Information Rigidities in Economic Growth Forecasts: Evidence from a Large International Panel

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Abstract

We examine the behavior of forecasts for real GDP growth using a large panel of individual forecasts from 36 advanced and emerging economies during 1989–2010. Our main findings are as follows. First, we show that the degree of rigidity in average growth forecasts is substantially higher than that in individual forecasts. Second, an analysis of the frequency of forecast updating at the individual level does not support the validity of the sticky information model (Mankiw and Reis, 2002) for describing the dynamics of professional growth forecasts. Instead, the empirical evidence is more in line with implications of "noisy" information models (Woodford, 2002; Sims, 2003). Third, we find that the level of information rigidity in emerging economies does not differ substantially from the level observed for advanced economies.

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I. Introduction

Expectations—and their reflection in forecasts—play a central role in macroeconomics. The development of the concept of rational expectations in the 1960s and 1970s was mirrored in the development of tests of forecast efficiency. The natural analog to rational expectations is the concept of forecast efficiency, which, in its strong form, states that forecast errors should be orthogonal to all relevant available information.

In practice, there are limitations on testing strong form efficiency, for example, because the information set used by forecasters may not be publicly known or available. Hence, Nordhaus (1987) and others developed the concept of weak efficiency, which states that forecast errors should be orthogonal to the information contained in the forecaster's set

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of past forecasts. Nordhaus states that: "*weak efficiency is an attractive concept, first, because past forecasts are likely to play a very important role in determining current forecasts. Forecasters tend to have a certain consistency (stickiness?) in their views of the world, so that recent forecasts will go far in explaining current forecasts. Second, of all variables that seem plausible candidates for inclusion in a forecaster's information set, surely the forecasters own views must rate quite high.*"

In the case of fixed event forecasts (i.e. a sequence of forecasts made about a given event, such as real GDP growth for a given year), Nordhaus develops two "simple and powerful tests" of weak efficiency. The first test is that the forecast error should be independent of past forecast revisions, and the second test is that today's forecast revision should be independent of past forecast revisions.

Over the years, a number of explanations have been offered for why forecast revisions may be correlated. One theory, due to Mankiw and Reis (2002), states that forecasters update their information sets infrequently because there are fixed costs of acquiring information. In a second theory, developed in Woodford (2002) and Sims (2003), forecasters continually update their information sets but, because they receive noisy signals about the true state of the economy, their forecast revisions are correlated. In an important set of papers, Coibion and Gorodnichenko (2010, 2012) showed that canonical versions of both classes of models—dubbed respectively as the 'sticky information' and 'imperfect information' models—have the feature that the forecast error should be correlated with the forecast revision, which is the first of the two tests proposed by Nordhaus. A third class of theories suggests behavioral explanations for forecast rigidity, and these are mentioned by Nordhaus as an explanation for his findings. Citing Tversky and Kahneman (1981), he states that "we tend to break the good or bad news to ourselves slowly, taking too long to allow surprises to be incorporated into our forecasts."

To summarize, smoothing appears to be a feature of forecasts and there are different classes of explanations, which are not mutually exclusive, for why this feature might arise.

Against this background, this paper provides evidence on correlation in forecast revisions in individual forecasts of real GDP growth for a large number of countries. Our use of both aggregate and individual forecast data is the unique feature of the paper. Many of the underlying theories for forecast smoothing are formulated at the level of the individual forecasters. Although their aggregate implications are often drawn based on averaging across individual forecasters, the mean estimate of forecast smoothing based on individual data need not be the same as the estimate of forecast smoothing based on the consensus data. The bias induced by aggregation has been well recognized in the literature (Crowe, 2010); such bias can be avoided by using individual data (Andrade and Le Bihan, 2013).

The evidence that we provide on positive correlation in forecast revisions confirms findings of several previous studies regarding the ubiquity of forecast smoothing (Pesaran and Weale, 2006). The value-added of our study is to show that the degree of smoothing estimated from individual forecast data is far lower than estimates obtained from average forecasts on which most of the previous studies have been based. Using the individual data

we show that the empirical evidence on forecast smoothing lends more validity to the models of "noisy" information than to the models of sticky information.

The broad country coverage of our study provides an opportunity also to compare the extent of smoothing in forecasts for advanced and emerging economies. We find that correlations of forecast revisions for emerging economies are broadly similar to those for advanced economies.

The paper is organized as follows: Section II discusses the methodology for testing for the degree of forecast smoothing using average and individual forecast data. Section III describes our data on international growth forecasts and highlights some important stylized facts. Section IV presents the empirical results. The last section concludes.

II. Methodology for Testing for Forecast Smoothing

A. Average Forecasts

The test for forecast smoothing (forecast efficiency) exploits the fact that we have a sequence of forecasts for the same event, viz., annual real GDP growth, i. e. we have a sequence of (average) forecasts $\bar{F}_{i,t,h}$ for country *i* and target year *t* made at horizons $h = 24, 23, \ldots, 1$. Furthermore, let $\bar{r}_{i,t,h} = \bar{F}_{i,t,h} - \bar{F}_{i,t,h+k*}$ denote the revision of the average forecast computed over *k** months. We set $k^* = 3$ throughout this paper; this value is a reasonable choice to balance a trade-off between losing too much of the high frequency dynamics (for larger values of *k*) against sampling too many "zero-revisions" due to the fact that some forecasters update their forecasts only quarterly (for lower values of *k*).

Under the null of full information rational expectations, the sequence of forecasts for one event must follow a martingale process. Nordhaus (1987) proposed a test that is based on regressing the contemporaneous revision on lagged forecast revisions:

$$\bar{r}_{i,t,h} = \beta_i + \lambda\, \bar{r}_{i,t,h+k} + u_{i,t,h} \tag{1}$$

where $k \geq k^*$ has to hold to avoid moving average effects in the residuals of the regression.[2] If $\lambda = 0$, forecasts are (weakly) efficient. Otherwise, forecast revisions are correlated, and the null hypothesis of forecast efficiency is rejected.

Reis (2006) shows that under sticky information the average forecast for an event $x_{i,t}$ is a weighted average of the lagged average forecast and the current rational expectation of the event:

$$\bar{F}_{i,t,h} = \lambda \bar{F}_{i,t,h+k} + (1-\lambda)\left[x_{i,t} + v_{i,t,h}\right], \tag{2}$$

[2] We assume $k = 3 (= k^*)$ throughout this paper.

where $v_{i,t,h}$ is the rational expectations error. It follows that

$$\bar{r}_{i,t,h} = \bar{F}_{i,t,h} - \bar{F}_{i,t,h+k} = \lambda \bar{r}_{i,t,h+k} + (1-\lambda)\left[v_{i,t,h} - v_{i,t,h+k}\right] = \lambda \bar{r}_{i,t,h+k} + u_{i,t,h}. \quad (3)$$

Thus, the regression coefficient from equation (1) translates directly into the degree of information rigidity in the sticky information framework (e.g. Mankiw and Reis, 2002, or Reis, 2006).

Likewise, also in the ”noisy” information framework (e.g. Woodford, 2002, and Sims, 2003) the degree of informational rigidity can be directly inferred from the parameter estimates of equation (1). Coibion and Gorodnichenko (2012) show that under the assumption of a standard loss function agents optimally use the Kalman filter to update their forecasts in each period as

$$\bar{F}_{i,t,h} = (1-G)\bar{F}_{i,t,h+k} + G\left[x_{i,t} + \omega_{i,t,h}\right], \quad (4)$$

where $\omega_{i,t,h}$ is the noise component of the information that agents have about the event $x_{i,t}$ at a particular point in time. Evidently, the formulation is very similar to equation (2). It follows that also in the imperfect information framework the parameter λ is equal to the degree of informational rigidity, which is given by *1-G* in the theoretical model.

An alternative test of forecast efficiency suggested by Nordhaus (1987) is to regress forecast errors—rather than contemporaneous revisions as in equation (1)—on past revisions. The two tests are equivalent, i.e. the alternative test equation also yields estimates of the degree of informational rigidities (Coibion and Gorodnichenko, 2010). The main advantage of using our specification is that it does not rely on the actual outcomes and, hence, side-steps the issue of what vintage of the actual data to use in computing the forecast error.

It is reasonable to expect that information rigidities vary over the forecast horizon. They might, for instance, be more pronounced at longer horizons because (under sticky information) agents might have less resources available to obtain information relevant for forecast updating[3] at a high frequency and/or (under imperfect information) face noisier signals and, hence, would place less weight on new information. While these two arguments suggest that the degree of information rigidity is monotonically increasing with the forecast horizon, there might be other effects at work that are non-monotonic functions of the forecast horizon (e.g. differences across institutions in their forecast cycles).

To examine empirically how the degree of forecast smoothing changes over the forecast horizon, we add interaction terms between forecast horizons and lagged revisions in equation (1). The resulting specification is:

$$\bar{r}_{i,t,h} = \beta_i + \lambda \bar{r}_{i,t,h+k} + \textstyle\sum_m \lambda_m I(h_m)\, \bar{r}_{i,t,h+k} + u_{i,t,h}, \quad (5)$$

[3] Note that in the original version of the sticky information framework (Mankiw and Reis, 2002) the degree of forecast rigidity is assumed to be an exogenously given constant.

where all variables are defined as above, *m* is the index for the interaction terms of forecast revisions and horizons, and $I(h_m)$ is an indicator function that equals 1 if the horizon of an observation is equal to h_m and 0 otherwise. The coefficients on the interaction terms are expected to be positive and rising with the forecast horizon.

We estimate the fixed-effect panel data model using the ordinary least squares (OLS) estimator. Since our data set potentially has a complicated correlation structure due to the three dimensions of the data, we correct standard errors by the method suggested by Driscoll and Kraay (1998), which does not require strong assumptions on the form of cross-sectional and temporal correlation in the error terms. Since the time dimension of our panel data set is large, the Nickell (1981) bias, which is of the order 1/*T*, is likely to be only of modest size.

B. Individual Forecasts

Testing efficiency of individual forecasts is analogous to the test for average forecasts. An individual forecast version of equation (5) is given by:

$$r_{j,i,t,h} = \beta_{j,i} + \lambda r_{j,i,t,h+k} + \sum_m \lambda_m I(h_m)\, r_{j,i,t,h+k} + u_{j,i,t,h}, \qquad (6)$$

where $r_{j,i,t,h}$ is the revision of an individual forecast by forecaster *j* for country *i* and target year *t* at horizon *h*.[4] Again, if $\lambda + \lambda_m = 0$, forecast revisions at horizon h_m are efficient. Otherwise, this null hypothesis is rejected.

When estimated on individual forecasts, the autocorrelation coefficient λ should be interpreted as a general measure of the degree of forecast smoothing, which reflects behavioral features or deviations from efficiency. It cannot be directly linked to the parameters of the theoretical models discussed above. In the case of sticky information, there is no correlation between current forecast revisions and last period's forecast revisions at the level of an individual agent because agents either fail to update their forecast or they update by moving directly to the full information rational expectations forecast. In the case of imperfect information, the error term in the regression of the current revision on past revisions will (most likely) be correlated with the current forecast revision (Coibion and Gorodnichenko, 2010, p. 7), and the OLS estimator will be biased in this case. An instrumental variable (IV) approach may be a solution but there are no obviously good instruments. Lagged revisions are inappropriate as instruments under the null hypothesis, which implies that individual forecast revisions are uncorrelated over time.

In any case, we also estimated model (1) using the general methods of moments (GMM) approach suggested by Arellano and Bond (1991) and Arellano and Bover (1995) as a robustness check. We allowed standard errors to be correlated between any observations

[4] As for average forecasts, we set $k^* = k = 3$ also for the analysis of individual forecasts.

that refer to the same country and the same forecasting period.[5] Overall, the results indicated that the differences between estimates based on the OLS estimator and those based on GMM are small and that the set of instruments is invalid or weak in most cases. Thus, we focus on OLS estimates in the remainder of this paper.

Although the autocorrelation coefficients λ cannot be directly linked to the degree of information rigidities, one can measure the extent of rigidities owing to sticky information non-parametrically by recovering the rate of information updating directly from the individual forecasts. An estimator for the probability of forecast updating is given by the fraction of individuals that update their forecasts (Andrade and Le Bihan, 2013). In our setting, these fractions can be calculated as the share of forecasters who revised their forecasts at least once during the 3 months prior to a given point in time. This approach makes the fractions comparable to the coefficients on the lagged revisions from equation (5) where we calculate revisions of the average forecasts over k^*=3 months.

III. DATA AND DESCRIPTIVE STATISTICS

Our analysis is based on forecasts for annual GDP growth from a cross-country survey data set compiled by *Consensus Economics Inc*. This data set contains a variety of macroeconomic forecasts made by public and private economic institutions, mostly banks and research institutes. Starting in October 1989, the survey has been conducted at a monthly frequency in a growing number of countries. The survey process is the same in all countries: during the first two weeks of each month the forecasters send their responses and the data are published in the middle of each month. Thus, when making their forecasts the panelists are likely to be aware of each of their competitors' forecasts from one month ago.

Because it covers a large number of countries (and variables) the data set has been used in a number of empirical studies, among others by Loungani (2001), Isiklar et al. (2006), Batchelor (2007), Ager et al. (2009) , Loungani et al. (2013), Gallo et al. (2002), Lahiri and Sheng (2008), Dovern and Weisser (2011) and Dovern, Fritsche and Slacalek (2012). Only the last four studies, however, make use of the fact that the data set provides all individual forecasts of the panel of forecasters for each country in addition to the central forecast tendency, which has been used in the other studies.

Due to the fact that *Consensus Economics Inc*. asks the forecasters to report their forecasts for the annual GDP growth rates of the current and the next calendar year, the data set has a three-dimensional panel structure of the kind formalized in Davies and Lahiri (1995). For each target year, the data set contains a sequence of 24 forecasts of each panelist made between January of the year before the target year and December of the target year.

[5] We use both the first lag of the revision and the first lag of underlying forecast as instruments in the two-step system GMM with Windmeijer (2005) corrected standard errors – taking into account a possible downward bias in two-step GMM estimations. The maximum lag length for the transformed model was set to 2.

We include all countries in our sample, for which *Consensus Economics Inc*. reports individual forecasts. We include only those forecasters that reported their growth forecasts at least 10 times. The data were retrieved directly from Consensus Economics Inc. and cleaned in the following way. First, since forecasters are not identified by a unique ID in the data set but by (sometimes different versions of their) names, we concatenated those forecast series that belong to a single forecaster who showed up under different names (e.g. we treat forecasts corresponding to "Mortgage Bankers Assoc", "Mortgage Bankers" and "Mortgage Bankers Association" as coming from the same forecaster). Second, when there were mergers or acquisitions, we kept the forecasts when it was evident which forecaster continued to produce the forecasts after the merger (e.g., we treated forecasts corresponding to "First Boston", "CS First Boston", "Credit Suisse First Boston" and "Credit Suisse" as coming from the same forecaster). The other forecaster involved in the merger or acquisition was assumed to leave the panel after the merger.

In total, we end up with 188,639 individual forecasts from 36 different countries, of which 104,894 are from 14 advanced economies (Table 1). The forecasts are made for target years between 1989 and 2011 with the number of observations increasing towards the end of the sample as more and more countries were covered by the survey and the average number of panelists per country increased. On average, our data set includes nearly 16 individual forecasts per period for each country. The forecasts seem to have a tendency to slightly overestimate growth in the emerging economies when measured against the current data vintages for GDP growth. (Real-time data vintages are not available for all countries in the sample.)

As expected, the average root mean squared forecasts error (RMSFE) declines with the forecast horizon (Figure 1). In other words, forecast errors become smaller towards the end of the target year (as the horizon, h, approaches 1). RMSFEs for emerging economies are, on average, more than twice as high as for advanced economies for large forecast horizons and still almost 75 percent higher at the end of the target year.

The size of forecast revisions evolves differently over the forecast horizons for advanced economies and emerging economies (Figure 2). Though the relationships are not monotonic for both country groups, their patterns differ. For advanced economies, the revisions are larger around the turn of the year than at very earlier and very late forecast horizons— and in general the average size of the revisions does not vary much with the forecast horizon. For emerging economies, revisions are much smaller for very long forecast horizons and much higher during the target year (h<=12). At the end of the target year (h=1) the average revision in emerging economies is about twice as large as for advanced economies. The latter indicates that in emerging economies uncertainty about the actual data is substantially higher than in advanced economies just before the end of the forecasting horizon, possibly owing to lags in statistical data collection and poor quality of initial data releases.

The distribution of forecast revisions shows that forecasts are frequently changed only little or not at all (as indicated by the high density around zero, Figure 3). Except for the large spikes at zero, the distributions at all horizons follow a neat unimodal bell-shaped distribution. The distribution of revisions is more flattened out for emerging economies than

for advanced economies; here, large forecast revisions are more frequent—reflecting higher volatilities of the target variables and, presumably, larger revisions to preliminary official statistics as well as the fact that forecasts initially remain unchanged more often than in advanced economies (the fraction of little or zero revisions is much higher than in advanced economies).

The data show a skewed distribution of the revisions for emerging economies and advanced economies: they are significantly negatively skewed for all horizons, i.e., there is a tendency for negative revisions to be less frequent but larger than upward revisions—reflecting the asymmetric nature of business cycles.

Forecasts become more clustered as the forecast horizon shrinks (Table 2). Deviations from the average forecast follow a unimodal distribution for all forecast horizons with most of the forecasts being close to the average forecast (Figure 4). For the advanced economies only very few deviations are larger than half a percentage point. In contrast, the dispersion is considerably larger for the emerging economies, where the data show a considerable degree of disagreement across forecasters even at the end of the target year (h=1). Again, this is a reflection of the fact that uncertainty about the actual data release is substantially larger here than in advanced economies.

IV. Empirical Findings

A. Average Forecasts

The left-hand side of Table 3 provides the results of estimating equation (5) on average forecasts. As stated above, we choose k=3 as the horizon over which revisions are calculated. This is in line with a quarterly frequency of updating forecasts. (Using one-month horizon results in many zero values.) The horizons we pick for our estimations are h=1, 4, 7, 10, 13 and 16.[6]

We find strong and consistent evidence of information rigidities in consensus forecasts. There is a strong positive correlation between the current forecast revision and its first lag for all country groups and for both estimation methods. Coefficients on lagged revisions are highly statistically significant in all cases.

The extent of information rigidities appears to be broadly similar in forecasts for advanced and emerging economies. The coefficient on lagged revisions for emerging economies at very short forecast horizons is 0.41 compared to 0.37 for advanced economies.

Information rigidities tend to be larger around the turn of the years, i.e., at forecast horizons between 13 and 10 (Figure 5). Possible explanations for this pattern could relate to

[6] Since all specifications include lagged revisions as an explanatory variable, we "loose" one observation per target year (h=19) for the estimation. Our results are robust to the choice of horizons; that is, for example, if we pick h=2, 5, 8, etc.

the fact that the quarter-on-quarter growth rates for the last quarter of a year have a particularly large effect on the annual growth rate of the following year. There may also be institutional or behavioral explanations where forecasters switch focus from the current year forecasts to the next year forecasts around the turn of the year. Coefficients on interaction terms between lagged revisions and the horizon-indicator function are positive and statistically significant, however, only for horizons 10 (emerging economies) and 13 (advanced economies) respectively.[7] For other horizons the additional effects are much smaller and not significantly different from zero.

When we do not condition on the length of the forecast horizon, the degree of informational rigidity estimated with our specification based on the average forecast revisions is equal to 0.5 for both advanced and emerging economies. Given that we measure revisions at a quarterly frequency, these estimates imply in the sticky information framework that forecasters update their forecasts about every six months on average. This is a higher updating frequency than it is found in other papers estimating sticky information models based on aggregate expectation data for smaller sets of countries (e.g. Mankiw and Reis, 2002, Khan and Zhu, 2006, Döpke et al., 2008). Analogously, for the imperfect information framework the estimates imply a weight of about 0.5 assigned to past forecasts in the construction of the current forecasts (see equation (4)). This is considerably higher than the estimate of 0.14 presented in Coibion and Gorodnichenko for the United States (2012, p. 143).

B. Individual Forecasts

Information Stickiness

Next, we measure the frequency of forecast updating from individual data. The share of forecasters who chose to update their forecasts at least once in the three months prior to a given forecast horizon ranges between 0.8 and 0.9 over the forecast horizons (Figure 6). This shows that most forecasters choose to update their forecasts quite frequently.[8] These estimates are close to those obtained by Andrade and Le Bihan (2013) for the European Survey of Professional Forecasters. Average fractions for advanced economies tend to be higher than those for emerging economies, suggesting that forecasts for advanced economies are revised more frequently than those for emerging economies.

There is a slight tendency that the share of forecasters that update their forecasts increases as the forecast horizon shrinks for both country groups. In addition, there is a hump around the turn of the year, i.e., at about h=13 for most countries. This is consistent with the

[7] As noted in the footnote to Table 3, if we do not exclude forecasts made in December 2008 for the growth rate of 2009, which are heavily driven by the adjustment of forecasts in the aftermath of Lehman collapse, we even obtain an estimate of the total degree of informational rigidity (for advanced economies and h=13) larger than 1. This is not consistent with informational rigidity theories and an extreme demonstration of the fact that the predictability of aggregate revisions tends to increase during recessions. The topic of information rigidities and uncertainty is explored in more detail in a companion paper (Dovern et al., forthcoming).

[8] Though, often they change it very little as shown in Section III.

basic statistical evidence on the pattern of the size of revisions over forecast horizons shown above.

Fractions obtained from individual forecast data are considerably higher than the implied estimates for the share of forecasters that updates their forecasts each quarter shown in the previous section. The coefficients on lagged revisions estimated using average forecast data range from .37-.12=.25 (advanced economies, h=4) to .37+.57=.94 (advanced economies, h=13); following equation (3) these imply estimates for the probability to update a forecast in a given quarter of between only 1-.94=0.06 and 1-.25=0.75—compared to 0.8-0.9 based on the individual data. Clearly, the latter results imply a higher frequency of updating than suggested by the regressions based on average forecast data shown before—and hence a smaller role of sticky information in explaining the overall degree of information rigidity in economic forecasts.

In contrast, a high share of forecasters who update their forecasts is perfectly consistent with the theory of imperfect information. In fact, in its pure form the theory actually predicts that all forecasters continuously update their forecasts. But Andrade and Le Bihan (2013) demonstrate that the friction introduced by the usual convention to round published forecasts to the first digit results in a plausible estimate of this share of about 0.8 to 0.9. Actually, their simulations predict that the share should be smaller for long forecast horizons than for short-term forecasts, which is in line with our estimates. Thus, our findings are broadly consistent with the theory of imperfect information but they provide evidence against the theory of sticky information.

Forecast Smoothing

Regression analysis shows strong evidence of forecast smoothing in individual forecasts. The right-hand side of Table 3 reports results of estimating equation (6) using the individual forecast data. The coefficient on the lagged revision (which, as discussed in Section II, provides a measure of general forecast smoothing rather than an exact mapping to the existing information theories) is positive and statistically significant in all specifications.

Thus, while the results of the previous section suggest that informational stickiness is not a big issue in our data set, these estimates imply that individual forecasters smooth their forecasts due to other factors. The degree of smoothing is estimated, however, to be smaller than that for the consensus forecasts. The magnitude of the difference is given in the row labeled “Ratio of Coefficients on Past Revisions”, which shows the ratio of the coefficient on lagged revisions estimated on individual forecasts to that estimated on average forecasts; the estimate of persistence in forecast revisions is about halved. This suggests that the process of averaging forecasts induces additional stickiness.

As with consensus forecasts, we find differences in the extent of smoothing in forecasts for advanced and emerging economies. Coefficients on lagged revisions are higher in the case of emerging economies (0.23 versus 0.13). These results are consistent with graphical evidence discussed in Section III (Figure 4) and suggest that information rigidities are more pronounced in forecasts for emerging economies, possibly owing to greater lags in data releases, weaker quality of economic statistics, and the fact that probably less resources

are spend for the production of these forecasts relative to those spend for advanced economies forecasts.

Also similar to the regressions based on average forecasts, those based on individual forecast data suggest that forecast smoothing is non-monotonic over forecast horizons. For advanced economies, coefficients on interaction terms between lagged revisions and horizon variables are strongly positive for horizons 7, 10 and 13; the largest size of the coefficients on the interaction terms is obtained at h=13. Looking at the Driscoll-Kraay standard errors, however, shows that the effects are not significantly different from zero in most cases. For emerging economies, the results pertaining to the interaction terms are even weaker; we do not report any significant effects. Overall, the conclusion is that while forecast smoothing at the individual level increases somewhat at the medium-range forecast horizons, the evidence for the horizon effect is even weaker than in the regressions based on aggregate forecast data.

Looking more closely at the distribution of forecast persistence across countries reveals substantial variation. Table 4 shows estimates from country-specific estimations of equation (1) based on revisions of average forecasts and summary statistics (for each country) for forecaster-specific estimations of the same model based on individual forecast revisions.[9] The results in this table provide strong confirmation of our previous findings. For 29 out of 31 countries, the smoothing parameter from the average forecasts is higher than that from the individual forecasts, in most cases by a substantial margin.[10] In some rare cases, the variation of individual forecast revisions is explained to a substantial degree by lagged revisions (based on the average R^2 from the regressions, e. g. in Germany (.35) or Italy (.44)); but in general, revisions seem to be quite unpredictable based on past revisions at the individual level.

Figure 7 shows the distribution of the estimated parameters across countries. Two main conclusions can be drawn from this graph, both of which confirm the previous panel-based findings. First, the degree of rigidity is less pronounced in the individual data than in the consensus data; in both advanced and emerging economies the average smoothing parameter based on average revisions is about 3 times as large as the average smoothing parameter based on individual revisions. Second, there is no substantial difference in the average rigidity between advanced economies and emerging economies. The only difference is that estimates are somewhat more dispersed within the group of emerging economies compared to the estimates within the group of advanced economies.[11] A similar conclusion can be

[9] We neglect any horizon-specific effects at this point, since the results from the panel regressions above indicate that most of these effects are not statistically significant and since the small number of available observations for some of the individual forecasters calls for a parsimonious specification.

[10] The country-specific estimates do reveal some negative values for the smoothing parameter for a few countries (e.g India). While negative estimates for λ are not consistent with any of the theoretical explanations for rigidity considered here in this paper, they are consistent with behavior in which forecasters react too strongly in response to new information—so that some of the revision has to be reversed during the next period.

[11] In general, the observation that the degree of forecast smoothing differs widely across individuals and countries is complementary and similar to the finding in Dovern (2013) who shows that the frequency of forecast updating differs substantially across individuals, countries and time.

drawn from the country-specific estimates for the fraction of forecasters that, on average, update their growth forecasts at least once during a three months period: The average estimate for advanced economies (0.85) is somewhat higher than the corresponding estimate for emerging economies (0.79), but given the standard deviation across countries (approximately 0.06 in both cases) this difference is statistically insignificant.

V. CONCLUSION

This paper has provided evidence on the dynamics of forecast revisions of real GDP growth using a large panel data set of individual forecasters in 36 advanced and emerging market economies for the period 1989 to 2011. The data set used in the paper is far larger than any panel of individual forecasts used in the previous literature, and it covers a wide range of different countries.

Previous work has documented that forecasts are characterized by a significant degree of smoothing or rigidity (Nordhaus, 1987; Coibion and Gorodnichenko, 2010), and a number of theories have been offered for explaining this phenomenon. In particular, Coibion and Gorodnichenko show that finding a correlation between forecast errors and past forecast revisions is consistent with two of the leading explanations for forecast smoothing, viz., the sticky information model and the "noisy" information model.

Using an equivalent test of forecast revisions on past forecast revisions, we confirm the finding of persistence in average forecast revisions. We also contribute novel perspectives on forecasters' behavior, drawing on our large set of individual forecasts for advanced and emerging countries.

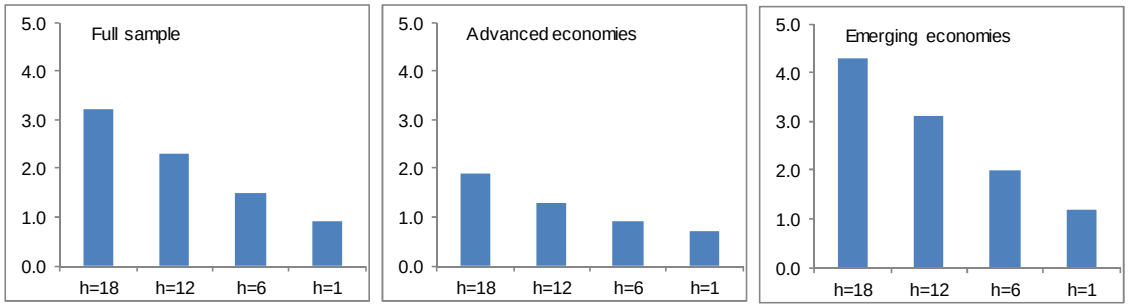
In particular, we provide evidence against the usefulness of the sticky information model to describe the dynamics of growth forecasts. We show that the estimates of informational rigidity based on consensus (average) forecasts overstate the true degree of forecasters' inattentiveness. When consensus forecasts are used, which has been the common practice in previous studies, estimates suggest that forecasts are updated on average every 6 months. Our analysis of fractions of forecasters who update their forecasts, however, points to a higher frequency of updating. The evidence based on fractions, hence, suggests a small role of sticky information in explaining the overall degree of information rigidity in economic forecasts. The predictability of individual forecast revisions also casts some doubt on the validity of the sticky information theory.

Many interesting issues are left for the future research. In particular, herding, another prominent feature of forecasters' behavior (Gallo et al., 2002), and its interaction with forecast smoothing deserve a closer look. In addition, there is evidence of nonlinearities in forecast smoothing in our sample.[12] Further topics that are worth being explored are

[12] Smoothing is less pronounced in the tails of the distribution of individual forecast revisions than in the main body of the distribution (see working paper version of this paper for preliminary evidence). It remains an open question, however, how these nonlinearities can be linked to the different theories of forecast generation mentioned in this paper.

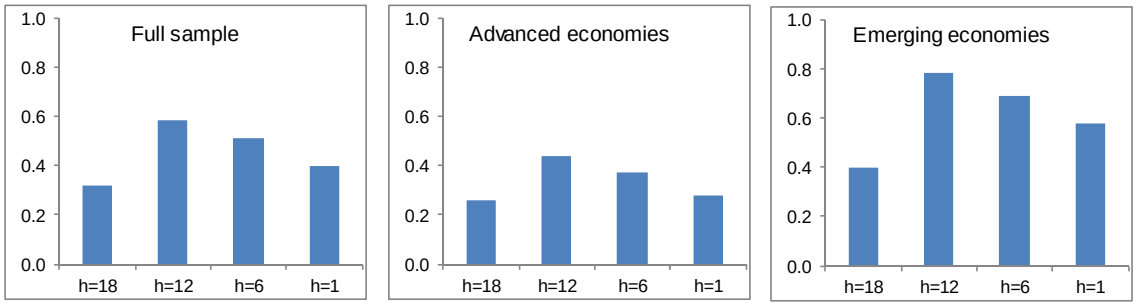
implications of uncertainty for the dynamics of macroeconomic forecasting and the evolution of forecast rigidities over the business cycle.

Figure 1. Root Mean Squared Forecast Errors over Forecast Horizons



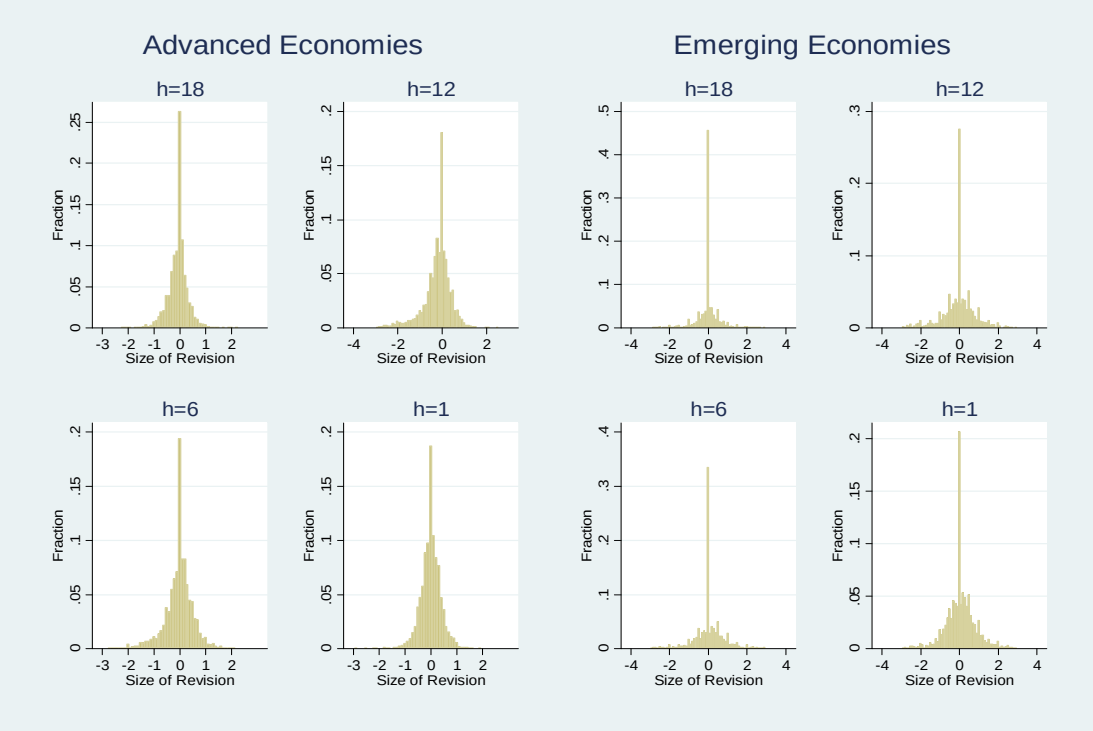
Note: *h* refers to the forecast horizon.

Figure 3. Mean Absolute Revisions over Forecast Horizons



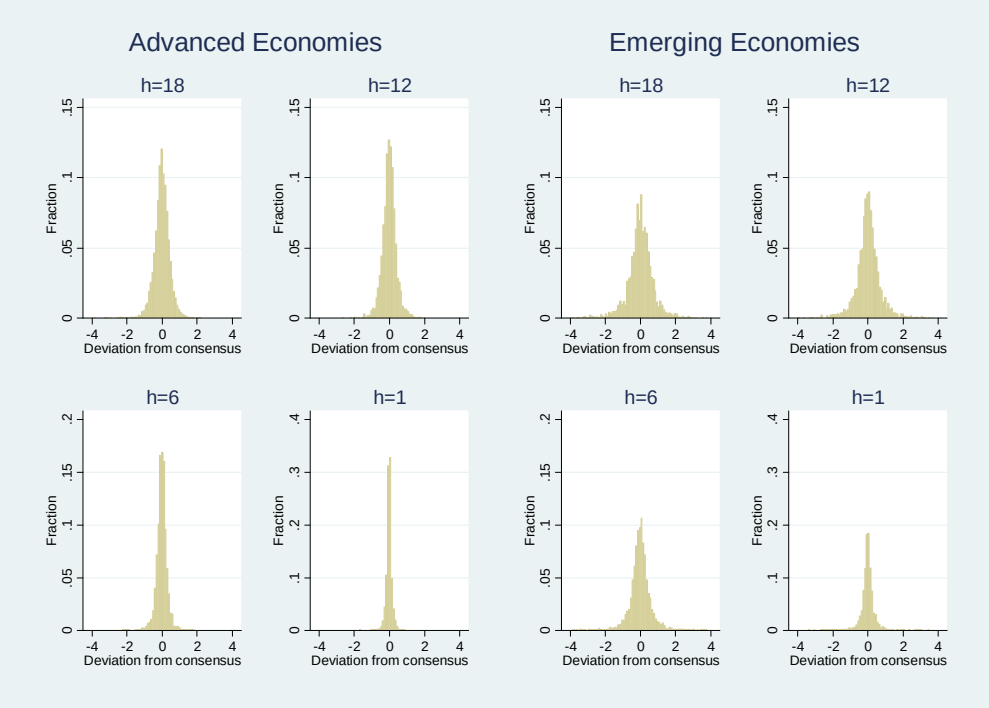
Note: *h* refers to the forecast horizon.

Figure 3. Distribution of Forecast Revisions



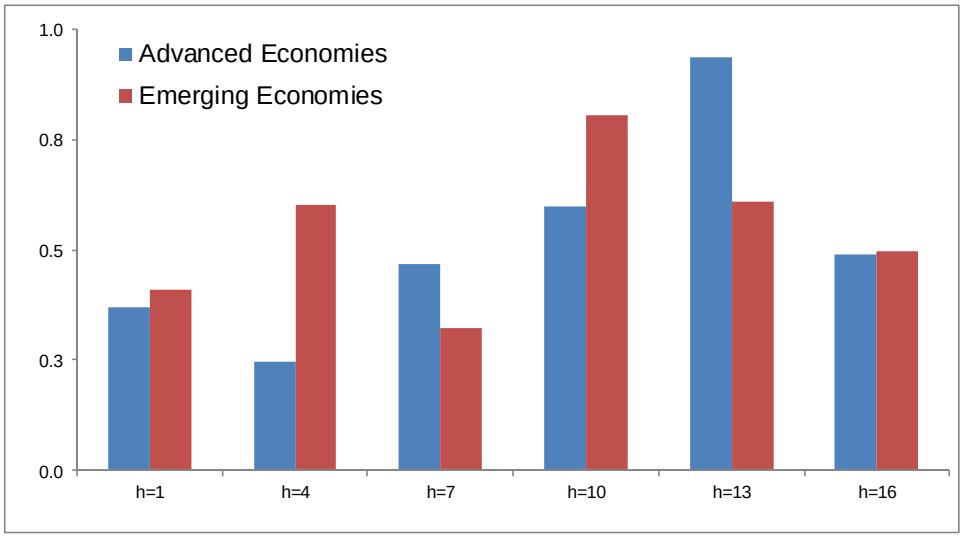
Note: *h* refers to the forecast horizon. For each case, revisions are computed over k=3 months.

Figure 4. Distribution of Deviation of Individual Forecasts from Average (Consensus)



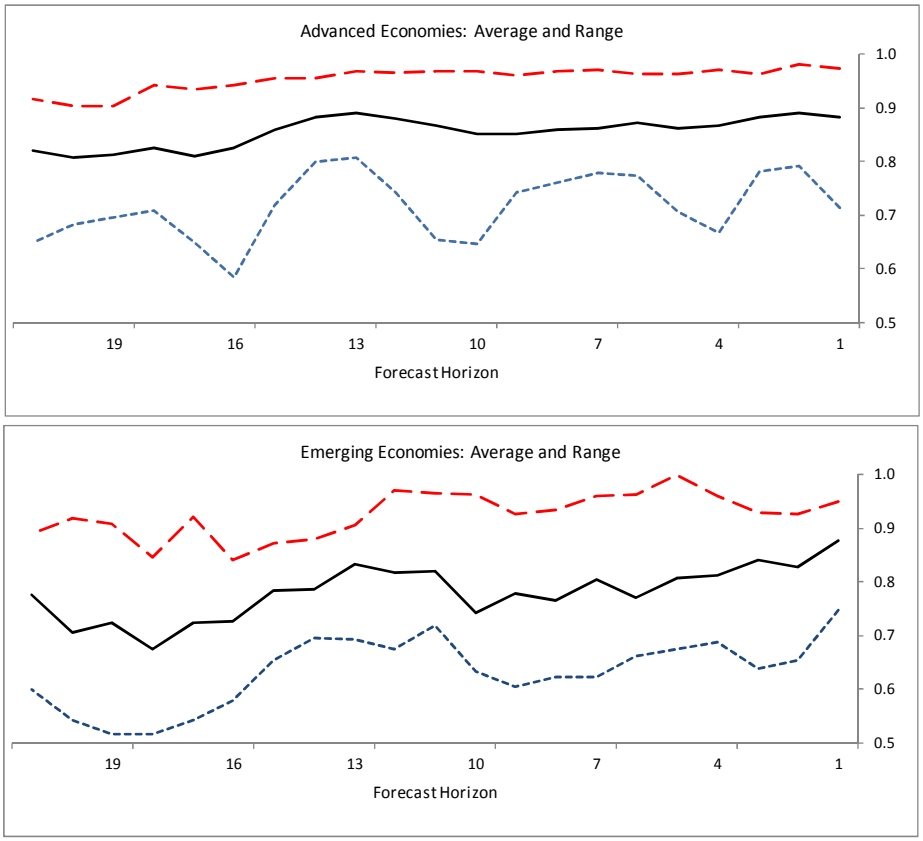
Note: *h* refers to the forecast horizon.

Figure 5. Informational Rigidities at Different Forecast Horizons (Consensus)



Note: *h* refers to the forecast horizon.

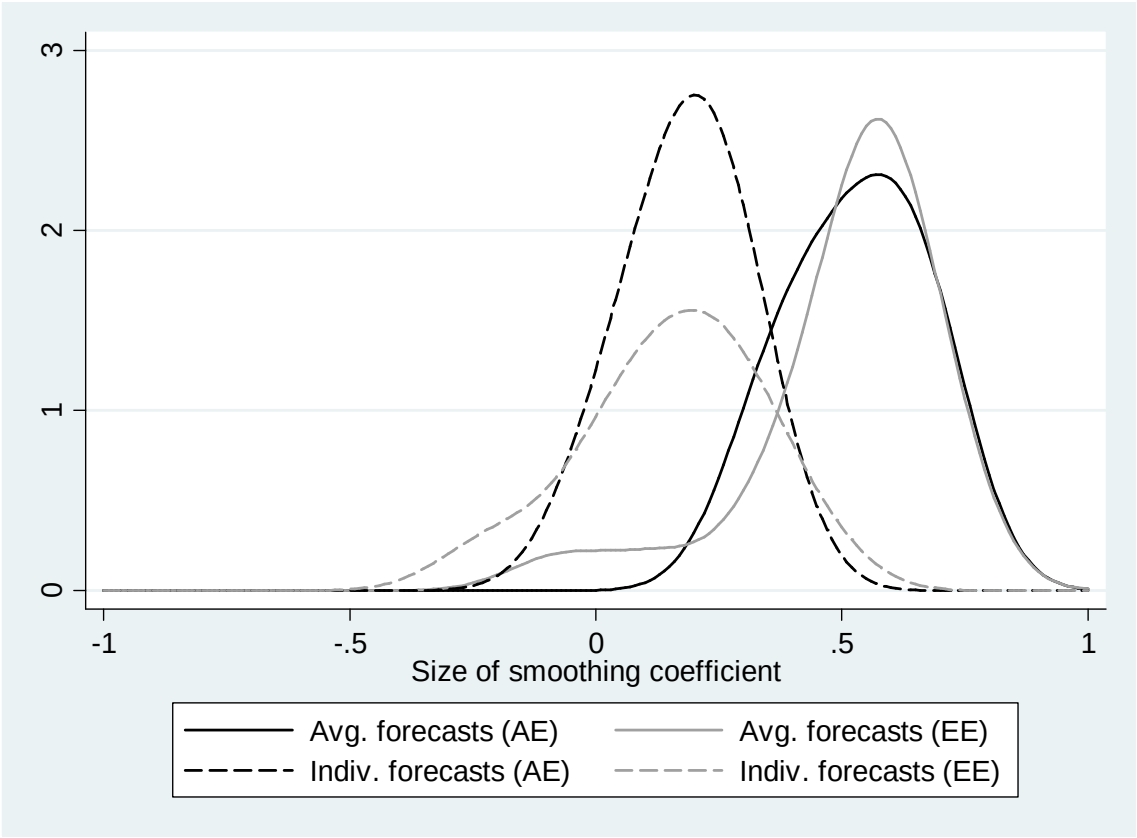
Figure 6. Fractions of Revised Individual Forecasts



Source: Authors' estimates.

Note: Fractions show how many forecasters on average revised their forecasts at least once three months prior to the forecast horizon indicated on the horizontal axis.

Figure 7. Distribution of Information Rigidity Coefficients across Countries



Source: Authors' estimates.

Note: Density estimates based on the different estimates for all countries in the sample using a Gaussian kernel and a bandwidth of 0.1.

Table 1. Basic Features of Forecast Data

	Full Sample	Advanced Economies	Emerging Economies
Number of target years	23	23	23
Number of countries	36	14	22
Number of individual forecast observations	188 639	104 894	83 745
Average number of forecasts per country per target year	15.5	17.2	13.7
Average forecast			
Mean	3.2	2.1	4.6
Median	3.0	2.4	4.8
Average forecast errors			
Mean	0.0	-0.1	0.1
Median	0.2	0.1	0.4

Note: The advanced economies in our sample are: Australia, Canada, France, Germany, Italy, Japan, The Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, United Kingdom and United States. The emerging economies in our sample are: Argentina, Brazil, Chile, China, Colombia, Hong-Kong, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Singapore, South Korea, Taiwan, Thailand and Venezuela.

Source: Authors' estimates.

Table 2. Revisions and Deviations from the Average Forecast

	Horizon (in months)			
	h=18	h=12	h=6	h=1
	Mean Absolute Deviation from Consensus			
Full sample	0.29	0.26	0.19	0.10
Advanced economies	0.24	0.22	0.15	0.07
Emerging economies	0.36	0.32	0.28	0.15
	Variance of Deviation from Consensus			
Full sample	0.42	0.39	0.31	0.17
Advanced economies	0.33	0.29	0.21	0.11
Emerging economies	0.56	0.52	0.45	0.25

Source: Authors' estimates.

Table 3. Information Rigidity and Forecast Smoothing

	Average Forecasts			Individual Forecasts		
	Full Sample	Advanced Economies	Emerging Economies	Full Sample	Advanced Economies	Emerging Economies
	Ordinary Least Squares with Driscoll-Kraay Robust Errors					
Past revision	0.404***	0.370***	0.409***	0.203***	0.127**	0.223***
	6.7	6.1	5.6	6.3	2.7	6.1
Past revision*Horizon 4	0.132	-0.125	0.192	0.045	-0.091	0.097
	0.9	-0.9	1.3	0.5	-1.1	1.0
Past revision*Horizon 7	-0.059	0.098	-0.085	-0.067	0.164*	-0.126
	-0.3	1.4	-0.3	-0.5	2.6	-0.9
Past revision*Horizon 10	0.350*	0.230	0.395**	0.239	0.316	0.219
	2.5	1.1	3.0	1.3	1.5	1.3
Past revision*Horizon 13	0.272	0.566***	0.202	0.026	0.144	-0.007
	1.3	4.2	0.8	0.2	1.7	-0.1
Past revision*Horizon 16	0.093	0.118	0.089	-0.065	-0.072	-0.048
	0.7	0.8	0.6	-1.0	-0.9	-0.6
Constant	-0.001	-0.028	0.025	-0.038	-0.048	-0.022
	0.0	-1.2	0.5	-0.9	-1.7	-0.3
Ratio of coefficients on past revisions				0.50	0.32	0.55
Number of observations	3408	1698	1710	35578	21054	14524

Source: Authors' estimates.

Note: Numbers below the coefficients are t-statistics . Asterisks indicate the degree of significance of coefficients: *** 1 percent, ** 5 percent, and * 10 percent. Regressions include a fixed effect for each country for average forecasts and a fixed effect for each forecaster for individual forecasts; the constants are identified by restricting the sum of all fixed effects to equal 0. The ratio of coefficients on past revisions is defined as the quotient of the baseline rigidity parameter for individual revisions and the equivalent for the revisions of the average forecast. Results are obtained by skipping the forecast data made in December 2008 for the growth rate of 2009, which are heavily driven by the adjustment of forecasts to the progression of the Great Recession. Including these observations leads to an incease of the effect of "Past revision*Horizon 13" to about 0.84 (for both estimators). This would imply a total rigidity parameter of above 1, which is not consistent with any theory of informational rigidities.

Table 4. Country-Specific Estimates

	Average Forecasts				Individual Forecasts					
Country	λ	sd	N	R^2	Avg. λ	Avg. sd	Avg. N	Avg. R^2	K	Avg. Frac.
Australia	0.337	0.052	365	0.10	0.065	0.057	131.1	0.02	36	0.86
Canada	0.414	0.049	364	0.16	0.165	0.098	165.0	0.19	29	0.73
France	0.527	0.047	364	0.26	0.179	0.132	118.5	0.12	40	0.85
Germany	0.613	0.044	364	0.35	0.337	0.103	200.3	0.35	42	0.78
Italy	0.534	0.046	364	0.27	0.170	0.196	126.3	0.44	32	0.86
Japan	0.492	0.048	364	0.22	0.216	0.174	109.2	0.06	38	0.92
Netherlands	0.615	0.044	363	0.35	0.187	0.175	96.3	0.00	23	0.83
New Zealand	0.389	0.056	341	0.13	-0.019	0.063	110.6	0.04	28	0.89
Norway	0.494	0.048	363	0.22	0.118	0.100	88.9	0.00	18	0.92
Spain	0.695	0.038	363	0.48	0.251	0.078	108.7	0.13	28	0.85
Sweden	0.666	0.045	363	0.38	0.246	0.393	100.3	0.00	31	0.95
Switzerland	0.631	0.047	363	0.34	0.298	0.068	124.9	0.16	19	0.79
UK	0.699	0.041	364	0.45	0.310	0.264	144.9	0.28	60	0.79
USA	0.330	0.051	364	0.10	0.037	0.339	121.4	0.02	60	0.84
Argentina	0.545	0.063	151	0.33	0.123	0.664	49.2	0.00	42	0.87
Brazil	0.512	0.078	151	0.22	0.021	0.136	57.3	0.00	42	0.81
Chile	0.570	0.065	151	0.34	0.281	0.098	64.8	0.23	38	0.82
China	0.577	0.052	277	0.31	0.032	0.276	106.4	0.00	39	0.66
Colombia	0.627	0.076	151	0.32	-0.002	0.314	50.5	0.02	30	0.75
Costa Rica	0.499	0.072	147	0.25	-	-	-	-	-	-
Dominican Republic	0.572	0.076	147	0.28	-	-	-	-	-	-
Ecuador	0.335	0.087	147	0.09	-	-	-	-	-	-
Hong Kong	0.543	0.049	350	0.26	0.237	0.113	92.1	0.52	38	0.72
India	-0.079	0.058	277	0.01	-0.243	0.154	63.3	0.02	30	0.83
Indonesia	0.624	0.041	350	0.40	0.102	0.027	76.1	0.01	39	0.67
Malaysia	0.717	0.039	350	0.49	0.331	0.348	77.3	0.15	44	0.72
Mexico	0.638	0.060	151	0.43	0.141	0.146	67.4	0.20	44	0.83
Panama	0.395	0.077	147	0.15	-	-	-	-	-	-
Paraguay	0.526	0.081	147	0.22	-	-	-	-	-	-
Peru	0.702	0.063	151	0.45	0.461	0.088	56.9	0.12	25	0.79
Philippines	0.390	0.065	277	0.12	-0.135	0.190	15.6	0.01	14	0.86
Singapore	0.699	0.050	350	0.36	0.372	0.112	84.8	0.14	38	0.79
South Korea	0.528	0.048	365	0.25	0.173	0.069	87.7	0.05	36	0.83
Taiwan POC	0.559	0.049	365	0.26	0.310	0.080	103.4	0.03	32	0.80
Thailand	0.616	0.045	350	0.35	0.203	0.135	68.9	0.19	41	0.81
Venezuela	0.119	0.085	151	0.01	0.227	0.259	60.8	0.04	33	0.82

Source: Authors' estimates.

Note: Estimates in the left part of the table refer to country-specific estimations based on the revision of the average forecast for each country. Estimates in the right part of the table are average figures based on separate estimations for each individual forecaster in each country. All country- and forecaster-specific models were estimated without any forecast-horizon controls. λ denotes the estimated coefficient for the first lag of the 3-months revision (Avg. λ refers to the average across all individual estimates for each country). Sd (Avg. sd) is the corresponding (average) standard deviation. N (Avg. N) shows the (average) number of observations for each estimation. K denotes the number of different forecasters in each country for which an estimate is obtained. Avg. Frac. displays the fraction of forecasters that, on average, adjust their forecasts at least once during a three

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