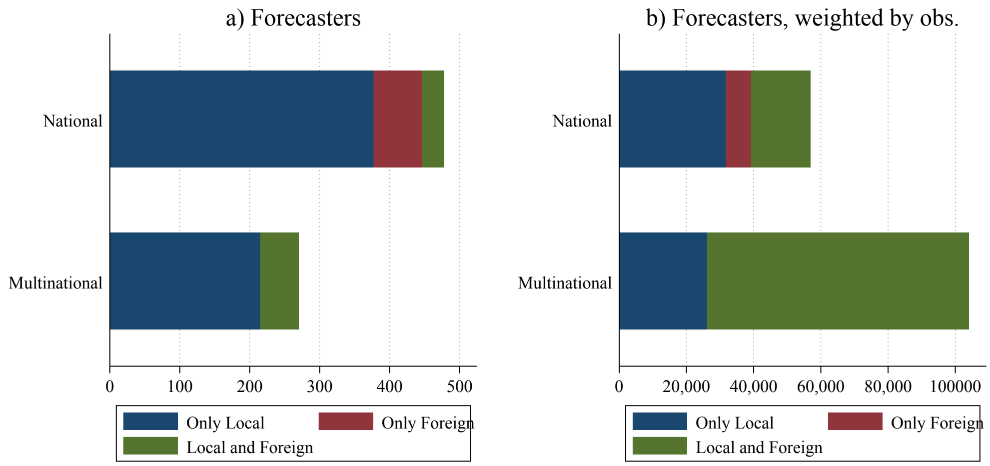


Figure D.3: Forecasters publishing Local and Foreign Forecasts

Notes: The figure shows the distribution of the forecasters depending on the nature of their forecasts. A forecaster either provides local forecasts only, or foreign forecasts only, or both local and foreign forecasts.

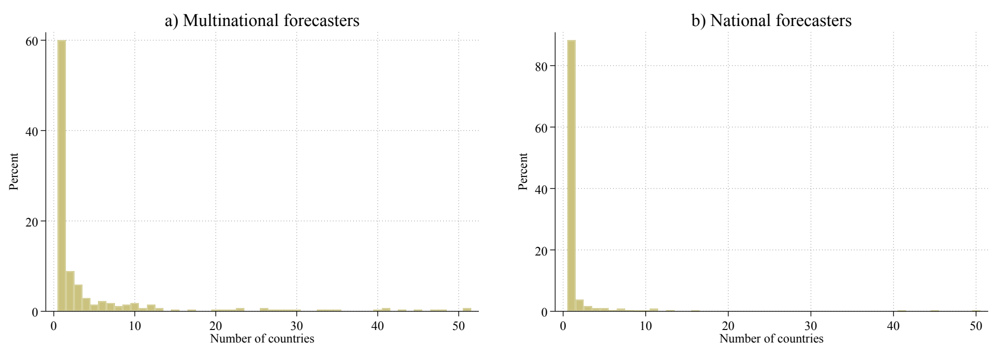
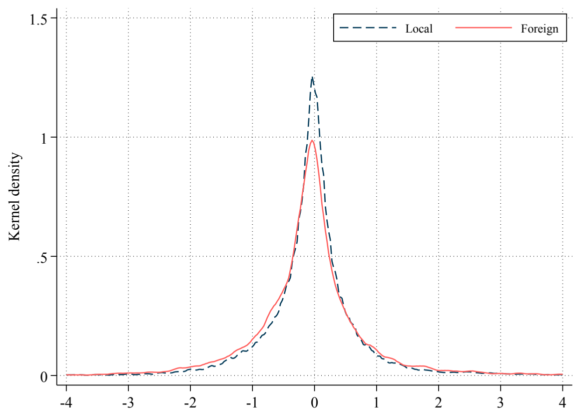
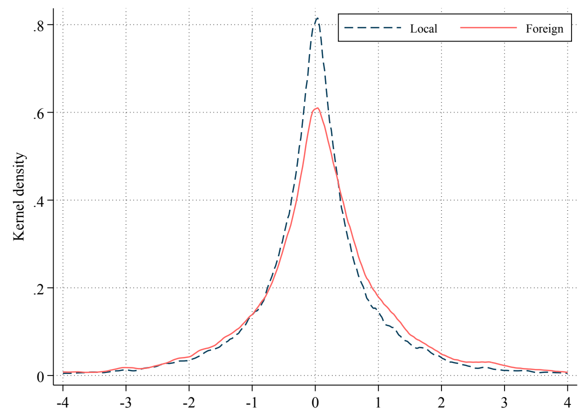


Figure D.4: Number of countries in forecasters' portfolio

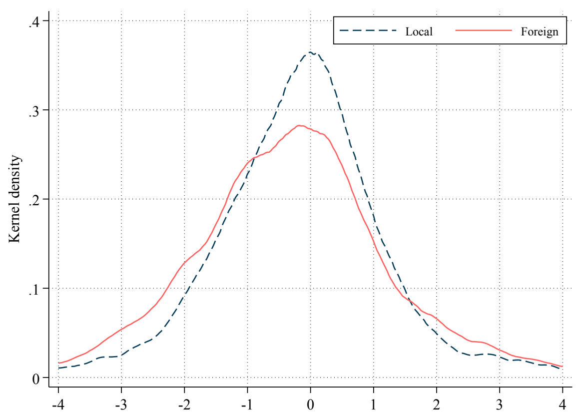
Notes: The figure shows the distribution, across forecasters, of the number of countries that are in a forecaster's portfolio, depending of the forecaster's scope (multinational or national firm). A country is in a forecaster's portfolio if the forecaster provides forecasts for that country.



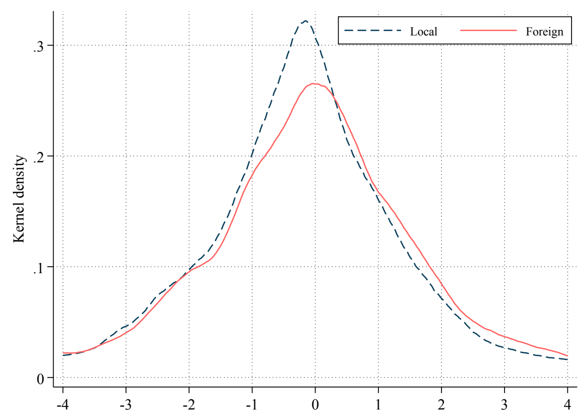
(a) $Error^{m}_{ijt,t}$: CPI$_t$



(b) $Error^{m}_{ijt,t}$. GDP$_t$



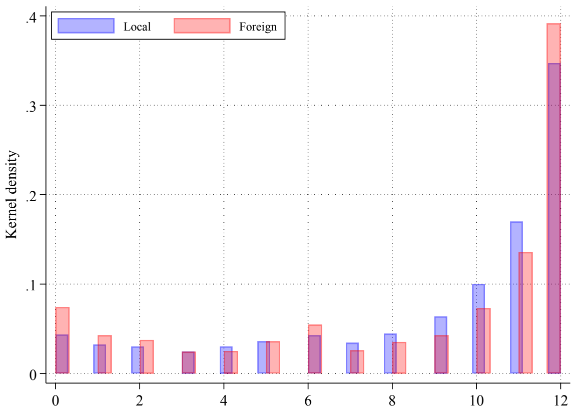
(c) $Error^{m}_{ijt,t}$: CPI$_{t+1}$



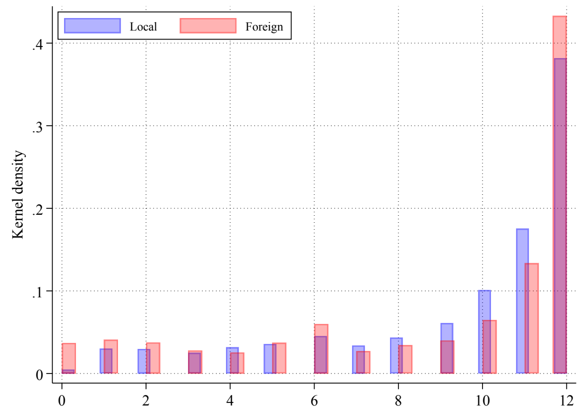
(d) $Error^{m}_{ijt,t}$. GDP$_{t+1}$

Figure D.5: Distribution of errors

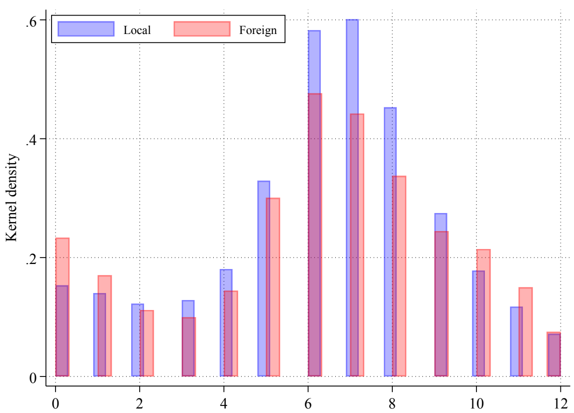
Notes: Panels (a) and (b) display the density of the current year forecast error $Error^{m}_{ijt,t}$ conditional on the location of the forecaster. Panels (c) and (d) display the density of the future year forecast error $Error^{m}_{ijt,t+1}$ conditional on the location of the forecaster. The population corresponds to all the country-forecaster-year units.



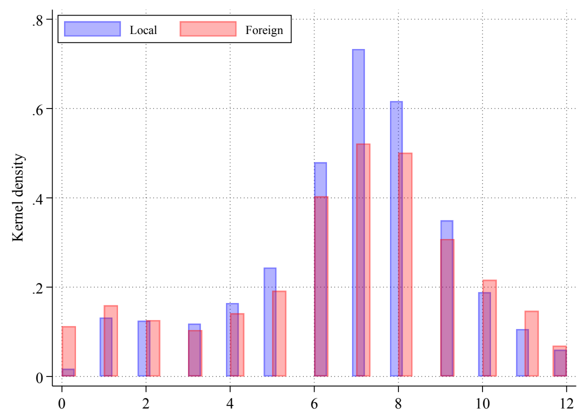
(a) N_{ijt}: CPI_t



(b) N_{ijt}: GDP_t



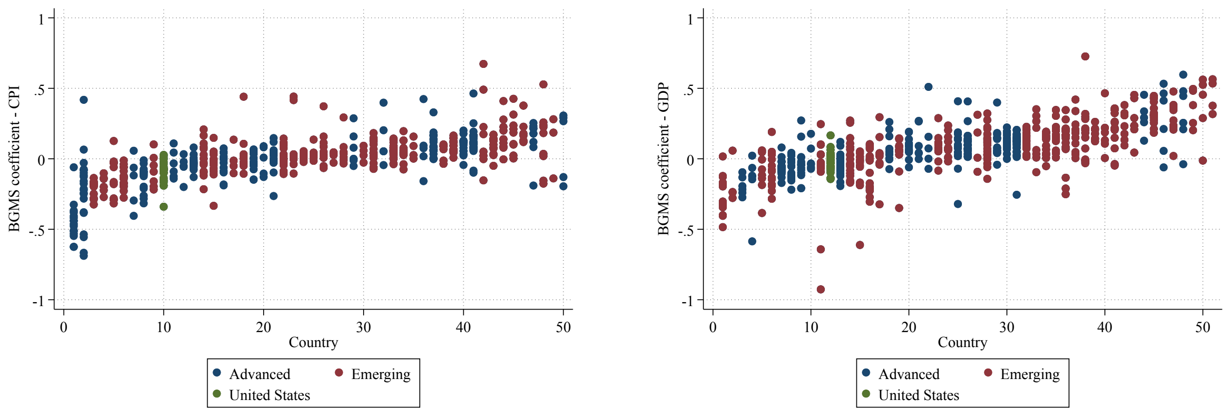
(c) N_{ijt}: CPI_t



(d) N_{ijt}: GDP_t

Figure D.6: Distribution of the number of yearly updates

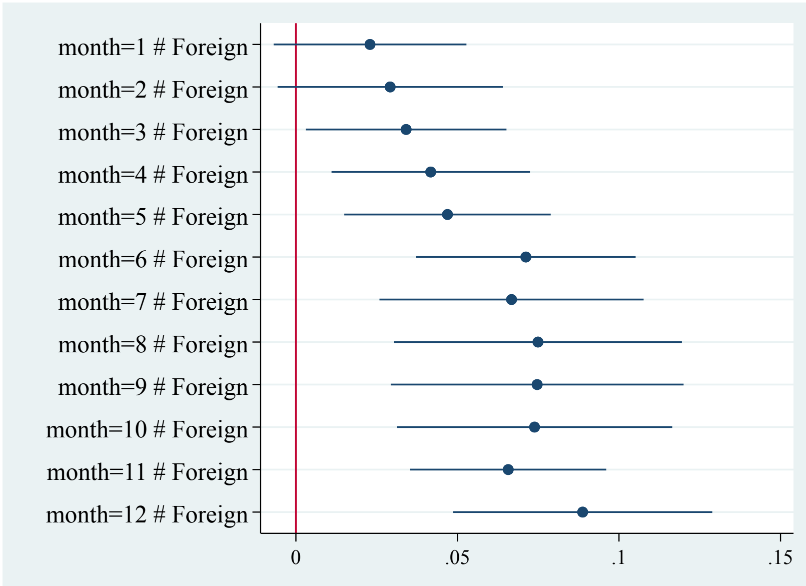
Notes: Panels (a) and (b) display the histograms of the number of current year forecasts N_{ijt} by location, where we consider all the published forecast. Panels (c) and (d) display the histograms of the number of current year forecasts by location, where we consider only the published forecasts that are distinct from the last published one.



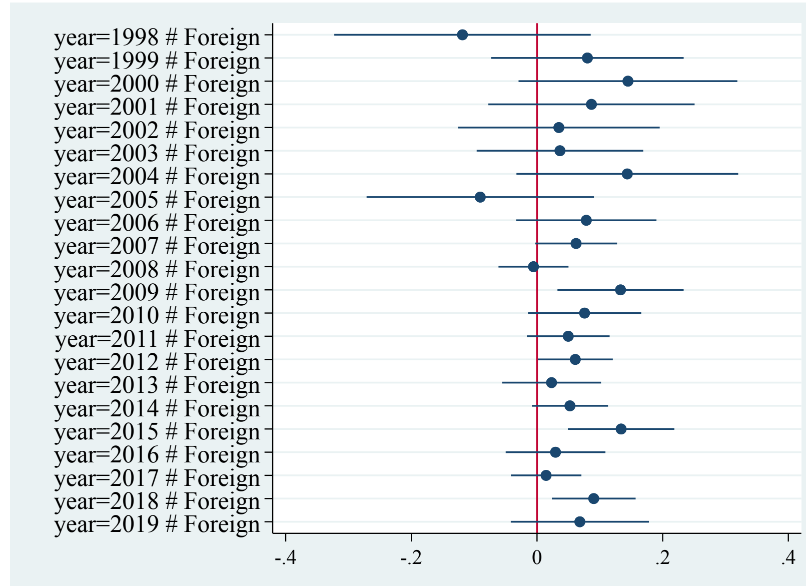
(a) CPI_t (b) GDP_t

Figure D.7: β^{BGMS} coefficients by country

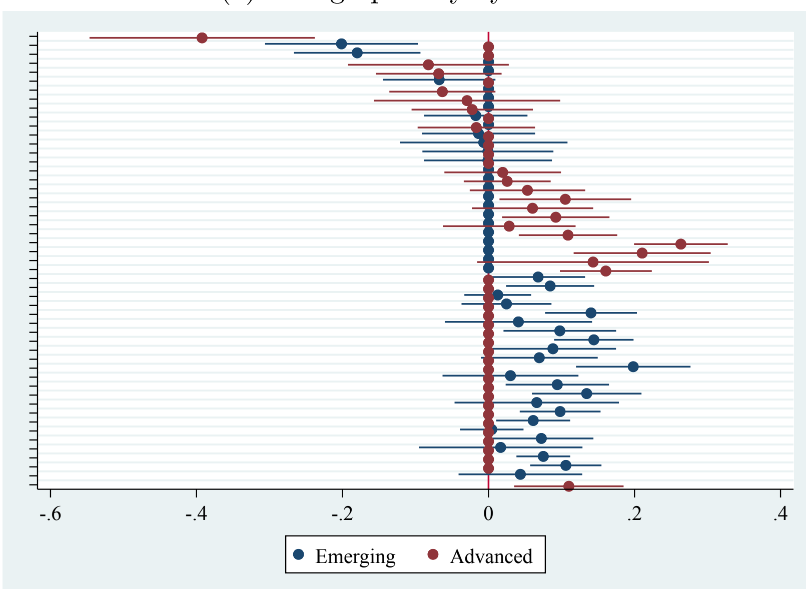
Notes: The figure displays the β^{BGMS} coefficients estimated for each country-forecaster pair, by country, where countries are ranked by their median value.



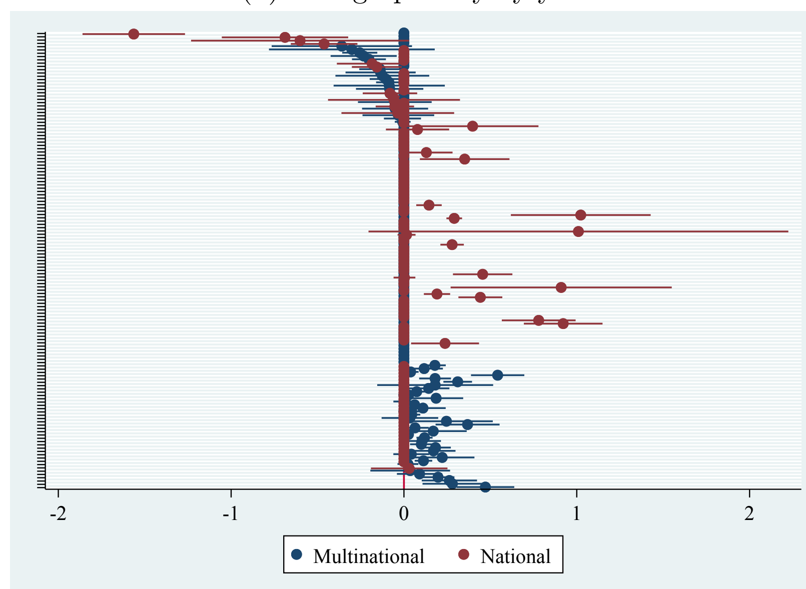
(a) Foreign penalty by month



(b) Foreign penalty by year



(c) Foreign penalty by country



(d) Foreign penalty by forecaster

Figure D.8: Heterogeneity in Foreign penalty

Notes: The figure displays the Foreign coefficients per year, month, country and forecaster. These estimates are obtained by estimating Equation (**??**) with $X^{m,x}_{ijt,h}$ successively replaced with the categorical variables year, month, and country and forecaster.

E Proofs

E.1 Proof of Proposition ??

We first demonstrate the following Lemma:

Lemma 1. *Under Assumption* **??** *(no behavioral biases), the variance of errors is given by:*

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

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

Proof. Under Assumption **??**, we have $\hat{\rho}_{ij} = \rho_j$ and $\hat{\tau}^m_{ij} = \tau^m_{ij}$.

The model can be written as follows:

$$\begin{aligned} x_{jt} &= \rho_j x_{jt-1} + \epsilon_{jt} \\ s^m_{ijt} &= x_{jt} + v^m_{ijt} \end{aligned} \tag{2}$$

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

Denote the one step-ahead forecast error associated to the Kalman filter by $\Phi^m_{ij} = V(Error^m_{ijt,t-1}) = V[x_{jt} - E^m_{ijt-1}(x_{jt})]$. 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 by

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

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 of the Lemma.

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

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

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

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

Hence the second result of the Lemma. ■

Since G_{ij}^m is increasing in τ_{ij}^m, then the variances are decreasing in τ_{ij}^m. This proves Proposition **??**.

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

$$\Phi_{ij}^m = \frac{1}{2}\left(\gamma_j^{-1} - (1-\rho_j^2)(\lambda_{ij}^m)^{-1} + \sqrt{(\gamma_j^{-1} - (1-\rho_j^2)(\lambda_{ij}^m)^{-1})^2 + 4\gamma_j^{-1}(\lambda_{ij}^m)^{-1}}\right) \tag{3}$$

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.

E.2 Proof of Proposition ??

First, we demonstrate the following Lemma:

Lemma 2. *Estimating Equation* (**??**) *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 below. 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 ($\hat{\rho}_{ij} - \rho_j > 0$).

Proof. Notice that $E^m_{ijt}(x_{jt})$ can be rewritten in its moving-average form as follows:

$$E^m_{ijt}(x_{jt}) = \frac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L} s^m_{ijt} \tag{4}$$

Forecast revision can then be written as

$$\begin{aligned} Revision^m_{ijt} &= E^m_{ijt}(x_{jt}) - E^m_{ijt-1}(x_{jt}) \\ &= E^m_{ijt}(x_{jt}) - \hat{\rho}_{ij} E^m_{ijt-1}(x_{jt-1}) \\ &= \tfrac{G^m_{ij}[1-\hat{\rho}_{ij}L]}{1-(1-G^m_{ij})\hat{\rho}_{ij}L} s^m_{ijt} \\ &= \tfrac{G^m_{ij}[1-\hat{\rho}_{ij}L]}{1-(1-G^m_{ij})\hat{\rho}_{ij}L} (x_{jt} + v^m_{ijt}) \end{aligned} \tag{5}$$

and the error as

$$\begin{aligned} Error^m_{ijt,t} &= x_{jt} - E^m_{ijt}(x_{jt}) \\ &= x_{jt} - \tfrac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L} s^m_{ijt} \\ &= \left(1 - \tfrac{G^m_{ij}}{1-(1-G^m_{ij})\rho_{ij}L}\right) x_{jt} - \tfrac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L} v^m_{ijt} \end{aligned} \tag{6}$$

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:

$$\tilde{E}rror^m_{ijt,t} = \left(1 - \frac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}\right)\tilde{x}_{ijt} - \frac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}\tilde{v}^m_{ijt} \tag{7}$$

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 $\tilde{Revision}^m_{ijt,t}$ similarly:

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

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

$$\begin{aligned}
Cov\left(Error^m_{ijt}, Revision^m_{ijt}\right) = \; & Cov\left(Error^m_{ijt} - \tilde{Error}^m_{ijt}, \tilde{Revision}^m_{ijt}\right) \\
& + Cov\left(\tilde{Error}^m_{ijt}, Revision^m_{ijt} - \tilde{Revision}^m_{ijt}\right) \\
& + Cov\left(Error^m_{ijt} - \tilde{Error}^m_{ijt}, Revision^m_{ijt} - \tilde{Revision}^m_{ijt}\right) \\
= \; & Cov\left(\left(1 - \tfrac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}\right)(x_{jt} - \tilde{x}_{ijt}), \tfrac{G^m_{ij}(1-\hat{\rho}_{ij}L)}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}\tilde{x}_{ijt}\right) \\
& + Cov\left(\left(1 - \tfrac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}\right)\tilde{x}_{ijt}, \tfrac{G^m_{ij}(1-\hat{\rho}_{ij}L)}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}(x_{jt} - \tilde{x}_{ijt})\right) \\
& + Cov\left(\left(1 - \tfrac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}\right)(x_{jt} - \tilde{x}_{ijt}), \tfrac{G^m_{ij}(1-\hat{\rho}_{ij}L)}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}(x_{jt} - \tilde{x}_{ijt})\right) \\
& - Cov\left(\tfrac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}\tilde{v}^m_{ijt}, \tfrac{G^m_{ij}(1-\hat{\rho}_{ij}L)}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}(v^m_{ijt} - \tilde{v}^m_{ijt})\right) \\
& - Cov\left(\tfrac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}(v^m_{ijt} - \tilde{v}^m_{ijt}), \tfrac{G^m_{ij}(1-\hat{\rho}_{ij}L)}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}\tilde{v}^m_{ijt}\right) \\
& - Cov\left(\tfrac{G^m_{ij}}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}(v^m_{ijt} - \tilde{v}^m_{ijt}), \tfrac{G^m_{ij}(1-\hat{\rho}_{ij}L)}{1-(1-G^m_{ij})\hat{\rho}_{ij}L}(v^m_{ijt} - \tilde{v}^m_{ijt})\right) \\
= \; & -(\hat{\rho}_{ij} - \rho_j)G^m_{ij}(1-G^m_{ij})\tfrac{2\hat{\rho}_{ij}(1-G^m_{ij})(1-\rho_j^2) - (\hat{\rho}_{ij}-\rho_j)[1+\rho_j\hat{\rho}_{ij}(1-G^m_{ij})]}{[1-\rho_j\hat{\rho}_{ij}(1-G^m_{ij})][1-\rho_j^2][1-\hat{\rho}^2_{ij}(1-G^m_{ij})^2]} \\
& -[(\tau^m_{ij})^{-1} - (\hat{\tau}^m_{ij})^{-1}]((1-h^m_{ij})G^m_{ij})^2\tfrac{1-\hat{\rho}^2_{ij}(1-G^m_{ij})}{1-\hat{\rho}^2_{ij}(1-G^m_{ij})^2}
\end{aligned}$$

We used

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

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

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

Here we used

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

■

According to Lemma 2, 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 straightforward. To prove Proposition **??**, we therefore linearize β_{ij}^{BGMSm}.

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 in Proposition **??**.

E.3 Proof of Proposition ??

First, we show the following Lemma:

Lemma 3. *Suppose that Assumptions* **??** *and* **??** *are satisfied: there are no behavioral biases and the precision parameters are identical within foreign forecasters and within local forecasters. Estimating Equation* (**??**) *for each* $j = 1, ..J$, $m = 1, .., 12$ *and* $k = l, f$ *by OLS gives the following coefficients:*

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

Proof. Suppose that there are no behavioral biases (Assumption **??**): $\hat{\rho}_{ij} = \rho_j$ and $\hat{\tau}_{ij}^m = \tau_{ij}^m$, and that the precision parameters are identical within foreign forecasters and within local forecasters (Assumption **??**): $\tau_{ij}^m = \tau_{jl}^m$ 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 $m = 1, .., 12$.

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

$$\beta_{jk}^{CGm} = \frac{Cov\left(Error_{jkt}^m, Revision_{jkt}^m\right)}{V\left(Revision_{jkt}^m\right)} \tag{8}$$

And we can write:

$$\begin{aligned}
Cov\left(Error_{jkt}^m, Revision_{jkt}^m\right) &= Cov\left(\left(1 - \frac{G_{jk}^m}{1-(1-G_{jk}^m)\rho_j L}\right)\frac{1}{1-\rho_j L}\epsilon_{jt}, \frac{G_{jk}^m}{1-(1-G_{jk}^m)\rho_j L}\epsilon_{jt}\right) \\
&+Cov\left(-\frac{G_{jk}^m}{1-(1-G_{jk}^m)\rho_j L}h_{jk}^m(\kappa_j^m)^{-1/2}u_{jt}^m, \frac{G_{jk}^m[1-\rho_j L]}{1-(1-G_{jk}^m)\rho_j L}h_{jk}^m(\kappa_j^m)^{-1/2}u_{jt}^m\right) \\
&= \frac{G_{jk}^m(1-G_{jk}^m)}{1-\rho_j^2(1-G_{jk}^m)^2}\gamma^{-1} - (G_{jk}^m)^2\left(1 - \frac{G_{jk}^m}{1-G_{jk}^m}\frac{\rho_j^2(1-G_{jk}^m)^2}{1-\rho_j^2(1-G_{jk}^m)^2}\right)(h_{jk}^m)^2(\kappa_j^m)^{-1}
\end{aligned}$$

and

$$V(Revision_{jkt}^m) = (G_{jk}^m)^2\frac{1}{1-\hat{\rho}_{jk}^2(1-G_{jk}^m)^2}\gamma^{-1} + (G_{jk}^m)^2\left(1 + \left(\frac{G_{jk}^m}{1-G_{jk}^m}\right)^2\frac{\hat{\rho}_{jk}^2(1-G_{jk}^m)^2}{1-\hat{\rho}_{jk}^2(1-G_{jk}^m)^2}\right)(h_{jk}^m)^2(\kappa_j^m)^{-1}$$

Here we used

$$\begin{aligned}
Error_{jkt}^m &= \left(1 - \frac{G_{jk}^m}{1-(1-G_{jk}^m)\rho_j L}\right)\frac{1}{1-\rho_j L}\epsilon_{jt} \\
&-\frac{G_{jk}^m}{1-(1-G_{jk}^m)\rho_j L}h_{jk}^m(\kappa_j^m)^{-1/2}u_{jt}^m \\
&= \left(\sum_{s=0}^{+\infty}\rho_j^s\left[1 - G_{jk}^m\left(\sum_{i=0}^{s}(1-G_{jk}^m)^i\right)\right]L^s\right)\epsilon_{jt} \\
&-G_{jk}^m\sum_{s=0}^{+\infty}\rho_j^s(1-G_{jk}^m)^sL^sh_{jk}^m(\kappa_j^m)^{-1/2}u_{jt}^m \\
Revision_{jkt}^m &= \frac{G_{jk}^m}{1-(1-G_{jk}^m)\rho_j L}\epsilon_{jt} \\
&+\frac{G_{jk}^m[1-\rho_j L]}{1-(1-G_{jk}^m)\rho_j L}h_{jk}(\kappa_j^m)^{-1/2}u_{jt}^m \\
&= G_{jk}^m\sum_{s=0}^{+\infty}\rho_j^s(1-G_{jk}^m)^sL^s\epsilon_{jt} \\
&+G_{jk}^m\left(1 - \frac{G_{jk}^m}{1-G_{jk}^m}\sum_{s=1}^{+\infty}\rho_j^s(1-G_{jk}^m)^sL^s\right)h_{jk}^m(\kappa_j^m)^{-1/2}u_{jt}^m
\end{aligned}$$

Therefore,

$$\begin{aligned}
\beta_{jk}^{CGm} = \beta^{CG}(\rho_j) &= \frac{\frac{G_{jk}^m(1-G_{jk}^m)}{1-\rho_j^2(1-G_{jk}^m)^2}\gamma^{-1}-(G_{jk}^m)^2\left(1-\frac{G_{jk}^m}{1-G_{jk}^m}\frac{\rho_j^2(1-G_{jk}^m)^2}{1-\rho_j^2(1-G_{jk}^m)^2}\right)(h_{jk}^m)^2(\kappa_j^m)^{-1}}{(G_{jk}^m)^2\frac{1}{1-\rho_j^2(1-G_{jk}^m)^2}\gamma^{-1}+(G_{jk}^m)^2\left(1+\left(\frac{G_{jk}^m}{1-G_{jk}^m}\right)^2\frac{\rho_j^2(1-G_{jk}^m)^2}{1-\rho_j^2(1-G_{jk}^m)^2}\right)(h_{jk}^m)^2(\kappa_j^m)^{-1}} \\
&= \frac{\frac{1-G_{jk}^m}{G_{jk}^m}\gamma^{-1}-[1-\rho_j^2(1-G_{jk}^m)](h_{jk}^m)^2(\kappa_j^m)^{-1}}{\gamma^{-1}+[1-\rho_j^2(1-2G_{jk}^m)](h_{jk}^m)^2(\kappa_j^m)^{-1}}
\end{aligned}$$

■

According to Lemma 3, $\beta_{jk}^{CGm} = (1-G_{jk}^m)/G_{jk}^m$ when there is no public signal, or, equivalently, when $\kappa_j^m = 0$, 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 ($\tau_{jf}^m > \tau_{jl}^m$).

In other terms, in the case where $\kappa_j^m = 0$, we have $\beta_{jk}^{CGm} = (1 - G_{jk}^m)/G_{jk}^m$ and thus $\partial\beta_{jk}^{CGm}/\partial\tau_{jk}^m = -(\partial G_{jk}^m/\partial\tau_{jk}^m)/(G_{jk}^m)^2 < 0$ because $\partial G_{jk}^m/\partial\tau_{jk}^m > 0$. This proves that the coefficients β_{jk}^{CGm} can be locally decreasing in τ_{jk}^m.

Now we focus on the case where $\kappa_j^m > 0$. We first show that $\beta_{jk}^{CGm} > 0$ when $\tau_{jk}^m > 0$.

Notice that

$$\begin{aligned} Cov\left(Error_{ijkt}^m, Revision_{ijkt}^m\right) = \; & Cov\left(Error_{jkt}^m, Revision_{jkt}^m\right) \\ & -(G_{jk}^m)^2\left(1 - \tfrac{G_{jk}^m}{1-G_{jk}^m}\tfrac{\rho_j^2(1-G_{jk}^m)^2}{1-\rho_j^2(1-G_{jk}^m)^2}\right)(1-h_{jk}^m)^2(\tau_{jk}^m)^{-1} \end{aligned}$$

Since we are considering a case without behavioral biais, we have $Cov\left(Error_{ijkt}^m, Revision_{ijkt}^m\right) = 0$. In that case, the above equation implies that $Cov\left(Error_{jkt}^m, Revision_{jkt}^m\right) > 0$ when $(1-h_{jk}^m)^2(\tau_{jk}^m)^{-1} > 0$, which is satisfied for $\tau_{jk}^m > 0$. As a consequence, $\beta_{jk}^{CGm} > 0$.

This equation also implies that $Cov\left(Error_{jkt}^m, Revision_{jkt}^m\right)$ converges to zero as τ_{jk}^m goes to zero. In contrast, $V(Revision_{jkt}^m)$ converges to a strictly positive value. As a result β_{jk}^{CGm} converges to zero as τ_{jk}^m goes to zero. Since $\beta_{jk}^{CGm} > 0$ is strictly positive for $\tau_{jk}^m > 0$, this implies that β_{jk}^{CGm} is incresing in τ_{jk}^m in the vicinity of $\tau_{jk}^m = 0$. This proves that the coefficients β_{jk}^{CGm} can be locally increasing in τ_{jk}^m.

Since β_{jk}^{CGm} can be both locally decreasing and locally increasing in τ_{jk}^m, then this proves Proposition **??**.

E.4 Proof of Proposition ??

We first demonstrate the following Lemma:

Lemma 4. *Suppose that Assumption* **??** *is satisfied: the behavioral biases and the precision parameters are homogeneous within foreign forecasters and within local forecasters. Estimating Equation* (**??**) *for each $j = 1, ..J$, $m = 1, .., 12$ and $k = l, f$ by OLS gives the following coefficients:*

$$\beta_{jk}^{FEm} = -\frac{1 - \hat{\rho}_{jk}(1 - G_{jk}^m)}{1 - \hat{\rho}_{jk}(1 - 2G_{jk}^m)}$$

Proof. Suppose that the parameters are homogeneous within foreign forecasters and within local forecasters (Assumption **??**): $\hat{\rho}_{ij} = \hat{\rho}_{jl}$, $\tau_{ij} = \tau_{jl}$ 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 $i \in \mathcal{S}^f(j)$.

Consider the revision and error. We can rewrite them as follows:

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

for $k = l, f$.

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

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

Hence the result.

■

If, additionally, forecasters have identical behavioral biases (Assumption **??**), that is, $\hat{\rho}_{jl} = \hat{\rho}_{jf} = \hat{\rho}_j$ and $(\hat{\tau}^m_{jl})^{-1} - (\tau^m_{jl})^{-1} = (\hat{\tau}^m_{jf})^{-1} - (\tau^m_{jf})^{-1}$, and if $0 < \hat{\rho}_j < 1$, then Lemma 4 implies that $\beta^{FEm}_{jf} < \beta^{FEm}_{jl}$ if and only if $\tau^m_{jl} > \tau^m_{jf}$. This proves Proposition **??**.

E.5 Proof of Proposition ??

We first demonstrate the following Lemma:

Lemma 5. *Suppose that Assumption* **??** *is satisfied: the behavioral biases and the precision parameters are homogeneous within foreign forecasters and within local forecasters. Estimat-*

*ing Equation (**??**) for each $j = 1, ..J$ and $m = 1, .., 12$ by OLS gives the following coefficients:*

$$\beta_j^{DISm} = \left(\frac{G_{jl}^m h_{jl}^m - G_{jf}^m h_{jf}^m}{\frac{1}{2}(h_{jl}^m G_{jl}^m + h_{jf}^m G_{jf}^m)} \right)$$

Proof. Suppose that the parameters are homogeneous within foreign forecasters and within local forecasters (Assumption **??**): $\hat{\rho}_{ij} = \hat{\rho}_{jl}$, $\tau_{ij} = \tau_{jl}$ 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 $i \in \mathcal{S}^f(j)$.

The first step is to write $Disagreement_{jt}$, $Revisionjt$ as a function of he regressors in the disagreeement regression (**??**) and of the common noise u_{jt}^m.

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

To obtain these formulas, we used the Kalman formula (**??**), the definition of $E_{jkt}^m(x_{jt})$, $s_{ijt}^m = x_{jt} + h_{ij}^m(\kappa_j^m)^{-1/2}u_{jt}^m + (1 - h_{ij}^m)(\tau_{ij}^m)^{-1/2}e_{ijt}^m$ and the fact that $G_{ij}^m = G_{jk}^m$ and $h_{ij}^m = h_{jk}^m$ are homogenous within location k so that $E_{jkt}^m(x_{jt})$ can be written as follows:

$$\begin{aligned}
E_{jkt}^m(x_{jt}) \;&= \tfrac{1}{N(j)^k}\textstyle\sum_{i \in S^k(j)} E_{ijkt}(x_{jt}) \\
&= \tfrac{1}{N(j)^k}\textstyle\sum_{i \in S^k(j)} \left[(1 - G_{ij}^m)\hat{\rho}_{ij}E_{ijt-1}^m(x_{jt-1}) + G_{ij}^m s_{ijt}^m\right] \\
&= (1 - G_{jk}^m)\hat{\rho}_{jk}E_{jkt-1}^m(x_{jt-1}) + G_{jk}^m \tfrac{1}{N(j)^k}\textstyle\sum_{i \in S^k(j)} s_{ijt}^m \\
&= (1 - G_{jk}^m)E_{jkt-1}^m(x_{jt}) + G_{jk}^m[x_{jt} + h_{jk}^m(\kappa_j^m)^{-1/2}u_{jt}^m]
\end{aligned}$$

for $k = l, f$, and we replaced $E_{jjt}^m(x_{jt})$ and $E_{jft}^m(x_{jt})$.

The variables x_{jt}, $E^m_{jlt-1}(x_{jt})$ and $E^m_{jft-1}(x_{jt})$ are controls in the disagreement regression. Therefore, according the the Frisch-Waugh-Lovell theorem, only the the variations in the noise u^m_{jt} will determine the coefficient of $Revision^m_{jt}$ in the regression. Namely, the β_j^{DISm} coefficient can be identified by regressing $\widehat{Disagreement}^m_{jt}$ on $\widehat{Revision}^m_{jt}$, where

$$\begin{aligned}
\widehat{Disagreement}^m_{jt} &= Disagreement^m_{jt} - \left[(G^m_{jl} - G^m_{jf})x_{jt} + (1-G^m_{jl})E^m_{jlt-1}(x_t) - (1-G^m_{jf})E^m_{jft-1}(x_t)\right] \\
&= (h^m_{jl}G^m_{jl} - h^m_{jf}G^m_{jf})(\kappa^m_j)^{-1/2}u^m_{jt} \\
\widehat{Revision}^m_{jt} &= Revision^m_{jt} - \left[\tfrac{1}{2}(G^m_{jl} + G^m_{jf})x_{jt} - \tfrac{G^m_{jl}}{2}E^m_{jlt-1}(x_{jt}) - \tfrac{G^m_{jf}}{2}E^m_{jft-1}(x_{jt})\right] \\
&= \tfrac{1}{2}(h^m_{jl}G^m_{jl} + h^m_{jf}G^m_{jf})(\kappa^m_j)^{-1/2}u^m_{jt}
\end{aligned}$$

The estimated coefficient is then given by

$$\begin{aligned}
\beta_j^{DISm} &= \frac{Cov\left(\frac{1}{2}(h^m_{jl}G^m_{jl}+h^m_{jf}G^m_{jf})(\kappa^m_j)^{-1/2}u^m_{jt}, (h^m_{jl}G^m_{jl}-h^m_{jf}G^m_{jf})(\kappa^m_j)^{-1/2}u^m_{jt}\right)}{V\left(\frac{1}{2}(h^m_{jl}G^m_{jl}+h^m_{jf}G^m_{jf})(\kappa^m_j)^{-1/2}u^m_{jt}\right)} \\
&= \frac{h^m_{jl}G^m_{jl}-h^m_{jf}G^m_{jf}}{\frac{1}{2}(h^m_{jl}G^m_{jl}+h^m_{jf}G^m_{jf})}
\end{aligned}$$

Hence the result.

■

To understand how the sign of β_j^{DISm} can be related to the information structure of local and foreign forecasters, consider first the rational expectations case without behavioral bias. We have $G^m_{jk} = \Phi_{jk}(\Phi_{jk} + (\lambda^m_{jk})^{-1})^{-1}$ and $h^m_{jk} = \kappa^m_j/\lambda^m_{jk}$. We can thus rewrite:

$$h^m_{jk}G^m_{jk} = \frac{\kappa^m_j}{\lambda^m_{jk} + \Phi^{-1}_{jk}}$$

For a given κ^m_j, for $h^m_{jk}G^m_{jk}$ to be decreasing in τ^m_{jk}, it is enough that $\lambda^m_{jk} + \Phi^{-1}_{jk}$ is increasing in λ^m_{jk}. We use the definition of Φ_{jk} in (3) to compute this derivative:

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

$h^m_{jk} G^m_{jk}$ is therefore decreasing in τ^m_{jk}.

Consider now the case with behavioral biases. h_{jk} and G_{jk} are similar, except that ρ_j and τ^m_{jk} are replaced by the perceived parameters $\hat{\rho}_{jk}$ and $\hat{\tau}^m_{jk}$. As a consequence, $h^m_{jk} G^m_{jk}$ is decreasing in $\hat{\tau}^m_{jk}$. Therefore, for a given $(\hat{\tau}^m_{jk})^{-1} - (\tau^m_{jk})^{-1}$, $h^m_{jk} G^m_{jk}$ is decreasing in τ^m_{jk}.

If, additionally, forecasters have identical behavioral biases (Assumption **??**), that is, $\hat{\rho}_{jl} = \hat{\rho}_{jf} = \hat{\rho}_j$ and $(\hat{\tau}^m_{jl})^{-1} - (\tau^m_{jl})^{-1} = (\hat{\tau}^m_{jf})^{-1} - (\tau^m_{jf})^{-1}$, then differences in $h^m_{jk} G^m_{jk}$ reflect differences in τ^m_{jk}. In that case, $h^m_{jl} G^m_{jl} < h^m_{jf} G^m_{jf}$, and hence, $\beta^{DISm}_j < 0$, if and only if $\tau^m_{jl} > \tau^m_{jf}$. This proves Proposition **??**.

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