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An Evaluation of World Economic Outlook Forecasts: Any Evidence of Asymmetry?

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An Evaluation of World Economic Outlook Forecasts: Any Evidence of Asymmetry? [*]

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ABSTRACT: Using a large cross-country dataset covering over 150 countries and more than 10 macroeconomic variables, this study examines the consistency of IMF World Economic Outlook (WEO) forecasts with the full information rational expectations (FIRE) hypothesis. Similar to Consensus Economics forecasts, WEO forecasts exhibit an overreaction to news. Our analysis reveals that this overreaction is asymmetric, with more measured response to bad news, bringing forecasts closer to the FIRE benchmark. Moreover, forecasts align more closely with FIRE hypothesis during economic downturns or when a country is part of an IMF program. Overreaction becomes more pronounced for macroeconomic variables with low persistence and for forecasts over longer horizons, consistent with recent theoretical models. We also develop a model to explain how state-dependent nature of attentiveness may drive this asymmetric overreaction.

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WORKING PAPERS

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Contents

1 Introduction

The Rational Expectations Revolution transformed economics, making expectations a pivotal element in economic modeling. Since then, expectations have become crucial in understanding a wide range of economic behaviors, including household consumption and saving patterns, firms' investment and pricing strategies, job search dynamics in labor markets, and the decision-making processes of fiscal and monetary authorities. While dynamic macroeconomics has made significant progress, an increasing body of survey-based evidence challenges the strict validity of the full information rational expectations (FIRE) hypothesis. Many models have moved away from the FIRE benchmark, yet the empirical evidence remains too limited to reach a consensus on how expectations are formed, despite their critical role in economics.

According to the FIRE hypothesis, no variable should be able to predict forecast errors, as agents are assumed to optimally incorporate all available information when forming expectations about the future.[1] This assumption can be tested empirically by analyzing the predictability of forecast errors. Coibion and Gorodnichenko (2015, 2012) propose a regression framework for this purpose, examining whether forecast revisions—i.e., changes in forecasts from one period to the next—can predict subsequent forecast errors. Through this model, we can evaluate whether the null hypothesis of FIRE holds. Moreover, this approach sheds light on how forecasters react to economic news, as forecast revisions reflect their response to newly available information.

Following this framework, numerous empirical studies have shown that forecast errors are indeed predictable, thereby violating the FIRE assumption (Coibion and Gorodnichenko 2015; Gennaioli et al. 2016; Kuchler and Zafar 2019; Bordalo et al. 2020). In response, various models have emerged that relax the strict assumptions of FIRE in different ways.[2] These modifications introduce various cognitive biases into the expectation formation process, each with different implications for how agents respond to new infor-

[1] This implies that forecast errors should not result from a lack of available information at the time of the original forecast. Additionally, there should be no delays or rigidities in processing signals and learning from new information, as agents are assumed to fully observe the state of the economy when forming their expectations.

[2] Early models focus on informational frictions and the limited ability of agents to process information (Mankiw and Reis 2002; Woodford 2003; Sims 2003), while more recent models also depart from rational expectations. These newer models emphasize diagnostic expectations to explain overreaction observed in survey data (Bordalo et al. 2020), introduce extrapolation and overconfidence in expectation formation (da Silveira and Woodford 2019; Nagel and Xu 2021; da Silveira et al. 2020; Angeletos et al. 2021; Bianchi et al. 2024), and incorporate cognitive discounting and level-k thinking into macroeconomic models (Farhi and Werning 2019; García-Schmidt and Woodford 2019; Gabaix 2020). Theories incorporating informational frictions, cognitive discounting, and level-k thinking often predict that beliefs will underreact to new information (Angeletos et al. 2021).

mation. While some models predict overreaction to news, others suggest that agents may underreact, reflecting a broader spectrum of behaviors in how expectations are adjusted over time.

Overreaction in forecasts refers to overestimating the probability of outcomes based on recent information, while underreaction involves underestimating the likelihood of such outcomes. [3] This under- or overreaction can be detected by analyzing forecast errors and forecast revisions. When forecasters overreact to new information, their revisions may overshoot, leading to overly optimistic or pessimistic predictions that do not materialize. These cognitive and judgment biases, which result in "imperfect expectations," are particularly important in macro-finance. News can heavily influence people's perceptions of future economic scenarios, thereby impacting decisions and pricing in financial markets (Shiller 1981; Gennaioli et al. 2015; Bordalo et al. 2018) as well as in the broader economy (Coibion et al. 2018; Armona et al. 2019; Bordalo et al. 2024). Given the importance of expectations in shaping macroeconomic dynamics, there is a strong need for empirical evidence to better understand these biases.

Survey-based empirical evidence for macroeconomic forecasts primarily relies on the Survey of Professional Forecasters (SPF), Blue Chip Surveys in the U.S., and Consensus Economics for other developed countries. Most of these studies focus on a limited set of countries, and the evidence on over- and underreaction varies across them. For instance, Coibion and Gorodnichenko (2015) document underreaction in consensus forecasts using the SPF data,[4] whereas Bordalo et al. (2020) find overreaction in individual forecasts using the same data and the Blue Chip Surveys.[5] Additionally, Bordalo et al. (2018), Greenwood and Shleifer (2014), Gennaioli et al. (2016), Bouchaud et al. (2019), Barberis et al. (1998), and Cieslak (2018) document evidence of overreaction in financial markets. At the firm level, Born et al. (2024) provide evidence for overreaction to individual news and underreaction to aggregate news. Experimental studies have also shown the predictability of forecast errors, as seen in the work of Afrouzi et al. (2023), Frydman and Nave (2017), Beshears et al. (2013), Hommes et al. (2005), Assenza et al. (2014), and Reimers and Harvey (2011).

[3] Overreaction of forecasts is in line with the excess volatility puzzle of asset prices in finance (Shiller 1981). Overreaction to positive or negative news makes investors' risk perceptions highly volatile, leading to increased volatility in market prices (Bordalo et al. 2018), and even to bubbles and crashes. Extrapolation bias, a strong tendency to project recent news into the future, or overconfidence bias can create overreaction that we observe in the data (Kohlhas and Walther 2021).

[4] They also extend this evidence to 11 other advanced economies using Consensus Economics forecast.

[5] Bordalo et al. (2020) reconcile these seemingly contradictory findings by developing a model that incorporates diagnostic expectations, explaining consensus-level underreaction alongside individual-level overreaction.

Despite significant progress in the literature, evidence from a larger set of countries remains scarce. In this paper, we address this gap by utilizing the IMF World Economic Outlook (WEO) forecasts. This dataset offers significant advantages due to its extensive coverage, encompassing nearly 180 countries and 13 macroeconomic variables over more than 30 years.The breadth of this dataset enables us to assess the predictability of forecast errors and forecast revisions in a broader context, providing valuable insights beyond advanced economies. It also allows us to explore new dimensions of expectations, such as asymmetry in belief formation and state dependency, and to provide further empirical evidence for competing theories of expectation formation.

Our analysis reveals that WEO forecasts, much like those from Consensus Economics, exhibit a tendency to overreact to news. However, this overreaction displays a distinct asymmetry: WEO forecasts overreact strongly to good news, while their response to negative news is more measured, resulting in more cautious forecast revisions that bring the forecasts closer to the FIRE benchmark. Moreover, these forecasts generally align with the FIRE assumption when predicting policy-related macroeconomic indicators such as unemployment and inflation.[6] In contrast, we observe notable overreaction for nearly all other macroeconomic variables. Additionally, forecast errors for advanced economies are less predictable from forecast revisions, while the overreaction mechanism is more pronounced in developing economies.

We also find evidence of state dependency in how forecasters react to news: overreaction is weaker during economic downturns and is less pronounced for countries under an IMF program compared to those not in a program. Given that one might expect forecasters to be more attentive during adverse economic situations or when a country has an IMF program, attentiveness may be a key factor in explaining the state dependency of overreaction.

Finally, we examine the role of a variable's persistence in overreaction. Our empirical findings confirm that overreaction is more pronounced for variables characterized by low persistence. Most macroeconomic variables are highly auto-correlated in advanced economies, which does not allow for testing that requires a variation in the persistence parameter. Therefore, having emerging markets in our dataset is crucial to be able to test the patterns expected from the theory. Lastly, this overreaction is particularly stronger over longer forecast horizons, supporting the recent findings of Afrouzi et al. (2023) and Bianchi et al. (2024).

Building on Afrouzi et al. (2023), we explain the state-dependent nature of overreaction through asymmetric loss functions coupled with imperfect expectations. The intu-

[6] However, our asymmetry analysis reveals significant overreaction specifically for unemployment.

ition is that the potential loss—both reputational and otherwise—from incorrect forecasts is greater during bad times than in good times, and similarly higher for countries in an IMF program compared to those without one. These higher potential costs lead to greater attentiveness, which in turn results in lower overreaction. In line with the theoretical propositions advanced by recent studies,[7] the overreaction in the model is notably significant for macroeconomic variables characterized by low persistence and for forecasts extended over longer horizons.

While our paper is the first to document this asymmetry in overreaction, we are not the first to utilize the WEO dataset. For example, Beaudry and Willems (2022) document over-optimism in IMF forecasts for real growth, showing that such an upward bias can induce short-run economic contractions. Gatti et al. (2024) compare IMF forecasts with those of the World Bank, highlighting differences in accuracy and optimism. An et al. (2018) assess the accuracy of IMF forecasts, particularly during recessions, while Baqir et al. (2005) examine the impact of IMF program targets on economic growth.[8] Additionally, Genberg et al. (2014) show how WEO forecasts influence economic policymaking in respective countries, and Timmermann (2007) evaluates the accuracy of WEO forecasts across 178 countries, finding relatively smaller forecast errors for advanced economies. Recently, Celasun et al. (2021) examine the performance of WEO growth forecasts over the period 2004–2017 and document consistent overprediction bias, regardless of whether a country is in the program group or not. These studies consistently document a tendency for GDP growth forecasts to exhibit negative errors, reflecting an optimistic bias among IMF forecasters, which aligns with our findings.

Overall, this paper seeks to fill gaps in the empirical literature by extending the analysis to a broader, cross-country dataset, offering deeper insights into the validity of competing theories. To this end, the paper is structured as follows: Section-2 describes the data and methodology, and presents the main empirical evidence. Section-3 explores the determinants of overreaction in forecasts, examining how this behavior varies with the business cycle and the influence of IMF programs. Section-4 introduces a model with

[7]The fact that agents tend to overreact to economic variables with lower persistence aligns with various models such as extrapolative expectations, adaptive expectations, diagnostics expectations, and constant gain learning models. It is worth noting that the overreaction mechanism is not consistent with sticky information models, as documented by Afrouzi et al. (2023). Bordalo et al. (2020) also presents a model in which individual overreaction depends on the characteristics of the data-generating process, such as persistence and volatility. Similarly, they find that more persistent series exhibit weaker overreaction.

[8]Performance is evaluated along three dimensions: accuracy, bias, and efficiency (Celasun et al. 2021). Accuracy pertains to the overall magnitude of forecast errors, which tends to worsen during periods of heightened volatility, making forecasting more challenging. This requires more attention to the news. Pfäuti (2023) recently demonstrated that in the context of inflation, individuals become more attentive to news once inflation surpasses a threshold of 4 percent.

diagnostic expectations to capture the observed asymmetry, and Section-5 concludes.

2 Data and Empirical Analysis

2.1 Data and Descriptive Statistics

We have collected data from 103 vintages spanning from May 1990 to January 2024. The dataset encompasses 188 countries and 13 variables, with some variables exhibiting variations in country coverage. The forecasts have been published quarterly since April 2007 and semiannually prior to that. The variables utilized for regression analysis and the number of countries for each variables are provided in Table-1. The vintage releases contain both annual and quarterly forecasts. Since the annual forecasts have better country coverage compared to quarterly forecasts in the dataset, we conduct the empirical analysis using the annual version of the data.[9] Typically, for earlier periods, we observe two vintages within a year, occurring around May and September. But the majority of vintages fall in January, April, July, and October. To standardize the vintage timing, we adjust March and May to April, June to July, and September to October. Furthermore, to get estimates robust to extreme observations in the data, we remove outliers from our sample by discarding observations below the 1st percentile and above 99th percentile for each country-variable pair.[10]

Each country desk is staffed by a small team of economists who produce forecasts for macroeconomic variables over a four-year horizon.[11] As a result, the data generated can be viewed as individual-level forecasts rather than consensus or aggregate-level forecasts. Therefore, the analysis throughout the paper is more similar to studies on individual forecasts rather than consensus forecasts of macroeconomic and financial variables. Further details and descriptive statistics regarding the variables, forecast revisions, and errors can be found in Table-A1.

Our methodology closely follows Coibion and Gorodnichenko (2015) and Bordalo et al. (2020). If the vintages are quarterly and the forecasts pertain to quarterly variables, we can evaluate the impact of forecast revisions on forecast errors using the following

[9]Consequently, we primarily present the results using the annual forecasts throughout the paper. In the appendix, as a robustness check, we provide results with quarterly forecasts.

[10]Additionally, observations above the 99th percentile or below the 1st percentile for each variable are eliminated. We apply these criteria to forecast error, forecast revision, and the actual value of a variable.

[11]For a more detailed explanation of the forecasting process, please refer to Genberg et al. (2014).

Table 1: Variables Utilized for Regression Analysis and Country Coverage

Variable	Definition	No. of Countries	
		Annual	Quarterly
LE	Total employment	111	25
LLF	Total labor force	98	91
$LULCM$	Unit labor costs, manufacturing sector	39	17
LUR	Unemployment rate	99	32
NCG	Public consumption expenditure, constant prices, National Currency	164	35
NCP	Private consumption expenditure, constant prices, National Currency	164	36
$NFDD$	Final domestic demand, constant prices, National Currency	159	31
NFI	Gross fixed capital formation, constant prices, National Currency	161	35
$NGDP$	Gross domestic product, current prices	188	48
$RGDP$	Gross domestic product, constant prices	184	63
NM	Imports of goods and services, constant prices, National Currency	165	35
NX	Exports of goods and services, constant prices, National Currency	161	35
$PCPI$	Consumer Prices, period average	184	62

Note: All variables, except the unemployment rate, are expressed as annual changes (in percent). The number of observations is higher for annual forecasts compared to quarterly forecasts. Throughout the paper, the primary analysis focuses on annual forecasts.

specification:

$$\underbrace{y^{v,c}_{t+h} - F_t y^{v,c}_{t+h}}_{\text{Forecast Error}} = \alpha_{v,c} + \beta^h_{CG} \underbrace{\left(F_t y^{v,c}_{t+h} - F_{t-1} y^{v,c}_{t+h} \right)}_{\text{Forecast Revision}} + error_{v,c,t}$$

where $F_t y^{v,c}_{t+h}$ is the forecast of an economic variable v for the horizon h, at time t, in country c. The term, $(F_t y^{v,c}_{t+h} - F_{t-1} y^{v,c}_{t+h})$, is the forecast revision ($FR^{v,c}_t$) over a quarter for the variable and the dependent variable, $(y^{v,c}_{t+h} - F_t y^{v,c}_{t+h})$, is the forecast error for variable y^v_t.

Under the FIRE hypothesis, β_{CG} should equal zero, indicating that forecast revisions should not be able to predict forecast errors. A statistically significant β_{CG}, however, rejects the null hypothesis of FIRE. Specifically, when $\beta_{CG} < 0$, it suggests that when the forecast revision is positive ($FR_t > 0$), forecasters are overly optimistic, leading to a negative forecast error. In cases of excessive optimism, forecasters revise their forecasts upward too much in response to new information, introducing a bias that results in negative forecast errors—contrary to what would be expected under FIRE. Conversely, when the forecast revision is negative ($FR_t < 0$), forecasters tend to be overly pessimistic, revising their forecasts downward too much, which leads to positive forecast errors. Therefore, a negative β_{CG} indicates an overreaction of forecasts relative to the FIRE benchmark.[12]

As mentioned earlier, vintages are released quarterly only after April 2007 and are available semiannually prior to that. Additionally, vintage releases are in different months of the year and the forecasts are for the calendar years. Therefore, we need to modify the specification to accommodate our sample. For instance, the January 2022 and July 2022 vintage releases provide the forecast of inflation rate in 2023 for a specific country. While the forecast horizons for these two vintages are different (twelve months in the former and six months in the latter), we group them in the same horizon category ($h = 1$ in this case). To be precise, we can define $\tau(t, h)$ which is a function that determines the forecast horizon based on the month of the vintage release date t and the horizon category ($h = 0, 1, 2, 3$). Now, we can rewrite the main specification as follows:

$$y^{v,c}_{t+\tau(t,h)} - F_t y^{v,c}_{t+\tau(t,h)} = \alpha_{v,c} + \beta^h_{CG} \left(F_t y^{v,c}_{t+\tau(t,h)} - F_{t-1} y^{v,c}_{t+\tau(t,h)} \right) + \gamma_t + month_t + error_{v,c,t} \tag{1}$$

For $h = 0$, $y^{v,c}_{t+\tau(t,0)}$ signifies the actual value of variable v in country c for the year in which the vintage was released, and $F_t y^{v,c}_{t+\tau(t,0)}$ denotes the nowcast for the same variable and country.[13] For $h = 1$, $y^{v,c}_{t+\tau(t,1)}$ represents the actual value for the year following the year of vintage release, while $F_t y^{v,c}_{t+\tau(t,1)}$ refers to the forecast for the same period. F_{t-1} denotes the forecast of the variable for the same horizon one year before the release of vintage t. Since $\tau(t, h)$ can vary for the same h depending on the month of vintage release date t, we include month dummies $month_t$ in our annual regressions.[14] γ_t stands for year fixed-effects to control for observed and unobserved aggregate forces and $\alpha_{v,c}$ controls for variable-country fixed-effects.[15]

2.2 Baseline CG estimation and Asymmetry

To test the predictability of individual forecast errors, we employ specification (1) and estimate the β_{CG} coefficients separately for each horizon. The results are presented in Table-2, which shows that β_{CG} is consistently negative across all horizons, with the mag-

[12] Similarly, $\beta_{CG} > 0$ indicates an underreaction of forecasts relative to FIRE.

[13] We take the actual values of variables from the January 2024 vintage of WEO.

[14] As mentioned above, not all vintages are released in the same months for the same quarters of the year. See Figure-A1 and Figure-A2 for the distributions of forecast errors and revisions for each variable.

[15] There might be concerns about bias in forecasts, specifically regarding systematically positive or negative errors. This fixed-effect helps to alleviate this issue.

Table 2: Benchmark Regression Results

	Dependent variable: FE_t		
	h=1	h=2	h=3
	(1)	(2)	(3)
FR_t	-0.321***	-0.292***	-0.265***
	(0.080)	(0.068)	(0.039)
Country-Variable FE	✓	✓	✓
Year FE	✓	✓	✓
No. of Obs.	123818	123500	122982
R-squared	0.078	0.045	0.064

Note: FE_t is the forecast error (actual value minus forecast). FR_t stands for forecast revisions. The model includes country-variable fixed effects, year fixed effects and vintage month dummies. The sample includes all 13 macroeconomic variables across 188 countries, though some variables may be missing for certain countries. The sample period is 1990-2024. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

nitude increasing as the forecast horizon shortens. In other words, forecasters tend to overreact to news, and this overreaction intensifies for shorter forecast horizons. A similar pattern is observed in the quarterly dataset, as shown in Table-C1 in the appendix. Additionally, Table-D1 demonstrates that the same overreaction exists when using Consensus Economics forecasts.

Our findings corroborate those of Bordalo et al. (2018), who document overreaction by individual forecasters to new information, even though we use a different dataset that spans over 180 countries. [16]

[16] Bordalo et al. (2018) find that overreaction to real variables is stronger at $h = 0$, as detailed in their appendix, compared to $h = 3$. Although they do not explicitly state this, their findings suggest that overreaction is more pronounced at shorter horizons. This contrasts with the theoretical prediction in Afrouzi et al. (2023), which posits that longer horizons should exhibit higher levels of overreaction. However, our empirical results in Table-3 indicate that overreaction is greater for positive revisions over longer horizons.

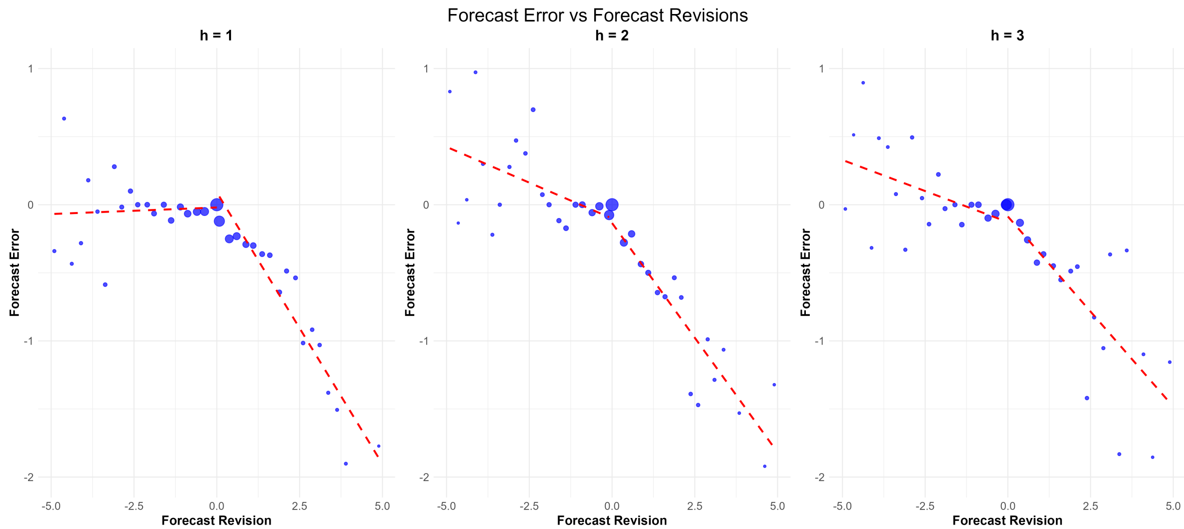

Figure 1: Forecast Errors and Revisions

Note: The figure displays a binscatter plot of IMF forecasters' forecast revisions versus their forecast errors. The sample includes LE, NCP, NFDD, NFI, RGDP, NM, NX, LUR, and PCPI. Please note that the signs of forecast revisions for LUR and PCPI are reversed. Additionally, the forecast revisions are constrained to the range of [-5, 5]. See Figure-B1 for the residualized version.

However, the visual evidence in Figure-1 suggests that this relationship may be asymmetric.[17] Specifically, the overreaction to bad news (which results in negative revisions) appears to be less pronounced compared to the overreaction to good news (which results in positive revisions). To test this hypothesis, we modify the CG regression as follows:

$$y^{v,c}_{t+h,t} - F_t y^{v,c}_{t+h,t} = \alpha_{c,v} + \beta_1 \underbrace{FR^{v,c-}_t}_{\text{Downward Rev.}} + \beta_2 \underbrace{FR^{v,c+}_t}_{\text{Upward Rev.}} + \gamma_t + month_t + error_{v,c,t} \tag{2}$$

where $FR^{v,c-}_t = \min\{0, F_t y^{v,c}_{t+h,t} - F_{t-1} y^{v,c}_{t+h,t}\}$ and $FR^{v,c+}_t = \max\{0, F_t y^{v,c}_{t+h,t} - F_{t-1} y^{v,c}_{t+h,t}\}$ are downward and upward revisions, respectively. This formulation allows us to capture the asymmetric impact by separating forecast revisions into upward and downward components. A negative coefficient on revisions suggests that when the forecast revision is positive ($FR^{v,c+}_t > 0$), forecasters are overly optimistic, leading to a negative forecast error. Conversely, when the forecast revision is negative ($FR^{v,c-}_t < 0$), forecasters tend to be overly pessimistic, resulting in a positive forecast error. Thus, a negative β implies overreaction relative to the FIRE benchmark, while a positive β would suggest information rigidity and underreaction.

To ensure that positive and negative revisions are consistent with good and bad news, we reverse the sign of revisions for variables where a positive revision signals bad news.

[17] Figure-B1 presents the residualized version of Figure-1, illustrating the correlation between forecast errors and forecast revisions after accounting for country-variable and time fixed effects. The asymmetric behavior remains evident in this residualized representation.

Table 3: Asymmetry in Overreaction: Good vs Bad news

Panel-A			
	Dependent variable: FE_t		
	h =1	h = 2	h = 3
	(1)	(2)	(3)
FR_t^-	-0.262^{***}	-0.294^{***}	-0.053
	(0.047)	(0.094)	(0.050)
FR_t^+	-0.414^{***}	-0.428^{***}	-0.485^{***}
	(0.014)	(0.038)	(0.060)
Country-Variable FE	✓	✓	✓
Year FE	✓	✓	✓
No. of Obs.	55382	54973	54762
R-squared	0.083	0.09	0.092
Panel-B (Wald test)			
	h = 1	h = 2	h = 3
χ^2	8.524^{***}	2.3527	31.801^{***}

Note: FE_t is the forecast error (actual value minus forecast). FR_t^- stands for negative revisions, and FR_t^+ stands for positive revisions. The model includes country-variable fixed effects, year fixed effects and vintage month dummies. The sample includes LE, NCP, NFDD, NFI, RGDP, NM, NX, LUR, and PCPI. Please note that the signs of forecast revisions for LUR and PCPI are reversed. The sample period is 1990-2024. Panel-B documents the statistical significance of the difference between the two estimates using Wald test. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01. Refer to Table-B2 for the subsample analysis spanning the 2008–2024 period.

Specifically, the sign of forecast for consumer price index (PCPI) and unemployment rate (LUR) are reversed. Additionally, we exclude variables where a higher value does not clearly indicate good or bad news, such as labor force (LLF), labor costs (LULCM), government spending (NCG), and nominal GDP (NGDP).[18]

Table-3 documents this asymmetry. Although the signs of the estimated coefficients are both negative, there is a clear asymmetry in the degree of overreaction. Forecasters exhibit excessive optimism in response to good news and excessive pessimism in response to bad news; however, the degree of pessimism is not as pronounced as the optimism. In other words, an upward revision is followed by an overprediction of the same variable, though this tendency is less pronounced in the case of a downward revision. For h=3, the overreaction to negative news is not even statistically significant and for all other horizons the degree of overreaction to bad news is smaller. In contrast, the overreaction to good news remains significant across all horizons, with the strongest response occurring when the forecast horizon is longer. Similarly, as a robustness check, the analysis conducted with the quarterly dataset shows that the degree of asymmetry in overreaction is

[18]In Table-B1, we document the results for asymmetry when we do not remove any variables from the sample. In fact, the asymmetry is even more pronounced.

Table 4: Asymmetry in Overreaction: [-10,10] percent Interval

Panel-A			
	Dependent variable: FE_t		
	h =1	h = 2	h = 3
	(1)	(2)	(3)
FR_t^-	-0.059^{***}	-0.118^{**}	0.005
	(0.021)	(0.050)	(0.054)
FR_t^+	-0.462^{***}	-0.467^{***}	-0.449^{***}
	(0.026)	(0.056)	(0.068)
Country-Variable FE	✓	✓	✓
Year FE	✓	✓	✓
No. of Obs.	54160	53707	53475
R-squared	0.081	0.093	0.097
Panel-B (Wald test)			
	h = 1	h = 2	h = 3
χ^2	137.11^{***}	50.72^{***}	47.495^{***}

Note: FE_t is the forecast error (actual value minus forecast). FR_t^- stands for negative revisions, and FR_t^+ stands for positive revisions. The forecast revision is constrained to [-10,10] percent interval. Larger revisions constitute approximately 2% of the full sample. The model includes country-variable fixed effects, year fixed effects and vintage month dummies. The sample includes LE, NCP, NFDD, NFI, RGDP, NM, NX, LUR, and PCPI. Please note that the signs of forecast revisions for LUR and PCPI are reversed. The sample period is 1990-2024. Panel-B documents the statistical significance of the difference between the two estimates using Wald test. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

highest at the longer horizon.[19]

In fact, as shown in Table-4, if we further remove outliers and focus on a sub-sample of revisions not exceeding 10% to eliminate the distortionary impact of relatively large revisions, the overreaction to bad news weakens, while the overreaction to good news remains strong across all forecast horizons.[20] The asymmetry intensifies when large revisions are excluded. In Table-B3, as a robustness check, we provide results for a sample of revisions smaller than 5%. Here, the overreaction to bad news becomes insignificant across all horizons, while the overreaction to good news remains nearly the same. Lastly, when focusing on the subsample analysis for the 2008–2024 period instead of the 1990–2024 period, a more pronounced asymmetry emerges, as documented in Table-B2.[21]

These findings suggest that individuals tend to overreact to news, violating the FIRE assumption; however, this occurs in a distinctly asymmetric manner, with the overreaction to good news being significantly stronger than that to bad news. Notably, there is no overreaction or underreaction to bad news when we focus on the sample of smaller revi-

[19] In the appendix, see Table-C2 for the analysis conducted with the quarterly data.

[20] Revisions larger than 10% constitute approximately 2% of the full sample.

[21] In earlier periods, data quality and information imperfections present significant challenges, with official statistics in EMDEs often subject to substantial periodic revisions due to evolving economic structures.

sions, indicating no violation of FIRE in one direction but not the other. Such asymmetry in expectation formation may have significant implications for the transmission of shocks in a general equilibrium setting.

2.3 Overreaction across Variables

Pooled estimates across macroeconomic variables and countries confirm the predictability of forecast errors based on ex-ante forecast revisions. However, the extent of overreaction or information rigidity might vary across these macroeconomic variables and also countries. We first run the baseline regression for each variable separately, and report the results in Figure-2.

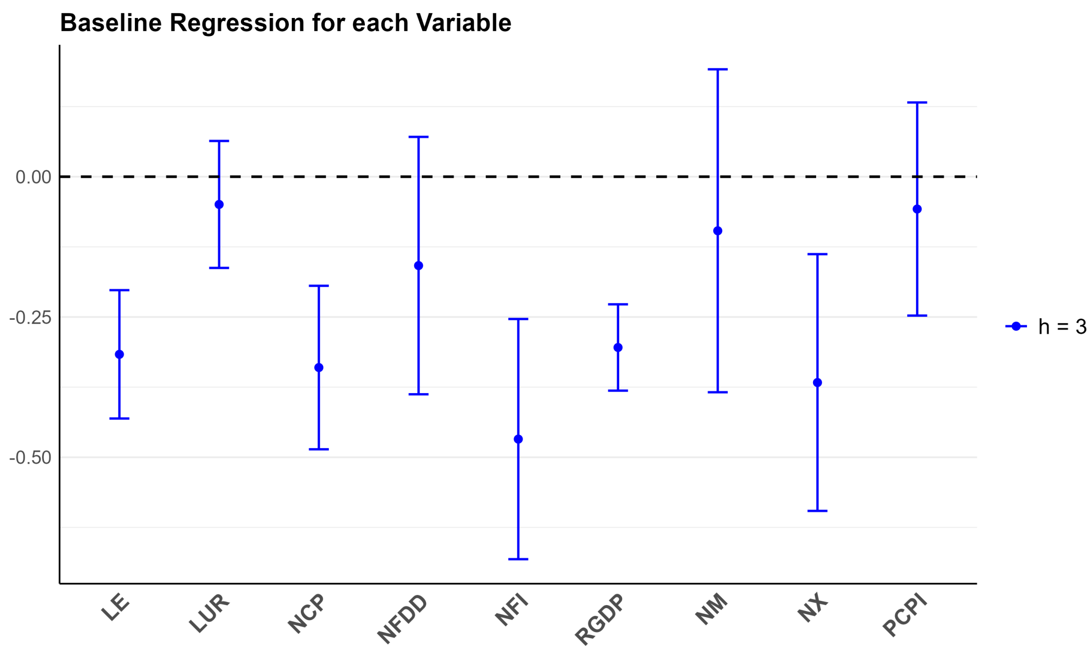

Figure 2: Overreaction in Forecasts for each Variable (3-year horizon)

Note: The figure presents the point estimate of β_{CG} with the two standard deviation error band (95% CI). The baseline specification is run separately for each variable. The model includes country FE, year FE, and vintage month dummies. The sample period is 1990-2024. Standard errors are calculated using Driscoll-Kraay method. Variables are LE (total employment), LUR (unemployment rate), NCP (real private consumption), NFDD (real final domestic demand), NFI (real fixed investment), RGDP (real GDP), NM (import), NX (export) and PCPI (consumer prices). For other horizons refer to Figure-B2.

Figure-2 illustrates how the degree of overreaction varies across different variables. Specifically, for the unemployment rate (LUR) and inflation rate (PCPI), there is no evidence of overreaction or underreaction, indicating no violation of the FIRE assumption for these key macroeconomic indicators. The estimated values for these variables are statistically indistinguishable from zero, meaning we cannot reject the null hypothesis of

FIRE. In contrast, for all other variables, the estimated values are significantly negative at the 95% confidence level.[22] This behavior is evident and statistically significant across nearly all horizons, as shown in Figure-B2. The varying levels of overreaction among the variables can be partially attributed to their persistence or volatility (Coibion and Gorodnichenko 2015), which we will analyze in the next section as determinants of overreaction. Overall, this analysis suggests that, in a sample of nearly 180 countries in a panel setting, overreaction to news is evident for nearly all variables, providing consistent evidence with Bordalo et al. (2020).

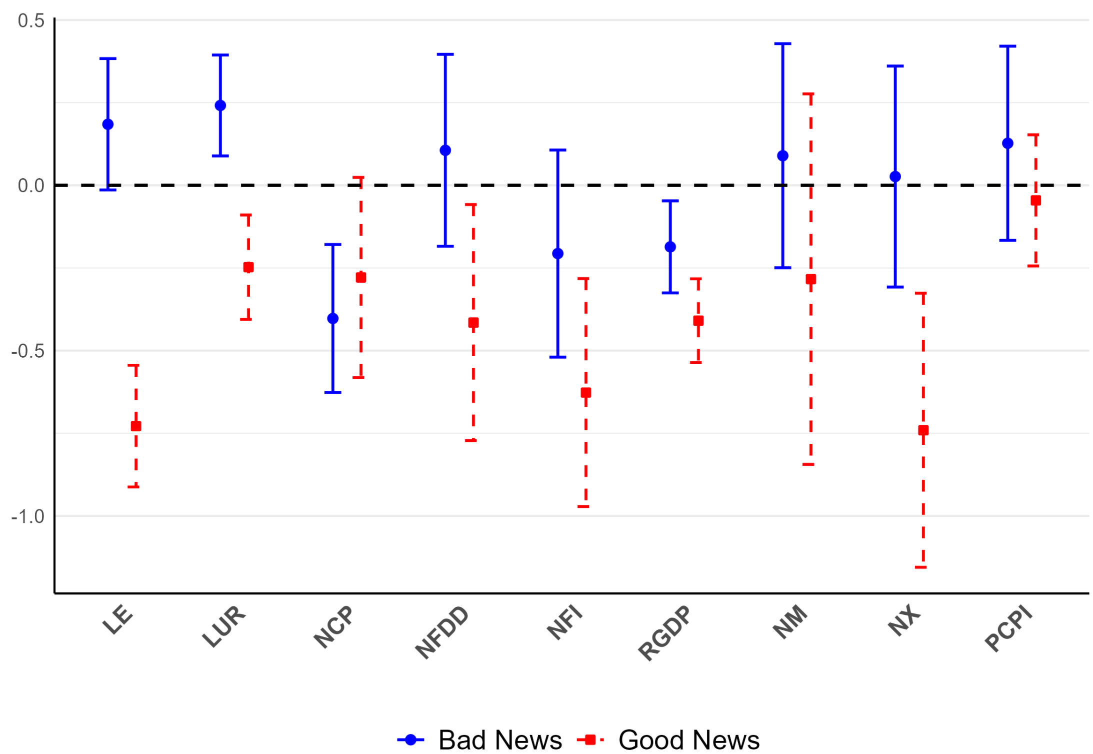

Figure 3: Asymmetry in Overreaction across Variables (3-year horizon)
Note: The figure presents the point estimate of β_{CG} for good and bad news with the two standard deviation error band (95% CI). The specification for asymmetry is run separately for each variable. The model includes country FE, year FE, and vintage month dummies. The sign for the forecast revision of PCPI and LUR are reversed. The sample period is 1990-2024. Standard errors are calculated using Driscoll-Kraay method. Variables are LE (total employment), LUR (unemployment rate), NCP (real private consumption), NFDD (real final domestic demand), NFI (real fixed investment), RGDP (real GDP), NM (import), NX (export) and PCPI (consumer prices).

However, there may be asymmetric behavior in response to good versus bad news at the variable level as well. Therefore, we test the asymmetry in response to news for each variable by running the following regression:

[22] To assess the validity of exercise as a robustness check, we examine the relationship between inflation revisions and GDP forecast errors. The demand-side perspective associates higher inflation expectations with stronger demand and real growth, resulting in a negative correlation between forecast revisions and errors, and this is documented in Table-E3.

$$y^c_{t+h,t} - F_t y^c_{t+h,t} = \alpha_c + \beta_1 \underbrace{FR^{c-}_t}_{\text{Downward Rev.}} + \beta_2 \underbrace{FR^{c+}_t}_{\text{Upward Rev.}} + \gamma_t + month_t + error_{c,t} \quad (3)$$

Figure-3 displays the estimated β values for these positive and negative forecast revisions. This figure suggest that the negative coefficients in the baseline regression are primarily driven by overreaction to good news. In general, there is no information rigidity or underreaction in response to bad news for most of the variables, which might suggest that individuals are attentive to bad news, making forecast errors less predictable.[23] However, overreaction to good news is evident for most variables, with the exception of inflation and imports, where the point estimates show a similar pattern but are not statistically significant.[24] With the exception of real private consumption, we observe a difference in the point estimates, where the estimated β_2 (good news) is consistently more negative than β_1 (bad news). For unemployment, although revisions do not explain forecast errors in Figure-2, we observe significant underreaction to bad news and significant overreaction to good news in Figure-3. These channels can cancel each other out if both directions are not examined separately.

2.4 Overreaction across Country Groups

Having documented heterogeneity at the variable level, we now turn our attention to regional heterogeneity. We categorize countries into distinct groups and to analyze the heterogeneity in overreaction across these groups, we run the benchmark model for each of them separately.

[23]See Kohlhas and Walther (2021) for asymmetric attention, where agents pay less attention to countercyclical variables and more attention to others. Empirically, they check the cyclicality of forecast errors, but not the asymmetry in revisions.

[24]In the appendix, Table-B4 shows the statistical significance of differences between overreaction to good and bad news.

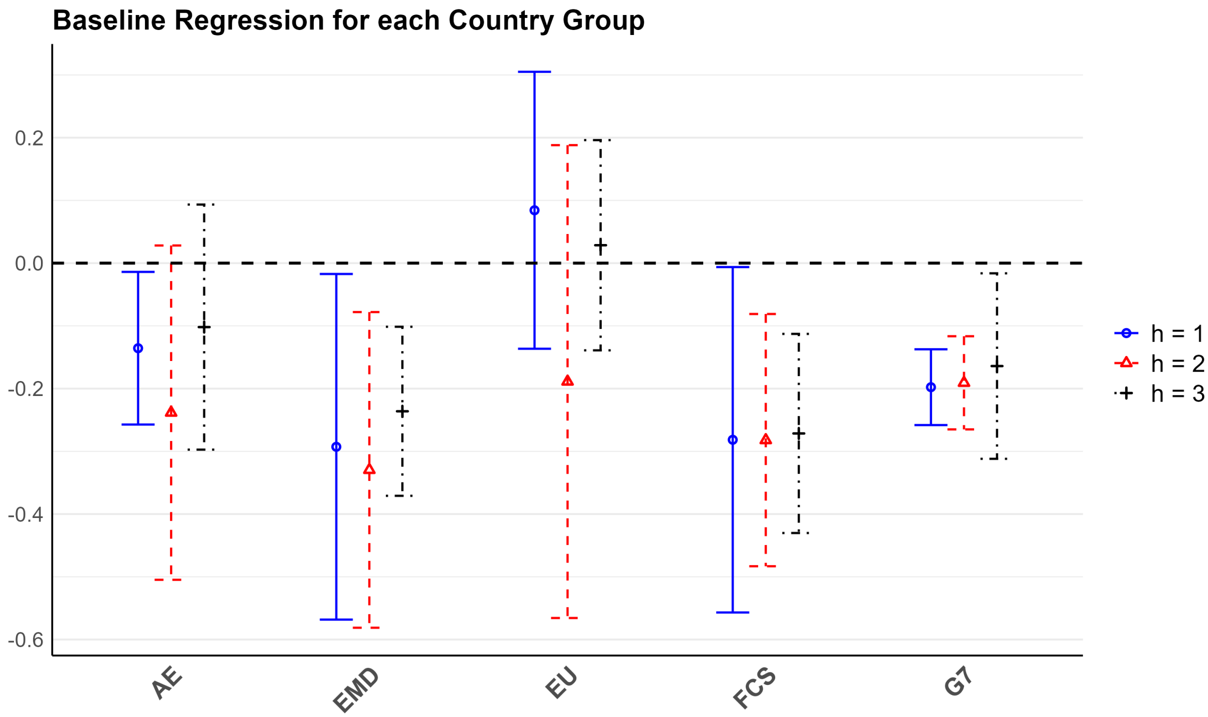

Figure 4: Overreaction in Forecasts for each Country Group

Note: The figure presents the point estimate of β_{CG} with the two standard deviation error band. The baseline specification is run separately for each country group: AE (Advanced Economies), EMD (Emerging and Developing Economies), EU (European Union), FCS (Fragile and Conflict-Affected States), and G7 (The Group of Seven). The model includes variable FE, year FE, and vintage month dummies. The sample includes all 13 macroeconomic variables across 188 countries, though some variables may be missing for certain countries. The sample period is 1990-2024. Standard errors are calculated using Driscoll-Kraay method.

Figure-4 illustrates that forecast errors are unpredictable in advanced economy groups (AE, EU), particularly at the longest horizons. In contrast, this unpredictability does not hold for emerging market groups such as EMD, and FCS, where forecasts exhibit overreaction across nearly all horizons.[25] This observation indicates a divergence in forecasting behavior across regions: individual forecasts for advanced economies align with the rational expectations hypothesis more closely, while forecasts for emerging economies deviate from the FIRE assumption, demonstrating overreaction.

[25] Celasun et al. (2021) show the optimism in the low-income country group, which is basically reflected as upward bias in growth forecasts. Here, we find overreaction to news for all country groups, particularly for short horizons.

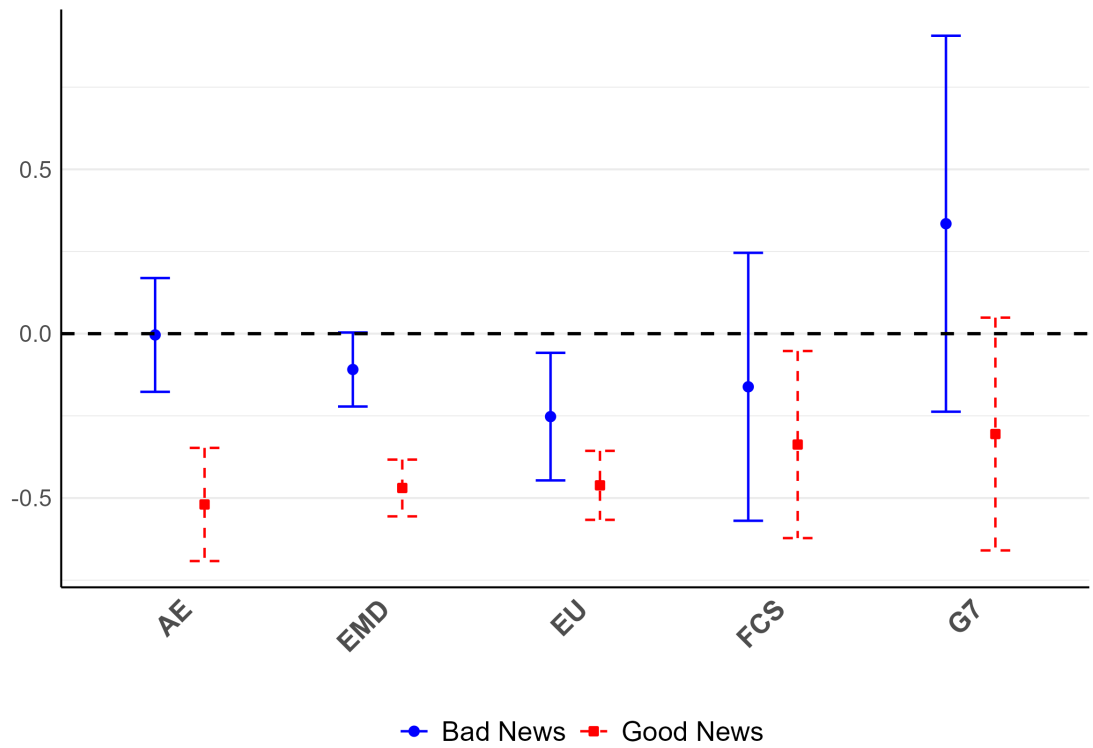

Figure 5: Asymmetry in Overreaction across Country Groups (3-year horizon)

Note: The figure presents the point estimate of β_{CG} for good and bad news with the two standard deviation error band. The specification for asymmetry is run separately for each country group: AE (Advanced Economies), EMD (Emerging and Developing Economies), EU (European Union), FCS (Fragile and Conflict-Affected States), and G7 (The Group of Seven). The model includes variable FE, year FE, and vintage month dummies. Standard errors are calculated using Driscoll-Kraay method. The sample includes LE, NCP, NFDD, NFI, RGDP, NM, NX, LUR, and PCPI. The sign for the forecast revision of PCPI and LUR are reversed. The sample period is 1990-2024.

To determine if there is any asymmetry in overreaction within these country groups, we conduct a similar analysis. Figure-5 indicates that there is nearly no overreaction or underreaction to bad news in any country group, while the overreaction to good news is evident for groups consisting of developing economies. Among advanced economy groups, overreaction to good news is also significant for AE and EU, and it is close to significance for the G7 countries. Most importantly, for each country group, we observe a difference in the point estimates of β_1 and β_2, where the estimated β_2 (good news) is consistently more negative than β_1 (bad news). Although Figure-4 indicates that forecast revisions do not predict errors, focusing on asymmetric revisions reveals a new dynamic, demonstrating that asymmetry persists across both variables and country groups.

3 Determinants of Overreaction

3.1 Persistence and Volatility of the Process

Bordalo et al. (2020) develop a diagnostic expectations model where individual overreaction depends on characteristics of the data-generating process, such as persistence and volatility. Consistent with Afrouzi et al. (2023), their findings suggest that more persistent series tend to exhibit weaker overreaction. To test this theory, we use our dataset by first fitting an AR(1) process to each country-variable pair to estimate the persistence. We then examine the relationship between these persistence estimates and the coefficients from the baseline regression for each country-variable. Figure-6 highlights this positive relationship, indicating that higher persistence, which may vary across countries, is associated with a higher estimated β_{CG} for the country-variable pairs. Bianchi et al. (2024) also propose a model with diagnostic expectations, where agents receive a noisy signal of a process and use it to make forecasts. They show that overreaction is stronger for weaker signals, which are the noisier ones. Assuming the standard deviation of the noise component is roughly similar across variables for forecasters, the volatility of these variables should impact the estimated β_{CG}.

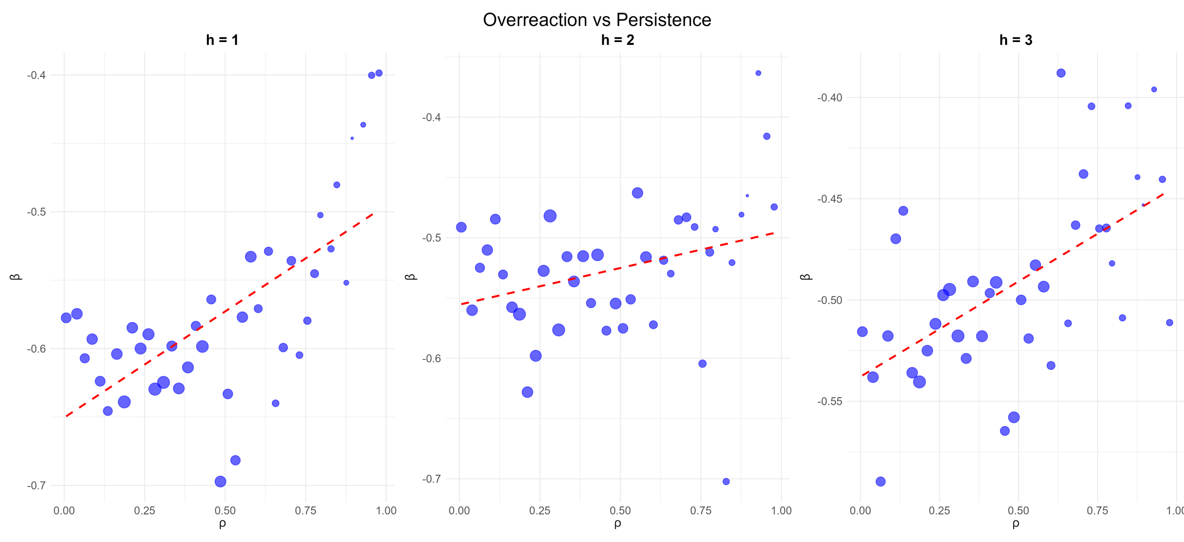

Figure 6: Persistence (ρ) and Overreaction (β_{CG})

Note: The baseline specification is run for each country-variable pair to obtain β_{CG}. The specification includes year FE and vintage month dummies.The persistence of each country-variable pair is calculated by fitting an AR(1) process to the actual data. The sample includes all 13 macroeconomic variables across 188 countries, though some variables may be missing for certain countries. The sample period is 1990-2024. Variable-country pairs with $\rho < 0$ or $\rho > 1$ are omitted.

We can check the importance of persistence and volatility of variables as determinants of overreaction with a simple regression as follows:

Table 5: Determinants of Overreaction

	Dependent variable: β_{CG}		
	$h = 1$	$h = 2$	$h = 3$
	(1)	(2)	(3)
σ	-0.007^{***}	0.005^{**}	0.001
	(0.002)	(0.002)	(0.002)
ρ	0.056^{***}	0.034^{**}	0.062^{***}
	(0.019)	(0.017)	(0.017)
Constant	-0.603^{***}	-0.551^{***}	-0.521^{***}
	(0.011)	(0.010)	(0.010)
No. of Obs	905	906	898
R^2	0.026	0.008	0.016

Note: The baseline specification is run for each country-variable pair to obtain β_{CG}. The volatility and the persistence of each country-variable pair is measured by fitting an AR(1) process to the actual data. To address outliers, the top and bottom 5 percent of observations from the dependent variable's distribution were excluded. The sample includes all 13 macroeconomic variables across 186 countries, though some variables may be missing for certain countries. The sample period is 1990-2024. *p<0.1; **p<0.05; ***p<0.01.

$$\beta_{CG}^{c,v} = \alpha + \gamma_1 \rho_{c,v} + \gamma_2 \sigma_{c,v} + error_{c,v}$$

where v denotes a macroeconomic variable, c stands for the country, and $\beta_{CG}^{c,v}$ is the estimated coefficient on forecast revisions for each country-variable pair in the dataset.

Table-5 shows that the coefficients on persistence are positive, while those on volatility are negative for the first two horizons and become positive for longer horizons. Additionally, the negative constants indicate overreaction in individual forecasts. This suggests that overreaction weakens as the persistence of the country-variable pair approaches 1, aligning with the findings of Afrouzi et al. (2023). However, the relationship between overreaction and volatility varies across horizons, which contrasts with recent theoretical models of expectations.[26]

We can investigate the role of persistence in determining overreaction to good and bad news. Table-6 shows that overreaction is weaker for highly persistent variables. This is primarily driven by a decline in overreaction to good news, as suggested by the interaction variable. This indicates a pronounced asymmetry, with significant overreaction to good news but not to bad news, which diminishes as the persistence of the variable increases. Notably, we do not observe significant changes in the reaction to bad news as persistence rises. Our model, based on Afrouzi et al. (2023) and presented in Section-4,

[26]See Bordalo et al. (2020); Bianchi et al. (2024).

Table 6: Asymmetric Overreaction and Persistence

	Dependent variable: FE_t		
	h =1	h = 2	h = 3
	(1)	(2)	(3)
FR_t^-	-0.010	-0.079	0.083
	(0.069)	(0.125)	(0.187)
FR_t^+	-0.414^{***}	-0.519^{***}	-0.623^{***}
	(0.013)	(0.023)	(0.115)
$FR_t^- \times \mathbb{1}_{\rho>\rho^m}$	-0.279^{**}	-0.190	-0.265
	(0.114)	(0.168)	(0.210)
$FR_t^+ \times \mathbb{1}_{\rho>\rho^m}$	0.074	0.289^{***}	0.381^{***}
	(0.091)	(0.065)	(0.099)
Country-Variable FE	✓	✓	✓
Year FE	✓	✓	✓
No. of Obs.	44999	44707	44557
R-squared	0.077	0.078	0.084

Note: FE_t is the forecast error (actual value minus forecast). FR_t^- stands for negative revisions, and FR_t^+ stands for positive revisions. $\mathbb{1}_{\rho>\rho^m}$ is a dummy that equals one if the persistence of the variable is above the median persistence and equals zero otherwise. The model includes country-variable fixed effects, year fixed effects and vintage month dummies. The sample includes LE, NCP, NFDD, NFI, RGDP, NM, NX, LUR, and PCPI. Please note that the signs of forecast revisions for LUR and PCPI are reversed. The sample period is 1990-2024. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

captures the dynamics related to persistence, but more importantly, it captures the asymmetry in overreaction.

3.2 State of the Economy

According to Coibion and Gorodnichenko (2015), periods of economic expansion are linked to stronger information rigidities. In contrast, recessions, characterized by increased volatility, should prompt economic agents to update and process information more rapidly due to the higher (relative) cost of ignoring macroeconomic shocks. Recently, Bianchi et al. (2024) introduce a model with diagnostic expectations and show that during expansions uncertainty and overreaction are low while in recessions agents overreact more due to higher uncertainty. In our case, there is individual level overreaction and we check whether the degree of overreaction depends on the state of the economy or not. For that, we slightly modify the specification (1) and estimate the following model:

$$y^{v,c}_{t+h,t} - F_t y^{v,c}_{t+h,t} = \alpha_{c,v} + \beta_1 FR^{v,c}_t + \beta_2 grow^c_t + \beta_3 FR^{v,c}_t * grow^c_t + error_{v,c,t}$$

where $grow^c_t$ is equal to one if last period's real GDP growth is positive and zero otherwise. The coefficient of interest is β_3 and a negative coefficient would suggest a stronger overreaction in good times.

Table 7: State-Dependence in Overreaction

	Dependent variable: FE_t		
	h=1	h=2	h=3
	(1)	(2)	(3)
FR_t	-0.216**	-0.170	-0.240***
	(0.088)	(0.119)	(0.049)
$grow_t$	-0.235	-0.295*	-0.286***
	(0.252)	(0.175)	(0.065)
$FR_t \times grow_t$	-0.147***	-0.147*	-0.034
	(0.038)	(0.087)	(0.036)
Country-Variable FE	✓	✓	✓
Year FE	✓	✓	✓
No. of Obs.	106990	106755	106347
R-squared	0.079	0.045	0.067

Note: $grow_t$ is 1 if current period's RGDP growth is positive and zero otherwise. I excluded RGDP itself from the sample. FR_t stands for forecast revisions, and FE_t is the forecast error. The sample includes all 13 macroeconomic variables across 188 countries, though some variables may be missing for certain countries. The sample period is 1990-2024. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table-7 illustrates the state dependency of overreaction over business cycles. The negative sign of the interaction term indicates that overreaction is more pronounced during good times compared to bad times. The variables exhibit overreaction, particularly when the economy is booming, and more so for shorter horizons. This suggests that during good times, forecasters may process and update information less attentively than in bad times, resulting in stronger overreaction. The finding is analogous to Coibion and Gorodnichenko (2015) in the context of individual forecasts: periods of economic expansion are linked to stronger overreaction.

We explain the state dependency of overreaction through loss aversion within the context of a model with imperfect expectations and asymmetric loss functions. The intuition is straightforward: the potential loss—both reputational and otherwise—from incorrectly forecasting variables in bad times may be greater than in good times (An et al. 2018). As a result, forecasters are more attentive to news during bad times, while the cost of errors is relatively low during favorable conditions, leading to less attentiveness to news. This channel is explicitly observed here: when real growth is high, agents are likely less attentive, leading to overreaction in forecasts, which is empirically captured by the interaction term in Table-7.

3.3 IMF Programs

Forecasters may show different levels of attentiveness to economic conditions and react differently to news when a country has a program with the IMF.[27] To evaluate the significance of this factor, we interact positive and negative revisions with a program dummy, $prog_t$. This binary variable indicates whether a country is part of an IMF program at time t.

[27] The data on IMF programs is from the MONA database. We restrict our analysis to countries that had a program at any point in our sample.

Table 8: Asymmetric Overreaction and IMF Programs

	Dependent variable: FE_t		
	h =1	h = 2	h = 3
	(1)	(2)	(3)
FR_t^-	-0.288^{***}	-0.409^{***}	-0.157^{***}
	(0.054)	(0.120)	(0.051)
FR_t^+	-0.462^{***}	-0.539^{***}	-0.588^{***}
	(0.026)	(0.066)	(0.074)
$FR_t^- \times prog_t$	-0.021	0.063	-0.266^{**}
	(0.143)	(0.087)	(0.125)
$FR_t^+ \times prog_t$	0.235	0.469^{**}	0.337^{*}
	(0.191)	(0.225)	(0.196)
Country-Variable FE	✓	✓	✓
Year FE	✓	✓	✓
No. of Obs.	28850	28710	28611
R-squared	0.082	0.086	0.085

Note: FE_t is the forecast error (actual value minus forecast). FR_t^- stands for negative revisions, and FR_t^+ stands for positive revisions. $prog_t$ is a dummy that equals one if the country has a program with the IMF. The model includes country-variable fixed effects, year fixed effects and vintage month dummies. The sample includes LE, NCP, NFDD, NFI, RGDP, NM, NX, LUR, and PCPI. Please note that the signs of forecast revisions for LUR and PCPI are reversed. The sample period is 1993-2024. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table-8 indicates that for countries in an IMF program, overreaction to positive news significantly diminishes. In contrast, overreaction to negative news remains largely unchanged.[28]

For program countries, WEO forecasters tend to be overly optimistic in long-term forecasts while adopting a more conservative stance on near-term growth. This is because short-term GDP forecasts are critical for program targets, such as fiscal and BoP goals, making forecast accuracy particularly important for near-term projections. While some conservatism is embedded in this process, as shown in Table-8, asymmetric overreaction

[28] In Table-E4 in the appendix, we examine the role of different types of IMF programs, with a focus on GRA-supported programs, which aim to address a country's balance of payments issues, and PRGT programs, the Fund's primary mechanism for providing concessional financing to low-income countries.

for program countries still persists, albeit to a lesser degree.

The underlying mechanism follows the state-dependency logic outlined above: for IMF forecasters, the potential costs—both reputational and otherwise—of inaccurately predicting variables for countries under IMF programs are likely higher than for those not in any program. This disparity could drive asymmetry in forecasters' attention, resulting in the observed asymmetry in overreaction. In our theoretical section, a minor extension to standard models accommodates this type of state-dependency, where having "skin in the game" heightens forecasters' attentiveness to program countries. After presenting empirical evidence supporting state-dependent overreaction, we proceed to the model designed to capture these dynamics.

4 A Model with Asymmetric Overreaction

In this section, we develop a simple model based on Afrouzi et al. (2023) to demonstrate how the state-dependence of forecasters' attentiveness can influence the degree of overreaction to economic news. We modify the objective function of forecasters used in Afrouzi et al. (2023) to allow it to change over time and depend on the state of the economy.[29] Finally, to link the overreaction bias observed in our empirical analysis with the model, we derive the β_{CG} in our framework and explore its key properties.

In the model, agents become less attentive and move further away from FIRE when they receive good news, thereby overreacting more to new information. Conversely, when they receive bad news, they revise their forecasts downward[30], but this revision comes with a higher level of attentiveness to fundamentals. As a result, agents behave more similarly to the FIRE case, meaning the level of overreaction will be lower.

The intuition behind overreaction in the model stems from the way agents process information. Instead of using all available data efficiently, agents focus on a subset of information that is "on top of mind," heavily influenced by recent observations due to the psychological phenomenon known as the recency effect. This cognitive bias leads agents to overestimate the importance of recent data when forming beliefs about the long-run mean of a process. Since processing additional, more comprehensive information comes with a cognitive cost, agents rely more on easily accessible, recent data, which causes their forecasts to overreact to new information. Overreaction is more pronounced when the underlying process is less persistent and when forecasts are made over longer horizons, as agents are more likely to misjudge the stability of long-term trends.

[29] We also adapted the information structure used by Afrouzi et al. (2023).

[30] Assuming that higher values for the variable are desirable and indicate good economic conditions.

We closely follow Afrouzi et al. (2023) with some modifications to the forecasters' objective functions and information set. Let us assume that agents attempt to forecast y_{t+h}, where

$$y_t = (1-\rho)\mu + \rho y_{t-1} + \varepsilon_t,$$

and $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$. If the agent had full information, the h-period ahead rational expectations forecast would be

$$\mathbb{E}_t[y_{t+h}] = (1-\rho^h)\mu + \rho^h y_t.$$

However, agents do not have full information. In each period, they know the exact value of the persistence of the underlying process ρ but are uncertain about the long-run mean μ: $\mu \sim N(\bar{\mu}, \sigma_\mu^2)$.[31] σ_μ^2 captures how confident they are about their initial belief before acquiring any information. Since forecasters need to have an accurate belief about the long-run mean to make forecasts, they begin collecting information and refining their beliefs as much as possible. At the first stage, they use all the information that are freely available to them. We assume that forecasters observe y_t and recall y_{t-1} without incurring any cost, allowing them to update their belief about μ.[32] The new conditional distribution of μ is: $\mu | y_t, y_{t-1} \sim \mathcal{N}(\tilde{\mu}_t, \underline{\tau}^{-1})$ where

$$\tilde{\mu}_t = E(\mu | y_t, y_{t-1}) = \bar{\mu} + \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\varepsilon^2/(1-\rho)^2}\left(\frac{y_t - \rho y_{t-1}}{1-\rho} - \bar{\mu}\right),$$

$$\underline{\tau}^{-1} = \text{var}(\mu | y_t, y_{t-1}) = \frac{\sigma_\mu^2 \sigma_\varepsilon^2}{(1-\rho)^2\sigma_\mu^2 + \sigma_\varepsilon^2}.$$

As this equation demonstrates, the level of confidence in the prior relative to the process's volatility determines how much weight forecasters place on new information when updating their beliefs. As σ_ε increases, forecasters rely less on their freely available information and adhere more closely to their prior belief about μ, placing greater weight on their prior.

In the second stage, forecasters gather additional information, despite the associated cost. We solve their optimization problem in two steps. First, and given the selected

[31] Afrouzi et al. (2023) argues that this is the most parsimonious way to capture how overreaction varies with process persistence and forecast horizon, as observed in the data, whereas biases in ρ alone are insufficient.

[32] This is justified by literature showing that the most recent observation is immediately foremost in people's minds. Therefore, observing y_t and recalling very recent observation y_{t-1} is a reasonable assumption.

information set, we determine the forecast that minimizes a quadratic loss function:

$$\min_{F_t y_{t+h}} \frac{1}{2}\mathbb{E}\left[K(\Delta y_t)\left(F_t y_{t+h} - y_{t+h}\right)^2 \middle| S_t\right],$$

where $K(\Delta y_t)$, which is the key addition that differentiates our model from Afrouzi et al. (2023), is decreasing in Δy_t. S_t is the information set of the agent. Intuitively, the cost of making forecast errors is lower when the economy is booming, which will be the driver of asymmetric attention. Taking derivative with respect to $F_t y_{t+h}$, we can show that the optimal forecast is the conditional expectation of y_{t+h}, and the minimum loss equals the conditional variance of y_{t+h} multiplied by $K(\Delta y_t)$.[33] In the second step, we identify the information set that minimizes the total loss, which includes both the cost of forecast error and the cost of information processing. Specifically

$$\min_{S_t} \mathbb{E}\left[K(\Delta y_t)\left((1-\rho^h)^2 \text{var}(\mu|S_t) + \sigma^2 \sum_{j=1}^{h} \rho^{2(h-j)}\right) + C(S_t) \middle| y_t, y_{t-1}\right],$$

subject to $\{y_{t-1}, y_t\} \subseteq S_t \subseteq A_t$, and the convex cost of processing S_t

$$C(S_t) = \omega \frac{\exp(\gamma \mathbb{I}(\mu; S_t|y_t, y_{t-1})) - 1}{\gamma},$$

where A_t is the full (largest available) information set, and

$$\mathbb{I}(\mu; S_t|y_t, y_{t-1}) = \ln\left(\frac{\text{var}(\mu|y_t, y_{t-1})}{\text{var}(\mu|S_t)}\right).$$

Defining $\tau \equiv \text{var}(\mu|S_t)^{-1}$ and assuming that the upper bound never binds, we can rewrite the problem as follows:

$$\min_{\underline{\tau} \leq \tau} \mathbb{E}\left[K(\Delta y_t)\frac{(1-\rho^h)^2}{\tau} + \omega \frac{\left(\frac{\tau}{\underline{\tau}}\right)^{\gamma} - 1}{\gamma} \middle| y_t, y_{t-1}\right],$$

Using the first-order condition, we get:

$$\tau^{*-1} = \underline{\tau}^{-1} \min\left\{1, \left(\frac{1}{K(\Delta y_t)} \frac{\omega \underline{\tau}}{(1-\rho^h)^2}\right)^{\frac{1}{1+\gamma}}\right\}.$$

As this equation suggests, the optimal precision varies over time and the the forecaster

[33] More details provided in Appendix-F.

chooses a higher precision as Δy_t decreases, given the assumption that $K(\Delta y_t)$ is decreasing in Δy_t.

For simplicity, we assume that the information set S_t has the following structure: $S_t = \{y_t, y_{t-1}, s_t\}$, where s_t is a Gaussian signal in the forms of true value of μ plus a noise. If they find it optimal to choose a signal with zero precision, they will not update their belief and therefore, their expectation of the long-run mean will equal $\tilde{\mu}_t$. Based on the optimal precision τ^* and the corresponding precision of the noise τ_ν that the forecaster chooses, we can show that the expected long-run mean equals

$$\mathbb{E}(\mu|S_t^*) = (1 - \frac{\underline{\tau}}{\tau^*})\mu + \frac{\underline{\tau}}{\tau^*}\tilde{\mu}_t + (1 - \frac{\underline{\tau}}{\tau^*})\nu_t,$$

where the noise term ν_t is orthogonal to μ, y_t, and y_{t-1} has a normal distribution $\sim \mathcal{N}(0, \tau_\nu^{-1})$, with $\tau_\nu = \tau^* - \underline{\tau}$. This equation suggests that after forecasters choose their optimal information set and if $\frac{\underline{\tau}}{\tau^*} < 1$, then their belief about the long-run mean moves closer to the true value and away from its prior $\tilde{\mu}_t$.

Using the last equation, we can find forecaster's optimal forecast for variable y_t at horizon h:

$$\begin{aligned} F_t y_{t+h} =& (1-\rho^h)\left((1 - \frac{\underline{\tau}}{\tau^*})\mu + \frac{\underline{\tau}}{\tau^*}\tilde{\mu}_t\right) + \rho^h y_t + \tilde{\nu}_t \\ =& \underbrace{\mathbb{E}_t y_{t+h}}_{\text{FIRE Forecast}} + \underbrace{(1-\rho^h)\frac{\underline{\tau}}{\tau^*}(\tilde{\mu}_t - \mu)}_{\text{Overreaction}} + \underbrace{\tilde{\nu}_t}_{\text{noise}}, \end{aligned}$$

where $\tilde{\nu}_t \sim \mathcal{N}\left(0, (1-\rho^h)^2 \frac{\tau^* - \underline{\tau}}{\tau^{*2}}\right)$. If the optimal precision chosen by the forecaster is high enough ($\tau^* > 2\underline{\tau}$), then the standard deviation of the noise in the forecast will be decreasing in τ^*. When τ^* increases, potentially due to higher levels of $K(\Delta y_t)$ (representing the state-dependent cost of forecast error), the overreaction diminishes, and the agent's forecast moves closer to the FIRE benchmark. A higher τ^* reflects greater investment in information processing, enabling agents to more accurately estimate the long-term mean of the process. This reduces the bias stemming from uncertainty about the long-run mean, leading to smaller deviations from rational expectations and mitigating overreaction in forecasts.

Let us normalize the true value of μ to zero and assume, for simplicity, that $\Delta y_t = \Delta y_{t-1}$, so that $K(\Delta y_t)$ and $K(\Delta y_{t-1})$ are equal. With this assumption, we can express the forecast error FE_t and the forecast revision FR_t, and calculate β_{CG} as follows:[34]

$$\beta_{CG} = \frac{\text{cov}(FE_t, FR_t)}{\text{var}(FR_t)}.$$

[34]Details provided in Appendix-F.

The following proposition outlines how β_{CG} depends on the parameters of the model:

Proposition 1. *Given $0 < \rho < 1$ and $\gamma > 1$, β_{CG} is always negative and approaches zero as $K(\Delta y_t) \to \infty$, $\omega \to 0$, or $\rho \to 1$.*

Proof. Appendix-1. □

Since agents' forecasts under imperfect information always include noise, this noise impacts both the forecast error (FE_t) and forecast revision (FR_t), contributing to the negative value of β_{CG}. The overreaction also plays a role in driving the negative regression coefficient, and both components vary with the model's parameters. When the underlying process is less persistent, the long-term mean becomes more important in forming h-period ahead forecasts. As a result, agents gather more information about the mean (reflected in a lower $\frac{\tau}{\tau^*}$), reducing the weight placed on recent observations. However, this adjustment remains imperfect, leading to higher levels of overreaction. Both ω and $K(\Delta y_t)$ influence the results in a similar manner. A higher $K(\Delta y_t)$ or a lower ω reduces the relative cost of information processing, leading to greater precision of long-term mean and lower tendency for overreaction. Consequently, the model successfully captures the empirical dynamics observed in the data.

5 Conclusions

This study employs a comprehensive dataset spanning over 180 countries and more than 10 macroeconomic variables to examine the rationality of forecasts and the predictability of forecast errors. The results indicate that IMF forecasts, like those from Consensus Economics, tend to overreact to news, but in an asymmetric manner. While substantial overreaction is observed in response to good news, forecast errors are generally not predictable following revisions to bad news. This suggests that deviations from rational expectations in individual forecasts occur primarily in response to positive news.

The analysis uncovers significant heterogeneity across countries and variables. Advanced economies exhibit less predictable forecast errors, likely due to superior information processing, whereas developing economies demonstrate more pronounced overreaction, potentially driven by higher informational frictions. Despite these differences, asymmetry in overreaction is evident across all country groups. Additionally, the study finds that overreaction is state-dependent, being more pronounced during economic booms. Notably, IMF forecasts align more closely with the FIRE (full-information rational expectations) benchmark when a country is under an IMF program, compared to when it is not.

The degree of overreaction is inversely related to the persistence of macroeconomic variables, with lower persistence leading to stronger overreaction. This effect is more pronounced for longer forecast horizons, indicating increased forecaster sensitivity to new information over extended periods. These findings are consistent with recent theoretical models proposed by Afrouzi et al. (2023) and Bianchi et al. (2024).

To explain the observed asymmetric overreaction, a simple model is presented, demonstrating how state-dependent forecaster attentiveness influences the degree of overreaction to economic news. In the model, forecasters become less attentive and deviate further from the FIRE benchmark when receiving good news, leading to greater overreaction. Conversely, when faced with bad news, forecasters adjust their forecasts downward with heightened attentiveness to fundamentals, resulting in behavior more closely aligned with the FIRE hypothesis and reduced overreaction. This model, grounded in recent theoretical frameworks, incorporates asymmetric attention and aligns well with the empirical findings documented in this paper.

These findings have important implications for policymakers and forecasters, emphasizing the need for models that account for asymmetric and state-dependent overreaction. Future research should focus on developing strategies to mitigate these biases and enhance forecast reliability, particularly in the context of developing economies.

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A Summary Statistics

Table A1: Forecast Error: 1-year ahead

indicator	mean	sd	min	5%	median	95%	max
LE	-0.059	2.319	-11.585	-4.290	0.000	3.469	9.105
LLF	0.026	1.762	-8.391	-2.882	0.020	2.718	7.372
LULCM	-0.103	3.524	-11.737	-6.169	0.000	5.619	14.411
LUR	0.102	2.206	-9.300	-3.190	-0.050	4.336	10.107
NCG	0.991	6.160	-25.292	-8.135	0.569	12.217	29.862
NCP	-0.424	4.723	-23.511	-8.427	-0.130	6.864	22.762
NFDD	-0.499	3.894	-19.012	-7.246	-0.220	5.505	14.727
NFI	-1.690	10.970	-59.392	-20.159	-1.053	15.164	47.765
NGDP	-4.369	8.300	-47.753	-16.667	-4.525	8.603	34.868
RGDP	-0.756	3.563	-18.807	-7.275	-0.300	4.296	10.347
NM	-1.144	9.492	-37.875	-18.200	-0.594	13.851	37.623
NX	-2.041	10.212	-57.693	-19.130	-1.418	12.232	56.346
PCPI	1.339	6.590	-15.313	-3.896	0.029	10.440	83.481

Note: The sample period is 1990-2024. Variables are LE (total employment), LUR (unemployment rate), NCP (real private consumption), NFDD (real final domestic demand), NFI (real fixed investment), RGDP (real GDP), NM (import), NX (export) and PCPI (consumer prices).

Table A2: Forecast Revision: 1-year ahead

indicator	mean	sd	min	5%	median	95%	max
LE	-0.046	0.668	-3.476	-1.144	0.000	0.967	3.669
LLF	-0.002	0.525	-2.800	-0.862	0.000	0.871	2.614
LULCM	-0.014	1.112	-4.500	-1.993	0.000	1.838	4.067
LUR	0.163	1.372	-5.365	-1.860	0.000	2.727	7.245
NCG	-0.529	3.171	-15.814	-6.499	-0.101	4.084	12.614
NCP	-0.179	2.587	-12.812	-4.417	-0.076	3.827	13.502
NFDD	-0.120	1.649	-8.477	-2.775	-0.055	2.506	7.688
NFI	0.489	5.084	-22.401	-6.245	0.000	8.456	37.002
NGDP	0.456	2.705	-9.805	-2.738	0.004	4.790	22.340
RGDP	-0.184	1.259	-6.100	-2.379	-0.020	1.733	5.833
NM	0.228	3.682	-14.904	-5.242	0.000	6.308	20.000
NX	0.440	4.561	-18.134	-5.122	0.000	7.759	34.119
PCPI	0.553	2.368	-8.500	-1.500	0.000	4.150	23.883

Note: The sample period is 1990-2024. Variables are LE (total employment), LUR (unemployment rate), NCP (real private consumption), NFDD (real final domestic demand), NFI (real fixed investment), RGDP (real GDP), NM (import), NX (export) and PCPI (consumer prices).

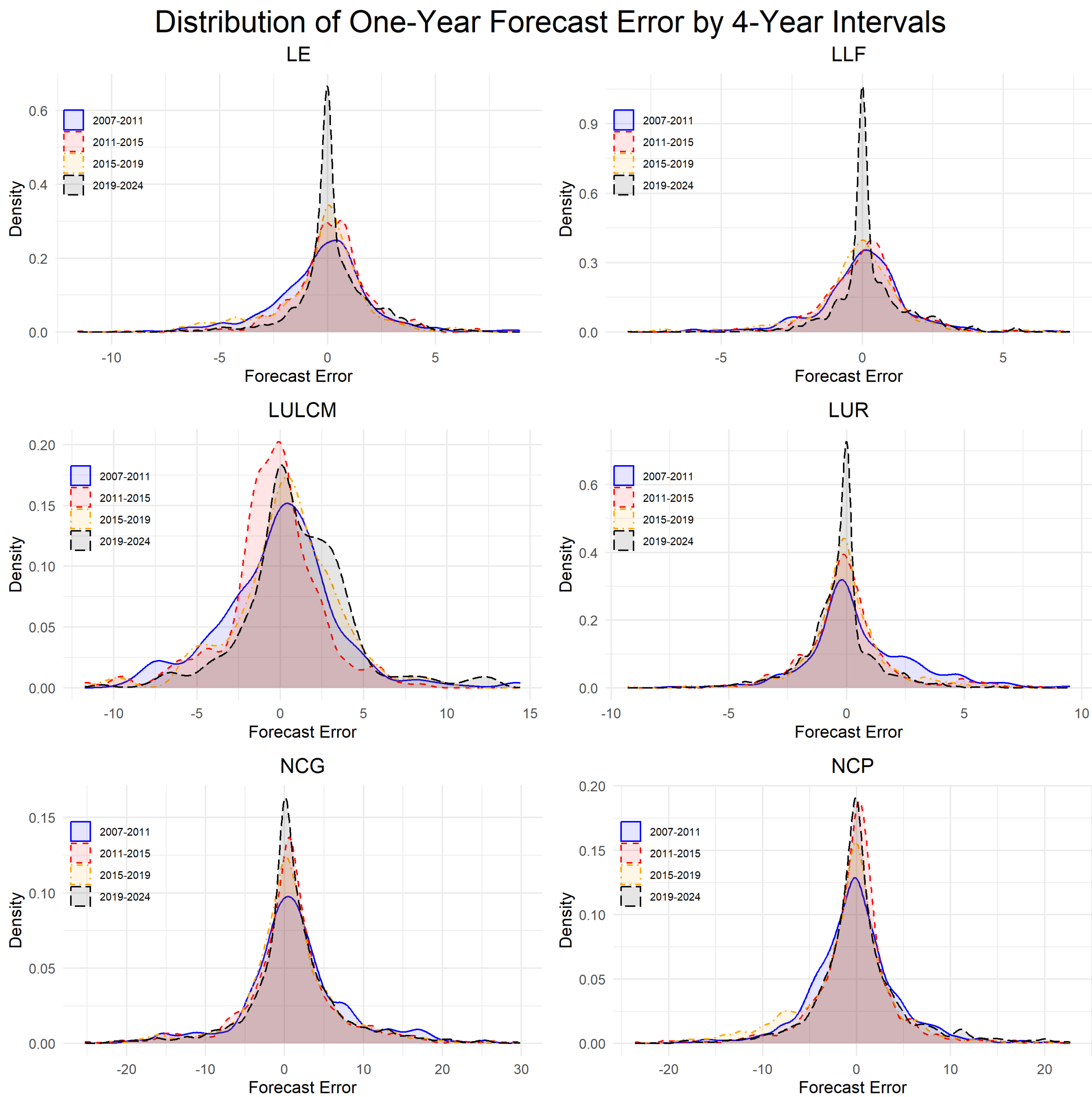

Figure A1: Distribution of 1-Year Forecast Errors

Note: The graph shows the kernel distributions for different variables over different time periods. Variables are LE (total employment), LUR (unemployment rate), NCP (real private consumption), NFDD (real final domestic demand), NFI (real fixed investment), RGDP (real GDP), NM (import), NX (export) and PCPI (consumer prices).

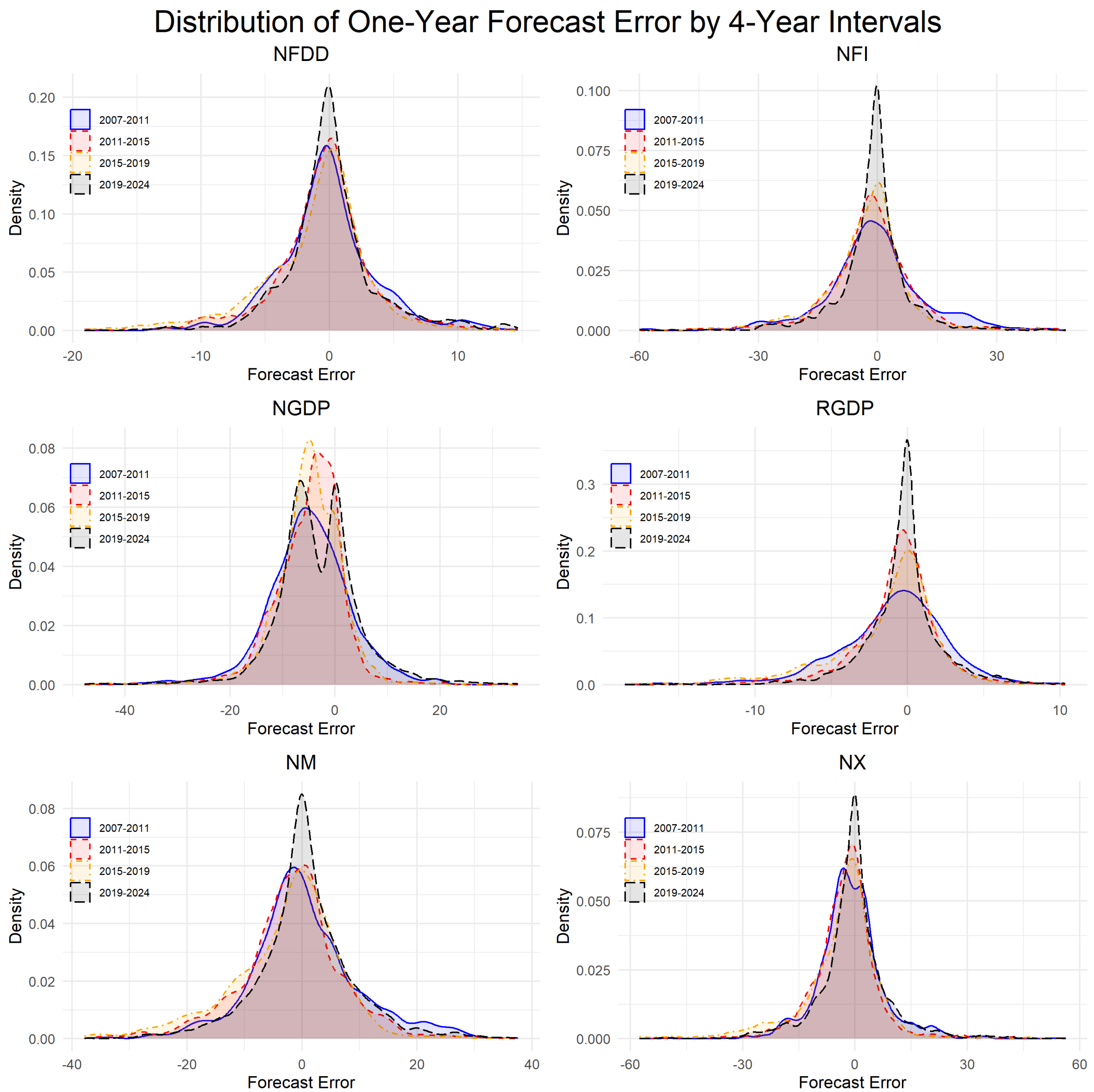

Figure A2: Distribution of 1-Year Forecast Errors

Note: The graph shows the kernel distributions for different variables over different time periods. Variables are LE (total employment), LUR (unemployment rate), NCP (real private consumption), NFDD (real final domestic demand), NFI (real fixed investment), RGDP (real GDP), NM (import), NX (export) and PCPI (consumer prices).

B Good News vs Bad News

Table B1: Asymmetry in Overreaction: Entire Sample

	Dependent variable: FE_t		
	h =1	h = 2	h = 3
	(1)	(2)	(3)
FR_t^-	-0.184	-0.107	-0.090
	(0.113)	(0.115)	(0.149)
FR_t^+	-0.323^{***}	-0.316^{***}	-0.292^{***}
	(0.090)	(0.050)	(0.038)
Country-Variable FE	✓	✓	✓
Time FE			
No. of Obs.	112438	111096	109984
R-squared	0.017	0.009	0.009

Note: FE_t is the forecast error (actual value minus forecast). FR_t^- stands for negative revisions, and FR_t^+ stands for positive revisions. The model includes country-variable fixed effects, year fixed effects and vintage month dummies. The sample includes all 13 macroeconomic variables across 188 ountries, though some variables may be missing for certain countries. The sample period is 1990-2024. Panel-B documents the statistical significance of the difference between the two estimates using Wald test. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table-B1 shows the asymmetry in overreaction to positive and negative revisions, without changing signs of any variables in the dataset. In fact, the asymmetry is more prominent in this specification.

Table B2: Asymmetry in Overreaction: Good vs Bad News

Panel-A: Full Sample (1990-2024)			
	Dependent variable: FE_t		
	h =1	h = 2	h = 3
	(1)	(2)	(3)
FR_t^-	-0.262^{***}	-0.294^{***}	-0.053
	(0.047)	(0.094)	(0.050)
FR_t^+	-0.414^{***}	-0.428^{***}	-0.485^{***}
	(0.014)	(0.038)	(0.060)
Country-Variable FE	✓	✓	✓
Year FE	✓	✓	✓
No. of Obs.	55382	54973	54762
R-squared	0.083	0.090	0.092
Panel-B: Subsample (2008-2024)			
FR_t^-	0.051^{**}	-0.119	0.074
	(0.023)	(0.078)	(0.050)
FR_t^+	-0.562^{***}	-0.460^{***}	-0.529^{***}
	(0.036)	(0.048)	(0.050)
Country-Variable FE	✓	✓	✓
Year FE	✓	✓	✓
No. of Obs.	35758	37305	37067
R-squared	0.029	0.097	0.114
Panel-C (Wald test)			
χ^2 (1990-2024 sample)	8.524^{***}	2.3527	31.801^{***}
χ^2 (2008-2024 sample)	203.48^{***}	24.416^{***}	119.98^{***}

Note: FE_t is the forecast error (actual value minus forecast). FR_t^- stands for negative revisions, and FR_t^+ stands for positive revisions. The model includes country-variable fixed effects, year fixed effects, and vintage month dummies. The sample includes LE, NCP, NFDD, NFI, RGDP, NM, NX, LUR, and PCPI. Please note that the signs of forecast revisions for LUR and PCPI are reversed. The full sample period is 1990-2024, while the subsample covers 2008-2024. Panels-B and D document the statistical significance of the difference between the two estimates using Wald tests. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

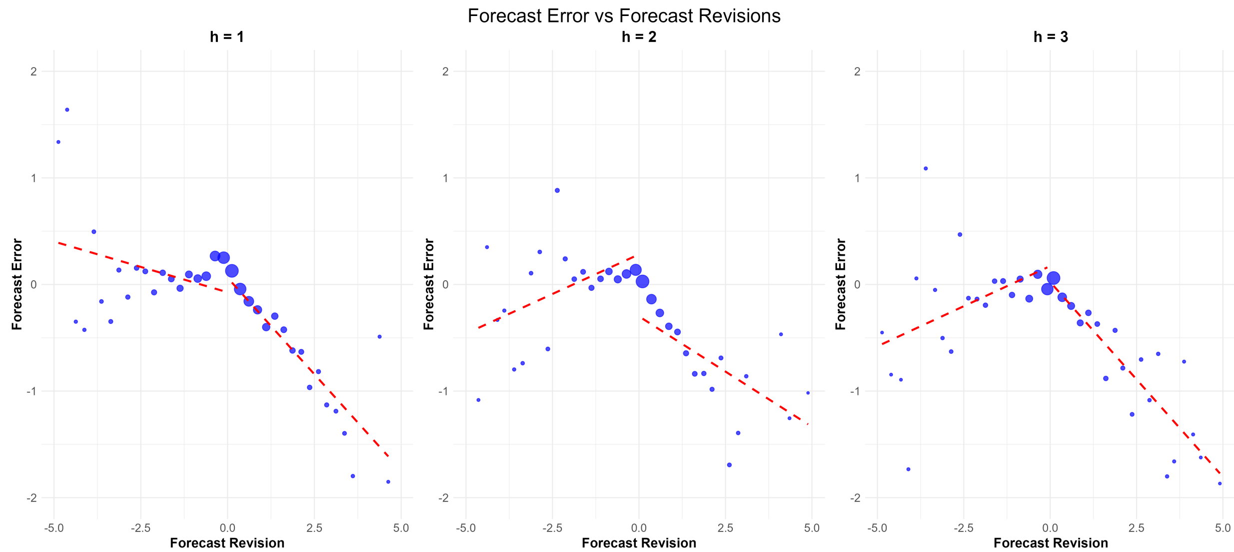

Figure B1: Forecast Errors and Revisions

Note: The figure displays a binscatter plot of IMF forecasters' forecast revisions versus their forecast errors. The sample includes LE, NCP, NFDD, NFI, RGDP, NM, NX, LUR, and PCPI. Please note that the signs of forecast revisions for LUR and PCPI are reversed. Both forecast error and forecast revisions are residualized by controlling for country-variable and year fixed effect. Additionally, the forecast revisions are constrained to the range of [-5, 5].

Table B3: Asymmetry in Overreaction: [-5,5] percent Interval

	Panel-A		
	Dependent variable: FE_t		
	h =1	h = 2	h = 3
	(1)	(2)	(3)
FR_t^-	0.011	-0.140^{*}	0.054
	(0.022)	(0.075)	(0.049)
FR_t^+	-0.524^{***}	-0.398^{***}	-0.431^{***}
	(0.043)	(0.055)	(0.058)
Country-Variable FE	✓	✓	✓
Time FE	✓	✓	✓
No. of Obs.	51214	50704	50431
R-squared	0.084	0.097	0.102
	Panel-B (Wald test)		
	$h = 1$	$h = 2$	$h = 3$
χ^2	93.876^{***}	7.8261^{**}	74.436^{***}

Note: FE_t is the forecast error (actual value minus forecast). FR_t^- stands for negative revisions, and FR_t^+ stands for positive revisions. The forecast revision is constrained to [-5,5] percent interval. The model includes country-variable fixed effects, year fixed effects and vintage month dummies. The sample includes LE, NCP, NFDD, NFI, RGDP, NM, NX, LUR, and PCPI. Please note that the signs of forecast revisions for LUR and PCPI are reversed. The sample period is 1990-2024. Panel-B documents the statistical significance of the difference between the two estimates using Wald test. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table-B3 shows the asymmetry in overreaction to positive and negative revisions for a sample, restricted to revisions smaller than 5 percent.

Table B4: Asymmetry in Overreaction across Variables

Panel-A									
	Dependent variable: $FE_{t+\tau(t,3)}$								
	LE	LUR	NCP	NFDD	NFI	RGDP	NM	NX	PCPI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FR_t^-	0.185*	0.242***	-0.403***	0.106	-0.206	-0.186***	0.090	0.027	0.127
	(0.101)	(0.078)	(0.114)	(0.148)	(0.160)	(0.071)	(0.173))	(0.171)	(0.150)
FR_t^+	-0.728***	-0.248***	-0.279*	-0.415**	-0.627***	-0.409***	-0.284	-0.741***	-0.046
	(0.094)	(0.081)	(0.154)	(0.182)	(0.176)	(0.065)	(0.286)	(0.211)	(0.101)
Country-Variable FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
No. of Obs.	7909	7022	2402	856	2635	15661	2311	2673	14787
R-squared	0.135	0.11	0.301	0.456	0.152	0.213	0.36	0.240	0.144
Panel-B (Wald test)									
	LE	LUR	NCP	NFDD	NFI	RGDP	NM	NX	PCPI
χ^2	33.780***	19.251***	0.295	4.355**	2.522	4.069**	0.990	6.024**	0.818

Note: FR_t^- stands for negative revisions, and FR_t^+ stands for positive revisions. $FE_{t+\tau(t,3)}$ is the forecast error for the $h = 3$ horizon category. The specification for asymmetry is run separately for each variable. The model includes country FE, year FE, and vintage month dummies. Standard errors are calculated using Driscoll-Kraay method. The sign for the forecast revision of PCPI and LUR are reversed. The sample period is 1990-2024. Panel-B documents the statistical significance of the difference between the two estimates using Wald test. The sample period is 2000-2024. *p<0.1; **p<0.05; ***p<0.01.

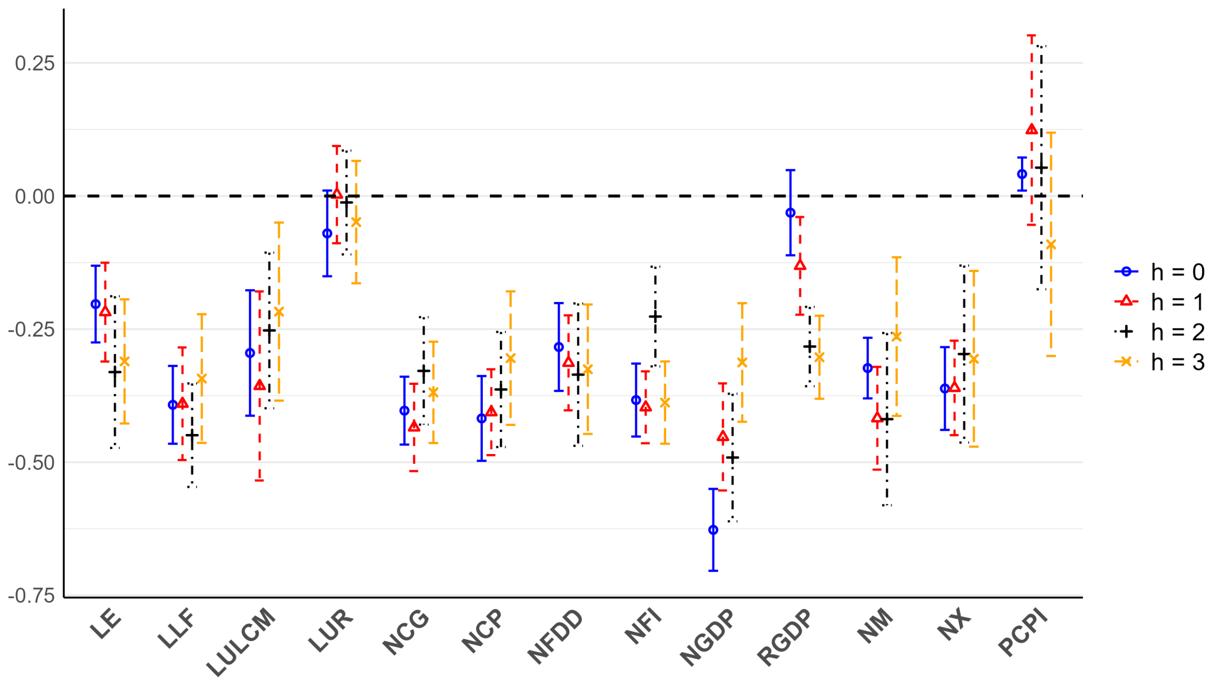

Figure B2: Overreaction in Forecasts for each Variable

Note: The figure presents the point estimate of β_{CG} with the two standard deviation error band. The baseline specification is run separately for each variable. The model includes country FE, year FE, and vintage month dummies. The sample includes all 13 macroeconomic variables across 188 countries, though some variables may be missing for certain countries. The sample period is 1990-2024. Standard errors are calculated using Driscoll-Kraay method.

C Quarterly Data

Table C1: Baseline Specification with Quarterly Data

	Dependent variable: FE_t		
	h =1	h = 2	h = 3
	(1)	(2)	(3)
FR_t	-0.269^{***}	-0.333^{***}	-0.382^{***}
	(0.018)	(0.039)	(0.025)
Country-Variable FE	✓	✓	✓
Time FE	✓	✓	✓
No. of Obs.	13141	13156	13044
R-squared	0.07	0.104	0.09

Note: FE_t is the forecast error (actual value minus forecast). FR_t stands for forecast revisions. The model includes country-variable fixed effects and time fixed effects. The sample includes all 13 macroeconomic variables across 61 countries, though some variables may be missing for certain countries. The sample period is 2010-2024. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table C2: Asymmetry in Overreaction: Quarterly Data

	Dependent variable: FE_t		
	h =1	h = 2	h = 3
	(1)	(2)	(3)
FR_t^-	-0.312^{***}	-0.228^{***}	-0.220^{***}
	(0.013)	(0.012)	(0.020)
FR_t^+	-0.323^{***}	-0.562^{***}	-0.803^{***}
	(0.034)	(0.042)	(0.083)
Country-Variable FE	✓	✓	✓
Time FE	✓	✓	✓
No. of Obs.	10237	10158	10007
R-squared	0.099	0.135	0.127
Panel-B (Wald test)			
	$h = 1$	$h = 2$	$h = 3$
χ^2	0.0887	56.2^{***}	43.586^{***}

Note: FE_t is the forecast error (actual value minus forecast). FR_t^- stands for negative revisions, and FR_t^+ stands for positive revisions. The model includes country-variable fixed effects and time fixed effects. The sample includes LE, NCP, NFI, RGDP, NM, NX, LUR, and PCPI. Please note that the signs of forecast revisions for LUR and PCPI are reversed. The sample period is 2010-2024. Panel-B documents the statistical significance of the difference between the two estimates using Wald test. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

D Consensus Forecast

Table D1: Baseline Regression Results with Consensus Forecast Data

	Dependent variable: FE_t
	h=0
FR_t	-0.041^{*}
	(0.021)
Country-Variable-Firm FE	✓
Time FE	✓
No. of Obs.	361442
R-squared	0.032

Note: FE_t is the forecast error (actual value minus forecast). FR_t stands for forecast revisions. The sample includes monthly vintages of LUR, LWR (Employment costs), NCP, NFI, RGDP, and PCPI from 2007M1 - 2024M1. The sample covers 43 countries and 80 forecasting firms. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table D2: Asymmetry in Overreaction: Consensus Forecast

	Dependent variable: FE_t
	h=0
FR_t^-	-0.100^{***}
	(0.026)
FR_t^+	0.019
	(0.033)
Country-Variable-Firm FE	✓
Time FE	✓
No. of Obs.	344886
R-squared	0.046

Note: FE_t is the forecast error (actual value minus forecast). FR_t^- stands for negative revisions, and FR_t^+ stands for positive revisions. The sample includes monthly vintages of LUR, LWR (Employment costs), NCP, NFI, RGDP, and PCPI from 2007M1 - 2024M1. The sign of forecast errors for LUR and PCPI are reversed. The sample covers 43 countries and 80 forecasting firms. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

E Additional Empirical Results

State-Dependence in Overreaction

Table E1: State-Dependence in Overreaction

	Dependent variable: FE_t		
	h = 1	h = 2	h = 3
FR_t^-	-0.188^{***}	-0.176^{***}	0.098^{*}
	(0.026)	(0.064)	(0.053)
FR_t^+	-0.480^{***}	-0.448^{***}	-0.587^{***}
	(0.020)	(0.046)	(0.069)
$FR_t^- \times (x_t^{RGDP} - \mu^{RGDP})$	0.128^{***}	0.203^{***}	0.196^{***}
	(0.043)	(0.043)	(0.021)
$FR_t^+ \times (x_t^{RGDP} - \mu^{RGDP})$	-0.075^{***}	-0.136^{***}	-0.022
	(0.025)	(0.017)	(0.024)
Country-Variable FE	✓	✓	✓
Time FE	✓	✓	✓
No. of Obs.	38434	38165	38076
R-squared	0.082	0.094	0.1

Note: $x_t^{RGDP} - \mu^{RGDP}$ is the deviation of RGDP from the long-term mean, normalized by its standard deviation. FR_t^+ stands for upward forecast revisions,FR_t^- is the downward revision, and FE_t is the forecast error (actual value minus forecast). The model includes country-variable fixed effects, year fixed effects and vintage month dummies. The sample includes LE, NCP, NFI, NM, NX, LUR, and PCPI. Please note that the signs of forecast revisions for LUR and PCPI are reversed. The sample period is 1990-2024. *p<0.1; **p<0.05; ***p<0.01.

Same regression this time with deviation from long term RGDP as the interaction term,[35] so that the state-dependent overreaction can be analyzed. The reaction to news might be different during sunny days compared to rainy days. In fact, as shown in Table-E1, when the economy is functioning above the trend, overreaction to good news is even stronger as documented by the interaction between the positive revisions and above trend growth. However, the overreaction to bad news is getting weaker, i.e. the deviation from FIRE is getting weaker.

[35]RGDP itself is excluded from the sample.

As further empirical support, if we add the interaction of the deviation of actual value at $h = 0$ from its long-term mean with the forecast revision, we would expect to see higher overreaction when the economy is above the actual mean (remember higher values of a variable is desirable). This higher level of overreaction should be seen on both direction, whether the forecaster is revising up or revising down. To check that, we run a slightly modified version of the specification (2) as follows:

$$y^{v,c}_{t+h,t} - F_t y^{v,c}_{t+h,t} = \alpha_{c,v} + \beta_1 FR^+_t + \beta_2 FR^-_t + \beta_3 FR^+_t * (y_t - \mu) + \beta_4 FR^-_t * (y_t - \mu) + error_{v,c,t}$$

where $(y_t - \mu)$ is the deviation of actual value from its long-term mean.

Table E2: State-Dependence in Overreaction: Asymmetry

	Dependent variable: FE_t		
	h = 1	h = 2	h = 3
	(1)	(2)	(3)
FR^-_t	-0.159^{***}	-0.195^{**}	-0.022
	(0.041)	(0.076)	(0.053)
FR^+_t	-0.467^{***}	-0.484^{***}	-0.464^{***}
	(0.018)	(0.055)	(0.092)
$FR^-_t \times (y_t - \mu)$	0.147^{*}	0.214^{***}	0.072
	(0.085)	(0.034)	(0.050)
$FR^+_t \times (y_t - \mu)$	-0.109^{***}	-0.079^{**}	-0.087
	(0.031)	(0.036)	(0.061)
Country-Variable FE	✓	✓	✓
Year FE	✓	✓	✓
No. of Obs.	50976	50512	50260
R-squared	0.091	0.102	0.101

Note: $y_t - \mu$ is the deviation of actual value from the long-term mean, normalized by its standard deviation. FR^+_t stands for upward forecast revisions, FR^-_t is the downward revision, and FE_t is the forecast error (actual value minus forecast). The model includes country-variable fixed effects, year fixed effects and vintage month dummies. The sample includes LE, NCP, NFDD, NFI, RGDP, NM, NX, LUR, and PCPI. Please note that the signs of forecast revisions for LUR and PCPI are reversed. The sample period is 1990-2024. *p<0.1; **p<0.05; ***p<0.01.

As shown in Table-E2, we see asymmetry here as well. We can interpret this in a different way. When the variable is above the long term mean, and the forecaster revises up, she is overreacting more on average and making her forecast worse, but when she decides to revise down, we are getting closer to the FIRE case.

Inflation and GDP Forecast Error

The demand-side perspective of the economy suggests a negative correlation between forecast errors in inflation and real economic growth. When forecasters raise their inflation expectations, they are likely to increase their real growth forecasts as well, associating higher inflation expectations with a heated economy driven by stronger demand. This dynamic results in a significant negative correlation between forecast revisions and forecast errors (defined as the actual value minus the forecast). This finding aligns with Andre et al. (2022), which highlights that professional forecasters predominantly adopt a demand-side view of the economy, in contrast to households and firms, who tend to perceive the economy through a stagflationary lens (McClure et al. 2024; Kamdar 2019; Candia et al. 2020; Coibion et al. 2019, 2022).

Table E3: Regression Results

	Dependent variable: FE_t^{RGDP}		
	h =1	h = 2	h = 3
	(1)	(2)	(3)
FR_t^{π}	-0.121^{***}	-0.136^{***}	-0.140^{***}
	(0.013)	(0.017)	(0.019)
Country-Variable FE	✓	✓	✓
Year FE	✓	✓	✓
No. of Obs.	15339	15277	15271
R-squared	0.221	0.218	0.225

Note: FE_t^{RGDP} is the forecast error (actual value minus forecast) of RGDP. $FR_t^{\pi_t}$ stands for the forecast revision of inflation. The model includes country fixed effects, year fixed effects and vintage month dummies. The sample period is 1990-2024. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Type of IMF Program

Table E4: Asymmetric Overreaction and the Type of IMF Programs

	Dependent variable: FE_t		
	h =1	h = 2	h = 3
	(1)	(2)	(3)
FR_t^-	-0.287^{***}	-0.408^{***}	-0.157^{***}
	(0.054)	(0.120)	(0.051)
FR_t^+	-0.462^{***}	-0.540^{***}	-0.588^{***}
	(0.027)	(0.066)	(0.074)
$FR_t^- \times GRA_t$	-0.004	-0.214^{*}	-0.179
	(0.086)	(0.111)	(0.147)
$FR_t^+ \times GRA_t$	0.154	0.136	0.249
	(0.096)	(0.511)	(0.238)
$FR_t^- \times noGRA_t$	-0.040	0.255	-0.345^{***}
	(0.217)	(0.211)	(0.096)
$FR_t^+ \times noGRA_t$	0.257	0.582^{***}	0.366^{**}
	(0.222)	(0.174)	(0.187)
Country-Variable FE	✓	✓	✓
Year FE	✓	✓	✓
No. of Obs.	28850	28710	28611
R-squared	0.082	0.086	0.085

Note: FE_t is the forecast error (actual value minus forecast). FR_t^- stands for negative revisions, and FR_t^+ stands for positive revisions. GRA_t is a dummy that equals one if the country has one of these facilities: SBA, EFF, RFI, FCL, SLL, PLL. $noGRA_t$ is a dummy that equals one if the country has a program with the IMF which is not listed as GRA. The model includes country-variable fixed effects, year fixed effects and vintage month dummies. The sample includes LE, NCP, NFDD, NFI, RGDP, NM, NX, LUR, and PCPI. Please note that the signs of forecast revisions for LUR and PCPI are reversed. The sample period is 1993-2024. Driscoll-Kraay standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

F Model

The objective function

$$\min_{F_t y_{t+h}} \frac{1}{2}\mathbb{E}\left[K(\Delta y_t)\left(F_t y_{t+h} - y_{t+h}\right)^2 \Big| S_t\right],$$

Taking derivative with respect to $F_t y_{t+h}$ and knowing that $K(\Delta y_t)$ comes out of the expectation since $\{y_t, y_{t-1}\} \subseteq S_t$ we will have

$$K(\Delta y_t)\mathbb{E}\left[(F_t y_{t+h} - y_{t+h})|S_t\right] = 0.$$

Therefore, the optimal forecast for a given choice of S_t is the expectation of y_{t+h} conditional on S_t: $F_t y_{t+h} = \mathbb{E}[y_{t+h}|S_t] = (1-\rho^h)\mathbb{E}[\mu|S_t] + \rho^h y_t$. The minimum loss then equals:

$$\mathbb{E}\left[K(\Delta y_t)\left(\mathbb{E}[y_{t+h}|S_t] - y_{t+h}\right)^2 \Big| S_t\right] = K(\Delta y_t)\text{var}(y_{t+h}|S_t),$$

where $\text{var}(y_{t+h}|S_t) = (1-\rho^h)^2\text{var}(\mu|S_t) + \sigma_\varepsilon^2 \sum_{j=1}^{h} \rho^{2(h-j)}$.

Proposition (1)

$$FE_t = y_{t+h} - F_t y_{t+h} = -(1-\rho^h)\frac{\underline{\tau}}{\tau^*}\tilde{\mu}_t - \tilde{\nu}_t + \sum_{j=1}^{h}\rho^{h-j}\varepsilon_{t+j}$$

$$FR_t = F_t y_{t+h} - F_{t-1} y_{t+h} = \rho^h(y_t - \rho y_{t-1}) + (1-\rho^h)\frac{\underline{\tau}}{\tau^*}\tilde{\mu}_t - (1-\rho^{h+1})\frac{\underline{\tau}}{\tau_1^*}\tilde{\mu}_{t-1} + \tilde{\nu}_t - \tilde{\nu}_{t-1}$$

Finally, we need to calculate $\beta_{CG} = \frac{\text{cov}(FE_t, FR_t)}{\text{var}(FR_t)}$:

$$\text{cov}(FE_t, FR_t) = -\left[(1-\rho^h)^2\left(\frac{\underline{\tau}}{\tau^*}\right)^2 + \rho^h(1-\rho^h)\frac{\underline{\tau}}{\tau^*}\frac{1-\rho}{W}\right]\frac{W^2}{(1-\rho)^2}\sigma_\varepsilon^2 - \sigma_{\tilde{\nu}}^2,$$

$$\begin{aligned}\text{var}(FR_t) = &\left[\left((1-\rho^h)\frac{\underline{\tau}}{\tau^*}\right)^2 + \left((1-\rho^{h+1})\frac{\underline{\tau}}{\tau_1^*}\right)^2 + 2\rho^h(1-\rho^h)\frac{\underline{\tau}}{\tau^*}\frac{1-\rho}{W}\right]\frac{W^2}{(1-\rho)^2}\sigma_\varepsilon^2 \\ &+\rho^{2h}\sigma_\varepsilon^2 + \sigma_{\tilde{\nu}}^2 + \sigma_{\tilde{\nu}_1}^2,\end{aligned}$$

where $W = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\varepsilon^2/(1-\rho)^2}$, $\sigma_{\tilde{\nu}}^2 = (1-\rho^h)^2\frac{\tau^* - \underline{\tau}}{\tau^{*2}}$, $\sigma_{\tilde{\nu}_1}^2 = (1-\rho^{h+1})^2\frac{\tau_1^* - \underline{\tau}}{\tau_1^{*2}}$,

$$\frac{\underline{\tau}}{\tau^*} = \min\left\{1, \left(\frac{1}{K(\Delta y_t)}\frac{\omega\underline{\tau}}{(1-\rho^h)^2}\right)^{\frac{1}{1+\gamma}}\right\},$$

and

$$\underline{\tau}^{-1} = \text{var}(\mu | y_t, y_{t-1}) = \frac{\sigma_\mu^2 \sigma_\varepsilon^2}{(1-\rho)^2 \sigma_\mu^2 + \sigma_\varepsilon^2}.$$

When $\omega \to 0$ or $K(\Delta y_t) \to \infty$, then $\tau^*, \tau_1^* \to \infty$. As a result $\text{cov}(FE_t, FR_t) \to 0$ and $\text{var}(FR_t) \to \rho^{2h}\sigma_\varepsilon^2$. Thus $\beta_{CG} \to 0$. When $\rho \to 1$, $\frac{\underline{\tau}}{\tau^*} \to 1$. It is easy to show that $\text{cov}(FE_t, FR_t) \to 0$ and $\text{var}(FR_t) \to \rho^{2h}\sigma_\varepsilon^2$. Thus $\beta_{CG} \to 0$.

PUBLICATIONS

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