Behavioral Influences in Professional Inflation Forecasters

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Abstract

In this research paper I ask the question, "Do we observe evidence of full-information rational expectations in inflation forecasting?" After forming an empirical, literature-guided foundation for rejecting the economic full-information rational expectations (FIRE) hypothesis, I address the more interesting second question, "What behavioral phenomena, such as economic uncertainty or belief extrapolation, can help to explain deviations from FIRE?" With much guidance[1], I conduct empirical analysis on inflation forecasts from the SPF, identifying autoregressive behavior in inflation forecasting, which implies deviation from FIRE. I then propose that these anomalous deviations are mitigated in professionals during periods of economic anxiety and are exaggerated during times of economic upturn. Running multiple regressions, picking variables to account for multicollinearity, I find that the resulting impacts of recession anxiety on forecasting errors are insignificant to inconclusive. Despite weak statistical significance, there is a potential point of interest as the β of recession anxiety flips across non-recession time periods.

[1] I thank my advisor Alfredo Mendoza, the Econ 191 course staff for their guidance, and friends and peers that have aided me in the writing of this paper.

I Introduction

If you are an economist, you no doubt care about inflation. It is an important metric that shapes the circulation of money in our society and shifts the demands in our lives (and, in some sense, for our lives). Thus, we take great care to predict its changes as accurately and efficiently as possible; yet, we find that people fail time and time again. Theorists tell us that individuals are perfectly rational, but literature and history has demonstrated that even the best forecasters lack perfect information and an uncompromising rationality. Though this is known to be true, why this is true continues to elude us. In this paper, my research aims to produce a better understanding of why even professionals fail to fulfill FIRE at the cross-section of behavioral economics and macroeconomic forecasting.

In this research paper I aim to answer the question, "Do we observe evidence of full-information rational expectations in the forecasting of real world variables, specifically, inflation?" After forming an empirical, literature-guided foundation for rejecting the economic full-information rational expectations (FIRE) hypothesis, I address the more interesting second question, "What behavioral phenomena–such as economic uncertainty or overconfident belief extrapolation–can help to explain deviations from FIRE?"

To address the first question, I seek evidence against the rational expectations theory[2], demonstrated by statistically significant empirical data in the real world from professional inflation forecasting errors. With this foundation, I will perform an empirical data analysis with this data on reasons for anomalous deviations from FIRE. What, then, do we mean by the full-information rational expectations theory and what

[2] First termed by John Muth in 1961, later developed by many other economists.

are the real-world variables that will be used to measure the validity of this theory's impact? Simply put, FIRE states that past information and experiences will influence the expectations of consumers, thereby determining the decisions they make. More on FIRE will be discussed in Section 2, Literature Review and Landscape.

Addressing the second question, having built up a foundation to reject FIRE, I seek to discern which behavioral factors contribute to the breach in rationality of economic agents. In particular, I am interested in the effect of recession anxiety on accuracy of forecasts. My primary dataset for this paper is the Survey of Professional Forecasters (SPF), provided by the Federal Reserve Bank of Philadelphia. This choice of data was inspired by its usage in other papers (e.g. Coibion and Gorodnichenko, 2015) and will be touched on in Section 2 and discussed further in Section 3, Preliminary EDA. Variables such as CPI, PCE, and RGDP will be utilized in an econometric multivariable regression as controls to hone the precise effect of recession anxiety on forecasting errors. Before running these regressions, an exploratory data analysis of this dataset will be conducted and discussed in Section 3. I postulate that inflation forecasts are a particularly useful econometric metric due to their granularity over time and the importance of inflation to the economy. Crucial to the design of this paper is the assumption that the devotion of time to inflation speculation makes professional forecasters prime candidates in which information sets can be controlled for. My strategy is to take the inflation forecasts from the SPF, calculate their errors against actual CPI, and run regressions to: (1) identify irrationality and/or incomplete information in professional forecasters, demonstrated by discrepancies between ex-ante and ex-post forecasting revisions and (2) postulate behavioral influences that are causing the irrational expectations. More on the strategic methodology of this paper will be discussed in Section 4, Research Design which will provide the empirical basis for the rejection of FIRE using historical data and a test of autoregression of forecast errors. The econometric models will be actualized in Section 5, Econometric Modeling, where the results are discussed and analyzed based on variable impact and statistical significance, as demonstrated by β coefficients and p-values respectively.

Data used in this research paper is being publicly sourced from the Federal Reserve Bank Philadelphia as well as CPI from the BLS, e.g. real inflation over time.

II Literature Review and Landscape

In this section, I will conduct a literature review and discuss the behavioral and corporate macroeconomic research landscape that this paper resides in. Covering these topics are important for filling in the picture of what is happening in the economic research field as well as to communicate the information set that this paper is written from.

i. What is the FIRE Hypothesis?

Let's begin with the latter half of FIRE. The rational expectations theory is the idea that past information and experiences will drive the expectations of consumers, thereby determining the kinds of decisions they end up making. Moving into the first half of FIRE, Muth tells us that past information refers to publicly available historical data (e.g. stock prices, market trends, etc.) while experiences refers to any personal experience held by the consumer themselves. Both of these provide the rational consumer with a base information set from which to make logical decisions from. It is given, however, that this assumption that every consumer will have full information is not true in reality; that is, all people do not have equal and exhaustive information available to them. This idea is explored deeper in a paper by Coibion and Gorodnichenko, discussed in the next subsection.

ii. A Brief Literature Review of Coibion and Gorodnichenko

In *Information Rigidity and the Expectations Formation Process*, the researchers Coibion and Gorodnichenko assert that forecasting errors are not due to irrationality on the agents' (the consumers) end, but are completely dependent on incomplete information. They use the SPF as their primary data source to illustrate their argument. This is the main point that my paper contends; with evidence that consumers lack rationality during the expectations-formation process, we open the door for speculation of other behavioral factors that might influence how our agents form their expectations. That being said, it is important that we are able to build up a better understanding of their research design and the context within which it takes place, especially because we utilize the same dataset.

Coibion and Gorodnichenko (C.G.) base their information model of ex-ante/ex-post forecasting revisions in reference to two other, older models from Mankiw: the sticky-information model and the noisy-information model. Understanding that both these models serve as explanations for any deviations from the rational expectations theory is crucial for us to take note of later in order to demonstrate the impact of irrationality in agents. We utilize economic uncertainty and belief extrapolation as concepts that explain the breach in our assumed "rational" agents.

At the core of their paper, also, is the dismissal of potential irrationality in economic agents. Does focusing on the information side of the rational expectations theory simplify their research process? Perhaps. Can we truly eliminate the possibility of irrationality by means of aggregation methods alone? I suspect not. I theorize that extrapolative beliefs, overconfidence, or economic uncertainty–examples of irrational bias in response to information–play a crucial role as confounding variables in the formation of expectations.

In addition to my own paper, other researchers have written in response C.G.'s assertions or have written with their paper in mind. One group of such researchers will be discussed in the next section.

iii. An Even Briefer Review of Farmer, Nakamura, and Steinsson

In *Learning About the Long Run*, Farmer, Nakamura, and Steinsson conduct research on how professional forecasters learn while seeking to answer the question of agent rationality. From their findings, they assert the opposite of C.G. in professional forecasters: despite having adequate information and low information frictions, professionals still forecast with biases that have to be attributed to rationality. That being said, I acknowledge that the depth of their literature is much more than I can adequately summarize and discuss within this brief subsection; I will make clear now that the models that they use to disprove FIRE that I discuss in the following paragraphs are only a small portion of an otherwise rich piece of literature.

Farmer et al. use four models (which I will elaborate on) as their foundation for refuting FIRE, two of which I choose to recreate in Section 3 in order to likewise refute FIRE. These models are the intrinsic forecasting biases (errors) and the autoregressive nature of forecasting. The models that I will avoid using are the previously mentioned sticky-information model and the noisy-information model.

Simply put, the intrinsic forecasting biases or forecasting errors are a demonstration that professional forecasters are not perfectly accurate. That is, when economic forecasting agents predict key economic metrics, such as inflation, they are wrong. This "model" refutes FIRE because an agent that acts with full-information and rationality would not predict incorrectly, on average. As expected, the historical data shows that forecasts have statistically significant biases on average, thus demonstrating a breach in FIRE. But which side of the full-information rational expectations hypothesis is being breached? That is what autoregressive forecasts seeks to answer.

Autoregression is a process in which time series data is influenced by its preceding data points. Within statistics and data science, it is a data randomization tool that assists in reducing some of the variance of a completely random walk. For our purposes, autoregression can function as an indicator of extrapolative beliefs the behavioral economic concept in which forecasters' beliefs about a good are influenced by previous beliefs about it. In this paper, our "good" of interest is the CPI and our agents use historical information about the CPI's value to inform their beliefs, which they then extrapolate from for future forecasts. The literature tells us that belief extrapolation can be irrational as forecasters will often extrapolate unequally; that is, negative and positive beliefs do not hold equal weight during future predictions. In particular, Da, Huang, and Jin have conducted research showing that investors tend to be more heavily impacted by negative past returns on an asset then by positive past returns.

Moving forward, I intentionally avoid recreating the sticky and noisy-information models within my data analysis, partially because of the scope of this rather small paper, but also considering the information sets of professional forecasters. Within their paper, Farmer et al. claim that the level of information that participating forecasters in the SPF hold should be near perfect, given that they are professionals. The next section dives deeper into guidance provided from other novel research papers.

iv. The Literature Landscape

Since C.G. first published their paper in 2015, numerous other researchers in the behavioral economics field have addressed the rationality of individuals during their own individual expectations-formation processes, and have further developed the assertion of biased forecasting made in the past (such as Zarnowitz in 1985). As this research paper progresses, I will use the following supplementary papers as guiding lights that direct us towards understanding reasons for anomalous deviations from FIRE. It is plausible that the new research[3] on rationality in consumers from novel papers (post 2015) will provide angles crucial to reevaluating the results from C.G., or, may potentially solidify their findings further. This research paper has been saliently influenced by the following contextual literature:

1. *Psychology-Based Models of Asset Prices and Trading Volumes* (Barberis). An account of the psychological/behavioral implications of extrapolative beliefs is contained in Barberis's work. Because extrapolative methods are most effective for metrics with high volumes of data, such as inflation, it is worth considering whether there are behavioral influences in its application.

2. *Extrapolative Beliefs in the Cross-Section: What Can We Learn From the Crowds?* (Da, Huang, and Jin). Similar to Barberis, this paper supports the idea that behavioral beliefs and individual biases play a significant role in financial forecasting. A notable takeaway is that investors of stocks and portfolios tend to

[3]Not to say that the novelty of the research is inherently correlated with its quality, as Carolyn Stein discussed.

place a higher weight on negative dips in the returns/value of their investments.

3. *Behavioral CEOs: The Role of Managerial Overconfidence* (Malmendier and Tate). Discussions of irrationality from overconfidence in industry/corporate professionals may relate to the key assumption that professional forecasters are the ideal sample to benchmark full-information rational expectations against. Interesting, too, may be exploring any differences in overconfidence between the various economic entities that are described in the SPF.

4. *Information Rigidity and the Expectations Formation Process* (Coibion and Gorodnichenko). See subsection ii.

5. *Learning About the Long Run* (Farmer, Nakamura, and Steinsson). See subsection iii.

It is worth noting that some of these research papers analyze rationality in corporate or finance settings, whereas C.G.'s work looked through the lens of cross-country inflation. I acknowledge the risk that the differences between the governmental economic world and the corporate world may neutralize any applications that this outside literature may provide, but I will continue the paper with the assumptions that forecasters operate in a largely similar way. These things considered, even very niche economic research can provide insightful analysis and spark discussion. This is the goal of this research paper: to conduct analytical research on empirical data that produces tangible insight which pushes the economic field forward. Our empirical assessment of rationality through anxiety or extrapolative beliefs in forecasters, within the context of the SPF, will provide insight into the causes of forecasting errors.

III Preliminary EDA

This section aims to provide a comprehensive overview of the dataset that will be used in this research paper as well as some findings resulting from data manipulation and analysis. Moving forward we will discuss the SPF, a basic description of its variables covered, as well as any particularly notable observations from select variables of interest.

i. The Survey of Professional Forecasters

The SPF[4] is a survey that provides a database of the responses from surveyed professionals that forecast macroeconomic performance indicators. Initially started by the American Statistical Association and the National Bureau of Economic Research (NBER) in 1968, the project was taken over by the Federal Reserve Bank of Philadelphia in 1990 and is the oldest quarterly survey of macroeconomic forecasting in the United States. This is a key quality as it means that the empirical data foundations for this paper will be of the highest quality and granularity that is offered historically. As a quarterly survey, the SPF is administered every quarter of the year on the following dates: January 1, April 1, July 1, and October 1. The identity of the participating individuals is kept anonymous, but we achieve a level of granularity through identification numbers for individual data points.

ii. Variables

The next part of this section takes time to consider the kinds of variable forecasting offered by the SPF to determine their relevance and usefulness to this research paper

[4] Data has been used with public permission from the SPF and their usage guidelines.

on deducing causes for anomalies in the errors of professional forecasters. Certain variables that show more promise will be noted and elaborated on.

First, there are economic performance metrics; for example, nominal gross domestic product, real gross domestic product*, natural rate of unemployment and unemployment rate, real net exports, and real GDP over 10 years. Forecasts of the real GDP may be of potential interest to us as it is not adjusted for inflation over time. In future studies, exploring discrepancies between inflation forecasts and GDP forecasts that have not been influenced by inflation may produce fascinating results.

Second, there are economic inflation metrics; for example, gross domestic product price index, index of industrial production, consumer price index (CPI)*, core CPI, personal consumption expenditures (PCE)*, core PCE, CPI inflation over 5/10 years*, and PCE inflation over 5/10 years*.

Third, there are financial side economic variables; for example, nominal corporate profits*, triple-A corporate bond yields, and SP 500 return over 10 years. Nominal corporate profits may provide insight into financial service providing forecasters' perceptions of the corporate markets/general economic success.

Fourth, there are government or policy-related variables; for example, 10-year treasury bond rates, real federal government consumption and investments, real state and local government consumption/investments, 3-month treasury bill rates, yield on constant maturity treasury bonds over 10 years, and return of 3-month treasury bills over 10 years.

Fifth, there are the miscellaneous variables; for example, nonfarm payroll employment, housing starts, real personal consumption, real change in personal inventories, real nonresidential/residential fixed investments, productivity over 10 years, and probability of RGDP growth decreasing*. The "RECESS" variable, has what is known as the "Anxiety Index," that is, a metric that demonstrates forecaster's worries about short term economic recession.

In sum, there are 43 total unique variables in our dataset: 6 which are 10-year forecasts; 5 which relate to recession probability in the coming year; and 5 which are density projections of previous variables. In addition to these, the SPF also provides 21 computed forecast variables which exist as linear combinations of the aforementioned variables. Variables with stars (*) will likely be considered in the next stages of regression analysis. Additionally, in the panel data, each forecaster (as denoted by their unique identification number) has a loose classification of their professional background; that is, whether they are financial service providers (denoted by a "1") or nonfinancial service providers (denoted by a "2"). A "3" indicates that we are unsure of the forecaster's industry. In future research, it may be worth aggregating data and running regressions based on professional background.

iii. Summary of Notable Variables

Moving into describing the data itself, here is a preliminary report on the shape and statistics of some of the initial variables of interest. Based on the number of ID observations, there are a total of 8787 data points in our data frame with 600 unique forecasters participating in the SPF at different periods of time. A tangential note: not every unique forecaster in the survey as denoted by their specific id no. has necessarily been consistently participating in the SPF until today.

The following summary statistics were found using data science tools coded in python:

Table 1: Summary Statistics of Notable Variables

	ID	INDUSTRY	RECESS2	CPI2	PCE2
Observations	8787	5137	8038	5798	2283
Mean	299.31	1.66	18.86	2.74	1.87
SD	213.95	0.57	20.72	1.94	1.64

Table 1: Summary Statistics of Notable Variables Cont.

	RGDP2	NGDP2	CPROF2	TBILL2	UNEMP2
Observations	8351	8303	6383	5676	8400
Mean	7711.53	8933.85	562.69	3.45	6.11
SD	6315.75	7045.14	654.87	3.09	1.83

Note: These tables were generated through the use of the .describe() Pandas package and provide details on observation counts, averages, and standard deviations.

I will briefly describe the methodology in merging the dataset coded in Python, then discuss the summary results. Beginning with the quarterly forecasted CPI changes from the SPF, I reformatted and cleaned each series and merged them together by date. The actual form of the dataset includes a "DATE" column, but it is not important to calculate any summary statistics for this information, rather, the main point to note is that observations for CPI first begin on October 1, 1981. Each variable has a different first observation date, indicating that the SPF began measuring certain metrics at different times. I sequentially merged each additional variable by the same date column and on the last panel I included the "INDUSTRY" dummy variable.

As mentioned earlier, not every forecaster continued with the SPF until today. Looking into the "INDUSTRY" dummy variable, we see that the average skews closer to a "2" value rather than "1" which may be an indication that more of the forecasters are non-financial service providers. That being said, any forecasters with a "3" may be skewing this average so it is worth revisiting this value later. The whole number quartiles make sense as the "INDUSTRY" variable is simply a categorical variable and is not continuous.

Moving into the Anxiety Index, or "RECESS2," this variable represents the probability of recession in the following quarter and has the second highest observation count in this slice of the data! Interestingly, economists have speculated on chances of a recession for almost as long as real GDP has been recorded. The average value is an 18% chance of recession with a 40% forecast of recession chance being the top 84%. Based on what we know of the bell curve, anything above 25% will be fairly uncommon for forecasters to predict.

"CPI2" represents the forecasters' predictions of change in CPI in the next quarter, that is, the CPI of the next quarter over the CPI of the current quarter. Judging from the mean, forecasters typically predict that inflation is going up, even though the minimum value has gone as low as -8.3. What this implies about forecasters is that they are more likely to have an expectation of future inflation rather than future deflation.

Similarly, "PCE2" represents the forecasters' forecasted change in PCE in the next quarter, that is, the PCE of the next quarter over the PCE of the current quarter; the remaining variables follow a similar structure of predictions for the named metric in the next quarter.

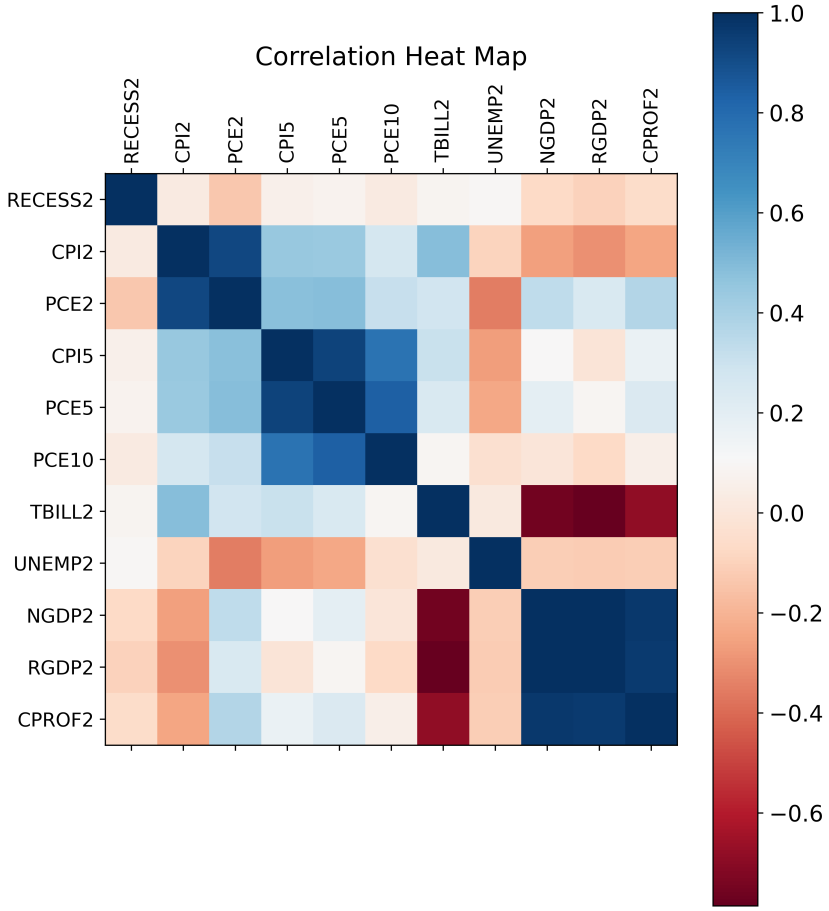
There are many potential variables to explore and picking the ones of interest will be rather challenging. That being said, in future expansions of this paper I hope to further explore other salient differences between other variables. NaNs and empty values will be dropped in our following data analysis.

iv. Correlations

In the next section we visualize the correlations of the chosen variables of interest and other controls. Understanding the relationships between variables before utilizing them in regressions is helpful in making more informed decisions on which combinations to construct.

Our first figure is a heat map of the correlations between our select variable forecasts:

Figure 1: Correlations of Notable Variables



Note: This map shows both positive (blue) and negative (red) correlations between variables. White demonstrates low correlation between variables.

A few things to note from the heat map to consider during modeling: (1) CPI and PCE are highly correlated across most time horizons; (2) RGDP2, NGDP2, and CPROF2 also have a high correlation and a strong negative correlation with TBILL2; and (3) UNEMP2 and TBILL2 are the most uncorrelated variables with our explanatory variable of interest, RECESS2. Moving forward, we want to avoid including too many variables in our regressions that are highly correlated with one another, for the sake of multicollinearity.

IV Research Design

In this section, I lay the foundation down for the strategy of this research design given the literature landscape and the dataset that this paper utilizes. A core part of the foundation for my research design is first refuting FIRE (addressing my first question from the introduction) in order to conduct further explantory analysis via econometric regressions (addressing my second question from the introduction).

i. Design Rationale

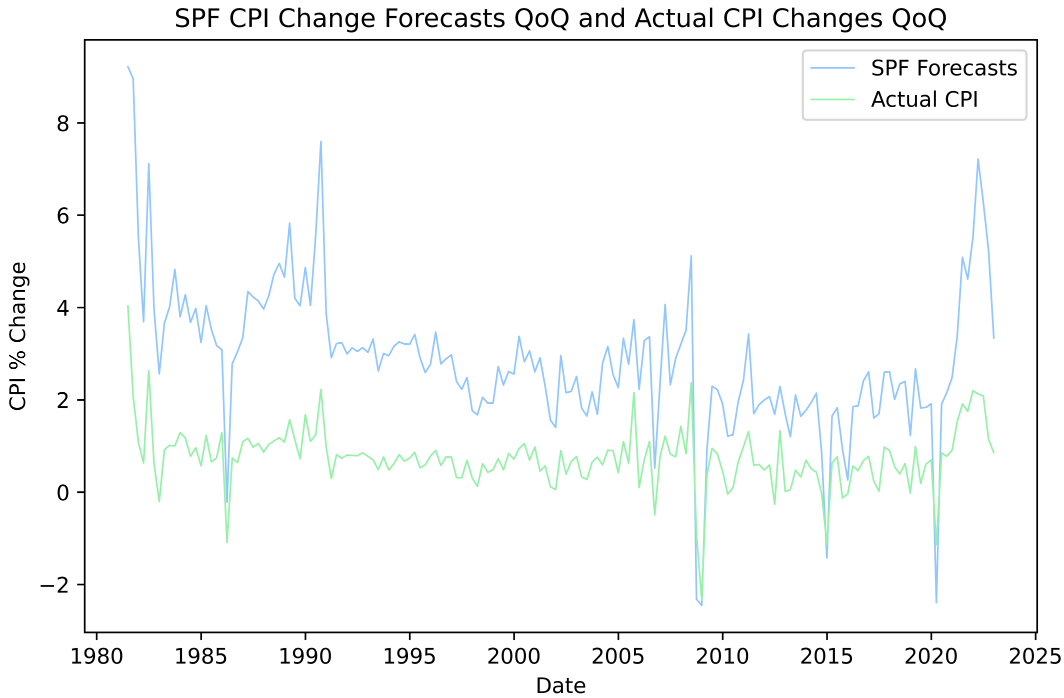
The design of our data analysis will take choice variables from the SPF and run regressions of these variables on inflation forecast errors. If, controlling for information, we continue to see discrepancies between ex-ante/ex-post forecasts, it is an indication that rationality is contributing to the variation. With this, my study can demonstrate the possibility of irrationality in agents and sequentially identify the driving behavioral factors.

There are a few assumptions that should be addressed. One major assumption I make is that participants in the SPF, regardless of industry, will have high-level information sets that are approximately equal. This qualitative perk is valuable and, in future analysis, may prove to demonstrate differences between different industrial lenses. This study also assumes that professional economists are most likely to have high-quality levels of information that are updated efficiently. The assumption of professional discernment addresses the noisy-information model while the short update times addresses the sticky-information model.

ii. Disproving FIRE

I begin the argument against FIRE with a line graph of the time series data on CPI forecasts. The following is an illustrative visualization that demonstrates proof against full-information rational expectations, demonstrated by discrepancies between forecasted CPI changes and real CPI changes:

Figure 2: CPI Forecasts vs. Actual CPI Changes



Note: Though the BLS provides CPI data at a higher granularity (e.g. MoM), we down convert real CPI to quarterly to match with the SPF's granularity.

As expected, even professional forecasters are significantly off from the real CPI changes that the world experiences. On average, the SPF shows that professionals greatly overestimate the changes in inflation that will occur, off-shooting by 2%-3%. Whether or not this error is the same for other macroeconomic metrics such as RGDP, interest rates, or even against another inflation index such as PCE will have to be looked into in future research. It is worth noting that during spikes of predicted deflation (e.g. in 1986, 2006, 2008, 2015, and 2020) it seems that forecasters predict closer to reality, as indicated by forecasted changes in CPI matching actual changes in CPI. Also consider whether CPI forecasts are influenced saliently by the aggregation—in future research it may also be worth providing error bars based on the non-aggregated data. Before delving further into the implications of these spikes, I first address extrapolative beliefs represented by an autoregression. Here is a representative equation of the regression I run:

$$E_t = a + \beta E_{t-1} + u$$

In this equation, E represents the aggregated bias in the CPI forecasting from the SPF data, a represents innate bias, and β represents the influence of past errors on current errors. As we note from the previous graph, E is, on average, greater than 0, indicating a level of bias in our forecasts. If our forecasters were under FIRE, then $a = 0$ and $\beta = 0$, because a fully-rational forecaster is not biased and past errors should not influence future errors. In our simple one-term regression, t is the present quarter and $t - 1$ represents the previous quarter. I expect that an economic agent that does not irrationally belief extrapolate would also have little to no indication of autocorrelation in their forecasting errors. The following table illustrates the numerical results of this regression:

Table 2: Autocorrelation in Forecast Errors

	Coefficients
constant	0.5872***
	(0.123)
$ERRORS_{t-1}$	0.7172***
	(0.052)
Observations	166
Adj. R^2	0.538
F-Statistic	$1.74 \cdot 10^{-29}$

Note: Values in columns are the β coefficients and the standard errors in parentheses.

*p < 0.1, **p < 0.05, ***p < 0.01.

As expected, past errors are statistically significant when determining future errors, demonstrating a breach in rationality. From the positive coefficient we notice that past bias contributes to increased bias in the present. In future studies it will be worth looking into how this error changes as we auto-regress back multiple quarters instead of just 1.

Thinking back to the recession spikes in Figure 2, could it be that times of economic recession–which are often commonly associated with lower GDP and deflation–actually improve the accuracy with which our forecasting agents predict key economic metrics? The next section constructs the models that will aid us in answering this question.

V Econometric Modeling

In this section I create an econometric model to predict forecasting errors based on recession outlook, with additional control variables. As in the previous research papers we have discussed and reviewed, econometric models are a key result to be synthesized from the data and demonstrates relationships between variables and the impact they have on one another. In this section I lay out an econometric regression modeling the relationship between recession anxiety and forecasting errors. Measures such as the outlook on recession or current state of the economy–whether that be boom or bust–should not negatively influence the rational forecasting of professionals. If anything, it is during times of recession that professional forecasters need to maintain a level head to guide general consumers back to a stable state; the same can be said for economic booms, during which professional forecasters should stay cautious of overconfidence to prevent bubbles from bursting. Thus, if negative outlook on the economy causes increased forecasting errors, we may have reason to believe that anxiety about economic recession may influence forecasters to act irrationally.

i. Standard Multivariate Regression

In this subsection I structure a multivariable linear regression and show the regression in tabular form. This is the full econometric equation I utilize:

$$E = \beta_0 + \beta_1 RECESS2 + \beta_2 CPI2 + \beta_3 UNEMP2 + \beta_4 TBILL2$$
$$+\beta_5 CPROF2 + \beta_6 RGDP2 + u$$

As before, E represents the bias from professional forecasters while B_0 is the constant and the betas following (β_1, β_2, etc.) are the coefficients respectively. First, I run a stripped regression with only our single variable of interest, RECESS2. See the corresponding results in the first column of Table 3, Reg. 1:

Table 3: Modeling Forecasting Errors

	Reg. 1	Reg. 2	Reg. 3
constant	1.9035***	0.8554***	0.2415***
RECESS2	0.0134**	0.0037**	0.0031*
CPI2		0.5612***	0.5685***
UNEMP2		-0.0211	0.0013
TBILL2		0.0163	0.0525***
CPROF2		0.0003**	
RGDP2		$-6.341 \cdot 10^{-5}$***	
Observations	167	167	167
Adj. R^2	0.021	0.934	0.931
F-Statistic	4.624	$6.44 \cdot 10^{-93}$	$8.99 \cdot 10^{-94}$

Note: Values in columns are the β coefficients. *p < 0.1, **p < 0.05, ***p < 0.01.

Among other things, we note that RECESS2 has a high statistical significance, but from our first regression alone the adjusted R-squared and F-stat values do not promise credibility from this model. I run two more models, one with an additional 5 variables and one with only 3. These are CPI2, UNEMP2, TBILL2, CPROF2, RGDP2 and CPI2, UNEMP2, and TBILL2 respectively; the summary of the OLS results for each regression are in Reg. 2 and Reg. 3 respectively. From the second regression, I notice a much higher R-squared and a much smaller F-stat which is promising; however, it is likely that multicollinearity is introduced due to both CPROF2 and RGDP2 being included. Recall from Figure 1 that TBILL has a strong negative correlation with

CPROF2 and RGDP2 which is not optimal for our control variables. To account for the risk of multicollinearity I run one final regression, dropping corporate profit forecasts and real gross domestic product forecasts due to their high negative correlations. Unfortunately, we lose a few hundred basis points of statistical significance for our explanatory variable, RECESS2. Furthermore, value of B_1 in all regressions are very small in comparison to the coefficients.

Taking a step back, consider that our regressions are explaining changes in errors due to economic recession anxiety over the whole period of recorded CPI history. I realize that if we are looking to distinguish the impact of recession anxiety, it makes most sense to isolate our dataset by times of recession. Recall in the Summary of Notable Variables section that the upper 84th percentile of chance of recession is a 25% of recession. In the next, and final, section I will take this information to conduct a split multivariate regression on two frames of data: one during periods of recession and one during periods of economic steadiness.

ii. Split Multivariate Regression

In this section, I split our 167 aggregated data points from the SPF into two sets depending on whether that observation is made during a period of recession anxiety. Note the results in the following table:

Table 4: Modeling Forecasting Errors In and Out of Recession

	Reg. 4 Recession	Reg. 5 Recession	Reg. 6	Reg. 7
constant	0.8296	0.2647	0.2482**	0.9322***
RECESS2	0.0062	0.0068	-0.0045	-0.0025
CPI2	0.5503***	0.5562***	0.5720***	0.5587***
UNEMP2	-0.0310	-0.0254	0.0139	-0.0180
TBILL2	0.0287	0.0613*	0.0525***	0.0121
CPROF2	0.0004**			0.0003**
RGDP2	$-7.298 \cdot 10^{-5}$			$-6.209 \cdot 10^{-5}$
Observations	30	30	137	137
Adj. R^2	0.935	0.947	0.909	0.912
F-Statistic	70.27	$1.55 \cdot 10^{-15}$	$2.32 \cdot 10^{-68}$	$2.28 \cdot 10^{-67}$

Note: Values in columns are the β coefficients. Reg. 4 and Reg. 5 are the data split during recession periods. *p < 0.1, **p < 0.05, ***p < 0.01.

Looking at the regression results, a few takeaways can be made. Across the board, recession anxiety lacks p-values that are statistically significant, even during periods of recession. That being said, the β_1 flips sign from positive to negative–though this anomaly needs to be further researched to understand. The correlation between corporate profits, RGDP, and T-bill forecasts are reliably mitigated in regressions 5 and 6 where I run a more sparse linear fitting. In these regressions, the F-stat is more favorable and T-bill's β_4 has a higher value. As a sanity check, CPI proves to be a major deterministic player of forecasting errors as we calculate CPI forecasting errors with CPI2 itself. In Reg. 6 T-bill's predictive power improves as its p-values drops significantly.

How can we get more definitive results of the effect of recession anxiety on forecasting errors? In this last segment, I will interpret results and consider potential next steps in lieu of my regression results to provide set up for future research to answer this question. One major concern is the number of observations I utilize—by nature of my data cleaning methods, the observation count drops immensely from over 8000 to 167 because of aggregation. To improve F-stat and potentially raise the statistical significance of the impact of anxiety about economic downturn, a relevant strategy can be to run the same regressions on the raw data without aggregation. Furthermore, running a matrix of variable combinations will allow for more holistic analysis, especially if split into aggregated and non-aggregated regressions. Ultimately, there is much potential for expansion and work to be done with this data and in this particular section of behavioral macroeconomics.

VI Conclusions

In this paper I have conducted empirical research on professional forecasters' errors in forecasting CPI. Guided by past literature, these errors can reasonably be attributed to behavioral factors such as belief extrapolation and recession anxiety, thereby demonstrating a breach in the rationality detailed by FIRE, the full-information rational expectations hypothesis. By running linear regressions, I have reason to suspect that forecasting errors can be attributed to irrational autocorrelation. Additionally, other econometric models demonstrate that recession anxiety has a small, yet statistically significant, effect on errors. A split regression shows that the coefficient of recession anxiety may flip in and out of regressions, though this needs to be studied. Overall, further research needs to be conducted in order to confidently assert that fears about the economic state have an impact on forecasting errors in professionals. Next steps to accomplish this goal can include the following: (1) including the impact of professional overconfidence depending on industrial background, (2) re-running both autocorrelation and normal regression models with larger time horizons both forward and backward, and (3) considering further how behavioral factors influence the expectations formation process within the context of forecasting.

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SPF data is accessible and approved by the Federal Reserve Bank of Philadelphia at the following link: https://www.philadelphiafed.org/surveys-and-data/data-files

Real CPI data from the FRED: https://fred.stlouisfed.org/series/CPIAUCSL