Cross-Country Inflation Expectations: Evidence of Heterogeneous & Synchronized 'Mistakes'

Karen Smith[1]

November 30, 2024

Abstract

This paper presents an evaluation of the assumption of Full-Information Rational Expectations (FIRE) in the inflation predictions of professional forecasters, across forty-six countries from 1990 to 2020. I make the central argument that there is a need for a more international approach to understanding the Expectation Formation Process. I document widespread heterogeneity in the magnitude and direction of departures from FIRE and show that these departures contradict established stylized facts about belief formation. I introduce a Bayesian Dynamic Factor Model which reveals synchronization in cross-country forecast errors accounting for as much as 15% of the variability in forecaster 'mistakes' across all countries, 26% across advanced economies, and 9% across emerging economies during the Global Financial Crisis. I augment the availability of international real-time data by introducing a novel dataset of cross-country CPI vintages to support my analysis.

JEL codes: D84, E31, E32, E71.
Keywords: expectations, behavioral macro, dynamic factor analysis, real-time

[1]Department of Economics, Drew University, Madison NJ. Email: ksmith7@drew.edu. I give special thanks to the Economics Department of Brandeis University, including George Hall, Blake LeBaron, Carol Osler, Davide Pettenuzzo, and Raphael Schoenle. I am also grateful for the comments by Francesco Bianchi at Johns Hopkins University. I thank the macroeconomic seminar participants of the Economics Department of the University of California, Berkeley, including Yuriy Gorodnichenko, Emi Nakamura, and Jon Steinsson, as well as the seminar participants of the Finance Department of the University of Connecticut for their comments on this paper. I am also grateful for the comments provided by the participants of the Inflation Drivers and Dynamics Conference 2024, organized by the Federal Reserve Bank of Cleveland.

1 Introduction

"In situations where there is a risk of shocks becoming larger and more persistent, *inflation expectations can de-anchor* [...] *Central banks must then react forcefully to prevent above-target inflation becoming entrenched.*"

Christine Legarde, President of the European Central Bank[2]

The COVID-19 pandemic has brought to the fore the importance of the relationship between inflation and inflation expectations in the implementation of monetary policy, at both the country-specific and international levels. Central bankers from around the world, amidst the diversity of their macroeconomic settings, have displayed an unprecedented level of coordination to combat the historical surge in global inflation, but more specifically, to maintain the credibility of their commitment to achieving low and stable price levels in the future – particularly as many of their models did not predict the upcoming surge in inflation. This has led to a renewed focus on understanding how expectations are formed and the impact on monetary policy transmission.

While we are yet to agree on a unified approach to modeling expectations, there is growing consensus that the longstanding assumption of Full-Information Rational Expectations (FIRE) insufficiently characterizes the Expectations Formation Process (EFP). It is therefore not surprising that findings from survey-based data – a widely-used approach to gauge agents' subjective expectations – point to the widespread departure of expectations from FIRE with distinctions across variables, demographics, and surveys.[3] While several models have emerged to account for these departures, notably missing from this line of research, however, is a systematic cross-country analysis of FIRE.[4] Such an approach would likely yield richer models of belief formation and more targeted monetary policy prescriptions.

The main contribution of this paper is to present evidence in support of the view that there is a need for a more international approach to modeling the EFP. I make the argument that there is no one-size-fits-all approach to modeling belief formation; generalizations about the outcome of well-known tests of FIRE are not ubiquitous across countries. In this paper I ask, what does the global landscape of departures from FIRE look like, what are the implications for modeling the EFP, and what is the potential impact of these findings on monetary policy transmission? My analysis begins with an assessment of the consensus inflation predictions of professional forecasters across 46 countries from 1990 to 2020, covering the geographical areas

[2]Introductory speech at the ECB Forum on Central Banking in Sintra, Portugal, July 2024.

[3]See, Mankiw et al. (2003);Souleles (2004); Bordalo et al. (2020).

[4]These include models of: (1) Information Frictions (see Mankiw and Reis (2002); Woodford (2003); Sims (2003); Coibion and Gorodnichenko (2015); Gabaix (2014); Fuster et al. (2010)); (2) Extrapolation Bias (see Greenwood and Shleifer (2014); Barberis et al. (2018); ; (3) A mix of information frictions and extrapolation bias (see Bordalo et al. (2020); Angeletos et al. (2020); Kohlhas and Walther (2021)); (4) Adaptive Learning (see Evans and Honkapohja (2001); Eusepi and Preston (2011); Bianchi and Melosi (2016); Farmer et al. (2021)); and (5) Experience Effects (see Malmendier and Nagel (2011)Malmendier and Nagel (2016)).

of North America, Latin America, Europe, and Asia Pacific.

Using the Coibion-Gorodnichenko and Mincer-Zarnowitz tests of FIRE, I first confirm that cross-country survey predictions of inflation, violate the assumption of FIRE. Next, I document the significant heterogeneity in the magnitude and direction of forecaster 'mistakes' (or violations of FIRE) and show that in many instances my findings contradict the established stylized facts about the nature of biases in consensus expectations and by extension, the EFP. For example, I present new evidence that points to the coexistence of under-reaction and extrapolation biases, two opposing forces in survey predictions – whereas the existing literature regards under-reaction as the dominant bias in subjective expectations at the consensus level.[5] My results also reveal a more extensive picture of the spectrum of FIRE violations across countries providing new insight into the role of country-specific factors in belief formation – an area that remains largely unexplored in the existing literature. To my knowledge, this is the first paper to document these findings on such a widespread basis.[6]

This paper also examines the extent to which departures from the assumption of FIRE are synchronized across countries. Exploring the role of cross-country linkages on domestic macroeconomic outcomes is part of an expansive and growing literature.[7] In the context of inflation, it has long been argued that domestic inflation is driven by a global factor.[8] The implication is that cross-country inflation can help forecast country-specific inflation and that, forecasters, particularly professionals, would have fully incorporated this phenomenon into their forecasting models. A finding of co-movement in forecaster 'mistakes' therefore represents an anomaly in the data and remains largely unexplored. This paper documents commonalities in expectational biases across countries and gives us further insight into how these biases drive domestic deviations from FIRE. Such an analysis carries significant implications for how we model the EFP and would likely lead us to revisit micro-founded theoretical underpinnings of monetary policy such as the New-Keynesian Phillips Curve.

I introduce a Bayesian Dynamic Factor Model (BDFM) to measure the extent of international synchronization in cross-country forecast errors. I document the existence of a *unique* latent factor that oscillates over time and explains on average 3% of the variability in forecast errors across all 46 countries, 6% across advanced economies and less than 1 % in emerging economies over the period 2001 to 2020. I show that during the global financial crisis (GFC), the contribution of this factor to domestic forecaster 'mistakes' increased to 15% across all countries, 26% across advanced economies and, 9% across emerging economies. The implication is that forecasters appear to be making similar mistakes during periods of economic uncertainty. Put differently, when the forecasting task becomes most challenging, deviations from FIRE are most strongly coordinated across countries and likely driven by common belief distortions.

[5] See Coibion and Gorodnichenko (2015) and Bordalo et al. (2020).

[6] Most of the existing studies have been concentrated on a small number of high-income countries, with limited attention to middle and low-income countries due to the availability of comprehensive data. While Kohlhas and Walther (2021) present evidence that these biases may coexist in expectation data, the authors do so in a summary fashion with their findings based on an analysis of surveys in the US and Euro area only.

[7] See Kose et al. (2003), Miranda-Agrippino and Rey (2020)

[8] See Borio and Filardo (2007) and Ciccarelli and Mojon (2010)

During these times, a country's forecasters are prone to predictable 'mistakes'– a finding that is particularly relevant to policymakers given the substantial role of inflation expectations in shaping monetary policy prescriptions.

The evidence of synchronization in forecaster 'mistakes' therefore allows us to formally quantify a measure of *cross-country bias* that exposes important inter-linkages in departures from FIRE across countries and forecaster geographical groups. To my knowledge, this is the first paper that ascribes measurable macroeconomic significance to the level of systematic belief distortions in the formation of expectations across countries. In so doing, this paper adds another dimension to the literature which examines the role of international fluctuations on national macroeconomic outcomes. The risk of ignoring this *cross-country bias* is that policymakers place an unduly disproportionate emphasis on the role of documented belief distortions in inflation predictions at the *domestic* country level, applying policy prescriptions that may be excessively restrictive or accommodative, particularly during times of heightened global economic uncertainty.

Within the literature, an important consideration in understanding how expectations depart from FIRE, is knowledge of the information available to forecasters at the time their predictions were made, that is, *real time data* or data that has not been revised. Among economists, there is consensus that the use of real-time data leads to substantially different and more accurate conclusions about forecaster performance compared to working with revised data (see Croushore and Stark (2001) and Croushore and Stark (2003)). While there has been significant progress for some countries such as the United States, the availability of consistent and reliable international real-time macroeconomic data is especially limited.[9] To my knowledge, there are two main sources of international real-time data. The first is the OECD's Revisions-Analysis data set – recently migrated to their Data Explorer platform – a database of 21 key economic variables with vintages of *monthly* real-time data from 1999 forward. The second which also uses OECD data, is the Dallas Fed's real-time data compilation by Fernandez et al. (2012) which contains *quarterly* vintages of 13 macroeconomic variables, from 1962 to 1998 for 26 OECD countries. This data set provides OECD real-time data for key variables such as the Money Supply, Unemployment, and GDP, that were not digitized by the OECD before 1999.

This paper, as one of its key contributions, augments the availability of international real-time data for macroeconomic analysis. I introduce a novel real-time dataset of the Consumer Price Index (CPI) variable for 18 OECD countries. Using hard copies of the OECD's historical Main Economic Indicators (MEI) publications gathered from various public sources, I digitized 10 years of monthly real-time CPI data for each country, from 1989 to 1999, complete with the accompanying vintages.[10] This dataset differs from the Dallas Fed's real-time data compilation

[9]For example, Croushore and Stark's (2001) Real-Time Data Set for Macroeconomists (RTDSM) administered by the Philadelphia Fed, contains data on the US economy from 1965 onward. The Federal Reserve Bank of St. Louis also maintains ALFRED, an archive of real-time data from 1969 for the US and some advanced economies.

[10]The OECD's Main Economic Indicators (MEI) publication is a monthly publication of macroeconomic statistics dating back to the organization's inception in 1961. Each publication presents data with a two-month publication lag. There are 12 publications per year, each representing a vintage of the data which may be subject to revisions as time progresses. In addition to data revisions by the respective countries' statistical agencies,

since it makes available *monthly* as opposed to *quarterly* data for all countries, making it a more extensive exercise, but also providing researchers a lower level of data aggregation which may be necessary at times. As an outcome of this study, this dataset will be expanded to include other variables and made freely available to anyone interested in international macroeconomic research.

Before concluding this section, it must be noted that there are some limitations to the analysis presented in this paper. While I conduct tests of rational expectations using the traditional approach of in-sample regressions, findings within the recent empirical literature suggest that the results of tests of FIRE may differ significantly when conducted using out-of-sample predictions (see Bianchi et al. (2022)). Further, Farmer et al. (2021), shows that many of the forecasting 'anomalies' observed in these tests, such as bias and autocorrelation, disappear in a model of slow learning when agents are endowed with 'reasonable' initial beliefs. These are undoubtedly areas for further consideration.

In summary, this paper presents an analysis of the cross-country departures from full-information rational expectations. Several tests of rational expectations reveal significant variation in the extent to which cross-country expectations depart from FIRE across forecast horizons. I find, however, that coexisting with these heterogeneous results are several commonalities. I discuss how these contrasting results can be reconciled. Through my application of dynamic factor analysis, I provide evidence of the existence of a common factor in forecast errors and argue that this factor likely accounts for commonalities observed in deviations from FIRE and the concomitant generalizations in the literature. I also show, that country-specific factors also feature prominently in the common factor. Together, these findings point to the need for a more global approach to understanding the expectation formation process. The broader implication of this study is that given the increasingly interconnected global environment, and the well-established endogeneity of inflation expectations, decision-makers must consider, more strongly, the impact of international factors on domestic monetary policy decisions.

Roadmap The remainder of the paper is organized as follows. The next section presents my empirical framework and estimates of cross-country departures from FIRE. Section 3 outlines the econometric framework used to model the synchronization of forecaster mistakes. Here I introduce the Bayesian Dynamic Factor Model and explain its application to cross-country forecast errors. In section 4 I estimate the Model on cross-country expectational errors and show that the latent factor explains a significant part of the common variation in the data. Section 5 concludes.

2 The Global Landscape of Departures from FIRE

In this section I present new evidence of departures from FIRE in the survey predictions of professional forecasters from forty-seven countries. The objective is to examine the variation

changes in the variables such as the move from CPI to HICP throughout Europe, are recorded, making these publications one of the most extensive and well-documented sources of real-time data available to the public.

in the direction and magnitude of violations of FIRE across countries and to discuss the extent to which these violations contradict established stylized facts about the nature of expectations. Within the existing literature of empirical studies using survey data, the following findings have emerged as characteristics of expectations:

1. Coibion and Gorodnichenko (2015) Coibion and Gorodnichenko (2015) in applying their novel test of FIRE to survey predictions of inflation from the Survey of Professional Forecasters (SPF), establish that *forecasts at the mean or consensus level display under-reaction to new information*. The authors argue that these forecasts are subject to information frictions that inhibit the instantaneous integration of new information into their forecasts.

2. In an expanded study and application of the Coibion-Gorodnichenko (CG) Test of FIRE — using forecast data from the SPF and Blue Chip Financial Forecasts across twenty-two variables — Bordalo et *al.* (2020) Bordalo et al. (2020) show that *over-reaction is the dominant bias in forecasts made at the individual level*.

3. Bianchi et *al.* Bianchi et al. (2022) show that the inflation predictions of forecasters are downward biased, that is, forecasters appear to be more pessimistic about future inflation — where the bias is measured as the difference between realized and predicted inflation.

Note that these facts have emerged primarily based on studies using US data. Interestingly, there has been less consensus on the extent to which these stylistic facts are upheld within the empirical data across macroeconomic settings — the key contribution of this paper.

In an application of three key tests of FIRE, I firstly confirm that consistent with the existing literature, FIRE is rejected in the data when examined across countries. Inconsistent with the literature, I find that the stylistic facts identified above, are contradicted when the same Tests of FIRE are applied across countries, with over-reaction being the dominant bias in consensus forecasts for some countries. Quantitatively, I show that my finding implies that across all countries forecasters update their information set every 4-5 months compared to the 6-7 months identified by Coibion and Gorodnichenko (2015). I also show that while forecasts are biased, the direction of this bias varies substantially across regions, with some regions displaying the tendency to over-predict inflation and some the tendency to under-predict inflation.

2.1 The Data

To conduct this analysis I combine two main sources of data; The first is the consensus survey predictions of professional forecasters across forty-six countries using data from Consensus Economics for the period 1990 - 2020. For each country, this dataset contains monthly predictions of average annual inflation for the current and subsequent calendar years. Table (1) lists the countries by their respective regions, the number of observations or forecasts for each country over the period of study, and some summary statistics on the forecasts by horizon.

Table 1. The Forecasts: Summary Statistics in Percentage Points

	Period	No. Obvs.	Median	SD	IQR
G7 & Western Europe					
USA	(1990 - 2021)	372	2.43	1.10	1.23
Japan	(1990 - 2021)	372	0.22	1.05	1.08
Germany	(1990 - 2021)	372	1.69	0.93	1.05
France	(1990 - 2021)	372	1.67	0.80	0.85
UK	(1990 - 2021)	372	2.40	1.51	0.82
Italy	(1990 - 2021)	372	2.10	1.69	1.83
Canada	(1990 - 2021)	372	1.87	1.06	0.78
Netherlands	(1990 - 2021)	372	2.16	0.84	1.10
Spain	(1990 - 2021)	372	2.58	1.80	2.00
Sweden	(1990 - 2021)	372	1.59	2.13	1.74
Norway	(1990 - 2021)	372	2.23	0.89	1.07
Switzerland	(1990 - 2021)	372	0.80	1.44	1.03
Austria	(1990 - 2021)	372	1.85	0.81	0.90
Belgium	(1990 - 2021)	372	1.90	0.80	0.98
Denmark	(1990 - 2021)	372	2.00	0.76	1.13
Finland	(1990 - 2021)	372	1.60	1.32	1.34
Greece	(1994 - 2021)	324	2.78	3.01	2.68
Ireland	(1990 - 2021)	372	2.32	1.56	2.34
Portugal	(1990 - 2021)	372	2.40	3.05	2.06
Asia Pacific					
Australia	(1990 - 2021)	372	2.42	1.29	1.23
China	(1994 - 2021)	313	2.30	3.86	1.92
Hong Kong	(1990 - 2021)	362	2.51	3.61	3.61
India	(1994 - 2021)	313	5.85	2.16	3.70
Indonesia	(1990 - 2021)	362	6.63	9.76	3.75
Malaysia	(1990 - 2021)	362	2.70	1.42	1.82
New Zealand	(1990 - 2021)	372	1.99	1.08	1.11
Philippines	(1994 - 2021)	313	4.33	2.19	3.4
Singapore	(1990 - 2021)	362	1.55	1.51	2.04
South Korea	(1990 - 2021)	372	2.95	2.37	2.83
Thailand	(1990 - 2021)	362	2.64	2.43	3.42
Bangladesh	(1994 - 2021)	313	6.20	1.44	1.65
Pakistan	(1994 - 2021)	313	8.20	3.09	5.20
Sri Lanka	(1994 - 2021)	313	7.70	3.58	4.89
Vietnam	(1994 - 2021)	313	6.80	4.64	5.23
Latin America					
Argentina	(1994 - 2021)	281	10.67	17.62	21.74

Continued on next page

Table 1. – Continued

	Period	No. Obvs.	Median	SD	IQR
Chile	(1994 - 2021)	281	3.21	1.85	1.34
Mexico	(1990 - 2021)	304	4.11	7.75	2.46
Colombia	(1994 - 2021)	281	4.52	5.02	3.00
Peru	(1994 - 2021)	281	3.63	1.22	
Bolivia	(1994 - 2021)	281	4.62	2.55	2.80
Costa Rica	(1994 - 2021)	281	7.64	4.17	7.24
Dominican Rep.	(1994 - 2021)	281	6.10	7.33	3.63
Ecuador	(1994 - 2021)	281	5.90	2.70	2.94
Panama	(1994 - 2021)	281	3.90	13.97	6.52
Paraguay	(1994 - 2021)	281	1.93	1.85	2.10
Uruguay	(1994 - 2021)	281	5.58	4.42	4.99

Notes: IQR - Inter-quartile Range; SD - Standard Deviation

The measure of ex-post inflation across countries, the second source of data in the paper, is taken from the World Bank's Global Database of Inflation.[11] Noted that for the OECD countries, however, real-time data are sourced from the OECD, including my compilation described in the introduction of this paper.

Together, the forecast and ex-post realized inflation data are used to assess the historical performance of cross-country forecasts made at time t in the application of tests of FIRE. As an additional note, when using real-time data the question of which vintage of the real-time data should be used to make the appropriate comparison to forecasts may arise. For this empirical application, I follow Coibion and Gorodnichenko (2015) Coibion and Gorodnichenko (2015) by comparing all forecasts to real-time data available one year after the period being forecasted over.

2.2 Evidence of Heterogeneous 'Mistakes'

Several econometric tests of Full-Information Rational Expectations (FIRE) have emerged over the years. This paper focuses on specifications that evaluate the consistency of *consensus* survey expectations with Muthian Rationality. In his ground-breaking Econometrica article, *"Rational Expectations and the Theory of Price Movement"* (1961), Muth asserts that, on average, an agent's subjective expectations of a variable, turn out to be the realized value of the variable itself. The implication here is that for a given information set, economic agents form expectations that are consistent with the actual stochastic behavior of the economy. In other words, their expectations are model-consistent.

[11] "One-Stop Source: A Global Database of Inflation." Policy Research Working Paper; No. 9737. World Bank, Washington, DC.

For this to hold, Muth makes the underlying assumption that the agent's subjective expectations share the same mathematical properties as probabilistic conditional expectations. Sheffrin (1996) Sheffrin (1996) takes this a step further to show that all tests of FIRE are essentially tests of the underlying properties of conditional expectations and can be classified accordingly.[12] Two well-known properties of conditional expectations which form the basis for several tests of FIRE, are 'Unbiasedness' and 'Forecast Error Predictability'. In the sections which follow I discuss these properties in relation to specified tests, display the associated regression results, and discuss the implications of the findings in the cross-section of the data.

2.3 Unbiasedness

Unbiasedness tests evaluate whether the forecast is an unbiased predictor of the realized variable. One such test is the Mincer-Zarnowitz (MZ) Test Mincer and Zarnowitz (1969). The test is specified as,

$$\pi^i_{t+h} = \alpha^i + \gamma^i F_t \pi^i_{t+h} + u^i_{t+h}, \tag{1}$$

where, the left-hand-side variable is the realized inflation of country i at time $t+h$, $F_t\pi^i_{t+h}$ is the h-period-ahead inflation forecast made at time t, and u^i_{t+h} is the rational expectations error term. FIRE implies that the joint null hypothesis of $(\alpha, \gamma) = (0,1)$ will not be rejected at standard confidence levels, indicating that forecasts should *on average* be unbiased and realized values should move one-for-one with the forecasted variable. Table (2) shows the estimated p-values from the joint test for each country and Figure (1) shows the respective alpha and beta coefficients organized by region.

From Table (2) the results confirm that FIRE is rejected within the data across most countries, with the survey predictions of inflation in twenty-nine of the forty-six countries rejecting the test. Figure (1) also reveals some interesting findings about the nature of inflation expectations across countries and regions. Firstly, across all countries, the average gamma coefficient stands at 0.89, indicating that realized inflation moves less than one-for-one with forecasted inflation on average.

Examining the results by region, across countries within the G7 and Western Europe and Asia Pacific, the estimated average gamma coefficients reveal that a 1% increase in forecasts is matched with an increase in realized inflation of less than 1%. That is, on average, during the period of this study, forecasters appear to over-predict inflation. The results also provide evidence to suggest that over-prediction is stronger within the Asia Pacific Region, where the average gamma is 0.77 compared to 0.90 in countries within the G7 and Western Europe. These results are consistent with the findings of Bianchi et al. (2022). Over the sample period 2000 to 2010, the authors show that on average forecasters in the well-known Survey of Professional Forecasters (SPF), were more pessimistic about inflation than warranted. That is, their fore-

[12] Sheffrin (1996) Sheffrin (1996) notes that in keeping with the properties of conditional expectations, tests of rational expectations can be classified into four main categories: (1) Unbiasedness, (2) Efficiency, (3) Forecast Error Predictability, and (4) Consistency.

Table 2. Mincer-Zarnowitz Test: *p-values*

G7 and Western Europe $(\alpha, \gamma) = (0, 1)$		**Asia Pacific** $(\alpha, \gamma) = (0, 1)$		**Latin America** $(\alpha, \gamma) = (0, 1)$	
USA	0.04	Australia	0.00	Argentina	0.03
Japan	0.08	Bangladesh	0.01	Bolivia	0.11
Germany	0.45	China	0.00	Brazil	0.12
France	0.05	Hong Kong	0.00	Chile	0.93
UK	0.94	India	0.06	Colombia	0.55
Italy	0.88	Indonesia	0.12	Costa Rica	0.00
Canada	0.01	Malaysia	0.00	Dom. Rep.	0.26
Austria	0.32	New Zealand	0.05	Ecuador	0.00
Belgium	0.00	Pakistan	0.21	Mexico	0.01
Denmark	0.00	Philippines	0.00	Panama	0.11
Finland	0.00	Singapore	0.03	Paraguay	0.00
Greece	0.16	South Korea	0.02	Peru	0.00
Ireland	0.20	Sri Lanka	0.04	Uruguay	0.00
Netherlands	0.64	Thailand	0.00		
Norway	0.00	Vietnam	0.14		
Portugal	0.79				
Spain	0.98				
Sweden	0.00				
Switzerland	0.00				

Notes: The table shows the estimated p-values under $H_0 : \alpha, \gamma = 0, 1$. Estimates are computed using Newey-West standard errors with lag length $L = [0.75 \times T^{1/3}]$. Average number of observations per country: G7 and Western Europe: 371; Asia Pacific: 340; Latin America: 283. *p $<$ 0.1, **p$<$ 0.05, ***p$<$ 0.01.

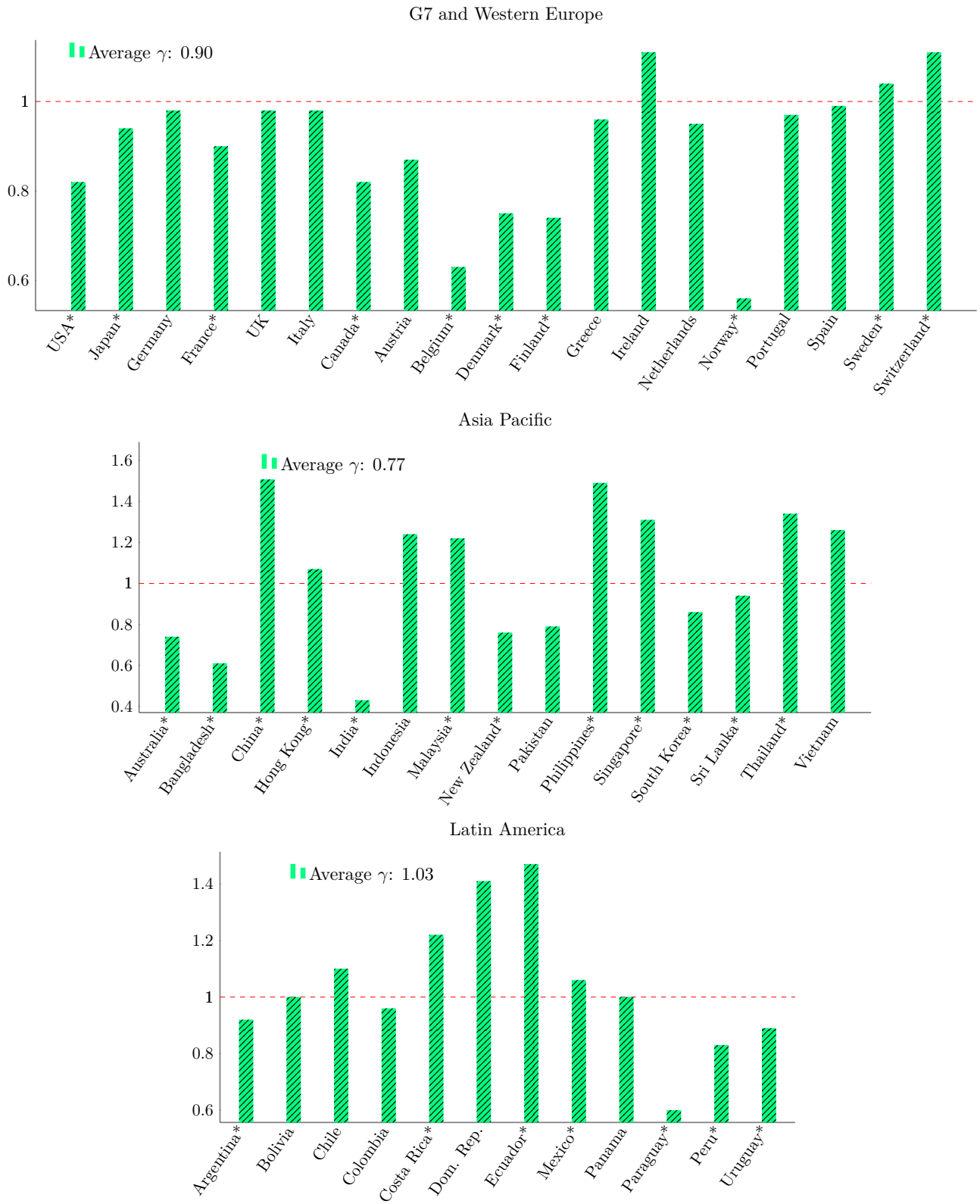
casts were biased upward.

Within the Latin American region, however, the findings are less consistent. On average, realized inflation appears to move almost exactly one-for-one with forecasted inflation, whilst, in some countries such as Costa Rica, Dominican Republic, Ecuador, Mexico, and Panama, a 1% increase in forecasted inflation is correlated with a larger percentage increase in realized inflation, indicating that in these countries, forecasters appear to under-predict inflation.[13]

What becomes clear from these results is that the direction of the bias, whether over or under-prediction of inflation, is inconsistent across countries and regions. While the average gamma coefficients tell a story of over-prediction, the presence of statistically significant outliers

[13]The average gamma coefficient among these five countries is 1.27.

Figure 1. Mincer-Zarnowitz Test - Estimated γ Coefficients



Notes: The figure shows the γ coefficient for each country estimated from the Mincer-Zarnowitz specification in equation (1) which tests the null hypothesis $(\alpha, \gamma) = (0, 1)$. The red dashed lines represent the evaluation line for $\gamma = 1$. Countries for which the test results are statistically significant are marked with *. All standard errors are Newey-West with lag length $L = [0.75 \times T^{1/3}]$. Average number of observations per country: G7 and Western Europe: 371; Asia Pacific: 340; Latin America: 283.

within each region provides some evidence that the direction of the bias may be driven by country-specific factors and makes a strong case for the argument that diversity in macroeconomic dynamics plays a significant role in the nature of violations of FIRE.

2.4 Forecast Error Unpredictability

Tests of forecast error predictability evaluate the agent's ability to incorporate all relevant information into the forecast and generally take the form of regressing the forecast error on relevant variables within the forecaster's information set such as the forecast revision or the current period's inflation. By construction, these tests follow from the orthogonality property of forecast errors, that is, errors should be uncorrelated with any information available to forecasters at time t or earlier. One common test within this category is the Coibion-Gorodnichenko (2015) Test. The general specification of the test is:

$$\pi^i_{t+h} - F_t\pi^i_{t+h} = \alpha^i + \beta^i(F_t\pi^i_{t+h} - F_{t-1}\pi^i_{t+h}) + u^i_{t+h}, \tag{2}$$

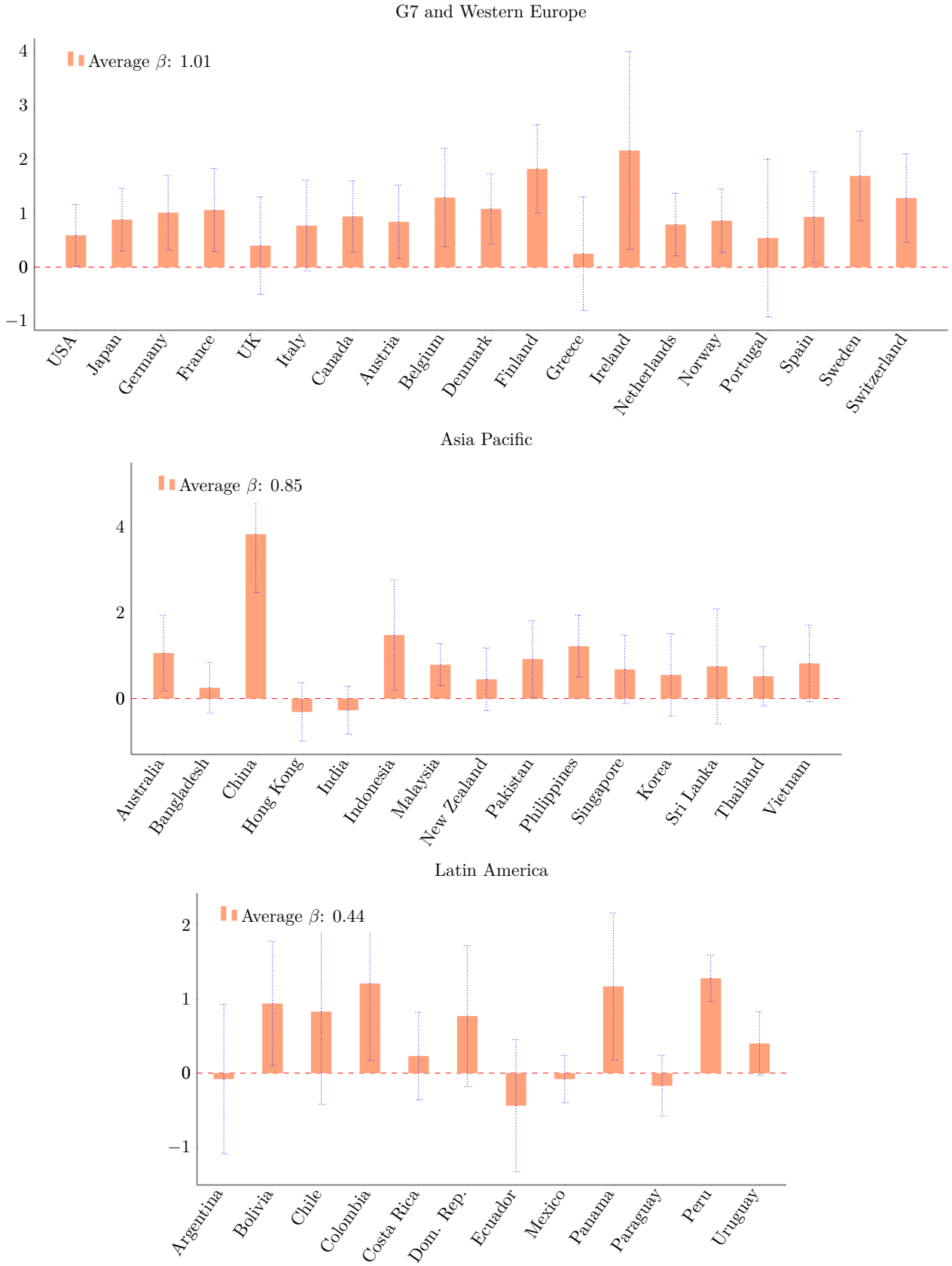
where, the left hand side of equation (2), $(\pi^i_{t+h} - F_t\pi^i_{t+h})$, represents the one-period ahead forecast error. This term is regressed against the time t forecast revision or one-period change in the forecast, $(F_t\pi^i_{t+h} - F_{t-1}\pi^i_{t+h})$, for each country. From a conceptual standpoint, the forecast revision measures the forecasters' reaction to new news on the state of the economy that has been incorporated into their information set. The final term u^i_{t+h} is the rational expectations error which should be uncorrelated with all information received at time t or earlier. Equation (2) tests $H_0 : \beta^i = 0$.

The novelty of this Test is that it also allows us to quantitatively and qualitatively assess the implication of a departure from FIRE on the agent's use of the available information set. For example, a positive beta coefficient, $\beta^i > 0$ implies that given the arrival of *negative* new information about the state of the economy, the forecaster's prediction of next period's inflation was revised higher, but insufficiently so. Consequently, the time t forecast revision is positive and the time $t+1$ forecast error is also positive. In a similar line of reasoning, given *optimistic* news about the state of the economy a positive beta implies that in this case the forecaster's inflation prediction was revised downward, but not low enough. This gives the general idea of some level of inertia or *under-reaction* to new information amongst forecasters.Coibion and Gorodnichenko (2015) argue that this *under-reaction* is a feature of consensus forecasts.

In their expanded study of the evolution of expectations across various macroeconomic and financial variables, Bordalo et al. (2020) show that a negative beta coefficient, $\beta^i < 0$, is indicative of *over-reaction*, a feature that characterizes individual-level forecasts. That is, given new information about the state of the economy, forecasters' predictions are revised too high or too low resulting in a negative relationship between the forecast error and the forecast revision. The authors argue that this is largely a result of the extrapolative tendencies of decision makers.

Figure (2) presents the results of the Coibion-Gorodnichenko Test for all forty-six countries

Figure 2. The Coibion-Gorodnichenko Test: Estimated β Coefficients



Notes: The figure shows the results of the Coibion-Gorodnichenko Test from equation (2) testing the null hypothesis, $\beta = 0$ across countries within each of the three regions. The dependent variable is the forecast error and the independent variable is the forecast revision. The orange bars represent the estimated coefficients and the blue dashed lines represent the respective 95% confidence intervals. All standard errors are Newey-West with lag length $L = [0.75 \times T^{1/3}]$. Average number of observations per country: G7 and Western Europe: 338; Asia Pacific: 312; Latin America: 255.

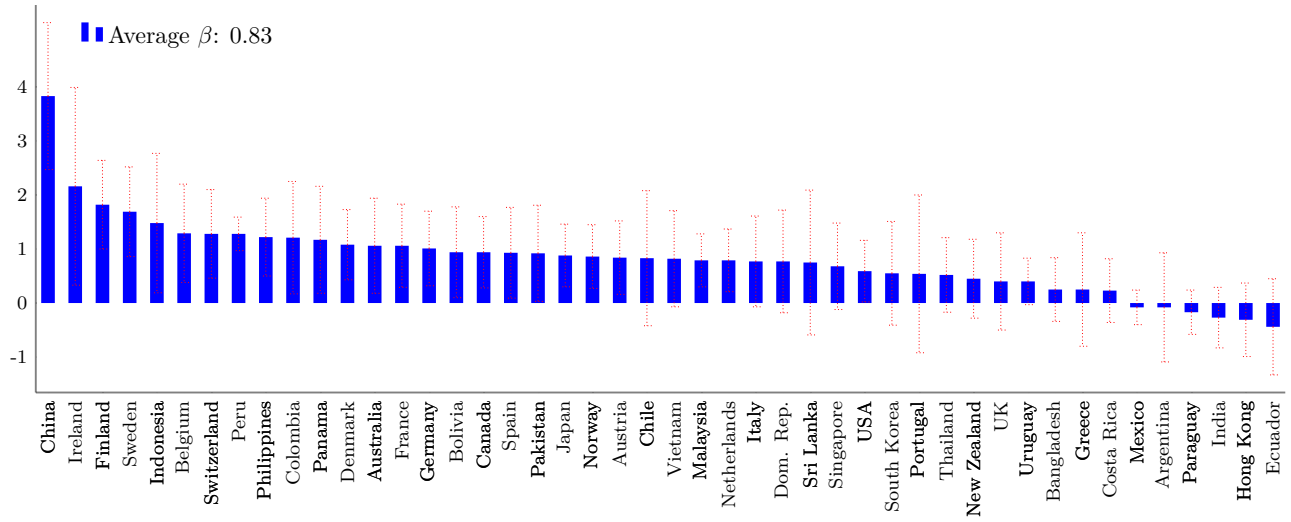
organized by region. Consistent with the existing literature, on average, FIRE is rejected in the inflation predictions of professional forecasters across several countries in all three regions, that is, $\beta \neq 0$, over the period of this study. The results also confirm that under-reaction is the dominant bias in forecasts across countries. From these results there are two novel findings that emerge.

Firstly, on average the magnitude of under-reaction observed varies substantially across regions and countries. Under-reaction or forecast inertia is strongest on average across the G7 and Western European countries and weakest across countries in the Latin American dataset where there were some instances of over-reaction at the aggregate level, though not statistically significant. One explanation for this finding is presented in Weber et *al.* (2023) Weber et al. (2023).[14] In their paper, the authors conduct randomized control trials (RCTs) across countries where inflation has been both historically high and low. They find that agents' inflation expectations vary with their attention to information and that attention is a function of the unique macroeconomic setting, or more specifically, the prevailing inflation regime. The implication is that in countries where inflation has been historically high, agents are likely more attentive to recent news and the strength of their reaction to new information on inflation is abated compared to countries where inflation has been lower. Consequently, the results presented in figure (2) *on average* may reflects the broad variation in information attention and its linkage to levels of historical inflation across regions.

Taking a closer look at the results by country, however, this explanation does not seem to fully reflect the findings. Figure (3) plots the estimated beta coefficients in ascending order, revealing that countries with historically diverse inflation experiences, are included within the first 22 observations which fall above the average–perhaps indicating that inflation inattention does not fully explain the variation in belief distortions across macroeconomic settings. One possible explanation is that these predictions reflect the position of professional forecasters who are likely more attentive to information despite their geographical locations. Variations in magnitude may reflect other specific macroeconomic dynamics not captured by surveys based on the expectations of households and firms.

[14]This paper falls within the larger literature which explores how information inattention varies as inflation rates rise. See Branch and McGough (2018), Korenok et al. (2023) and Pfäuti (n.d.). It is also related to the literature which examines the role of experience effects in decision-making. See Malmendier and Nagel (2011).

Figure 3. The Coibion-Gorodnichenko Test: Estimated β Coefficients



Notes: The figure shows the estimated β coefficient for each country results of the Coibion-Gorodnichenko Test from equation (2) testing the null hypothesis, $\beta = 0$ across countries organized in descending order.

2.5 Summary of Findings

The results of the tests presented in this section provide consistent empirical micro-evidence that cross-country inflation expectations of professional forecasters systematically depart from the assumptions of full-information rational expectations (FIRE). What is novel, however, is the extent of the heterogeneity in the magnitude and direction of departures so far as they provide evidence that the established stylized facts listed at the beginning of this section, are contradicted. It therefore provides an opportunity to explore more closely, the validity of these facts given the empirical evidence — affording us greater clarity on the EFP in a more dynamic international setting.

I begin by broadly classifying the results across all countries using the estimated gamma and beta coefficients from the MZ and CG tests, respectively. The scatter diagram in figure (4) shows that countries fall into one of four quadrants and what emerges is four distinct behavioral approaches to forecasting inflation represented by the location of countries within each quadrant. Quadrant I contains those countries for which the estimated MZ Gamma is greater than 1 indicating a tendency to under-predict inflation relative to the realized value, and those countries with a negative CG Beta, indicating over-reaction. In essence, there are two opposing forces at work within this quadrant — inertia or under-reaction and extrapolation or over-reaction.

Quadrant II documents those countries for which forecasters' predictions display simultaneous under-reaction and under-prediction — biases consistent with forecast inertia. Interestingly, this quadrant contains three countries from Latin America a region that has historically had numerous high-inflation episodes. Quadrant III contains those countries where predicted inflation displayed a bias toward over-reaction, given the negative CG beta and over-prediction relative to the realized value of inflation, given the MZ gamma less than 1 — consistent with agents'

tendency to extrapolate from recent events. It must be noted that this finding represents a direct contradiction of stylized fact (1). At the consensus level, forecasts have been known to display under-reaction or be characterized by inertia. Still, very few countries fall within this region.

Quadrant IV, contains those countries for which forecaster predictions are characterized by under-reaction and over-prediction and appears to characterize the bias in most inflation predictions. Similar to quadrant I, countries within this quadrant present two opposing forces — inertia and extrapolation. This quadrant is mostly occupied by advanced economies and countries within the Asia Pacific region with a few countries from Latin America. Though at odds with the literature, the coexistence of inertia and extrapolation in forecasts, has been documented within the literature. Kohlhas and Walther (2021) Kohlhas and Walther (2021) using two different tests of FIRE, show that consensus forecasts of output from the Survey of Professional Forecasters (SPF) display simultaneous extrapolation and under-reaction over the period 1970 - 2019. The authors present a model of asymmetric attention to account for this empirical findings.

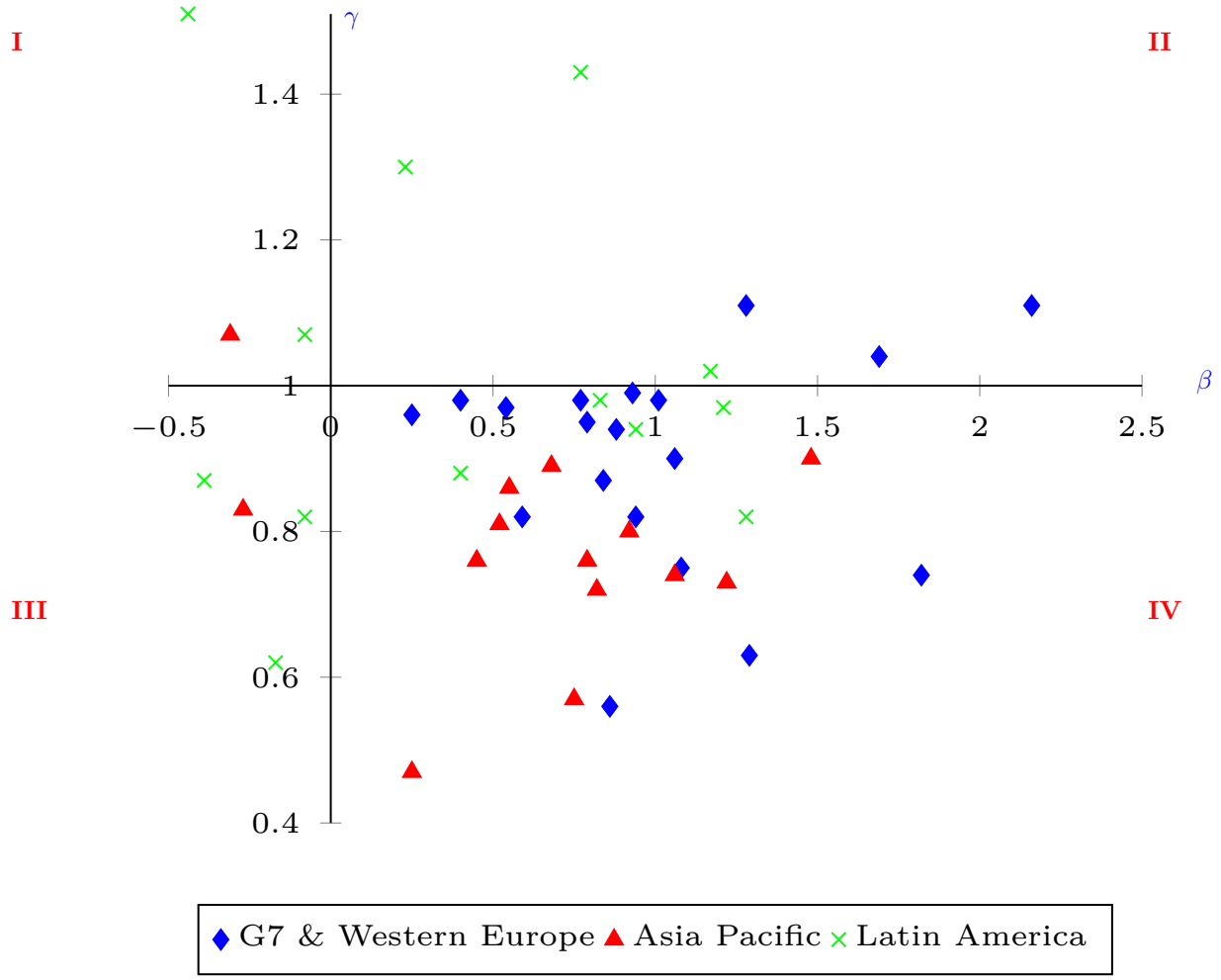
Overall, we observe that countries fall into all four quadrants indicating that strict classifications about the manner in which expectations depart from FIRE are not ubiquitous. To my knowledge, this is the first documented evidence of the positioning of countries by the nature of their expectational biases. There are very few countries where the dominant bias is exclusively inertia or extrapolation (quadrants II and III), indicating a more prominent role for the variation in macroeconomic settings or country-specific macroeconomic dynamics in determining departures from FIRE in subjective beliefs. It also calls for a closer examination of the parameters governing the data generating process, and the interaction of these parameters with country and region-specific macroeconomic dynamics.

This is not to say that we discard existing stylistic facts or past empirical findings. Indeed, Figure (3) shows that there is a cluster of countries within quadrant IV, which may suggest the existence of commonalities across countries in the formation of expectations. That is, belief distortions driving departures from FIRE ("mistakes"), likely reflect the unique coexistence of heterogeneity in macroeconomic settings, with a level of synchronization across countries and regions, likely reflecting the impact of the global transmission of macroeconomic shocks.

Ciccarelli and Mojon (2010) Ciccarelli and Mojon (2010), in their seminal paper on global inflation, come to a similar conclusion. The authors, in their analysis of inflation in 22 OECD countries from 1960 to 2008, found that approximately 70% of the variation in a country's domestic inflation was driven by the existence of a common global factor, with the implication that as little as 30% of the variation was being driven by country-specific factors.

This paper analyzes the extent to which departures from FIRE, driven by underlying belief distortions in the inflation expectations of professional forecasters, display co-movement. It attempts to deliver a measurement of both the cross-country and country-specific biases in inflation expectations. In the sections that follows, I use a well-known econometric approach to identify common trends in data — a Bayesian Dynamic Factor Model. Then in Section (4)

Figure 4. Estimated Cross-Country Coefficients



Notes: The figure shows the estimated γ and β coefficients from equations (1) and (2), respectively for each country color-coded by region. Negative values on the x-axis represent over-reaction and positive values represent under-reaction. On the y-axis, values greater than 1 represent forecasters' bias toward under-prediction, since realized inflation moves more than one-for-one with the forecast and values less than 1 represent a bias toward over-prediction since realized inflation move less than one-for-one with survey predictions within that country.

I discuss the findings of this model and show that the strength of this factor varies over time and across regions.

3 A Bayesian Dynamic Factor Model

Given the evidence of heterogeneity in departures from FIRE across countries, I now examine the extent to which forecaster 'mistakes' may co-move across countries and the implications of this comovement for modeling the formation expectations and the formulation of effective monetary policy. To conduct this analysis I turn to a widely used class of models that decomposes a macroeconomic time series variable into components that are not directly observable by the econometrician - that is, *unobserved components models*. Included within this class of models are *state space models* where the observed time series depends linearly on a possibly

unobserved state driven by a stochastic process. *Factor models* which distill information in large data-sets to a lower-dimensional set of (unobserved) factors, also fall within the class of state space models and can be modeled in a linear state space representation. In these models, it is assumed that a set of n observed variables depends linearly on m unobserved common factors and on an individual or idiosyncratic component.[15]

This paper presents an empirical application of a *dynamic* factor model. A distinguishing feature of this model compared to a *static* factor model is that all inter-temporal cross-correlations among variables are accounted for by the dynamic unobserved factors.

3.1 Econometric Framework

Let $e_t = [e_{1t}, e_{2t}, ..., e_{nt}]', t = 1, ..., T, i = 1, ..., n$ denote a stationary $n \times 1$ vector of observable cross-country inflation forecast errors standardized to mean zero and unit variance at time t. Here, e_t is the difference between realized inflation at time t and predicted inflation at time *t-1* or $\pi_t - \pi^e_{t-1}$. A general representation of the factor model is given by:

$$e_t = \lambda f_t + u_t, \tag{3}$$

where f_t is an $m \times 1$ vector of unobserved common factors which are believed to capture the co-movement of the cross-country panel of forecast errors and λ is an $n \times m$ matrix of unknown factor loadings which determine the exact linear combination of the m latent factors. Here, $\chi_t = \lambda f_t$ is referred to as the common component and $u_t = [u_{1t}, u_{2t}, ..., u_{n,t}]'$ as the idiosyncratic component or country-specific noise of the model. It is assumed that $u_t \sim iid\ N(0, \Sigma)$ where Σ is set to be a diagonal matrix. This implies that $Eu_{it}u_{jt-s} = 0$ for $i \neq j$ or that the idiosyncratic shocks are uncorrelated. Therefore, u_{jt} is a shock idiosyncratic to equation i and e_{it} is said to follow an *exact* factor model since all co-movements in the data arise from the latent factors plus an idiosyncratic shock.

Note that the above model is static since it does not allow for autocorrelation in the factors. For time series applications, however, the factors may be serially correlated and follow an autoregressive process of order q,

$$f_t = \Phi^f_1 f_{t-1} + ... + \Phi^f_q f_{t-q} + \eta^f_t, \tag{4}$$

where, Φ^f_i is the $m \times m$ coefficient matrix corresponding to the ith lag of factor f_t and $\eta^f_t = [\eta^f_{1t}, \eta^f_{2t}, ..., \eta^f_{n,t}]'$ is the error term. Note here that $\eta^f_t \sim iid\ N(0, \Sigma^f)$, where Σ^f is assumed to be diagonal, that is $E\eta^f_{it}\eta^f_{it-s} = \sigma^2_f$ for $s = 0; 0$ otherwise.

Similarly, the evolution of the idiosyncratic errors may also follow an autoregressive process of order p,

$$u_t = \Phi_1 u_{t-1} + ... + \Phi_p u_{t-p} + \eta_t, \tag{5}$$

[15] Where $m < n$.

where, Φ_i is a matrix of autoregressive coefficients corresponding to the ith lag of u_t and the innovations, similar to the factor innovations, are assumed to be zero mean, contemporaneously uncorrelated normal random variables, $\eta_t \sim iid\ N(0, \Sigma)$, where Σ is set to be a diagonal matrix. Finally, note here that $E\eta^f_{it}\eta_{it-s} = 0\ \forall\ i, s$. That is, the idiosyncratic terms of the latent factor and the observables are contemporaneously uncorrelated normal random variables.

This allowance for serial correlation in the idiosyncratic errors and the latent factors is what makes the model dynamic. Together, equations (3) through (5) represent the dynamic factor model used to evaluate the inter-temporal co-movement of forecast errors across countries.[16] In the context of the linear Gaussian state space model, equation (3) represents the measurement equation and equations (4) and (5) the transition equations.

3.1.1 Identification Restrictions

It is well known that the dynamic factor model presented in equations (3) through (5) is not identifiable without further restrictions. It can be shown that pre-multiplying the dynamic factor by any arbitrary full-rank $m \times m$ matrix defines a new model which is observationally equivalent to the original model. For example, for any non-singular matrix C, $\lambda f_t = \lambda C C^{-1} f_t$, therefore, a model with factors f_t and factor loadings λ will give the same fit as one with factors $C^{-1}f_t$ and factor loadings λC. As a result of this normalization issue, neither the signs nor the *scale* of the dynamic factors nor the associated factor loadings are separately identified.

Two additional restrictions are required for unique identification. Firstly, it is common to set the variance of η^f_t to the identity matrix, as in Bai and Wang (2015) Bai and Wang (2015). That is,

$$var \begin{bmatrix} \eta^f_{1t} \\ \eta^f_{2t} \\ \vdots \\ \eta^f_{nt} \end{bmatrix} = I_m.$$

This restriction addresses the *scale* issue. The second normalization restriction addresses the sign issue by setting λ to be a lower triangular matrix with ones on the diagonal.[17] Appendix A details the mathematical proof that these two restrictions are sufficient to uniquely identify the dynamic factor model presented in equations (3) through (5).

[16] This is the standard model put forward by Stock and Watson (1989) Stock and Watson (1989) and applied in the context of international business cycles by Kose et *al.* (2003) Kose et al. (2003).

[17] There are several variations to address the normalization issue in this model. For example, to address the *scale* issue, Sargent and Sims (1977) Sargent and Sims (1977) and Stock and Watson (1989, 1993) Stock and Watson (1993, 1989) assume that σ^2_f is equal to a constant, which is quite similar to the approach taken in this paper. Further, it is common to identify the signs by requiring one of the factor loadings to be positive as in Otrok and Whiteman (1998) Otrok and Whiteman (1998) or to require λ to be a lower triangular matrix with strictly positive diagonal elements as specified in Bai and Wang (2015) Bai and Wang (2015).

3.1.2 Selecting the Number of Dynamic Factors

Prior to the estimation of the dynamic factor model, an important consideration is the number of common latent factors to be included. This decision is largely approached via optimization of an *Information Criterion* to consistently estimate the number of factors. The objective is often to select the smallest number of latent trends without the loss of too much information.

Within the empirical literature, among the most widely used approaches to factor selection, are the Bai and Ng (2002) Bai and Ng (2002) criterion for static factor models where the minimization of the information criteria is based on a trade-off between the quality of the adjustment of the model to the data and the risk of over-adjustment.

In the context of dynamic factor models, the Bai and Ng (2007) criteria Bai and Ng (2007) builds on the Bai and Ng (2002) Bai and Ng (2002) criteria by first taking the optimal number of factors selected as given. The authors then estimate a VAR*(p)* on these factors using the Bayes Information Criterion (BIC) and then as a final step, use the Bai and Ng (2007) Bai and Ng (2007) criteria to obtain the optimal number of dynamic factors.

Finally, Stock and Watson (2005) Stock and Watson (2005) and Amengual and Watson (2007) Amengual and Watson (2007) show that the Bai and Ng (2002) Bai and Ng (2002) criteria can, in fact, be used to estimate the number of dynamic factors.

3.1.3 Estimation

Following Stock and Watson (1989, 1993) Stock and Watson (1993, 1989) the classical approach to this system of equations has been to apply statistical techniques which make use of the Kalman filter to estimate model parameters and the Kalman smoother to extract an estimate of the latent factor, however, there are a few drawbacks to this method. Firstly, when n is large, this method can be computationally demanding, and secondly, since the factors are random variables when n is finite, estimators will not be consistent.

In the more recent literature (see Otrok and Whiteman (1998) Otrok and Whiteman (1998)), these equations have also been estimated using Bayesian inference which makes use of *posterior simulation*. Here, a Monte Carlo Markov chain (MCMC) procedure can be employed to generate samples from a given target distribution. In the empirical application of this paper, the distribution of interest is the *joint posterior distribution* of the model parameters and latent factors given the observed data, that is, $p(\Theta, f|\text{data})$. Here Θ represents the parameters, $\lambda, \Sigma, \Sigma^f, \phi_i^f, i = 1, ..., q$, and $\phi_i, i = 1, ..., p$.

Given the large cross-sectional data-set used in this paper, however, sampling from the joint posterior distribution directly is complex and even prohibitive. The Gibbs sampler, an MCMC sampling algorithm, addresses this problem by first expressing this distribution in terms of its complete set of conditional distributions and then iteratively sampling from the individual *posterior conditional distributions*.[18] Casella and George (1992) Casella and George (1992) show

[18]Based on the assumption that the joint distribution can be characterized by its complete set of conditional distributions. Usually applied to standard continuous distributions such as Normal, *t*, Beta or Gamma or

that under weak conditions, this iterative sampling converges to drawing from the joint posterior distribution directly as the number of sampling draws, $j \to \infty$. With this approach, the complexity of sampling directly from the joint posterior distribution is simplified via a series of smaller more manageable problems.[19]

As an example of how the Gibbs sampling methodology cycles through conditional distributions, starting with an initial (specified) value, f^0, a sample is drawn from the posterior distribution of the parameters conditional on the factor, $p(\Theta|f^0, data)$, which produces a drawing, Θ^1. Next, a sample is drawn from the distribution of the latent factor, conditional on the parameters, $p(f|\Theta^1, data)$ which produces a drawing, f^1. This completes one Gibbs sample or the first step of the *Markov Chain*.[20]

Continuing this process generates a *Gibbs sequence* of random variables, $f^0, \Theta^1, f^1, ...\Theta^j, f^j$. That is, once the initial value f^0 is specified, the remainder of the sequence is obtained iteratively by alternately generating, at each step, drawings from,

$$\begin{aligned} \Theta^j &\sim p(\Theta|f^{j-1}, data) \\ f^j &\sim p(f|\Theta^j, data), \end{aligned} \tag{6}$$

for $j = 1, ..., J$. Once the samples are obtained, the sample mean and median of the posterior distributions represent the traditional point estimates, while the percentiles can be used as confidence intervals.

4 The Cross-Country Dynamic Factor: A Model of Synchronized 'Mistakes'

Figure (5) presents evidence of the existence of a cross-country common component in forecast errors among professional forecasters from 2001 - 2010. It is represented by the median posterior distribution of the first latent factor estimated from equations (3) through (5) that is,

$$e_t = \lambda f_t + u_t, \tag{7}$$

where f_t and u_t follow autoregressive processes of orders $q = 1$ and $p = 1$, respectively.[21] The fluctuations in the factor indeed reflect the major economic events throughout this study, such as the 2007 to 2008 Global Financial Crisis (GFC), and the recent COVID-19 pandemic with

discrete distributions such as Binomial, Multinomial, or Dirichlet.

[19]Chan et *al.* (2019) Chan et al. (2019) present a comprehensive introductory example of the Gibbs sampling routine.

[20]Note that the order of sampling, that is, which conditional is sampled first or second does not matter, what matters is that a sample is drawn from each of the unknown blocks. In the application presented in this paper, there are two blocks (parameters and the cross-country factor). Kose et al. (2003) Kose et al. (2003) present an application of the Gibbs sampler with four blocks in their application of dynamic factor analysis to international business cycles with a multi-level factor structure.

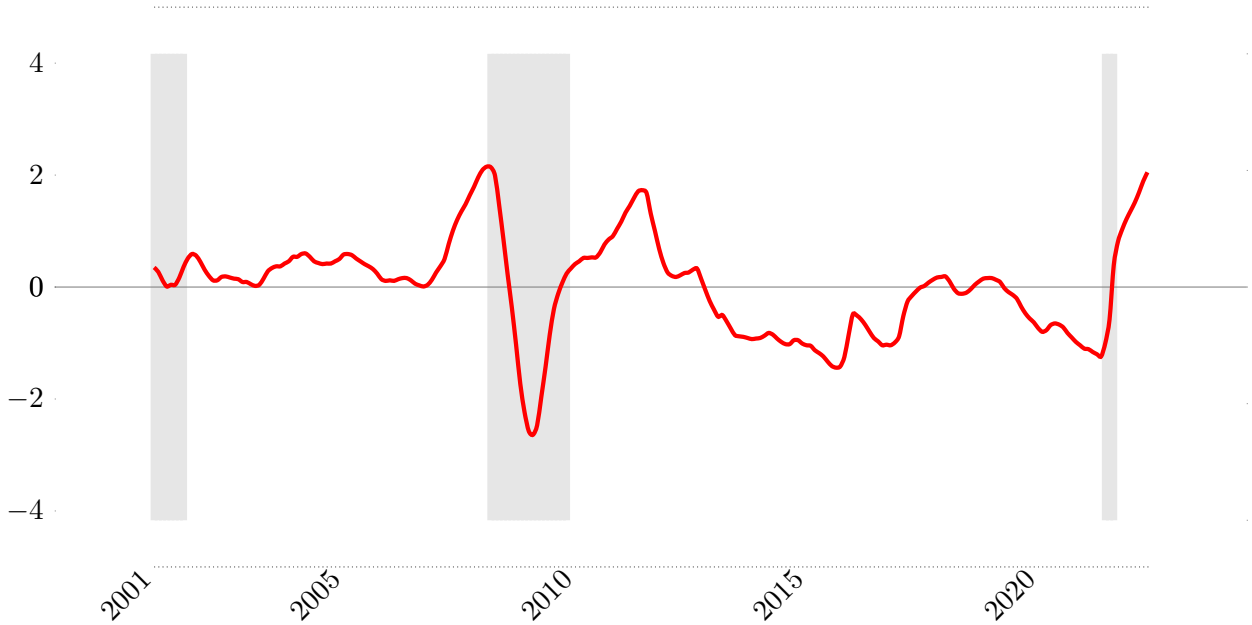
[21]Note that this analysis begins from 2001, the latest date in the data set when data for all countries are available as estimation requires a balanced panel.

the factor appearing to increase in strength during macroeconomic shocks. This assertion is consistent with the findings of Borio and Filardo (2007) Borio and Filardo (2007). The authors suggest that the relevance of global inflation is time-varying and becomes more relevant during economic shocks. An interesting extension of this paper is to assess the increased relevance of this factor coming out of the pandemic, as more data becomes available.

One can also observe that forecasters' predictions oscillate between under-prediction of inflation when the factor is positive, and over-prediction when the factor is negative. Interestingly, the factor displays differences in the direction of forecasters' bias leading up to and during the crises presented. For example, the period leading up to the GFC reflects a bias toward under-prediction whereas one can observe a bias toward over-prediction leading up to the COVID-19 pandemic.

Additionally, there appears to be a strong '*reversal*' in the bias after the respective crises, with forecaster predictions emerging from over to under-prediction. Notably, the speed of the '*reversal*' was faster emerging out of the COVID-19 pandemic, with forecasters' predictions biased toward under-prediction at a level that had not been seen since its peak in 2010. This may reflect their views that inflationary pressures would ease, even in the short-term, or be an adjustment to their overly pessimistic views during the pandemic. It may also suggest the existence of well-anchored long-term inflation expectations compared to other periods of economic disruptions.

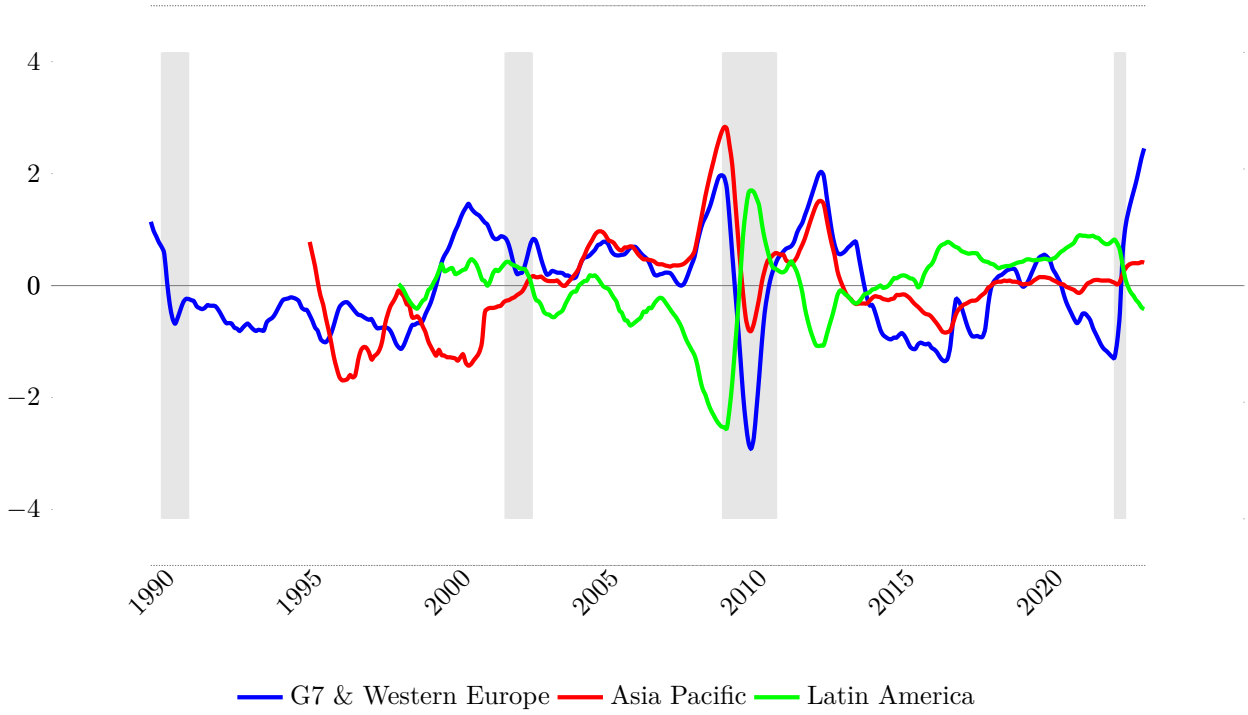
Figure 5. Cross-Country Dynamic Factor in Forecast Errors



Notes: The figure shows the estimated dynamic latent factor in monthly forecast errors across 46 countries from Jan. 2001 - Dec. 2020. Forecast errors have been standardized to mean zero and unit variance. Shaded areas denote NBER recession dates. For all countries n = 247.

Across each of the three regions, a different picture of the dynamics of the factor emerges. Figure (6) presents the Cross-Country Dynamic Factor by region.[22] Firstly, one can observe the similarity between the factor for the G7 and Western European Region to the factor for all countries presented in Figure (5). It is likely that this region contributes most significantly to the cross-country factor or that the factor is strongly driven by the macroeconomic dynamics of these economies. While the factor within the Asia Pacific Region bears similarity to the cross-country factor as well as the G7 and Western Europe regional factor, it comes more into alignment during economic shocks and even appears to be inversely related to the factor for the advanced economies before 2005.

Figure 6. Cross-Country Dynamic Factor in Forecast Errors by Region



Notes: The figure shows the estimated dynamic latent factor in monthly forecast errors across 46 countries displayed by region from Jan. 2001 - Dec. 2020. Forecast errors have been standardized to mean zero and unit variance. Shaded bars represent NBER recession dates. For the G7 and Western Europe Region n = 371, for Asia Pacific n = 312, and for Latin America n = 279.

The cross-country dynamic factor within the Latin American region, reveals a trend that appears to go in the opposite direction to the overall cross-country factor in Figure (5) as well as the factors within the first two regions. One can observe that during the period leading up to the Global Financial Crisis, forecasters within this region were biased toward over-predicting inflation, whereas, in the period leading up to the pandemic, forecasters were predisposed to under-predicting inflation. This is quite consistent with Section (2) of this paper, where we see

[22]Note that the respective dynamic factors for each region may vary by start date given the nature of the dataset.

countries within the Latin American Region displaying departures from FIRE in magnitude and directions that varied significantly from countries within other regions.

Together, these findings strengthen the case for greater consideration of the dynamics of variations in macroeconomic settings across countries and regions, on the formation of expectations. I now turn to assessing the relative contribution of these factors to country and region-specific departures from FIRE.

4.1 The Contribution of the Cross-Country Factor

While the presence of a global factor reflects commonalities among forecasters across countries, the more relevant and insightful finding is the contribution of this factor to fluctuations in each country's forecast errors and the extent to which these errors depart from FIRE. To examine this, I begin with a measure of the relative contribution of the cross-country factor to variations in the forecast errors in each country. Here, I decompose the variance of each observable into the fraction that is due to the cross-country factor (or common unobserved component) and the fraction driven by the idiosyncratic or country-specific component. In an approach similar to Kose et *al.* (2003), the variance of the observable forecast errors due to the cross-country factor i can be written as:

$$var(e_{it}^h) = (\lambda_i^h)^2 var(f_t^h) + var(u_{it}^h), \tag{8}$$

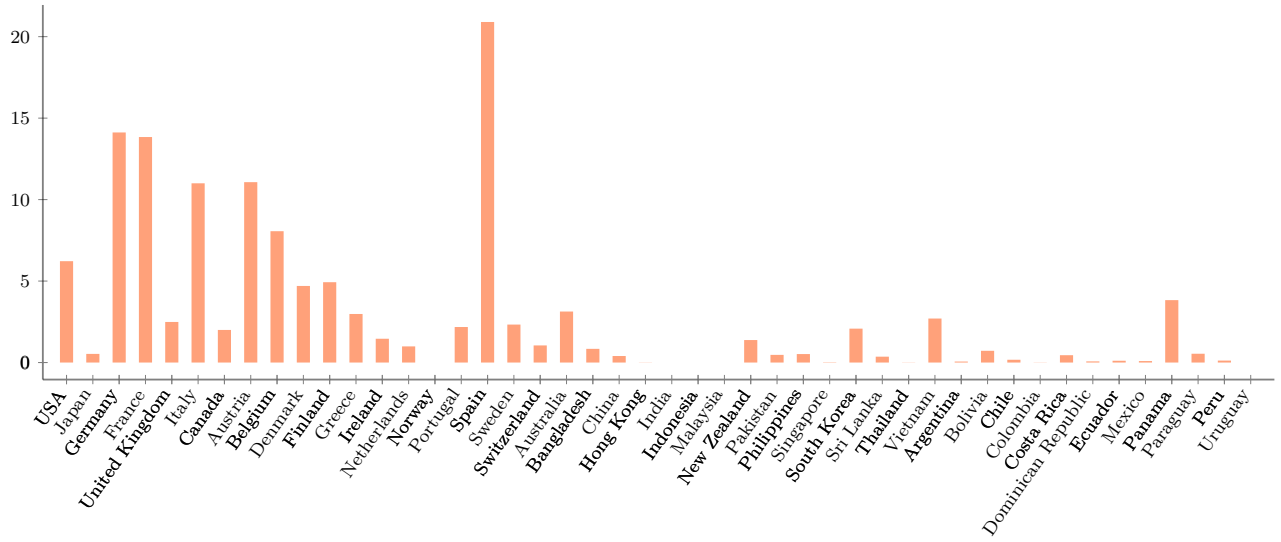
where the fraction of volatility attributed to the cross-country factor for each country is measured as,

$$var(f_{it}^h) = \frac{(\lambda_i^h)^2 var(f_t^h)}{var(e_{it}^h)} \ .$$

Figure (7) presents the variance shares attributable to the cross-country latent factors for each country. Note here that the fraction of the variance of the observable (forecast errors) due to the idiosyncratic or country-specific component is simply $1 - var(e_{it}^h)$.

Across all countries, the factor explains around 3% of the total variation in forecast errors and appears to be most relevant across countries within the G7 and Western Europe region where the factor contributes as much as 6% to the variability in forecast errors. Notably, for countries such as Germany, France, Italy, Spain, and Austria, the factor explains more than 10% of the variability of each country's forecast errors. The implication is that while the role of domestic macroeconomic conditions appears to dominate expectations formation across most countries, there is a compelling argument to be made for the role of region-specific factors, particularly when countries share a common currency union such as the Euro area.

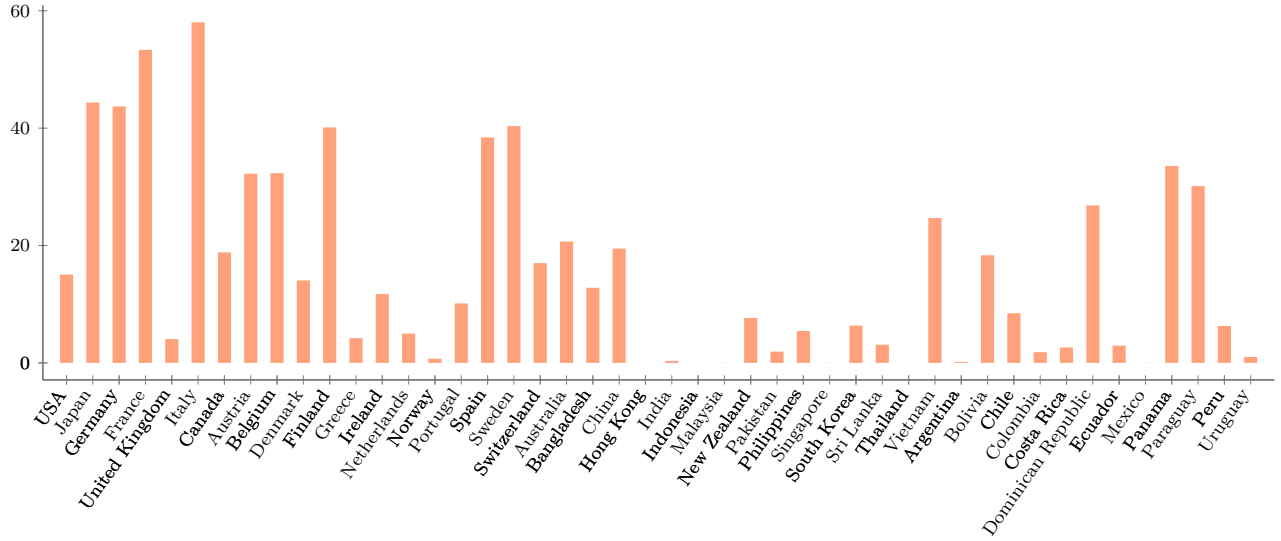
Figure 7. Variance Decomposition



Notes: The figure shows the contribution of the cross-country dynamic latent factor to each country's forecast errors over the period 2001 to 2020 in percentage points.

The findings also reveal that the factor is less influential across the Asia Pacific and Latin American Regions, indicating that variations in forecast errors or departures from FIRE are more dominated by country-specific dynamics.

Figure 8. Variance Decomposition: Global Financial Crisis



Notes: The figure shows the contribution of the cross-country dynamic latent factor to each country's forecast errors over the period 2006 to 2012 in percentage points.

Figure (8) reveals the relevance of the cross-country during the Global Financial Crisis (GFC) evaluated over the period 2006 to 2012. What stands out most is the relative importance of the factor across almost all countries during this period. Not only is the factor significantly more relevant across advanced economies, but across developing countries, particularly in Latin

America, it becomes clearer to see that forecasters' cognitive distortions are commonly driven during periods of crisis.

4.2 Implications for Monetary Policy

The existence of the latent factor in the forecast errors across countries brings to the fore the role of forecaster biases in the formation of expectations and how these biases, which comove internationally, bear upon forecasters' predictions in a country-specific context. While it is well-known that agents' belief distortions impact the formulation of expectations, less is known about the extent to which these belief distortions are driven by forecaster biases in the context of global macroeconomic dynamics. The challenge for the central banker is to assess the transmission of biases through the expectations channel and its relevance for country-specific outcomes in the EFP.

This paper shows that while the factor is less relevant across emerging economies within the Asia Pacific and Latin American Region, across advanced economies, the transmission of biases is prevalent. It suggests that monetary policy formulation as it relates to the role of inflation expectations hinges on the ability of policymakers to understand more deeply the role of macroeconomic dynamics across these economies in understanding and interpreting how professional forecasters and other agents form expectations.

More insightful, however, is the fact that the results of the variance decomposition reveal that the limited role of the factor across countries in other regions may translate into the fact that established methodologies or models of capturing departures from FIRE may not be applicable in all macroeconomic settings. This analysis likely reflects the fact that regional macroeconomic dynamics may differ to such an extent, as in the case of Latin America, that the existing models are simply inadequate to capture the underlying forces that shape the formation of expectations. It is often convenient to say that the factor does not contribute significantly to departures from FIRE within these regions, however, it may be that the structure of the Expectation Formation Process (EFP) may differ so significantly across regions that the factor is less relevant. This paper therefore calls for a more careful and deliberate examination of the structural parameters of the EFP and the manner in which structural differences may impact departures from FIRE across agents, regions, and countries. The results of such an analysis will likely bring us closer to understanding the impact of violations of FIRE in monetary policy transmission.

5 Conclusion

The findings outlined in Sections (2) through (4) present a consistent yet heterogeneous perspective on cross-country inflation expectations. The overwhelming message from the tests of rational expectations is that while forecasters across countries make predictions that violate

the assumptions of full-information rational expectations they do so in a distinctively heterogeneous manner, to the extent that traditional models which account for these departures are unable to sufficiently address the findings. In other words, there is no one-size-fits-all model when examining the expectation formation process across countries. The results of the dynamic factor analysis admit a similar story. We observe compelling evidence of the existence of a cross-country latent factor in forecast errors , however, upon close examination, there is significant heterogeneity driving these results.

Undoubtedly, over the years, there has been significant progress in our understanding of the expectation formation process and in particular how we account for departures from full-information rational expectations. As discussed throughout this paper, models of sticky information and inattentiveness (Mankiw and Reis, (2002, 2010)) Mankiw and Reis (2002) Mankiw and Reis (2010), rational inattention (Sims (2003)) Sims (2003), adaptive learning, (Evans and Honkapohja, (2001))Evans and Honkapohja (2001), memory (Malmendier and Nagel (2016)) Malmendier and Nagel (2016) and diagnostic expectations (Bordalo et *al.* (2020)) Bordalo et al. (2020) to name a few, have emerged as some of the leading approaches to accounting for forecaster 'mistakes'.

It is difficult, however, to overlook the fact that researchers have yet to settle on a unified approach to explaining key findings. This paper sits at the core of this issue. While we observe commonalities, the breadth and depth of the heterogeneity in findings often stand in the way of the broad adoption of our models. It is not surprising, therefore, that foundational macroeconomics classes still espouse the underlying tenets of full-information rational expectations as the bedrock upon which macroeconomic modeling is built.

Progress toward a more unified approach, perhaps in the form of a more parsimonious model to account for departures from full-information rational expectations, begins with the recognition of the need for flexibility in analyzing expectations. It also calls for an even more comprehensive analysis of the expectations across agents and countries. This is the key insight of this paper and the premise upon which much of the analysis rests.

Appendix A Proof of Identification of the Dynamic Factor Model

The objective of this mathematical proof is to show that the two identification restrictions outlined in section 3.1.1 uniquely identify the factor loadings and dynamic factors outlined in the dynamic factor model specified in equations (3) through (5).

In a similar approach as Bai and Wang (2015) Bai and Wang (2015), let C be a full-rank $m \times m$ rotation matrix. Left-multiply the dynamic factor from equation (3) by C and right-multiply the matrix of unknown factor loadings, λ, by C^{-1}. This rotation defines the new factor $\tilde{f}_t = Cf_t$ which allows us to restate equation (4) as,

$$\tilde{f}_t = \Phi_1^f \tilde{f}_t + ... + \Phi_q^f \tilde{f}_{t-q} + C\eta_t^f. \tag{9}$$

After the rotation, the measurement equation (3) becomes,

$$e_t = \lambda C^{-1} \tilde{f}_t + u_t. \tag{10}$$

To establish identification, it must be that the only C that should be acceptable is a diagonal matrix with either 1 or -1 on the diagonal, in which case, both the factors and factor loadings are identified up to a sign change.

From equation (9) the first normalization requirement implies that $var\ (C\eta_t^f) = I_m$. This implies that,

$$CC' = I_m, \tag{11}$$

or that C is an orthogonal matrix.[23]

To address the second normalization requirement that λC^{-1} be a lower triangular matrix with ones on the diagonal, let

$$\lambda = \begin{bmatrix} 1 & 0 & \dots & 0 \\ \lambda_{21} & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ \lambda_{m1} & \dots & \dots & 1 \\ \vdots & \dots & \dots & \vdots \\ \lambda_{n1} & \dots & \dots & \lambda_{nm} \end{bmatrix} \text{ and } C^{-1} = \begin{bmatrix} c_{11} & \dots & c_{1m} \\ \vdots & \ddots & \vdots \\ c_{m1} & \dots & c_{mm} \end{bmatrix}.$$

[23] The implication here is also that $CC^{-1} = I_m$ and therefore, $C' = C^{-1}$

Carrying out the operation λC^{-1} gives us,

$$\begin{bmatrix} 1 & 0 & \dots & 0 \\ \lambda_{21} & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ \lambda_{m1} & \dots & \dots & 1 \\ \vdots & \dots & \dots & \vdots \\ \lambda_{n1} & \dots & \dots & \lambda_{nm} \end{bmatrix} \begin{bmatrix} c_{11} & \dots & c_{1m} \\ \vdots & \ddots & \vdots \\ c_{m1} & \dots & c_{mm} \end{bmatrix} = \begin{bmatrix} 1 & 0 & \dots & 0 \\ \lambda^*_{21} & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ \lambda^*_{m1} & \dots & \dots & 1 \\ \vdots & \dots & \dots & \vdots \\ \lambda^*_{n1} & \dots & \dots & \lambda^*_{nm} \end{bmatrix}. \tag{12}$$

Equation (12) shows that the $n \times m$ matrix, λC^{-1}, is a lower triangular matrix where $\lambda^*_{ij} = 0$ $\forall\ j > i$ and assuming that $\lambda^*_{ii} \neq 0$, $i = 1, ..., m$. A further implication of equation (11) is that $C^{-1}(C^{-1})' = I_m$. Hence, multiplying both sides of equation (12) by $(C^{-1})'$ we have,

$$\begin{bmatrix} 1 & 0 & \dots & 0 \\ \lambda_{21} & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ \lambda_{m1} & \dots & \dots & 1 \\ \vdots & \dots & \dots & \vdots \\ \lambda_{n1} & \dots & \dots & \lambda_{nm} \end{bmatrix} = \begin{bmatrix} 1 & 0 & \dots & 0 \\ \lambda^*_{21} & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ \lambda^*_{m1} & \dots & \dots & 1 \\ \vdots & \dots & \dots & \vdots \\ \lambda^*_{N1} & \dots & \dots & \lambda^*_{nm} \end{bmatrix} \begin{bmatrix} c_{11} & \dots & c_{1m} \\ \vdots & \ddots & \vdots \\ c_{m1} & \dots & c_{mm} \end{bmatrix}, \tag{13}$$

from which we can deduce that $c_{ij} = 0\ \forall i, j$ when $i > j$. This proves therefore that C^{-1} is a diagonal $m \times m$ matrix. Further, since $C^{-1}(C^{-1})' = I_m$, it must be that $c_{ii} = 1$ for all $i = 1, ..., m$, so that the rotation matrix C is also a diagonal matrix with either 1 or -1 on the diagonal. This proves, therefore, that the dynamic factors and the associated factor loadings are identified up to a sign change.

Finally, note that the normalization assumption that $\lambda^*_{ii} = 1$, $i = 1, ..., m$, imposes a positive sign, therefore, both the dynamic factors and the associated factor loadings are fully identified. **Q.E.D.**

References

Amengual, Dante and Mark W Watson, "Consistent Estimation of the Number of Dynamic Factors in a Large N and T Panel," *Journal of Business & Economic Statistics*, January 2007, *25* (1), 91–96.

Angeletos, George-Marios, Zhen Huo, and Karthik A. Sastry, "Imperfect Macroeconomic Expectations: Evidence and Theory," June 2020.

Bai, Jushan and Peng Wang, "Identification and Bayesian Estimation of Dynamic Factor Models," *Journal of Business & Economic Statistics*, 2015, *33* (2), 221–240. Publisher: [American Statistical Association, Taylor & Francis, Ltd.].

_ **and Serena Ng**, "Determining the Number of Factors in Approximate Factor Models," *Econometrica*, 2002, *70* (1), 191–221. Publisher: [Wiley, Econometric Society].

_ **and** _ , "Determining the Number of Primitive Shocks in Factor Models," *Journal of Business & Economic Statistics*, 2007, *25* (1), 52–60. Publisher: [American Statistical Association, Taylor & Francis, Ltd.].

Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer, "Extrapolation and bubbles," *Journal of Financial Economics*, August 2018, *129* (2), 203–227.

Bianchi, Francesco and Leonardo Melosi, "Modeling the Evolution of Expectations and Uncertainty in General Equilibrium," *International Economic Review*, 2016, *57* (2), 717–756.

_ **, Sydney C. Ludvigson, and Sai Ma**, "Belief Distortions and Macroeconomic Fluctuations," *American Economic Review*, July 2022, *112* (7), 2269–2315.

Bordalo, Pedro, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer, "Overreaction in Macroeconomic Expectations," *American Economic Review*, September 2020, *110* (9), 2748–2782.

Borio, Claudio E. V. and Andrew J. Filardo, "Globalisation and Inflation: New Cross-Country Evidence on the Global Determinants of Domestic Inflation," May 2007.

Branch, William A. and Bruce McGough, "Chapter 1 - Heterogeneous Expectations and Micro-Foundations in MacroeconomicsWe are grateful to the editors, Cars Hommes and Blake LeBaron, as well as Guillaume Rocheteau and three anonymous referees for many helpful comments.," in Cars Hommes and Blake LeBaron, eds., *Handbook of Computational Economics*, Vol. 4 of *Handbook of Computational Economics*, Elsevier, January 2018, pp. 3–62.

Casella, George and Edward I. George, "Explaining the Gibbs Sampler," *The American Statistician*, 1992, *46* (3), 167–174. Publisher: [American Statistical Association, Taylor & Francis, Ltd.].

Chan, Joshua, Gary Koop, Dale J. Poirier, and Justin L. Tobias, "Bayesian Econometric Methods," August 2019. ISBN: 9781108525947 Publisher: Cambridge University Press.

Ciccarelli, Matteo and Benoît Mojon, "GLOBAL INFLATION," *The Review of Economics and Statistics*, 2010, *92* (3), 524–535. Publisher: The MIT Press.

Coibion, Olivier and Yuriy Gorodnichenko, "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts," *The American Economic Review*, 2015, *105* (8), 2644–2678. Publisher: American Economic Association.

Croushore, Dean and Tom Stark, "A real-time data set for macroeconomists," *Journal of Econometrics*, 2001, *105* (1), 111–130. Publisher: Elsevier.

_ **and** _ , "A Real-Time Data Set for Macroeconomists: Does the Data Vintage Matter?," *The Review of Economics and Statistics*, 2003, *85* (3), 605–617. Publisher: The MIT Press.

Eusepi, Stefano and Bruce Preston, "Expectations, Learning, and Business Cycle Fluctuations," *American Economic Review*, October 2011, *101* (6), 2844–2872.

Evans, George W. and Seppo Honkapohja, *Learning and Expectations in Macroeconomics*, Princeton University Press, 2001.

Farmer, Leland, Emi Nakamura, and Jón Steinsson, "Learning About the Long Run," Technical Report 29495, National Bureau of Economic Research, Inc November 2021. Publication Title: NBER Working Papers.

Fernandez, Adriana Z, Evan F Koenig, and Alex Nikolsko-Rzhevskyy, "Real-Time Historical Dataset Enhances Accuracy of Economic Analyses," 2012, p. 4.

Fuster, Andreas, David Laibson, and Brock Mendel, "Natural Expectations and Macroeconomic Fluctuations," *Journal of Economic Perspectives*, December 2010, *24* (4), 67–84.

Gabaix, Xavier, "A Sparsity-Based Model of Bounded Rationality *," *The Quarterly Journal of Economics*, November 2014, *129* (4), 1661–1710.

Greenwood, Robin and Andrei Shleifer, "Expectations of Returns and Expected Returns," *The Review of Financial Studies*, 2014, *27* (3), 714–746. Publisher: [Oxford University Press, The Society for Financial Studies].

Kohlhas, Alexandre N. and Ansgar Walther, "Asymmetric Attention," *American Economic Review*, September 2021, *111* (9), 2879–2925.

Korenok, Oleg, David Munro, and Jiayi Chen, "Inflation and Attention Thresholds," *The Review of Economics and Statistics*, November 2023, pp. 1–28.

Kose, M. Ayhan, Christopher Otrok, and Charles H. Whiteman, "International Business Cycles: World, Region, and Country-Specific Factors," *American Economic Review*, September 2003, *93* (4), 1216–1239.

Malmendier, Ulrike and Stefan Nagel, "Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?*," *The Quarterly Journal of Economics*, February 2011, *126* (1), 373–416. Publisher: Oxford Academic.

_ **and** _ , "Learning from Inflation Experiences *," *The Quarterly Journal of Economics*, February 2016, *131* (1), 53–87.

Mankiw, N. G. and R. Reis, "Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve," *The Quarterly Journal of Economics*, November 2002, *117* (4), 1295–1328.

Mankiw, N. Gregory and Ricardo Reis, "Chapter 5 - Imperfect Information and Aggregate SupplyWe are grateful to students at Columbia University and Faculdade de Economia do Porto for sitting through classes that served as the genesis for this survey, and to Stacy Carlson, Benjamin Friedman, John Leahy, and Neil Mehrotra for useful comments.," in Benjamin M. Friedman and Michael Woodford, eds., *Handbook of Monetary Economics*, Vol. 3, Elsevier, January 2010, pp. 183–229.

_ **,** _ **, and Justin Wolfers**, "Disagreement about Inflation Expectations," Working Paper 9796, National Bureau of Economic Research June 2003.

Mincer, Jacob A. and Victor Zarnowitz, "The Evaluation of Economic Forecasts," in "Economic Forecasts and Expectations: Analysis of Forecasting Behavior and Performance," NBER, 1969, pp. 3–46.

Miranda-Agrippino, Silvia and Hélène Rey, "U.S. Monetary Policy and the Global Financial Cycle," *The Review of Economic Studies*, November 2020, *87* (6), 2754–2776.

Otrok, Christopher and Charles H. Whiteman, "Bayesian Leading Indicators: Measuring and Predicting Economic Conditions in Iowa," *International Economic Review*, 1998, *39* (4), 997–1014. Publisher: [Economics Department of the University of Pennsylvania, Wiley, Institute of Social and Economic Research, Osaka University].

Pfäuti, Oliver, "Inflation—Who Cares? Monetary Policy in Times of Low Attention," *Journal of Money, Credit and Banking*, *n/a* (n/a).

Sargent, Thomas and C.A. Sims, "Business Cycle Modeling Without Pretending to Have Too Much a Priori Economic Theory," in "New Methods in Business Cycle Research," Federal Reserve Bank of Minneapolis, October 1977, pp. 45–109.

Sheffrin, Steven M., *Rational Expectations*, Cambridge University Press, June 1996.

Sims, Christopher A., "Implications of rational inattention," *Journal of Monetary Economics*, April 2003, *50* (3), 665–690.

Souleles, Nicholas S., "Expectations, Heterogeneous Forecast Errors, and Consumption: Micro Evidence from the Michigan Consumer Sentiment Surveys," *Journal of Money, Credit and Banking*, 2004, *36* (1), 39–72. Publisher: Blackwell Publishing.

Stock, James and Mark Watson, *Business Cycles, Indicators and Forecasting*, University of Chicago Press, 1993. Pages: 95-156.

Stock, James H. and Mark W. Watson, "New Indexes of Coincident and Leading Economic Indicators," in "NBER Macroeconomics Annual 1989, Volume 4," MIT Press, 1989, pp. 351–409.

_ **and** _ , "Implications of Dynamic Factor Models for VAR Analysis," July 2005.

Weber, Michael, Bernardo Candia, Hassan Afrouzi, Tiziano Ropele, Rodrigo Lluberas, Serafin Frache, Brent H. Meyer, Saten Kumar, Yuriy Gorodnichenko, Dimitris Georgarakos, Olivier Coibion, Geoff Kenny, and Jorge Ponce, "Tell Me Something I Don't Already Know: Learning in Low and High-Inflation Settings," July 2023.

Woodford, Michael, "Imperfect common knowledge and the effects of monetary policy," *Knowledge, information, and expectations in modern macroeconomics : in honor of Edmund S. Phelps*, 2003.