Horizon Bias in Expectations Formation*

Stefano Cassella†
Tilburg University

Huseyin Gulen§
Purdue University

Benjamin Golez‡
University of Notre Dame

Peter Kelly¶
University of Notre Dame

This version: January 2021

Abstract

We provide empirical evidence that optimism bias increases with the forecasting horizon. We label this empirical regularity the *horizon bias*. We document significant horizon bias in the macroeconomic expectations of professional forecasters, both in the U.S. and abroad. In our empirical setting, horizon bias is unlikely to be the result of strategic considerations, information rigidities, or common heuristic rules of belief formation. At the same time, we show theoretically that horizon bias can arise in theories of motivated beliefs. Moreover, following the conceptual framework of Bénabou (2015), we show that many theory-based drivers of motivated beliefs can help explain time-series variation in horizon bias.

JEL Classifications: C53, D03, D83, D84, D90, D91, E37**.**
Keywords: Motivated beliefs, Optimal expectations, Wishful thinking, Economic forecasting, Economic models, Expectations, Optimism Bias, Survey Forecasts, Macroeconomic forecasts.

*We would like to thank Adem Atmaz, Nicholas Barberis, Zhi Da, Ralph Koijen, Cameron Peng, Carolin Pflueger, Nicholas Reinholtz, Andrei Shleifer, Charles Trzcinka, Michael Weber, Chen Wang, and Wenyu Wang for helpful comments.

†Tilburg University, E-mail: s.cassella@uvt.nl.
‡University of Notre Dame, E-mail: bgolez@nd.edu
§Purdue University, E-mail: hgulen@purdue.edu.
¶University of Notre Dame, E-mail: pkelly6@nd.edu

1 Introduction

A central question in economics is how agents form expectations. Agents' expectations are critically important for consumption, savings, and investment decisions. As a result, expectations can affect micro-level outcomes, as well as the implications of policy for macroeconomic outcomes. Given the central role that expectations have in determining individual and aggregate economic outcomes, a growing body of research has tested many theories of expectations formation, ranging from full-information rational expectations (Muth (1961)) to theories of information rigidities (Mankiw and Reis (2002), Woodford (2003), Coibion and Gorodnichenko (2015)), to behavioral theories of over-reaction (Bordalo, Gennaioli, Ma, and Shleifer (2020)) and experience effects (Malmendier and Nagel (2011), Malmendier and Nagel (2016)).

Although prior work has investigated the expectations formation process extensively, one question about expectations that has received less attention is how agents form expectations differently at different forecasting horizons. Differences in agents' optimism at different horizons have implications for a wide variety of problems that policy makers, corporations, and individuals face regularly, as they trade-off short-term versus long-term consumption, investments, and well-being. It is this term structure of optimism that we shed light on in this paper.

To investigate how short-horizon expectations differ from long-horizon expectations, we focus on forecasts of future macroeconomic states. Studying macroeconomic expectations has the key benefit of allowing for a comparison of forecasts with readily available data on macroeconomic realizations. Thus, we are able to construct forecast errors at different forecasting horizons, and assess how deviations from rational expectations change with the forecasting horizon.

Our focus is on how optimism changes with the forecasting horizon. Performing this analysis necessitates restricting the focus to a set of macroeconomic quantities for which the definition of optimism is uncontroversial and likely shared among forecasters. Thus, we focus on real GDP growth, growth in industrial production, growth in corporations' profits, and the unemployment rate.

Using professional forecasters' survey expectations from multiple sources, we show that forecasters' optimism (e.g., the forecast of higher annualized GDP growth, or lower unemployment rate) increases with the forecasting horizon. Stronger optimism bias at longer horizons

is evident at the level of the individual forecaster, as well as in consensus expectations and median forecasts. The evidence that optimism bias increases with the forecasting horizon is also robust to split-sample analysis. We document this phenomenon in the U.S. Survey of Professional Forecasters (1968-2018), as well as internationally, using the European Central Bank Survey of Professional Forecasters (1999-2018). This second source of data on beliefs allows us to show that the optimism bias in macroeconomic forecasts extends for horizons of up to 5 years. We label this novel feature of the expectations formation process the *horizon bias*.

A natural question is why there is greater optimism bias in long-horizon macroeconomic forecasts than in short-horizon forecasts. In standard theories of full-information rational expectations, forecasts are unbiased at all horizons. Thus, full-information rational expectations cannot generate horizon bias. Importantly, this benchmark scenario of rational expectations in which forecasts are unbiased rests on three assumptions: (i) the forecaster lacks the incentive to strategically issue forecasts that differ from his subjective beliefs; (ii) the forecaster does not face bounded-rationality constraints, nor does he incur the cost of information acquisition and processing; (iii) the forecaster maximizes his expected utility of future consumption or wealth, while beliefs do not have any intrinsic utility value. Previous research has documented that relaxing any of these assumptions generates biases in forecasting. Therefore, we ask whether horizon bias can arise when any of these three conditions above is not met.

Incentives to strategically issue forecasts can generate systematically biased forecasts (Francis, Hanna, and Philbrick (1997); Chen and Matsumoto (2006)). For instance, hoping to advance their careers, sell-side analysts working at investment banks can issue optimistically biased forecasts about a firm's prospects.[1] Although it is possible that strategic considerations generate forecasts that are consistent with horizon bias, these considerations are unlikely to account for horizon bias in our survey data, since the forecasters in our sample issue their predictions under the condition of anonymity, and the survey organizers pride themselves for having maintained this condition intact for many decades (Garcia (2003), Croushore and Stark (2019)). Moreover, the forecasts we consider are about macroeconomic outcomes, rather than the prospects of individual firms. Therefore strategic considerations are unlikely to generate horizon bias in our setting.

[1] See Scharfstein and Stein (1990), Ehrbeck and Waldmann (1996), and Frankel, Kothari, and Weber (2006), among others.

Another potential impediment to fully rational forecasts is the processing capacity constraint that the forecasters in our sample face. They likely cannot incorporate all relevant information into their forecasts in real time. Additionally, they do not know the data generating process. In this respect, we consider two possible deviations from full-information rational expectations: information rigidities (Mankiw and Reis (2002), Woodford (2003), and Coibion and Gorodnichenko (2015)) and bounded rationality (Kahneman and Tversky (1974), Barberis and Thaler (2003), Fuster, Laibson, and Mendel (2010) and Rabin and Vayanos (2010)). The main models of information rigidities in macroeconomic forecasting, namely the sticky-information model and the noisy-information model, have proved successful in explaining the dynamics of beliefs about inflation. We consider both a standard version of these models with time-invariant rigidities and a version of the models in which rigidities are time-varying.[2] In both cases, information rigidities cannot account for horizon bias.

Even absent information rigidities, forecasts can be systematically biased if forecasters are unaware of the data generating process, and instead rely on intuitive heuristics to make predictions. In the broad literature of forecasting under bounded rationality, models of extrapolation, adaptive expectations, and incorrect beliefs about persistence are featured prominently.[3] While these heuristics can generate biases in forecasting, we show theoretically that optimism bias and horizon bias are unlikely to stem from these heuristics.

We last examine whether horizon bias is consistent with theories of motivated beliefs, in which agents derive utility from holding optimistic expectations about the future. In these theories, an agent gains anticipation utility by portraying his future prospects more optimistically than an outside rational observer would (Brunnermeier and Parker (2005), Bénabou (2015), Bénabou and Tirole (2016), Caplin and Leahy (2019)). To investigate formally whether horizon bias in macroeconomic forecasts can be the result of motivated beliefs, we consider two prominent models of motivated beliefs, namely, Brunnermeier and Parker (2005)'s theory of

[2]To model time-varying rigidities, we rely on earlier work by Gorodnichenko (2008) and Coibion and Gorodnichenko (2015).

[3]Extrapolation and adaptive expectations have a long tradition in macroeconomics. See, for instance, Keynes (1936), Koyck (1954), and Nerlove (1958). More recent evidence of extrapolation and adaptive expectations is surveyed in Barberis and Thaler (2003) and Barberis (2018). Adaptive learning is also the foundation for recent evidence of lifetime experiences (Malmendier and Nagel (2011), Malmendier and Nagel (2016)). Fuster, Laibson, and Mendel (2010) and Rabin and Vayanos (2010) consider incorrect perceptions concerning the persistence of the data generating process. They argue that these perceptions can be the consequence of the representativeness heuristic.

optimal expectations and Caplin and Leahy (2019)'s theory of wishful thinking. In the former, the behavioral agent trades off the anticipation utility he gains from envisioning strong future macroeconomic growth, against the suboptimal investment outcomes that such unwarranted optimism leads to. In the latter, the agent trades off the anticipatory utility benefits of optimistic beliefs, against the cost of practices such as information avoidance (Golman, Hagmann, and Loewenstein (2017)), memory suppression, and self-deception (Sharot, Korn, and Dolan (2011), Bénabou (2015), and Zimmermann (2020)), which help maintain such optimism in the face of incoming information. To study whether horizon bias obtains in these settings, we extend both Brunnermeier and Parker (2005) and Caplin and Leahy (2019) to a multi-period setting, and demonstrate that horizon bias can arise in both settings. Overall, motivated beliefs offer a natural micro-foundation for our novel evidence of horizon bias.

The last part of the paper investigates whether motivated beliefs also explain the large time-series variation in horizon bias that is observed in the data. To this end, we follow Bénabou (2015)'s demand-supply framework for dissecting motivated beliefs. We consider five separate drivers of horizon bias in macroeconomic forecasts. Demand-side drivers of motivated beliefs capture the psychological mechanisms that make optimistically biased beliefs desirable from the forecaster's viewpoint. For instance, it can be desirable for the forecaster to hold optimistically biased beliefs when such beliefs help cope with or reduce feelings of anxiety and stress. Supply-side drivers of motivated beliefs include the features of the process being forecasted that alter the costs of being optimistic. Two examples of costly ways to maintain optimism are the active avoidance of negative signals about the future (Epley and Gilovich (2016) and Golman, Hagmann, and Loewenstein (2017)), and the manipulation of memory and the selective recall of past experiences (e.g., Sharot, Korn, and Dolan (2011), Cheng, Raina, and Xiong (2014), and Zimmermann (2020)). The costs of these behaviors change with the underlying features of the process being forecasted. In particular, theory work suggests that optimism bias and horizon bias can change as a result of changes in the conditional uncertainty and the conditional skewness of the underlying process.[4] Importantly, these drivers exhibit time-series variation, and could hence help explain time variation in horizon bias.

Using data on the forecasts of real GDP growth, industrial production growth, growth in

[4]Brunnermeier and Parker (2005) and Brunnermeier, Gollier, and Parker (2007) show that beliefs are more optimistically biased when investment outcomes are more positively skewed. Caplin and Leahy (2019) show that a larger optimism bias arises in settings with larger conditional uncertainty, since in these settings the agent can more easily defend optimistic beliefs.

corporate profits, and unemployment rate from the US Survey of Professional Forecasters, we analyze the role of each of five separate demand and supply drivers of motivated beliefs for optimism bias and horizon bias in macroeconomic forecasts. To the best of our knowledge we are the first to investigate the relevance of these drivers of motivated beliefs for the formation of macroeconomic forecasts and for the term structure of bias in optimism. In multivariate regressions of U.S. forecasters' expectations conducted over a 50-year long sample, our results offer strong support for motivated-beliefs theories of macroeconomic expectations formation. We show that, ceteris paribus, the optimism bias (i) increases at all horizons during recessions, possibly as a means to reduce feelings of anxiety that are particularly severe during these periods (Marjanovic, Greenglass, Fiksenbaum, and Bell (2013), Mucci et al. (2016)); (ii) declines, particularly at long horizons, following periods of protracted and widespread negative news, consistent with increasing costs of information avoidance leading to lesser ability to avoid negative information; (iii) increases (declines) at all horizons following recent good economic conditions, consistent with recency bias in the recall from memory (Malmendier, Pouzo, and Vanasco (2019)); (iv) increases with conditional macroeconomic uncertainty, consistent with the Caplin and Leahy (2019) theory of wishful thinking; and (v) increases when the distribution of future macroeconomic outcomes is more positively skewed, consistent with Brunnermeier and Parker (2005) theory of optimal expectations. Importantly, some of the aforementioned findings carry over to explain variation in horizon bias. In particular, our results indicate that higher uncertainty, positive skewness, and a decline in the cost of information avoidance can lead to stronger horizon bias.[5]

In sum, we contribute to three distinct strands of the literature. First and foremost, we contribute to the literature on expectations formation. Our contribution to this literature is to document that beliefs about future macroeconomic states are, on average, more optimistically biased at long horizon than they are at short horizon. After showing that this aspect of macroeconomic expectations formation is difficult to reconcile with rational expectations, and cannot be easily explained using theories of belief formation that have received recent attention, we provide a theoretical foundation for horizon bias within theories of motivated beliefs. We show that motivated beliefs do not only help reconcile horizon bias unconditionally, but theory-based drivers of motivated beliefs help explain variation in horizon bias over

[5]Using our two models of motivated beliefs, we are able to confirm that these results are theoretically in line with the implications of motivated beliefs for horizon bias.

time. Taken together, our evidence provides strong support for motivated-beliefs theories of macroeconomic expectations formation.

Second, we contribute to a large literature in economics and psychology on the optimism bias. The optimism bias, a belief process that leads to systematically inflated self-views and excessively optimistic expectations about agents' future prospects, has been documented in many settings, ranging from health and the perception of health risk (Friedman et al. (1995), Oster, Shoulson, and Dorsey (2013)) to financial decision-making at the individual level (Puri and Robinson (2007)) as well as in corporations (Kahneman and Lovallo (1993)).[6] Despite the evidence that the optimism bias is pervasive, the question of whether and how it affects agents' expectations of future macroeconomic states has received little attention. Our results indicate that the optimism bias affects macroeconomic forecasts in a way that increases with the forecasting horizon. Our evidence also indicates that theories of optimism bias that are rooted in motivated beliefs (Bénabou and Tirole (2016)), optimal expectations (Brunnermeier and Parker (2005)), and wishful thinking (Caplin and Leahy (2019)) can help explain horizon bias and its time-series variation.

Finally, we contribute to the literature on economic forecasting with asymmetric loss (Elliot, Komunjer, and Timmermann (2005), Patton and Timmermann (2007), Elliott and Timmermann (2008), and Capistrán and Timmermann (2009)). This literature argues that systematic forecast biases can arise when forecasters face asymmetric loss over their positive versus negative forecast errors.[7] Importantly, as Elliott and Timmermann (2008) note, "construction of a loss function requires a deep understanding of the forecaster's objectives and this may not always be easily accomplished". Without such a deep understanding, econometric models of forecasting with asymmetric loss are equally likely to generate positive or negative biases in forecasts. In this respect, our results add to the asymmetric loss literature. We provide evidence of systematic optimism in professional forecasters' macroeconomic expectations that is consistent with the notion of forecasters' asymmetric loss, and offer a clear micro-foundation (motivated beliefs) for the direction that the asymmetry takes in the data.

[6]For prior work on the optimism bias, see Weinstein (1980), Scheier and Carver (1985), Scheier, Carver, and Bridges (1994), Sharot (2011), Coval and Thakor (2005), and Ashton and Roberts (2011) among others.

[7]For instance, Patton and Timmermann (2007) show that asymmetric loss can help explain the systematic biases in the forecasts issued by analysts working at the Federal Reserve, while Elliot, Komunjer, and Timmermann (2005) document that government-issued forecasts tend to systematically over-predict budget deficit, in a way that is consistent with asymmetric loss.

2 Data and Empirical Methodology

To investigate how optimism evolves over the term structure, we use beliefs from survey data. To be included in the analysis, survey data must meet two criteria. First, the survey must elicit beliefs about short and long-term outcomes. We find two surveys often used in the economics and finance literature that meet this criterion: the Federal Reserve Survey of Professional Forecasters (SPF), and the European Central Bank Survey of Professional Forecasters (ECB-SPF). The former, whose data starts in 1968, provides the longest sample period at our disposal to study how optimism evolves with the horizon. The survey elicits beliefs at a quarterly frequency, and for horizons ranging from the quarter in which survey responses are collected, i.e., nowcasts, up to 4 quarters into the future. The ECB-SPF started only at the end of the 1999. However, using the ECB-SPF data allows one to assess the significance of our results in an international setting. Moreover, the data from ECB allows us to further examine what happens to optimism when extending the forecasting horizon up to 5 years. It is therefore highly informative to include this data in the analysis. Since we base our main empirical design on the SPF, we defer a description of the ECB-SPF data to the robustness section where this data is used. Finally, using multiple surveys offers implicit out-of-sample evidence for our findings and allows us to assess whether the horizon bias is pervasive.[8]

The second criterion concerns the selection of the macroeconomic outcomes being forecasted. To draw inference on how optimism evolves over the term structure, what constitutes an optimistic forecast for the average forecaster in the survey much be clear. This is not always straightforward, since what a given outcome implies for a forecaster's utility and well being is likely to depend on the forecaster's wealth, financial investments or obligations, job role, or industry. For example, consider the forecast of wage growth for two hypothetical forecasters; a firm owner and an employee. When forecasting future wages, an optimistic employee may expect salaries to increase. On the other hand, an optimistic firm or employer may forecast lower wages since lower wages may increase the firm profits.[9] Moreover, the relationship between

[8]Recent work that relies on the SPF data includes Coibion and Gorodnichenko (2015). The ECB-SPF has been used in Reitz, Ruelke, and Stadtmann (2012).

[9]A similar example would apply to macroeconomic variables that are linked to financial investments. An investor who is optimistic about the future investment opportunity set could forecast higher interest rates in the future, whereas a household or the manager of a firm looking to obtain debt financing or refinance existing debt in the future, would express optimism by forecasting lower interest rates in the future.

optimism and a given outcome may not be monotonic. For example, optimistic consumers surveyed on inflation may predict low inflation since this implies more buying power. On the other hand, if prices fall too much and the economy experiences deflation, the effect of such decline can ultimately be detrimental for economic growth, employment, and consumers' well-being. Similarly, central bank officials, who may set monetary policy to stir inflation toward a given inflation rate target, can express optimism about future inflation in the form of a progressive convergence of inflation toward the target, so that optimism in inflation forecasts does not take the form of a higher or lower future inflation per se.

These considerations lead us to restrict our study to the forecast of macroeconomic quantities for which the definition of optimism is uncontroversial. These are real GDP growth, growth in industrial production, growth in corporations' profits, and the unemployment rate. The straightforward relation between these four variables and the business cycle makes it easy to identify what constitutes optimism for the average forecaster in our sample. For example, it is natural to characterize stronger economic expansion, e.g. higher GDP growth, or lower unemployment levels, as good news for the average forecaster in the panel. As a result, an optimistic forecaster can be identified easily as one who predicts higher GDP growth, higher industrial production growth, larger growth in corporations' profits, and lower unemployment.

To assess how optimism changes with the forecast horizon, we focus on the comparison between a short-term forecast F_{ST}, and a long-term forecast F_{LT}. In the SPF, F_{ST} is the annualized forecast of the macroeconomic outcome of interest in the quarter q in which the survey is administered [10], while F_{LT} is the annualized forecast of growth in quarter $q+4$.[11]

To measure how long-term belief distortions compare to short-term distortions, we form measures of forecast errors at long horizons, FE_{LT} and short horizons, FE_{ST}. These are constructed in one of two ways. The first is based on Coibion and Gorodnichenko (2012, 2015), as we estimate forecast errors as the difference between ex-ante forecasts and realized outcomes

[10] For real GDP, industrial production, and corporate profits, short-term forecasts represent prediction of growth in quarter q, where growth is based on the forecaster's self-reported estimate of the level of the macroeconomic variable of interest in quarter $q-1$. For the unemployment rate, the short-term forecast refers to the predicted level of unemployment at the end of quarter q.

[11] Using "nowcasts" for short-term forecasts increases the time distance between the horizon of short-term forecasts and the horizon of long-term forecasts. However, this choice may be subject to the critique that, at least to some extent, these forecasts reflect perceptions of current economic conditions, rather than predictions of future outcomes. In the Appendix A we show that our conclusions concerning how optimism changes with the horizon remain the same when we adopt an alternative definition of F_{ST}.

according to the historical vintage-date estimates of macroeconomic activity. We refer to this as the "initial release" estimates of forecast errors. The second approach to measuring belief distortions replicates the one above, but replaces historical estimates of macroeconomic outcomes with stable estimates of economic activity as of the end of the most recent vintage date in our sample (2018). Since we are interested in whether differences exist in optimism at different forecasting horizons, the next step is to define a metric of horizon bias, $HB = FE_{LT} - FE_{ST}$, that is either based on the initial-release estimates of macroeconomic realizations, HB_{Init}, or on the stable estimates of such realizations, HB_{Stable}. Finally, in our tests of whether there are unconditional differences between long-term horizon and short-term horizon forecasts, a third definition of horizon bias is possible. We refer to this as $HB_{Stat} = F_{LT} - F_{ST}$, that is obtained as the difference between long-term forecasts and short-term forecasts, and is a valid metric to assess unconditional horizon bias under the assumption, often entertained in prior literature, that the macroeconomic outcomes considered in this paper, exhibit stationary behavior.[12]

3 Results

If the term-structure of optimism is upward-sloping, we expect to observe higher long-term growth forecasts (e.g., larger GDP growth, larger industrial production growth) than short-term growth forecasts for real gross domestic product (GDP), industrial production (IP) and corporate profits (PROF), as well as lower long-term unemployment rate (UNEMP) forecasts than short-term unemployment rate forecasts. More importantly, an upward-sloping term structure implies that horizon bias should be positive for GDP, IP, and PROF, and negative for UNEMP. Conversely, downward-sloping optimism has opposite implications for horizon bias.

Table 1 shows micro-level evidence concerning the term structure of optimism. The tests are conducted in a panel setting, so as to ascertain whether there is evidence of systematic differences in short-term and long-term forecasts at the individual level. The table reports short-term forecast F_{ST}, long-term forecasts, F_{LT}, as well as the three distinct metrics for

[12]Formally, having defined $HB_q = (F_{q,q+s} - Y_{q+s}) - (F_{q,q+j} - Y_{q+j}), j < s$ as the difference in one-step ahead forecast errors for generic horizon s and j, $j < s$, stationarity in the macroeconomic outcome of interest $\{Y\}$ implies $E[Y_{q+s}] = E[Y_{q+j}] \forall j, s$. Therefore, for the purpose of estimating horizon bias unconditionally, one can construct horizon bias simply as the difference between long-term forecasts and short-term forecasts.

horizon bias we have outlined above. In parentheses are t-statistics based on double clustering by date and forecaster. The results in the table provide strong support for an upward-sloping term structure of optimism. Across all surveys and macroeconomic variables, we find more optimistic forecasts at long horizons relative to short horizons. Short-term forecasts of growth in GDP, IP, and PROF are systematically lower than long-term forecasts. Similarly, forecast of short-term unemployment are higher than forecasts of long-term forecasts. Horizon bias is not only statistically significant, but also economically significant. For instance, had the U.S. economic output grown in our sample at the annualized long-term growth rate being forecasted, by the end of 2018 it would have been almost 50% larger than if it had grown at the short-term growth forecast.[13]

Figure 1 complements the empirical evidence in Table 1 by showing how horizon bias evolves with the forecasting horizon. We define $FE_{t,t+h}$ as the forecast error in the prediction at time t of macroeconomic outcomes to be realized in quarter $t+h$. We then construct a horizon-specific measure of horizon bias as $HB_{t,t+h} = FE_{t,t+h} - FE_{t,t+m}, \quad m < h$. Like in Table 1, we set $m = 0$, i.e., we use nowcasts as short-term forecasts. Horizon bias is based on forecast errors that are obtained using the historical initial-release estimates of macroeconomic outcomes. The figure shows the full-sample average horizon bias for horizons $1 \leq h \leq 4$. The graph provides evidence that horizon bias increases with the forecasting horizon for all the four macroeconomic variables of interest.

In Appendix A we complement this main result with an extensive set of additional tests. First, given recent evidence that points to the possibility of very different behavior in micro-level forecasts as opposed to consensus forecasts (Bordalo, Gennaioli, Ma, and Shleifer (2020)), we repeat the analysis based on consensus forecasts as opposed to micro-level evidence. We find similar results. Second, we show evidence that horizon bias is present both in the first half of the sample and in the late part. Third, we replicate our main result based on an alternative definition of horizon bias that does not rely on nowcasts, so as to avoid concerns that what we are capturing stems from the difference between perception and prediction. Fourth, we

[13]For the unemployment rate, differences in short-term versus long-term forecast appear to be small. This may be a byproduct of the high persistence in the unemployment rate time-series, that forecasters are likely aware of, and the fact long-term forecasts in the SPF are constrained to a horizon of one year. In fact, when reassessed the result later using data from the ECB-SPF, where short and long-term forecasts differ by a horizon of three to four years, horizon bias in unemployment forecasts is about 1 percentage point, implying an expectation of unemployment rate in the long-run that is about 11% lower than the average unemployment rate in the Euro Area over the sample period.

present evidence of horizon bias in an international setting, as we document horizon bias in the ECB survey of professional forecasters. Working with the ECB-SPF data provides an implicit out-of-sample test for the validity of the conclusions drawn based on US data. We find evidence consistent with a pervasive horizon bias. This alternative data source also allows one to investigate whether the evidence of horizon bias extends beyond the 1-year forecast horizon. Moreover the evidence indicates that the slope of the term structure of optimism can be positive for horizons up to 5 years. Overall, this section provides evidence consistent with an upward-sloping term structure of optimism. Next we turn to the question of what the micro-foundation for this finding might be.

4 The Micro-foundation of Horizon Bias

In this section we examine the micro-foundation of horizon bias. We consider three possible sets of explanations for an optimism bias that increases with the forecasting horizon. These are (i) rational expectations models, where either the forecaster has full information but an asymmetric loss function over forecast errors (e.g., Capistrán and Timmermann (2009)), or there are rational information rigidities (Mankiw and Reis (2002), Woodford (2003)); (ii) behavioral models of bounded rationality that entail cognitive mistakes and biased expectations (Barberis, Greenwood, Jin, and Shleifer (2015), Fuster, Laibson, and Mendel (2010), Malmendier and Nagel (2011), 2016); and (iii) models of belief-based utility and motivated beliefs (Brunnermeier and Parker (2005), Bénabou (2015), Caplin and Leahy (2019)). In all the analysis that follows, we are going to refer to the macroeconomic process being forecasted as $\{\pi\}$, and we are going to assume as it is standard in the literature, that $\{\pi\}$ is stationary with mean μ. Wherever necessary, we are going to further assume a AR(1) law of motion, $\pi_{t+1} = a + b\pi_t + \nu_{t+1}$, |b|<1, and unless otherwise stated we will assume this process has homoskedastic and serially independent innovations, i.e., $\nu_t \sim I.I.D.(0, \sigma_\nu^2)$.[14] To align the analysis as closely as possible with the results of Table 1, we shall think of π as a process tracking quarterly macroeconomic growth, and we are going to define horizon bias as the difference between forecast errors at different forecasting horizons $HB_t = FE_{t,t+h} - FE_{t,t+1}, \quad h > 1$. However, differing from our definition of forecast errors in the previous section, and for con-

[14] In some of the derivations below we rewrite for convenience the AR(1) model above in the equivalent form $\pi_{t+1} = \mu + b(\pi_t - \mu) + \nu_t$.

sistency with prior literature, in the remainder of this section we define forecast errors as the difference between realized outcome and the forecast, i.e., $FE_{t,t+j} = \pi_{t+j} - F_{t,t+j}, \forall j$, so that in this section an upward-sloping term-structure of optimism would be captured by a negative value of HB_t.

4.1 Rational Expectations

4.1.1 Strategic Considerations

A large literature in economics studies how strategic considerations can affect forecaster's incentive toward accuracy. In this literature, forecasters trade off the reputational benefits of accurate forecasts against the foregone career benefits of issuing optimistically biased predictions.[15] To see whether strategic considerations could in principle generate horizon bias, In Appendix B2 we write a simple model of a forecaster who, when issuing predictions, faces both career considerations (which reward positively biased forecasts), as well as reputational considerations (which incentivize accuracy). The forecaster issues predictions both at short horizon and at long horizon, and the marginal benefits and costs of accuracy and optimism are horizon-specific. The forecaster, who has perfect foresight, chooses the short-term and the long-term bias so as to maximize his expected payoffs. The model delivers conditions under which optimism bias increases with the horizon.

While possible in theory, the validity of strategic considerations as an explanation of our empirical findings rests on the notion that the forecasters in our sample do gain reputational benefits and career benefits from their forecasts in the SPF. We argue that neither benefit exists for these analysts. Reputational benefits are absent at all horizons since forecasters in the SPF are anonymous, and the survey prides itself with having maintained this condition for a long time Croushore and Stark (2019).[16] Similarly, career benefits are unlikely, both due to the anonymity of the survey, and because the forecasts we study concern the macroeconomy, rather than any individual firm a forecaster might want to cater due to career motives. We conclude that, although possible, strategic considerations are unlikely to generate horizon bias

[15]For example, analysts who work in the sell-side of large investment banks may prefer to systematically issue optimistic recommendations as opposed to unbiased ones, since upward-biased forecasts curry favor with management (Michaely and Womack (2005))

[16]Later in the paper we also use the ECB survey of professional forecaster, that maintains a similar anonymity condition (Garcia (2003)).

in macroeconomic expectations.

4.1.2 Information Rigidities

Previous work by Sims (2003), Reis (2006), Mackowiak and Wiederholt (2009), and Woodford (2003), indicates that rational expectations do not necessarily imply that forecast errors are unpredictable. In fact, theories of rational inattention and information rigidities argue that biases in expectations can result from rational forecasts when information acquisition is costly or when information is noisy (e.g., Coibion and Gorodnichenko (2012)). In what follows, we ask whether the most common theories of information rigidities, namely the sticky-information model (Mankiw and Reis (2002)) and the noisy-information model (Woodford (2003)) can help reconcile the evidence of horizon bias.

Sticky-information model

Mankiw and Reis (2002) propose a model of belief formation whereby a forecaster does not acquire information or update his beliefs in every period. Rather, in each period the forecaster acquires information and updates his forecast with probability $(1-\lambda)$, while information acquisition does not occur with probability $\lambda < 1$.[17] To see whether this model can generate horizon bias, we follow Coibion and Gorodnichenko (2012, 2015) and start by writing the forecast $F^{SI}_{t,t+h}$ of the h-period ahead outcome of interest under sticky information (SI),

$$F^{SI}_{t,t+h} = (1-\lambda)\sum_{j=0}^{\infty}\lambda^j E_{t-j}\pi_{t+h} \tag{4.1}$$

where $E_{t-j}\pi_{t+h}$ indicates the j-period ago rational expectation of the outcome of interest.[18] Based on Equation (4) we can write the unconditional forecast error in the h-step ahead forecast as follows:

$$\mathrm{E}\left(\pi_{t+h} - F^{SI}_{t,t+h}\right) = -\frac{(1-\lambda)}{(1-\lambda)}E\left(E_{t-j}\pi_{t+h}\right) = E(\pi) \tag{4.2}$$

[17] The lack of information acquisition need not be inconsistent with rational expectations, if acquiring information or updating beliefs causes the forecaster to incur a recurring fixed cost (e.g., Reis (2006)).

[18] The rational forecast at time t-j of the realized outcome x at time t+h is $F_{t-j,t+h} = \pi_{t+h} - v_{t-j,t+h}$, where $v_{t-j,t+h}$ is a j + h periods expectations error whose conditional mean at time $t-j$ is zero.

Equation (5) uses the law of iterated expectations and the stationarity of process $\{\pi\}$ to show that the sticky-information model delivers unconditionally unbiased forecasts at all horizons.[19] As a consequence, the unconditional horizon bias under sticky information is equal to:

$$E\left[HB_t^{SI}\right] = \mathrm{E}\left[\left(\pi_{t+h} - F_{t,t+h}^{SI}\right) - \left(\pi_{t+1} - F_{t,t+1}^{SI}\right)\right] = 0 \tag{4.3}$$

Therefore, the sticky-information model does not generate horizon bias.

Noisy-information model

A forecaster receives an imperfect signal about the latent AR(1) process $\{\pi\}$,

$$\tilde{\pi}_t = \pi_t + \delta_t, \quad \delta_t \sim N\left(0, \sigma_\delta^2\right) \tag{4.4}$$

where π is demeaned for convenience but without loss of generality. Based on this signal, the forecaster updates his belief $F_t^{NI}\pi_t$ about π_t following a Kalman filter:

$$F_t^{NI}\pi_t = G\tilde{\pi}_t + (1-G)F_{t-1}^{NI}\pi_t \tag{4.5}$$

where $0 \leq G < 1$ is the filter gain parameter. Using the filtered belief about π_{t+h}

$$F_t^{NI}\pi_{t+h} = b^h F_t^{NI}\pi_t \tag{4.6}$$

Under noisy information, forecasts are unconditionally unbiased at all horizons. To see this, write the ex-post forecast error for a generic horizon h

$$\pi_{t+h} - F_t^{NI}\pi_{t+h} = b^h\left[\pi_t - \frac{G}{1-(1-G)b}\sum_{j=0}^{\infty} w^p \pi_{t-j}\right] + \varphi_{t,t+h} + \eta_t \tag{4.7}$$

where $\sum_{j=0}^{\infty} w^p = 1, \varphi_{t,t+h}$ is the rational-expectations zero-mean conditional error, and η_t is a zero-mean linear combination of past realizations of the noise process $\{\delta_t\}$.[20] Taking

[19] The intuition for why the sticky-information model generates unconditionally unbiased forecasts is that, in the model, the forecaster is equally likely to miss good news and bad news. Missing good news generates under-prediction, whereas missing bad news generates over-predictions. On average these two effects balance each other out, generating unconditional unbiasedness.

[20] Formally, $\varphi_{t,t+h} = \sum_{j=0}^{h-1} b^j \nu_{t+h-j}$ and $\eta_t = b^h G \sum_{j=0}^{\infty} b^j (1-G)^j \delta_{t-j}$

unconditional expectations, one obtains:

$$\mathrm{E}\left[\pi_{t+h} - F_t^{NI}\pi_{t+h}\right] = 0 \tag{4.8}$$

The standard noisy-information model of belief formation with constant gain generates a flat term structure of optimism unconditionally, and hence it cannot account for the evidence of horizon bias documented in this paper.[21]

Time-varying information rigidities

Whereas the two baseline models with time-invariant rigidities that we have presented above cannot generate horizon bias unconditionally, Gorodnichenko (2008) and Coibion and Gorodnichenko (2015) argue that information rigidities can be state-dependent and time-varying. In Appendix B2 we investigate formally whether time-series variation in information rigidities that is documented in prior work can help explain the evidence of unconditional horizon bias that was uncovered in Table 1. We derive the equation for horizon bias in closed form for a setting with time-varying rigidities, and note that the extent and sign of horizon bias that obtains in this setting depend on the covariance structure of the rigidity parameter with the lagged realizations of the macroeconomic variable of interest. To model such covariances we rely on evidence in Coibion and Gorodnichenko (2015) that rigidities are negatively correlated with macroeconomic volatility, and they decline during recessionary periods. Using simulations calibrated to the evidence of time-varying rigidities in Coibion and Gorodnichenko (2015), we conclude that state-dependent information rigidities cannot easily explain horizon bias, and if anything they would contribute to lower optimism in macroeconomic forecasts at long horizons compared to short horizons. Overall, information rigidities are unlikely to rationalize the evidence of horizon bias presented in this paper.

4.2 Bounded Rationality and Cognitive Mistakes

A vast literature in economics and psychology documents that errors in expectations are due to cognitive mistakes (Kahneman and Tversky (1974)). Within this vast literature, we concentrate on the main theories of belief formation that have received attention in recent

[21] The unconditional unbiasedness property of forecasts obtained via the noisy-information model will hold also if the latent process had a mean different from zero.

years , namely (i) adaptive expectations and extrapolation; and (ii) natural expectations. We ask whether, theoretically, these belief-formation rules can generate horizon bias in the forecasts that we have studied.

4.2.1 Extrapolation

To model extrapolative beliefs, we rely on Pesaran and Weale (2006). We refer to extrapolative expectations using the $E_t^X(\cdot)$ operator. Referring again at defined $\{\pi_t\}$ as the process that is being forecasted, extrapolators' subjective expectations of future π follow the law of motion below:

$$E_t^X\left(\pi_{t+1}\right) = \sum_{k=0}^{T} w_k \pi_{t-k} \tag{4.9}$$

for some T $\geq$ 0 and where, for convenience, $\sum_{k=0}^{T} w_k = 1$. In words, extrapolators' expectations of the future value of process $\pi, E_t^X\left(\pi_{t+1}\right)$, are obtained as the average of the past process realizations. The equation above can accommodate Keynes (1936) model of static extrapolation when T = 0 and $w_0 = 1$. It can also accommodate a model of adaptive experiential learning (Malmendier and Nagel (2011) Malmendier and Nagel (2016) Malmendier, Pouzo, and Vanasco (2019)) for $w_k = \left\{\frac{\theta^k\left(1-\theta^T\right)}{1-\theta}\right\}$, with a decaying-memory parameter $\theta < 1$, and a choice of T that reflects the average lifespan in the population of forecasters. In what follows, for simplicity, the horizon parameter T is assumed to be equal to infinity, and the weight parameter features geometric decay, i.e.,

$$E_t^X\left(\pi_{t+1}\right) = (1-\gamma)\sum_{k=0}^{\infty} \gamma^k \pi_{t-k} \tag{4.10}$$

for some parameter $0<\gamma<1$. Moreover, we assume subjective beliefs to be consistent in the sense that extrapolative expectations satisfy the laws of probability, i.e., $E_t^X[E_{t+1}^X(.)] = E_t^X(.)$. This allows to easily write the equation for $E_t^X \pi_{t+2}$ as

$$E_t^X(\pi_{t+2}) = E_t^X[E_{t+1}^X(\pi_{t+2})] = E_t^X\left[w^0\pi_{t+1} + (1-w^0)E_t^X(\pi_{t+1})\right] = E_t^X[\pi_{t+1}] \tag{4.11}$$

Iterating this equation forward one can easily see that the term structure of forecasts for $\{\pi\}$ is conditionally flat for all horizons. Moreover, taking unconditional expectations under the

objective probability metric one obtains:

$$E[E_t^X(\pi_{t+h})] = E[E_t^X(\pi_{t+1})] = \mu \tag{4.12}$$

where the last equality in Equation 4.12 is the result of the assumption of stationarity of process $\{\pi\}$ and the adding-up condition for the weights in extrapolators' forecasting model. Overall, forecasts of a stationary process obtained in standard extrapolation models are unconditionally unbiased at all horizon, so that $E[HB^X] = 0$, i.e., the term structure of optimism is flat under extrapolative expectations. Therefore the results in this paper cannot be accounted for by a standard model of extrapolation.

4.2.2 Incorrect Beliefs about Persistence

A large literature in economics and psychology argues that cognitive mistakes in forecasting can emerge due to agents' over or under-estimation of the actual persistence of a data generating process.[22]

In a model with incorrect beliefs about persistence, the forecaster believes that the data generating process for $\{\pi_t\}$ is:

$$\pi_t = a^N + b^N \pi_{t-1} + \varepsilon_t, \varepsilon_t \sim IID\left(0, \sigma^2\right) \tag{4.13}$$

where

$$\begin{cases} b^N = b\left(\delta^N\right) \\ a^N = \mu\left(1 - b^N\right) \end{cases} \tag{4.14}$$

Equation (12) above is similar to the actual law of motion that generates the data. The main difference is the fact that the persistence parameter posited by the forecaster, b^N differs from the actual persistence of the process by a factor $\left(\delta^N\right)$. A value of δ^N larger than 1 captures

[22]Incorrect beliefs about the persistence of a process can be the result of forecasters' use of intuitive models. For instance, Fuster, Laibson, and Mendel (2010) propose a model of natural expectations where forecasters' neglect of the complex process that generates the data leads to incorrect beliefs about the persistence of the data. Rabin and Vayanos (2010) propose a parsimonious model of belief formation where a forecaster alternates a gambler's fallacy (an over-estimation of reversal, Rabin (2002)) with a hot-hand fallacy (an over-estimation of persistence, Gilovich, Vallone, and Tversky (1985)) Similarly, in the theory model of Barberis, Shleifer, and Vishny (1998) an agent alternates between beliefs in continuation and beliefs in reversal, despite the true data generating process being I.I.D noise.

instances in which the forecaster over-estimates persistence, whereas a value of δ^N smaller than 1 reflects beliefs in imminent correction and quicker reversal.

Based on Equations (12) and (13), we can write the forecasts at short and long horizon, $E_t^N(\pi_{t+1})$ and $E_t^N(\pi_{t+h})$, respectively:

$$\begin{aligned} E_t^N[\pi_{t+1}] &= \mu\left(1-b^N\right)+b^N\pi_t \\ E_t^N[\pi_{t+h}] &= \mu\left(1-\left(b^N\right)^h\right)+\left(b^N\right)^h\pi_t \end{aligned} \tag{4.15}$$

We can also write the short and long-term forecast errors:

$$FE_{ST,t}^N = (\pi_t-\mu)\,b\left(1-\delta^N\right) \tag{4.16}$$

$$FE_{LT,t}^N = (\pi_t-\mu)\,b^h\left[\left(1-(\delta^N)^h\right)\right] \tag{4.17}$$

It is easy to see that when $\delta^N = 1$, i.e., there are no misperceptions about persistence, forecasts are optimal, forecast errors are not predictable, and horizon bias is equal to zero. If the forecaster over-estimates persistence, i.e., $\delta^N > 1$, forecast errors will be larger in absolute terms at long-horizon than at short-horizon. This is consistent with the setting in the natural-expectations model of Fuster, Laibson, and Mendel (2010). The opposite will be true instead if the forecaster exhibits an incorrect belief in reversal, i.e., $\delta^N < 1$. More importantly for our purpose, equations 4.16 and 4.17 imply that incorrect beliefs about persistence generate unconditionally unbiased forecasts at all horizons. As a result, the evidence of horizon bias in this paper cannot be ascribed to incorrect beliefs about persistence.[23] Overall, some of the most standard theories of cognitive mistakes cannot easily account for our evidence of horizon

[23]It is worth pointing out that the model of belief formation in Equation 4.13 is a special case of a more general regression-to-normality (RNN) set of belief formation rules (Pesaran and Weale (2006)). In these models, subjective expectations take the form of $E_t^{RNN}[\pi_{t+1}] = (1-b^N)\pi_t + b^N\pi*_t$, where $\pi*_t$ is the forecaster's perceived long-run value of π. In the model of incorrect beliefs about persistence presented here, $\pi*_t$ is made constant and equal to the actual long-run mean of the process. Pesaran and Weale (2006) propose that a more general expression for $\pi*_t$ is a linear combination of current and past realizations of the process, where the sum of the weights assigned to these realizations is equal to 1. Thus, expectations under regression-to-normality can be reformulated as $E_t^{RNN}[\pi_{t+1}] = (b^N)\pi_t + (1-b^N)E^X[\pi_{t+1}]$. After adding and subtracting $\mu(1-b^N)$ and rearranging the equation, one obtains $E_t^{RNN}[\pi_{t+1}] = E_t^N[\pi_{t+1}] + (1-b^N)\left[E_t^X(\pi_{t+1}-\mu)\right]$, i.e., RNN expectations are a convex combination of beliefs about persistence and standard extrapolative expectations about the zero-mean process $(\pi_{t+1}-\mu)$. Based on our result in Equations 4.11, 4.16, and 4.17, it is straightforward to conclude that also more general RNN belief formation rules are unlikely to generate horizon bias.

bias.

4.3 Horizon Bias, Asymmetric Loss, and Motivated Beliefs

Early tests of rational expectations are centered around the idea that rational forecasts ought to be unbiased on average i.e., $E\left(FE_{t,t+h}\right) = 0 \ \forall \ h$ (e.g., Mincer and Zarnowitz (1969)). Based on this idea, the evidence of horizon bias is Section 3 is inconsistent with rational expectations. However, a large literature notes that forecast unbiasedness is a property of rational expectations only if a forecaster faces a symmetric loss function L over forecast errors, e.g., $L\left(FE_{t,t+h}\right) = \alpha + \beta FE^2_{t,t+h}$ where β>0. If instead the forecaster faces an asymmetric loss function, forecasts can be systematically biased.

We argue that asymmetric loss can, but won't necessarily, generate horizon bias. To see this, we follow work by Capistran and Timmermann (2009), who hypothesize that forecasters' asymmetric loss over forecast errors is well described by a linex loss function:

$$L\left(\varepsilon_{(t,t+h)}, \phi\right) = \frac{1}{\phi^2}\left(e^{\phi\varepsilon_{(t,t+h)}} - \phi\varepsilon_{(t,t+h)} - 1\right) \tag{4.18}$$

where $\varepsilon_{(t,t+h)} = \pi_{t+h} - F_{t,t+h}$ is the realized forecast error in the prediction of the h-period ahead macroeconomic outcome π_{t+h},. The central parameter in the loss function is ϕ, a coefficient that determines whether the forecaster has an incentive or disposition toward under-prediction (i.e., $\varepsilon^*_{(t,t+h)} > 0, \phi < 0\Big)$ or over-prediction (i.e., $\varepsilon^*_{(t,t+h)} < 0, \phi > 0$). With asymmetric loss, the standard assumptions concerning the autoregressive behavior of process $\{\pi\}$ laid out at the beginning of this section, deliver the following closed-form equation for horizon bias in forecasts whose horizon differs by h periods:

$$E[HB^{AL}] = E[\varepsilon^{*AL}_{(t-1,t+h)} - \varepsilon^{*AL}_{(t-1,t)}] = -\phi\frac{\sigma^2_\nu}{2}\Big(\frac{1-b^{2(h+1)}}{1-b^2} - 1\Big) \tag{4.19}$$

As Equation 4.19 shows, a model of forecasts with asymmetric loss can generate horizon bias. However, forecasting under asymmetric loss need not generate a positive horizon bias. In fact, without proper guidance from economics and a clear description of the forecasters' maximization problem, models of forecasts with asymmetric loss leave ϕ unspecified, and are hence equally likely to generate positive and negative horizon bias. Therefore, in order for asymmetric loss to provide a micro-foundation for the evidence of horizon bias in this paper,

one needs to supplement the notion of loss-asymmetry over forecast errors with a model of belief formation that generates larger costs (or smaller benefits) of under-prediction than over-predictions.

With respect to this, prior work suggests that individuals may derive utility not only from higher consumption or larger wealth, but also from the anticipation of such better outcomes (Jevons (1905); Lowenstein (1987); Brunnermeier and Parker (2005); Bénabou and Tirole (2016); Caplin and Leahy (2001); Caplin and Leahy (2019); Banerjee, Davis, and Gondhi (2019)). When agents derive utility from the optimistic anticipation of future events, the ensuing expectations formation process is one of motivated beliefs, whereby the economic agent chooses to hold beliefs that are too positive from the rational individual's viewpoint, and yet are desirable as they reduce the adverse health effects of fear and anxiety about the future (Akerlof and Dickens (1982)), improve self-efficacy (Johnson and Fowler (2011); Bénabou and Tirole (2002)), and boost anticipated utility (Bénabou (2015)). Two leading models of motivated beliefs are Brunnermeier and Parker (2005) optimal expectations framework and Caplin and Leahy (2019) theory of wishful thinking. Whereas these theories point to the existence of the optimism bias in forecasts of future macroeconomic states, in what follows we ask whether systematic differences in optimism bias across forecasting horizons can arise in these models, and thus whether these models can reconcile our evidence of horizon bias in macroeconomic forecasting.

4.3.1 Horizon Bias and Optimal Expectations

Brunnermeier and Parker (2005) develop a theoretical framework that generates optimism bias. In their model, an agent's welfare stems from two sources: (i) the anticipation utility due to optimistic beliefs about future consumption, and (ii) the agent's expected utility of consumption. The agent chooses her beliefs, and does so by trading off the greater anticipatory utility that she derives from the choice of being optimistic, with the suboptimal investment choices and lower consumption that she attains based on her chosen level of optimism. To investigate whether horizon bias can arise within theories of motivated beliefs, we extend the model of Brunnermeier and Parker (2005) such that agents maximize their welfare in a multi-period context.

An agent's well-being is a time-average of her felicity U in period 0, period 1, and period 2, where U is monotonically increasing over consumption, and it is concave. The agent considers

investing in three assets; a risk-free asset; an risky asset that pays a liquidating dividend in period 1; and a risky asset that pays a liquidating dividend in period 2.[24] We assume that the objective distribution of asset returns is the same for investments that pay off in period 1 and investments that pay off in period 2. We denote with R the gross risk-free rate or return, and with Z_s the excess return paid by a risky asset in every period, where s indices one of S possible states of nature such that $Z_1 < Z_2 < ... < Z_s < Z_S$. [25] We assume that the R and Z_s have the same i.i.d distribution in every period. We denote with $\{\pi_s\}$ the objective probability of state$s$, and we refer to $\{\hat{\pi}_s\}$ as the subjective probability that state is realized.

In period 0, the agent's felicity is the subjectively expected discounted utility flow in the next two periods. In period 1, the agent's felicity comes from both anticipated utility in the second period and actual consumption in the second period. The agent's second-period utility flow is based on actual consumption in the 2nd period. Under optimal expectations, the agent solves the following program:

$$\max_{\{\widehat{\pi}_1\},\{\widehat{\pi}_2\}} \frac{1}{3}\left[\begin{array}{c} \beta\sum_{s=1}^{S}\widehat{\pi}_{1,s}U\left(R+\alpha^{*}\left(\{\widehat{\pi}_1\}\right)Z_{s_1}\right)+ \\ \beta^2\sum_{s=1}^{S}\widehat{\pi}_{2,s}U\left(R+\alpha^{*}\left(\{\widehat{\pi}_2\}\right)Z_s\right)+\beta\sum_{s=1}^{S}\pi_{1,s}U\left(R+\alpha^{*}\left(\{\widehat{\pi}_1\}\right)Z_s\right)+ \\ \beta^2\sum_{s=1}^{S}\widehat{\pi}_{2,s}U\left(R+\alpha^{*}\left(\{\widehat{\pi}_2\}\right)Z_s\right)+\beta^2\sum_{s=1}^{S}\pi_{s}U\left(R+\alpha^{*}\left(\{\widehat{\pi}_2\}\right)Z_s\right) \end{array}\right] \quad (4.20)$$

that is, the agent chooses a probability distribution for her period-1 investment, $\{\widehat{\pi}_1\}$, and a probability distribution for her period-2 investment, $\{\widehat{\pi}_2\}$, to maximize her expected felicity at time 0. β is a time discounting factor $\alpha^{*}\left(\hat{\pi}_i\right)$ is the optimal share of the agent's wealth at the beginning of period i that is invested in the risky asset that liquidates at the end of the period.

Based on this setup, in Appendix C we show that this setting generates a horizon bias. Specifically, we show that there exists an equilibrium in which investors will be, on average, more optimistic at long horizons relative to short horizons when they make a positive

[24] If we assume the long-term asset pays dividends in periods 1 and 2, we would generate similar results.

[25] Although the return to the risky asset do not map one-to-one with macroeconomic growth, we assume that risky asset returns increase monotonically with macroeconomic growth.

investment.[26] That is, for $\alpha^* > 0$:

$$\sum_{s=1}^{S} \left(\widehat{\pi}_{2,s} - \widehat{\pi}_{1,s}\right) U'\left(R + \alpha^*\left(\{\widehat{\pi}_2\}\right) Z_s\right) Z_s > 0 \tag{4.21}$$

The intuition behind the model outcome is simple: optimism at long horizon serves a greater anticipation benefit than optimism at short horizons since agents get to enjoy increased anticipation utility for more periods and the cost to suboptimal investment choices is the same for distorted beliefs at short horizons and distorted beliefs at long horizons. Overall, optimal expectations can help reconcile the evidence of evidence of unconditional horizon bias in our paper. Finally, in Appendix D2 we show that under optimal expectations horizon bias can increase with the skewness of the distribution of risky asset returns. This result, which extends earlier findings by Brunnermeier, Gollier, and Parker (2007), will be used later to test more directly the linkage between optimal expectations and horizon bias.

4.3.2 Horizon Bias and Wishful Thinking

After showing that horizon bias can arise in a model of optimal expectations, in this section we ask whether horizon bias also arises in a model of wishful thinking (Caplin and Leahy (2019)). Unlike the optimal expectations framework, where agents trade off higher ex-ante utility from anticipation against lower ex-post financial returns and lower final wealth, Caplin and Leahy (2019) posit that agents trade off utility from the anticipation of high future consumption against the costs of maintaining optimistic views about the future in the face of incoming information. These costs can have many sources, ranging from information avoidance (Golman, Hagmann, and Loewenstein (2017)), to the manipulation of one's memory (Bénabou (2015), Zimmermann (2020)) that facilitates indulging in one's wishful thinking.

To study horizon bias in a wishful thinking setting, we setup a model in the spirit of Caplin and Leahy (2019). An agent who lives for three periods derives utility at time t from consumption at time t, c_t, plus the anticipation of consumption at times $t+1$ and $t+2$. Consumption over the next two periods is determined by the current level of consumption and the one-step and two-step ahead per-period stochastic growth rates of consumption, π_{t+1}

[26] We assume that this optimistic choice is a unique local maximum in the region of positive portfolio weight on the risky asset.

and π_{t+2}. [27].

We define $u(c)$ as the agent's utility from consumption, such that $u(c) > 0 \; \forall c > 0$, $u^{'}(c) > 0 \; \forall c > 0$, and $u^{''}(c) <= 0 \; \forall c > 0$. The wishful thinker's expected utility from current and future consumption is

$$\begin{aligned} U_t =& u(c_t) + \beta \int_{\pi_{t+1}} u(c_t(1+\pi_{t+1}))f(\pi_{t+1})d\pi_{t+1} + \\ & \beta^2 \int_{\pi_{t+1}} \int_{\pi_{t+2}} u(c_t(1+\pi_{t+1})(1+\pi_{t+2}))f(\pi_{t+1},\pi_{t+2})d\pi_{t+2}d\pi_{t+1} \end{aligned} \tag{4.22}$$

where the functional $f(.)$ denotes the wishful thinker's subjective distribution of future consumption growth.[28] Equation 4.22 suggests that the agent could increase his anticipation of future utility from consumption by selecting a subjective probability distribution of future consumption growth that assigns larger (smaller) probability to states of higher (lower) growth.[29] To discipline the agent's selection of subjective beliefs, we introduce a cost of belief distortions that is modeled in the spirit of Hansen and Sargent (2008) and Caplin and Leahy (2019), as a Kullback-Leibler divergence of the wishful thinker's chosen distribution f(.), from the econometrician's non-distorted probabilistic assessment, which we denote with the functional $\overline{f}(.)$. Thus, the cost of distorting beliefs takes the following form:

$$\begin{aligned} C_t =& \frac{1}{\theta}\left[\beta \int_{\pi_{t+1}} f(\pi_{t+1}) ln \frac{f(\pi_{t+1})}{\overline{f}(\pi_{t+1})} d\pi_{t+1} \right. \\ & \left. + \beta^2 \int_{\pi_{t+1}} \int_{\pi_{t+2}} f(\pi_{t+1},\pi_{t+2}) ln \frac{f(\pi_{t+1},\pi_{t+2})}{\overline{f}(\pi_{t+1},\pi_{t+2})} d\pi_{t+2}d\pi_{t+1}\right] \end{aligned} \tag{4.23}$$

[27] In our setting, we study optimism about future consumption growth, and use such optimism to infer optimism about macroeconomic growth. This approach makes sense if consumption growth and macroeconomic growth are highly positively correlated. This is the case empirically, since the correlation between quarterly consumption growth and quarterly real GDP growth is 73% in the sample period 1959-2020.

[28] Throughout the analysis, we follow Caplin and Leahy (2019) and assume that the wishful thinker's beliefs are consistent with the laws of probability.

[29] The model could in principal be extended to incorporate an investment decision that shifts consumption across time and states of the world. However, this addition to the model would not only make it more difficult to provide a solution of the wishful thinker's problem in closed form, but it would also introduce similarities between our analysis here and the analysis of horizon bias under optimal expectations of Section XXX. Since here we aim at investigating the specific implications of wishful thinking for horizon bias, we prefer a simpler setting where the only trade-off the agent faces when forming beliefs is the key one in Caplin and Leahy (2019).

The first term in Equation 4.23 captures the cost of distorting the beliefs of one-step ahead consumption growth. The second term of the Equation captures the costs of distorting beliefs 2 periods into the future.[30] The parameter θ determines how costly it is to engage in wishful thinking. θ will be small (i.e., ceteris paribus, a larger C_t) when it is too difficult to engage in practices such as information avoidance or self-deception and denial of incoming information, that help maintain one's optimistic views about the future. Overall, the wishful thinker's problem is to choose subjective distributions $f(\pi_{t+1})$ and $f(\pi_{t+1}, \pi_{t+2})$ so as to maximize at time t $U_t - C_t$.

We assume, like we have done throughout most of the analysis of this Section, that consumption growth evolves according to an AR(1) process with IID normal innovations. Moreover we assume that, like the econometrician, the wishful thinker also believes consumption growth to have an autoregressive component, and agrees on the parameters governing such component, as well as the distribution of the innovations in consumption growth. [31] However, the wishful thinker can choose to deviate from optimal forecasts at short and long horizon, and the extent of this deviation is determined endogenously as part of the forecasters' maximization problem.

Having imposed this simple, yet reasonable structure, we are able to solve the agent's maximization problem. In Appendix D we present the solution to the maximization problem in detail, and derive the following condition for horizon bias:

$$\frac{u'(\overline{c_{t+2}})}{u'(\overline{c_{t+1}})} > \frac{1-b}{(1+\mu_g)(1+\beta b^2)} \tag{4.24}$$

[30] Like in Caplin and Leahy (2019), the cost of distorting beliefs concerning outcomes that are realized h periods into the future is expressed as the cost of a sequence of beliefs up to horizon h.

[31] In principal, nothing prevents the wishful thinker from selecting from a wide range of possible laws of motion for consumption growth, or using different model parameters. However, deviating entirely from the econometrician's model entails a cost which can be very large. In the wishful thinker's world, the costs of choosing beliefs is linked to how easy it is to refute the wishful thinker's choice. Since the parameters of an autoregressive model are easily estimated with data that is publicly available, the cost of avoiding such data and choosing different parameters can be large. Moreover, the AR(1) law of motion is a rather simple and standard model of macroeconomic growth. Thus, If the wishful thinker chose to believe in an entirely different law of motion and a different probability distribution for the innovations of the growth process, the costs of justifying these deviations to himself or to others could be too high to bear. One way to restate all the above is that, to the extent that experts mostly agree on the law of motion of consumption growth, and use the same data to estimate model parameters, there is little divergence of experts' opinion to allow the wishful thinker to disregard such a united front of expert opinions. Finally, we impose that the wishful thinker believes innovations in consumption growth to be normally distributed for mathematical convenience.

where μ and b are the objective mean and persistence of the AR(1) process governing macroeconomic growth, β is a time-discount coefficient, and $\overline{c_{t+j}} = c_t(1+\mu)^j$. In Appendix D we also show some key comparative statics results. Namely, horizon bias is stronger when conditional macroeconomic uncertainty is higher. Moreover, horizon bias is stronger when the costs associated with wishful thinking decline, i.e., when θ increases.[32] In the next section we test these additional insights as we study the time-series variation in horizon bias.

5 What Drives Time-series Variation in Horizon Bias?

Having established above that motivated beliefs offer a possible micro-foundation for horizon bias, we seek to identify potential drivers of horizon bias by relying on a relevant conceptual framework that is due to Bénabou (2015). In that framework, motivated beliefs have both demand-side and supply-side drivers.

Demand-side drivers describe why people choose to hold optimistically biased beliefs about the future. For instance, optimism can be desirable due to its affective value, since it helps cope with fear or anxiety (e.g., Akerlof and Dickens (1982), Lowenstein (1987)). Prior work notes that fear and anxiety change over the business cycle, and are high during economic recessions (Marjanovic, Greenglass, Fiksenbaum, and Bell (2013), Mucci et al. (2016)), so that demand drivers of optimistically biased beliefs are time-varying and can lead to time-series variation in optimism bias and horizon bias.

Supply-side drivers are concerned with how people can maintain their optimistic beliefs. For example, forecasters can engage in information avoidance (Golman, Hagmann, and Loewenstein (2017)), either through physical avoidance and willfull blindness (e.g., Oster, Shoulson, and Dorsey (2013)), or through the biased interpretation and selective dismissal of information previously acquired (e.g.,Lord, Ross, and, Lepper (1979), Zimmermann (2020)). Crucially, information avoidance entails a cost, physical or mental, which in the context of macroeconomic forecasting is likely to be time varying. For instance, a recency bias in the intuitive recall of past events Malmendier, Pouzo, and Vanasco (2019) can make the avoidance of negative information more costly in the face of recent macroeconomic news. Similarly, to the extent that negative macroeconomic news is more or less pervasive over time, the cost of avoiding such evidence is inherently time-varying. Higher costs of information avoidance

[32] These results resonate with earlier results in Caplin and Leahy (2019).

reduce forecasters' overall benefits from maintaining optimistic beliefs, so that variation in such costs over time can generate variation in optimism and horizon bias. Supply-side drivers can be also defined more broadly to incorporate the features of an uncertain outcome that allow a forecaster to more-easily justify her optimistically biased beliefs. Theoretically, Caplin and Leahy (2019) propose that optimism is more likely to arise when uncertainty about an outcome of interest increases, while Brunnermeier and Parker (2005) suggest that biased optimism is stronger when the distribution of the outcome of interest exhibits larger positive skewness.

To test whether and how demand-side and supply-side drivers of motivated beliefs contribute to horizon bias, we analyze the determinants of forecast errors in macroeconomic forecasts from the SPF using standard regression analysis. To this end we regress ex-post forecast errors in short-horizon predictions (FE_{ST}), long-horizon predictions (FE_{LT}), and their difference (HB), on a set of theory-based potential determinants of biases in forecasting. The empirical proxy for demand-side drivers that we consider, $I(REC)$, is an indicator variable that is equal to one in months that the NBER has classified as part of a recession, and 0 otherwise. The measures that we adopt for supply-side drivers fall into four distinct categories. We proxy for macroeconomic uncertainty using Jurado, Ludvigson, and Ng (2015) conditional quarter-ahead and year-ahead uncertainty metrics, which we label σ^Y_{ST} and σ^Y_{LT} respectively. We measure skewness using the cross-sectional average conditional probability of a macroeconomic expansion (i.e., a rise in real GDP) in the quarter ahead and 4 quarters ahead, which we refer to as $p(Expansion_{ST})$ and $p(Expansion_{LT})$, respectively. To measure the time-series variation in the costs of information avoidance, we construct a count variable for the number of quarters with declining macroeconomic activity in the year prior to a forecast date. To better capture the notion that the cost of information avoidance is higher when negative news is widespread, our count variable, $N_{badnews}$, combines data on past macroeconomic growth from four distinct macroeconomic indicators, namely, real GDP, industrial production, corporate profits, and unemployment rate. Finally, we measure the role that the recall of past events plays for horizon bias in two ways. First, following evidence of recency effects in memory retrieval, we use macroeconomic growth in the quarter prior to the date in which the SPF forecasts are collected, $EG_{t-5,t-1}$.$EG_{t-5,t-1}$ is obtained as the first principal component of four time-series of macroeconomic growth: growth in real GDP, industrial production growth, growth in corporate profits, and growth in unemployment rate. Second, following a

recent literature of experience effects (Malmendier and Nagel (2011), Malmendier and Nagel (2016)), we construct a macroeconomic-experience variable, $Memory_{MN11}$, that captures the experience of macroeconomic growth for a representative economic agent.[33] Table 2 reports summary statistics for these candidate theory-based drivers of horizon bias.

Table 3 presents the results of our tests on the drivers of the time-series variation in horizon bias. Panel A reports the results of the predictability analysis of short-term forecast errors (FE_{ST}). Panel B analyzes the determinants of long-term forecast errors, and Panel C studies the drivers of horizon bias. In the Table we follow the convention adopted in Table 1, as we defined forecast errors as the difference between forecasts and ex-post realized outcomes. Following Coibion and Gorodnichenko (2012) and Coibion and Gorodnichenko (2015), we calculate bias in forecasters' predictions using the real-time estimates of realized macroeconomic outcomes. We concentrate on the principal component of forecast errors for the same four macroeconomic variables we have studied earlier in the paper. [34] Inference in the table is based on Newey and West (1987) standard-errors with 4 lags (i.e., one year). Results of the analysis of Table 3 for individual macroeconomic outcomes are reported in the Appendix, Section A3. Table 3 reports both univariate results and multivariate regressions results. For brevity, here we mainly discuss the results of the multivariate tests in column (6) of each panel, which allow to infer the marginal contribution of each driver of optimism bias, while holdings the other drivers constant.

The results of these tests provide new insights both on the linkage between motivated beliefs and optimism bias in macroeconomic forecasts, and on the relation between motivated beliefs and horizon bias. The first insight concerns the role that demand-side drivers of motivated beliefs play in macroeconomic forecasts. The table shows that demand-side drivers

[33]The macroeconomic-experience variable is obtained as a weighted sum of past macroeconomic growth realizations, where weights are based on the estimate of the decay parameter λ in Malmendier and Nagel (2011), and the representative agent in the economy is an individual whose age is equal to the median age of employed according to data from the Bureau of Labor and Statistics. $Memory_{MN11}$, $N_{badnews}$, and $EG_{t-5,t-1}$ are all based on the real-time data on macroeconomic realizations to better reflect the forecasters' information set and experiences at the time of the forecast.

[34]This first principal component explains 56% of the common variation in horizon bias across macroeconomic forecasts. It loads positively on horizon bias in the forecast of future real GDP growth, future industrial production growth, and future growth in corporate profits, and it loads negatively on horizon bias in the forecasts of future unemployment. Therefore, an increase in the principal component is associated with an increase in optimism bias at long horizon compared to short horizon. In Appendix A3, we repeat the analysis with multiple approaches to the measurement of forecast errors in macroeconomic forecasting, and for individual macroeconomic variables. Results are qualitatively similar.

are a much stronger determinant of short-term forecast errors than long-term forecast errors, and the role of demand-side drivers is limited to short-term forecasts once we control for other drivers of motivated beliefs. Moreover, demand-side drivers do not seem to play a major role in explaining time-series variation in horizon bias.

Table 3 also provides evidence on the role of information avoidance for macroeconomic forecasting. We show that when bad news is more pervasive (i.e., $N_{badnews}$ is higher) the ensuing optimism bias is lower, both in short-term forecasts and in long-term forecasts. This result is broadly consistent with work on motivated beliefs, whereby increasing costs of information avoidance lead to a reduction of optimism bias in equilibrium. However the effect is mostly concentrated in long-term forecasts. As a result, larger costs of information avoidance result in a decline in horizon bias. This result is statistically significant at the 5% level.

Next, Table 3 provides evidence of how the memory of recent events affects errors in macroeconomic forecasts. We show that following recent positive macroeconomic experiences (i.e., a higher value of $EG_{t-5,t-1}$), the optimism bias increases both in short-term and in long-term forecasts. This is consistent with motivated beliefs arising through the retrieval of events from memory, and with theories of recency bias in such retrieval. However, whereas recent events play a role for the optimism bias, they do not have a strong impact on the slope of the term structure of optimism, since there is no evidence of a statistical linkage between $EG_{t-5,t-1}$ and horizon bias.

Table 3 also investigates whether lifetime experiences of macroeconomic events have an impact on biases in macroeconomic forecasts. We find that an increase in our metric for lifetime macroeconomic experiences, $Memory_{MN11}$ is negatively related to the optimism bias at both long and short horizon, with the relation being economically and statistically stronger for long-term forecast errors. The stronger impact of macroeconomic experiences for long-horizon forecast errors leads to a negative overall link between lifetime experiences and the horizon bias, although the relation is not statistically significant at standard levels. Overall, our evidence indicates that recent and more distant events contribute to generating errors in macroeconomic forecasts, but do so with opposite signs. Moreover, variation in memory seems to shift the term structure optimism upward or downward, but does not appear to impact the slope of the term structure.

Results in Table 3 indicate that the optimism bias in macroeconomic forecasts is linked to macroeconomic uncertainty. In particular, short-horizon (long-horizon) optimism bias in-

creases when short-horizon (long-term) uncertainty increases. Similarly long-horizon optimism bias increases when long-term uncertainty increases. These results are consistent with Caplin and Leahy (2019) theory of wishful thinking, whereby biased optimism about an outcome of interest increases when the objective distribution of that outcome feature higher volatility. Perhaps more importantly, horizon bias increases when long-horizon uncertainty increases, and it decreases when short-horizon uncertainty rises. Moreover, an upward shift in macroeconomic uncertainty at all horizons leads to an increase in horizon bias.[35] This result is in line with the comparative statics results of the model of wishful thinking that we have presented in Section 4.3.2, which are in Appendix D.

Finally, the results in Table 3 also link optimism bias and horizon bias in macroeconomic forecasts to macroeconomic skewness. Specifically, consistent with Brunnermeier and Parker (2005) and Brunnermeier, Gollier, and Parker (2007), and in a way that mirrors our findings concerning uncertainty, an increase in short-term (long-term) skewness leads to an increase short-term (long-term) optimism bias. Furthermore, higher long-term skewness leads to stronger horizon bias, while higher short-term skewness is linked to lower horizon bias. Finally, an upward shift in our metric for skewness at all horizons leads to an increase in horizon bias.[36] This result is in line with the model of optimal expectations that we have presented in Section 4.3.1 and in Appendix .

Which of the five distinct mechanisms investigated in this section is more important in explaining the time-series variation in optimism horizon bias? We infer this from the adjusted-R^2 obtained in the first five columns of each subpanel of Table 3, where each mechanism is investigated separately. We note that, while demand-side drivers play the most important role in explaining optimism bias at both short and long-horizon, supply-side drivers, and in particular macroeconomic uncertainty, have the strongest explanatory power for the slope of the term structure of optimism.

These findings could potentially be driven by some of our empirical design choices. To assess the robustness of the results to different plausible choices we repeat the analysis in the Appendix, Section A3. There we also present the result of the multivariate regressions

[35] A 10 percentage point increase in both short-term uncertainty and long-term uncertainty, which corresponds to roughly 1 standard deviation of both long-term uncertainty and short-term uncertainty, raises horizon bias by one standard deviation.

[36] A 10 percentage point increase in both short-term skewness and long-term skewness raises horizon bias about one quarter of a standard deviation above its long-run mean.

for each of the four macroeconomic variables we have considered. The results remain in line with our evidence in Table 3. In sum, this section further strengthens the linkage between motivated beliefs and biases in macroeconomic forecasting, and provides prima-facie evidence of how different aspects of theories of motivated beliefs contribute to biases in the forecast of future macroeconomic states.

6 Discussion and Conclusion

Using survey data in the US and abroad we document that the optimism bias in macroeconomic expectations increases with the forecasting horizon. We label this empirical regularity the *horizon bias*. In our data, horizon bias is unlikely to result from strategic considerations. Moreover, we show that information rigidities, bounded rationality and cognitive mistakes are unlikely to account for the evidence of horizon bias.

We establish theoretically that horizon bias can arise in theories of motivated beliefs (Bénabou and Tirole (2016)), and show empirically that many theory-based drivers of motivated beliefs help explain variation in optimism bias and horizon bias over time. All in all, this paper offers evidence of horizon bias in macroeconomic expectations, and it provides both theoretical and empirical evidence that micro-founds such horizon bias in theories of motivated beliefs.

We believe the evidence in this paper has many potential applications. For instance, horizon bias could reconcile the finding that the slope of the term structure of equity premia is downward-sloping (Binsbergen, Brandt, and Koijen (2012)) and time-varying. Both the average slope of the term structure and its variation over time are difficult to explain with asset pricing models (Binsbergen and Koijen (2017)), where the emphasis is on whether the term structure of discount rates can account for these empirical regularities. However, differences in expectations of cash flow growth at short and long horizon could potentially reconcile these findings. The evidence presented in this paper suggests that over-optimism about long-term cash flows compared to short-term cash flows could help explain the negative average slope of the term structure. Moreover, the theories of motivated beliefs that offer a micro-foundation for horizon bias could also offer new predictions on the drivers of the time variation in the slope of the term structure.

Horizon bias could also help make sense of how expectations are formed in other asset markets, such as the housing market. In this respect, survey evidence by Case and Shiller (2003)

points to an upward sloping term structure of optimism for house price growth in the early 2000, when individuals living in four major cities in the US forecasted an annualized growth over a period of 10 years to exceed price growth over the next-12 month by up to 50 percent. However, in the aftermath of the 2007-2009 financial crisis, house price expectations appear to display more optimism at short horizon compared to long horizon (e.g., Kindermann, Le Blanc, Piazzesi, and Schneider (2020)). This result may be consistent with a well-understood mechanism, namely, learning about the data generating process. However, the results in this paper suggest that a more nuanced view of this evidence is also possible. In particular, in our multi-period models of motivated beliefs, horizon bias can experience "inversions", in that when the objective distribution of returns from a potential investment exhibits excessive negative skewness, optimal expectations will turn optimism into pessimism, and pessimism will be increasing with the forecasting horizon. Thus it is possible that, in addition to having learned about payoffs in the real estate market, investors who have lived through the financial crisis have learned that the downside events in this market can be so pronounced to warrant a post-crisis switch to pessimistic expectations and an "inverted" horizon bias.[37] Whether and how motivated beliefs contribute to belief formation in the housing market, as well as in other markets or contexts, is an open question which we leave to future research.

Finally, we believe that our results can offer new insights into theories of forecasting under asymmetric loss. The fact that forecasters' incentives can generate asymmetric loss is well understood in this literature. However, in the seminal work on asymmetric loss of Elliott and Timmermann (2008), such incentives have a narrow definition, in that "forecasts do not have any intrinsic value and are only useful in so far as they help improve economic decisions." In contrast to this view, the extant literature on motivated beliefs portrays the mind as a consumption organ Schelling (1988) and indicates that beliefs have a direct and powerful affective impact on an agents' utility Bénabou and Tirole (2016). Thus, theories of asymmetric loss can be extended to accommodate such an affective value of beliefs. These are only some of the potential applications of the idea of horizon-specific biases in belief formation. We leave the investigation of these and other venues to future research.

[37]Moreover, the fact that post-crisis pessimism about house prices is more pronounced among homeowners than among renters is potentially an indication that motivated beliefs are at play, with the market participants who are more exposed to a decline in house prices (i.e., the homeowners) forming endogenously beliefs that are more pessimistic.

References

Akerlof, G.A. and W.T. Dickens. The economic consequences of cognitive dissonance. 1982. *The American Economic Review*, 72(3), pp.307-319.

Ashton, R., and M. Roberts. Effects of dispositional motivation on knowledge and performance in tax issue identification and research. 2011. *Journal of The American Taxation Association*. 33(1), 25-50

Aspinwall, L., and S. Taylor. Modeling cognitive adaptation: A longitudinal investigation of the impact of individual differences and coping on college adjustment and performance. 1992. *Journal of Personality And Social Psychology*. 63(6), 989-1003

Banerjee, S., J. Davis, and N. Gondhi. Choosing to disagree in financial markets. 2019. *Working Paper*.

Barberis, N. Psychology-based models of asset prices and trading volume. 2018. In *Handbook of Behavioral Economics: Applications and Foundations* (Vol. 1, pp. 79-175). North-Holland.

Barberis, N., R. Greenwood, L. Jin, and A. Shleifer. X-CAPM: An extrapolative capital asset pricing model. 2015. *Journal of Financial Economics*. 115(1), 1-24

Barberis, N., A. Shleifer, R. Vishny. A model of investor sentiment. 1998. *Journal of Financial Economics*, 49(3), 307-343.

Barberis, N., and R. Thaler. A survey of behavioral finance. 2003. *Handbook of The Economics of Finance*. 1, 1053-1128

Bénabou, R. The economics of motivated beliefs. 2015. *Revue D'Économie Politique*. 125(5), 665-685

Bénabou, R. and J. Tirole. Self-confidence and personal motivation. 2002. *The Quarterly Journal of Economics*, 117(3), 871-915.

Bénabou, R., and J. Tirole. Mindful economics: The production, consumption and value of beliefs. 2016. *Journal of Economic Perspectives*. 30, 141-164

Binsbergen, J., and R. Koijen. The term structure of returns: Facts and theory. 2017. *Journal of Financial Economics*. 124(1), 1-21

Binsbergen, J., M. Brandt, and R. Koijen. On the timing and pricing of dividends. 2012. *American Economic Review*. 102(4), 1596-1618

Bordalo, P., N. Gennaioli, Y. Ma, and A. Shleifer. Over-reaction in macroeconomic expectations. 2020 *American Economic Review*, forthcoming.

Brunnermeier, M., and J. Parker. Optimal expectations. 2005. *American Economic Review*. 95(4), 1092-1118

Brunnermeier, M., C. Gollier, and J. Parker. Optimal beliefs, asset prices, and the preference for skewed returns. 2007. *American Economic Review P&P.*, 159-165

Capistrán, C. and A. Timmermann. Disagreement and biases in inflation expectations. 2009. *Journal of Money, Credit and Banking*, 41(2-3), 365-396.

Caplin, A., and J. Leahy. Psychological expected utility theory and anticipatory feelings. 2001. *The Quarterly Journal of Economics*. 116, 55-79

Caplin, A., and J. Leahy. Wishful thinking. 2019. *Working Paper*.

Case, K.E. and R.J. Shiller. Is there a bubble in the housing market?. 2003. *Brookings papers on economic activity*. 2003(2), 299-362.

Chen, S. and D.A. Matsumoto, D.A. Favorable versus unfavorable recommendations: The impact on analyst access to managementâprovided information. 2006. *Journal of Accounting Research*, 44(4), 657-689.

Cheng, I.H., S. Raina, and W. Xiong. Wall Street and the housing bubble. 2014. *American Economic Review*, 104(9), 2797-2829.

Coibion, O., and Y. Gorodnichenko. What can survey forecasts tell us about information rigidities?. 2012. *Journal of Political Economy*. 120(1), 116-159

Coibion, O., and Y. Gorodnichenko. Information rigidity and expectations formation process: A simple framework and new facts. 2015. *American Economic Review*. 105(8), 2644-2678

Coval, J., and A. Thakor. Financial intermediation as a beliefs-bridge between optimists and pessimists. 2005. *Journal of Financial Economics*. 75(3), 535-569

Croushore, D., and T. Stark. Fifty Years of the Survey of Professional Forecasters. 2019. *Economic Insights*. 4(4), 1-11

De la O, R., and S. Myers. Subjective cash flow and discount rate expectations. 2019. *Working Paper*.

Delong, B., A. Shleifer, L. Summers, and R. Waldmann. Noise trader risk in financial markets. 1990. *Journal of Political Economy*. 98(4), 703-738

Ehrbeck, T. and R. Waldmann, R. Why are professional forecasters biased? Agency versus behavioral explanations. 1996. *The Quarterly Journal of Economics*, 111(1).

Elliott, G. and A. Timmermann. Economic forecasting. 2008. *Journal of Economic Literature*, 46(1), pp.3-56.

Elliott, G., I. Komunjer, and A. Timmermann. Estimation and testing of forecast rationality under flexible loss. 2005. *The Review of Economic Studies*, 72(4), pp.1107-1125.

Elliott, G., I. Komunjer, and A. Timmermann. Biases in macroeconomic forecasts: irrational-

ity or asymmetric loss?. 2008. *Journal of the European Economic Association*, 6(1), 122-157.

Epley, N., and T. Gilovich. The mechanics of motivated reasoning. 2016. *Journal of Economic Perspectives*. 30(3), 133-40

Francis, J., J.D. Hanna, J.D. and D.R Philbrick. Management communications with securities analysts. 1997. *Journal of Accounting and Economics*, 24(3).

Frankel, R., Kothari, S.P. and Weber, J. Determinants of the informativeness of analyst research. 2006. *Journal of Accounting and Economics*, 41(1-2)]

Friedman, L., J. Webb, S. Bruce, A. Weinberg, and H. Cooper. Skin cancer prevention and early detection intentions and behavior. 1995. *American Journal of Preventitive Medicine*. 11(1), 59-65

Fuster, A., D. Laibson, and B. Mendel. Natural expectations and macroeconomic fluctuations. 2010. *Journal of Economic Perspectives*. 24(4), 67-84

Garcia, J. An introduction to the ECB's survey of professional forecasters. 2003. *European Central Bank Paper*. 8

Gilovich, T., R. Vallone, and A. Tversky. The hot hand in basketball: On the misperception of random sequences. 1985. *Cognitive Psychology*. 17(3), 295-314

Golez, B. Expected returns and dividend growth rates implied by dividend markets. 2014. *The Review of Financial Studies*. 27(3), 790-822

Golman, R., D. Hagmann, and G. Loewenstein. Information avoidance. 2017. *Journal of Economic Literature*. 55(1), 96-135

Gorodnichenko, Y., Endogenous information, menu costs and inflation persistence. 2008. Working Paper.

Hansen, L.P. and T.J. Sargent. Robustness. 2008. Princeton university press.

Jurado, K., S. Ludvigson, and S. Ng. Measuring uncertainty. 2015. *American Economic Review*. 105(3), 1177-1216

Jevons, W. Essays on economics. 1905. *Macmilan*, 1905

Johnson, D., and J. Fowler. The evolution of overconfidence. 2011. *Nature*. 477, 317-320

Kahneman, D. and D. Lovallo. Timid choices and bold forecasts: A cognitive perspective on risk taking. 1993. *Management Science*, 39(1), pp.17-31.

Kahneman, D., and A. Tversky. Judgment under uncertainty: Heuristics and biases. 1974. *Science*. 185(4157), 1124-1131

Keynes, J. The general theory of employment, interest and money. 1936. MacMillan, London.

Kindermann, F., J. Le Blanc, M. Piazzesi, and M. Schneider. Learning about housing cost: Survey evidence from the German house price boom. 2020. Working Paper.

Koyck, L.M. Distributed lags and investment analysis. 1954. North-Holland Publishing Company.

Litt, M., H. Tennen, G. Affleck, and S. Klock. Coping and cognitive factors in adaptation to in vitro fertilization failure. 1992. *Journal of Behavioral Medicine*. 15(2), 171-187

Lord, C.G.,L. Ross, and M.R. Lepper. Biased assimilation and attitude polarization: The effects of prior theories on subsequently considered evidence. 1979. *Journal of Personality and Social Psychology*, 37(11), 2098.

Lowenstein, G. Anticipation and the valuation of delayed consumption. 1987. *The Economic Journal*. 97, 666-684

Lucas, R.E. Econometric policy evaluation: A critique. 1976. In *Carnegie-Rochester conference series on public policy* (Vol. 1, No. 1, pp. 19-46).

Mackowiak, B. and M. Wiederholt. Optimal sticky prices under rational inattention. 2009. *American Economic Review*, 99(3), pp.769-803.

Malmendier, U., and S. Nagel. Depression babies: do macroeconomic experiences affect risk taking?. 2011. *The Quarterly Journal of Economics*. 126(1), 373-416

Malmendier, U., and S. Nagel. Learning from inflation experiences. 2016. *The Quarterly Journal of Economics*. 131(1), 53-87

Malmendier, U., D. Pouzo, and V. Vanasco. Investor experiences and financial market dynamics. 2019. *Journal of Financial Economics*.

Mankiw, N.G., and R. Reis. Sticky information versus sticky prices: a proposal to replace the New Keynesian Phillips curve. 2002. *The Quarterly Journal of Economics*, 117(4), 1295-1328.

Marjanovic, Z., E.R. Greenglass, L. Fiksenbaum, and C.M. Bell. Psychometric evaluation of the Financial Threat Scale (FTS) in the context of the great recession. 2013. *Journal of Economic Psychology*, 36, 1-10.

Michaely, R., and K. Womack. Brokerage recommendations: Stylized characteristics, market responses, and biases. 2005. *Advances in Behavioral Finance II*, 389-422/

Mincer, J.A. and Zarnowitz, V. The evaluation of economic forecasts. 1969. In Economic forecasts and expectations: Analysis of forecasting behavior and performance. NBER.

Mucci, N., G. Giorgi, M. Roncaioli, J. Perez, and G. Arcangeli. The correlation between stress and economic crisis: a systematic review. 2016. *Neuropsychiatric Disease And Treatment*. 12, 983

Muth, J.F. Rational expectations and the theory of price movements. 1961. *Econometrica*. 315-335.

Nerlove, M. Adaptive expectations and cobweb phenomena. 1958. *The Quarterly Journal of Economics*, 72(2), pp.227-240.

Newey, W., and K. West. Hypothesis testing with efficient method of moments estimation. 1987. *International Economic Review.*, 777-787

Oster, E., I. Shoulson, and E. Dorsey. Optimal expectations and limited medical testing: evidence from Huntington disease. 2013. *American Economic Review*. 103(2), 804-30

Patton, A.J. and A. Timmermann. Testing forecast optimality under unknown loss. 2007. *Journal of the American Statistical Association*, 102(480), pp.1172-1184.

Pesaran, M.H. and M. Weale. Survey expectations. 2006. Handbook of economic forecasting, 1, 715-776.

Puri, M., and D. Robinson. Optimism and economic choice. 2007. *Journal of Financial Economics*. 86(1), 71-99

Rabin, M. Inference by believers in the law of small numbers. 2002. *The Quarterly Journal of Economics*. 117(3), 775-816

Rabin, M., and D. Vayanos. The gambler's and hot-hand fallacies: Theory and applications. 2010. *The Review of Economic Studies*. 77(2), 730-778

Reis, R. Inattentive producers. 2006. *The Review of Economic Studies*, 73(3), pp.793-821.

Reitz, S., J. Ruelke, and G. Stadtmann. Nonlinear expectations in speculative markets - Evidence from the ECB survey of professional forecasters. 2012. *Journal of Economic Dynamics and Control*. 36, 1349-1363

Scharfstein, D.S. and J.C. Stein. Herd behavior and investment. 1990. *The American Economic Review.*

Schelling, T. C. The Mind as a Consuming Organ. Chap. 15 in Decision Making: Descriptive, Normative, and Prescriptive Interactions, edited by David E. Bell, Howard Raiffa, and Amos Tversky. 1988. Cambridge University Press.

Scheier, M., and C. Carver. Optimism, coping and health: Assessment and implications of generalized outcome expectancies. 1985. *Health Psychology*. 4(3), 219-247

Scheier, M., C. Carver, and M. Bridges. Distinguishing optimism from neuroticism (and trait anxiety, self-mastery, and self-esteem): a reevaluation of the Life Orientation Test. 1994. *Journal of Personality And Social Psychology*. 67(6), 1063-1078

Sharot, T. The optimism bias. 2011. *Current Biology*. 21(23), 941- 945

Sharot, T., C. Korn, and R. Dolan. How unrealistic optimism is maintained in the face of reality. 2011. *Nature Neuroscience*. 14(11), 1475-1479

Schulz, R., J. Bookwala, J. Knapp, M. Scheier, and G. Williamson. Pessimism, age and cancer mortality. 1996. *Psychology And Aging*. 11(2), 304-309

Sims, C.A. Implications of rational inattention. 2003. *Journal of monetary Economics*, 50(3), pp.665-690.

Taylor, S. Positive illusions: Creative self-deception and the healthy mind. 1989. Basic Books, 1989.

Taylor, S., and J. Brown. Illusion and well-being: A social psychological perspective on mental health. 1988. *Psychological Bulletin*. 103(2), 193

Weinstein, N. Unrealistic optimism about future life events. 1980. *Journal of Personality And Social Psychology*. 39(5), 806-820

Woodford, M. Imperfect Common Knowledge and the Effects of Monetary Policy. In *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps*. Princeton: Princeton University Press.

Zimmermann, F. The dynamics of motivated beliefs. 2020. *American Economic Review*. 110(2), 337-61

Table 1
Horizon Bias

We use panel data on macroeconomic expectations from the Federal Reserve Survey of Professional Forecasters. We focus on four macroeconomic variables, namely real GDP growth (GDP), industrial production growth (IP), growth in corporate profits (PROF), and the unemployment rate (UNEMP). Data is at the quarterly frequency. Growth rate forecasts are annualized. For each variable we report short-term forecasts (F_{ST}), long-term forecasts (F_{LT}), and horizon bias (HB). Short-term forecasts in quarter t are forecasts of the outcome of interest for the quarter in which the survey is conducted. Long-term forecasts are forecasts of the outcome of interest in quarter *t+4*. Three distinct measures of horizon bias are reported. HB_{Init} is the difference between long-term forecast errors and short-term forecasts errors, where forecast errors are the difference between the ex-ante forecast and the ex-post realization of the macroeconomic variable of interest according to the historical vintage estimate of that variable. HB_{Stable} is defined similarly, with the only difference being the use of estimates of realized macroeconomic activity as of the most recent vintage date. Finally, HB_{Stat} is a measure of horizon bias that is obtained as the difference between long-term forecast and short-term forecast. This metric for horizon bias is based on the observation that if the macroeconomic process being forecasted is stationary, then there should be no unconditional difference between the short-term and the long-term realized outcome, and hence an unconditional measure of horizon bias does not depend on the actual realizations of the macroeconomic variable of interest. In parentheses are t-statistic double clustered by forecaster and time. More details on data construction are in Section 3. The sample period is 1968-2018.

Macro Variable	F_{ST}	F_{LT}	HB_{Init}	HB_{Stable}	HB_{Stat}
GDP	2.420	3.178	0.826	0.829	0.746
	[13.49]	[37.51]	[2.90]	[2.74]	[4.13]
N	7462	7280	7192	7192	7262
IP	2.602	4.031	1.362	1.444	1.407
	[7.33]	[25.19]	[2.02]	[2.10]	[3.67]
	7060	6929	6849	6849	6912
PROF	7.484	8.996	1.909	1.986	1.496
	[7.14]	[18.30]	[0.62]	[0.77]	[1.25]
N	5592	5654	5461	5461	5483
UNEMP	6.229	6.095	-0.12	-0.119	-0.135
	[50.27]	[53.71]	[-1.68]	[-1.67]	[-4.02]
N	7534	7373	7372	7372	7372

Table 2
The Drivers of Horizon Bias - Summary Statistics

Summary statistics for the variables used in our analysis concerning the time-series variation in horizon bias. $I(REC)$ is an indicator variable that is equal to 1 during NBER recessionary periods, and 0 otherwise. $N_{badnews}$ is a count variable for the number of quarters characterized by a decline in economic activity over the past year. $EGt-5,t-1$ measures economic growth in the fourth quarters prior to the forecast. σ^Y_{ST} and σ^Y_{LT} are Jurado, Ludvigson, and Ng (2015) conditional macroeconomic uncertainty estimates for the quarter and year ahead, respectively. $p(Expansion_{ST})$ and $p(Expansion_{LT})$ are SPF forecasters' cross-sectional average probabilities of growth in real GDP over the next quarter and 4 quarters ahead, respectively. $Memory_{MN11}$ is a macroeconomic-experiences variable in the spirit of Malmendier and Nagel (2011). More details on these variables are in Section 5.

Variable	N	Mean	STD	Min	Max	Source
$I(REC)$	201	0.134	0.342	0	1	NBER
$N_{badnews}$	196	5.000	2.117	1	10	Federal Reserve
σ^Y_{ST}	201	0.803	0.099	0.683	1.199	Sydney Ludvigson
σ^Y_{LT}	201	0.928	0.07	0.848	1.189	Sydney Ludvigson
$p(Expansion_{ST})$ (%)	201	80.487	24.657	1.000	100	Federal Reserve
$p(Expansion_{LT})$ (%)	197	84.997	5.934	67.5	100	Federal Reserve
$EG_{t-5,t-1}$	199	0.003	1.674	-7.527	4.645	Federal Reserve
$Memory_{MN11}$	201	0.070	0.012	0.045	0.087	Federal Reserve

Table 3
Determinants of Time-Series Variation in Horizon Bias

Time-series regressions of short-horizon forecast errors (FE_{ST}, Panel A), long-horizon forecast errors (FE_{LT}, panel B) and horizon bias (HB, Panel C) on a set of explanatory variables measured as of the forecast date. Short-horizon forecasts are the annualized "nowcast" forecasts of macroeconomic outcomes in the quarter in which the survey is held. Long-horizon forecasts are the annualized forecasts of macroeconomic outcomes 4 quarters from the forecast date. For brevity, the table presents results for the principal component of the forecast errors of real GDP growth, industrial production growth, growth in corporate profits, and the unemployment rate. Forecast errors are calculated as the difference between the cross-sectional average mean forecasts and the ex-post realized outcome. Following Coibion and Gorodnichenko (2012, 2015), these ex-post realizations refer to the vintage date that is closest to the date in which a forecast was generated. Further details on the data and the methodology are in Section 5, and robustness checks are presented in Appendix A3. Inference is based on Newey-West (1987) standard errors with 4 lags (i.e., one year). The sample period is 1968-2018.

		Panel A: FE_{ST}					
Mechanism	Variable	(1)	(2)	(3)	(4)	(5)	(6)
Demand Side	$I(REC)$	1.178					1.164
		[4.99]					[3.551]
Info Avoidance	$N_{badnews}$		0.023				-0.012
			[0.572]				[-0.253]
Memory	$EG_{t-5,t-1}$			-0.052			0.133
				[-0.817]			[1.779]
	$Memory_{MN11}$			-6.199			-2.297
				[-1.196]			[-0.401]
Uncertainty	σ^Y_{ST}				12.450		8.786
					[3.201]		[2.687]
	σ^Y_{LT}				-14.763		-13.727
					[-2.495]		[-2.877]
Skewness	$p(Expansion_{ST})$					-0.011	-0.009
						[-3.125]	[-1.751]
	$p(Expansion_{LT})$					-0.009	-0.006
						[-0.614]	[-0.435]
	N	201	197	200	202	198	194
	Adj. Rsq (%)	15.709	-0.281	0.307	8.921	6.739	19.737

Table 3
Determinants of Time-Series Variation in Horizon Bias (Continued)

		Panel B: FE_{LT}					
Mechanism	Variable	(1)	(2)	(3)	(4)	(5)	(6)
Demand Side	$I(REC)$	0.691					0.171
		[1.799]					[0.354]
Info Avoidance	$N_{badnews}$		-0.032				-0.117
			[-0.72]				[-2.401]
Memory	$EG_{t-5,t-1}$			-0.030			0.083
				[-0.85]			[1.458]
	$Memory_{MN11}$			-0.067			-12.141
				[-0.009]			[-1.748]
Uncertainty	σ^Y_{ST}				-3.148		-6.685
					[-0.707]		[-1.395]
	σ^Y_{LT}				9.715		15.619
					[1.436]		[2.204]
Skewness	$p(Expansion_{ST})$					-0.010	-0.005
						[-2.583]	[-0.779]
	$p(Expansion_{LT})$					0.016	0.026
						[1.132]	[1.964]
	N	195	193	194	195	195	193
	$Adj.R^2$ (%)	4.867	-0.058	-0.791	14.17	6.143	23.893
		Panel C: HB					
Mechanism	Variable	(1)	(2)	(3)	(4)	(5)	(6)
Demand Side	$I(REC)$	0.127					-0.373
		[0.334]					[-0.747]
Info Avoidance	$N_{badnews}$		-0.026				-0.092
			[-0.573]				[-1.822]
Memory	$EG_{t-5,t-1}$			-0.026			-0.005
				[-0.512]			[-0.071]
	$Memory_{MN11}$			3.004			-9.280
				[0.422]			[-1.346]
Uncertainty	σ^Y_{ST}				-7.787		-9.542
					[-1.787]		[-2.107]
	σ^Y_{LT}				14.686		19.525
					[2.176]		[2.919]
Skewness	$p(Expansion_{ST})$					-0.004	-0.001
						[-1.17]	[-0.136]
	$p(Expansion_{LT})$					0.018	0.025
						[1.119]	[1.744]
	N	195	193	194	195	195	193
	$Adj.R^2$ (%)	-0.336	-0.215	-0.714	10.083	1.672	15.956

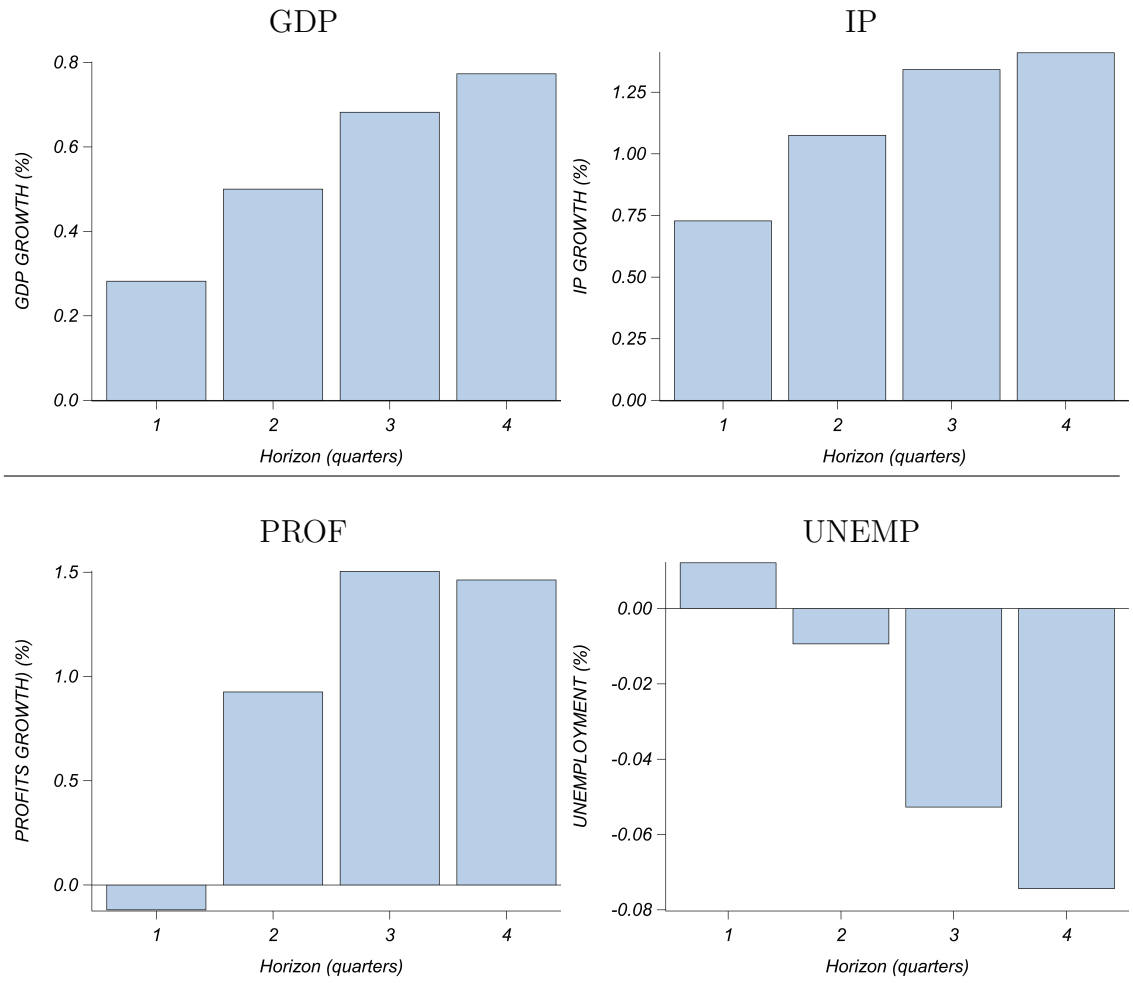


Figure 1

Macroeconomic Expectations: Horizon Bias and the Forecasting Horizon

We define $FE_{t,t+h}$ as the forecast error in the prediction at time t of macroeconomic outcomes to be realized in quarter $t+h$. We then construct a horizon-specific measure of horizon bias as $HB_{t,t+h} = FE_{t,t+h} - FE_{t,t+m}, \quad m < h$. The figure shows the full-sample average horizon bias for horizons $1 \leq h \leq 4$. Like in Table 1, we set $m = 0$, i.e., we use nowcasts as short-term forecasts. The graph reports variation in horizon bias with the forecasting horizon for real GDP growth (GDP), industrial production growth (IP), growth in corporate profits (PROF), and the unemployment rate (UNEMP). Horizon bias is based on forecast errors that are obtained using the historical initial-release estimates of macroeconomic outcomes.

A Horizon Bias: Robustness Evidence

A1 Horizon Bias in Consensus Expectations

.

In Table 1 we show evidence of a systematic increase in optimism bias when the forecast horizon increases. We name this empirical regularity the horizon bias. Our baseline evidence relies on micro-level data on belief formation. Whereas that evidence points to the widespread nature of horizon bias, the evidence could be also driven by a small subset of individuals who are prone to a large horizon bias, with the vast majority of forecasters not really exhibiting such a bias. Moreover, recently Bordalo, Gennaioli, Ma, and Shleifer (2020) have showed that micro-level belief formation can have very different features compared to the belief formation process that governs consensus expectations. The natural question is whether horizon bias survives aggregation. We hence repeat the analysis of Table 1 for consensus expectations. To this end we form a time-series of cross-sectional average expectations (Table A1, Panel A), and a time-series of cross-sectional median expectations (Table A1, Panel A). The results are very similar to the ones of our main table. This result suggests that both micro-level and consensus expectations are subject to horizon bias, and reinforce the notion this bias is widespread.

A2 Horizon Bias: Alternative Construction, Sub-Sample evidence, and International Evidence

. The evidence of horizon bias presented in the paper is based on a few choices that are largely dictated by data availability. First, what we define as "long horizon" does not refer to a very long horizon, as it uses forecasters' prediction of year-ahead outcomes. Second, the short-horizon forecasts used in our main tests are the so called nowcasts. Using nowcasts allows one to measure horizon bias with the largest possible spread between short and long horizon data. However nowcasts could capture biased perceptions of contemporaneous economic conditions, as opposed to expectations of future macroeconomic outcome. Furthermore, horizon bias could be a feature of the data that only characterizes forecasts in a particular portion of our sample. Finally, it is possible that horizon bias is mainly a feature of professional forecasts in the US, while it is absent in other countries.

To address the aforementioned concerns we perform some additional tests. Table A2 shows that the evidence of horizon bias presented in Table 1 is similar in the early portion of the sample (1968-1993, Panel A) and in the later part (1994-2018, Panel B). Thus horizon bias is unlikely to be the result of some very specific event or very special economic conditions.

Table A3 changes the definition of short-term forecasts, as it replaces nowcasts with forecasts of annualized growth between quarter t-1 and t+1 (for real GDP, industrial production, and corporate profits) or with forecasts of the outcome of interest at the end of quarter t+1

(for unemployment). This change in the definition of short-term forecasts does not alter the conclusion that the term structure of macroeconomic optimism is upward-sloping on average.

Table A4 investigates whether the findings of horizon bias in the US extend to other countries and to forecasting horizons beyond one year. To this end we replicate the evidence in Table 1 for macroeconomic forecasts collected as part of the European Central Bank Survey of Professional Forecasters (ECB-SPF). Here, due to data availability, we concentrate on forecasts of future real GDP growth and future unemployment rate in the Euro Area, and we construct forecast errors using estimates of macroeconomic states that are based on the most recent vintage date. The table show that the evidence of horizon bias indeed extends to forecasters outside of the US. In addition,the short-term forecasts in Table A4 are predictions of 1-year ahead macroeconomic states, and the long-term forecasts in the table refer to a horizon of 4 to 5 years into the future. Thus, finding evidence on horizon bias in the ECB-SPF suggests that horizon bias extends to horizons beyond one year. In sum, the additional results in this section indicate that horizon bias is a pervasive and robust feature of macroeconomic expectations.

A3 Time-series Variation in Horizon Bias: Robustness Checks

The results provided in Table 3 indicate that optimism bias and horizon bias in macroeconomic forecasting are linked to theory-based determinants of motivated beliefs. In the Table, the results are obtained using: (i) the principal component of forecast errors for four distinct macroeconomic variables; (ii) historical-release data on macroeconomic outcomes; (iii) "nowcast" as short-term forecasts; (iv) the time-series of cross-sectional mean expectations. In this section we ask whether the evidence in the paper hinges critically on any of these aspects. To this end, Table A5 replicates the results of the multivariate regressions of Table 3. In each of the Panels, the Table assesses whether our results are sensitive to one of the four choices outlined above. In Panel A, we generate the evidence in Table 3 separately for real GDP, industrial production, corporate profits, and the unemployment rate. The regression results, presented alongside the principal component result that was already showed in Table 3, indicate that similar conclusions about the linkage between motivated beliefs and macroeconomic forecasts hold for individual macroeconomic variables.[38]

Panel B of Table A5 repeats the analysis using median forecasts as opposed to mean forecasts, so as to reduce concerns that our results may be driven by a very skewed distribution of forecasts with a handful featuring extreme predictions. The results are virtually unchanged.

[38]It should be noted that, for GDP growth, growth in industrial production, and growth in corporate profits, the sign of the estimated regression coefficients is expected to be the same as the one obtained with the principal component. For regressions of unemployment rate forecasts, where optimism bias and horizon bias are captured by lower, as opposed to higher, forecast errors, the coefficient signs are expected to be opposite to the ones in Table 3. This is precisely what the table shows evidence of.

Similarly, calculating forecast errors based on the most recent estimates of macroeconomic activity (Panel C) does not materially change our results. Finally, when we replace nowcast forecasts as our short-term forecast with forecasts of next-quarter outcomes (Panel D), the results are qualitatively similar, although they become weaker, particularly in the horizon bias estimates. This is to expect, given that in these regressions the short and the long horizon predictions refer to outcomes that are closer in time. Overall, the analysis confirms the relevance of drivers of motivated beliefs for horizon bias and optimism bias in macroeconomic forecasting.

Table A1
Horizon Bias in Consensus Expectations

We aggregate microeconomic expectations data from the Federal Reserve Survey of Professional Forecasters to create quarterly time-series of forecasters' consensus expectations. These consensus beliefs are either measured using cross-sectional average expectations (Panel A), or are proxied for using the beliefs of the median forecaster in a quarter (Panel B). We then repeat the analysis of our main Table 1. More details are in Section 2. t-statistics, in brackets, are based on Newey-West (1987) standard errors with 4 lags (i.e., one year). The sample period is 1968-2018.

	Panel A: Time-Series Means				
Macro Variable	F_{ST}	F_{LT}	HB_{Init}	HB_{Stable}	HB_{Stat}
GDP	2.338	3.059	0.784	0.802	0.693
	[9.396]	[27.148]	[2.515]	[2.467]	[2.600]
N	201	196	194	194	196
IP	2.496	3.825	1.392	1.423	1.296
	[5.424]	[16.180]	[1.944]	[1.966]	[2.337]
N	201	196	194	194	196
PROF	7.201	8.291	1.370	1.477	0.795
	[5.689]	[11.661]	[0.541]	[0.551]	[0.535]
N	201	196	195	195	196
UNEMP	6.209	6.149	-0.080	-0.079	-0.115
	[28.353]	[31.258]	[-0.746]	[-0.736]	[-2.172]
N	201	196	194	194	196
	Panel B: Time-Series Medians				
Macro Variable	F_{ST}	F_{LT}	HB_{Init}	HB_{Stable}	HB_{Stat}
GDP	2.351	3.157	0.863	0.881	0.772
	[9.376]	[26.832]	[2.761]	[2.705]	[2.918]
N	201	196	194	194	196
IP	2.480	3.880	1.465	1.496	1.370
	[5.414]	[18.440]	[2.048]	[2.068]	[2.569]
N	201	196	194	194	196
CPROF	5.340	7.800	2.595	2.703	2.030
	[4.76]	[12.23]	[1.025]	[1.011]	[1.509]
	201	196	195	195	196
UNEMP	6.204	6.143	-0.088	-0.087	-0.123
	[28.291]	[31.282]	[-0.824]	[-0.814]	[-2.321]
N	196	201	196	196	196

Table A2
Horizon Bias: Split-Sample

We repeat the micro-level tests of unconditional horizon bias of Table 1 over two subsamples. These are 1968-1993 (Panel A), or 1994-2018 (Panel B). In brackets are t-statistic double clustered by forecaster and time. More details on the data are in Sections 2.

	Panel A: Sample 1968 - 1993				
Macro Variable	F_{ST}	F_{LT}	HB_{Init}	HB_{Stable}	HB_{Stat}
GDP	2.474	3.617	1.258	1.239	1.125
	[7.146]	[26.882]	[2.378]	[2.313]	[3.269]
N	3480	3416	3399	3399	3399
IP	2.814	4.907	1.870	1.917	2.052
	[4.179]	[20.256]	[1.582]	[1.685]	[2.814]
N	3420	3368	3351	3351	3351
PROF	7.822	10.96	3.680	4.036	3.076
	[4.542]	[16.684]	[0.739]	[1.146]	[1.576]
N	3200	3198	3139	3139	3139
UNEMP	6.656	6.464	-0.217	-0.214	-0.184
	[39.327]	[42.687]	[-1.982]	[-1.994]	[-3.286]
N	3574	3497	3497	3497	3497

	Pane B: Sample 1994 - 2018				
Macro Variable	F_{ST}	F_{LT}	HB_{Init}	HB_{Stable}	HB_{Stat}
GDP	2.380	2.797	0.440	0.462	0.412
	[16.135]	[51.197]	[1.785]	[1.508]	[2.868]
N	3946	3828	3793	3793	3827
IP	2.417	3.215	0.875	0.990	0.797
	[8.974]	[32.538]	[1.290]	[1.255]	[2.957]
N	3608	3529	3498	3498	3529
PROF	7.044	6.471	-0.484	-0.785	-0.6
	[8.292]	[12.327]	[-0.183]	[-0.213]	[-0.679]
N	2370	2432	2322	2322	2322
UNEMP	5.862	5.782	-0.026	-0.026	-0.090
	[33.759]	[35.297]	[-0.285]	[-0.274]	[-2.360]
N	3924	3840	3839	3839	3839

Table A3
Horizon Bias: Alternative Definition

We repeat the micro-level tests of unconditional horizon bias of Table 1 over an alternative definition of short and long-term forecasts. Specifically F_{ST} is the forecast of annualized growth between the quarter prior to the forecast date, i.e.,$t-1$, and the quarter after, i.e., $t+1$. F_{LT} is the forecast of annualized growth between $t+1$ and $t+4$. In brackets are t-statistic double clustered by forecaster and time. More details on the data are in Sections 2 and A .

Macro Variable	F_{ST}	F_{LT}	HB_{Init}	HB_{Stable}	HB_{Stat}
GDP	2.568	3.072	0.453	0.487	0.497
	[16.817]	[34.400]	[2.098]	[2.308]	[4.075]
N	7462	7282	7195	7195	7265
IP	2.978	3.900	0.857	0.995	0.902
	[10.612]	[23.228]	[1.636]	[2.027]	[3.566]
N	7055	6928	6848	6848	6911
PROF	7.095	8.584	2.174	2.071	1.493
	[8.278]	[17.289]	[1.032]	[1.117]	[1.810]
N	5590	5654	5463	5463	5485
UNEMP	6.236	6.095	-0.124	-0.126	-0.141
	[50.980]	[53.710]	[-1.960]	[-2.042]	[-6.106]
N	7533	7373	7373	7373	7373

Table A4
Horizon Bias: International Evidence

We repeat the micro-level tests of unconditional horizon bias of Table 1 using the European Central Bank Survey of Professional Forecasters. We consider two sets of macroeconomic expectations, namely the ones about real GDP growth (GDP) in the Euro Area, and the one about the unemployment rate in the Euro Area. Based on data availability, we define forecasts as follows. F_{ST} is the short-term forecast is an average of the forecaster's prediction for the calendar year in which the survey is taken and the subsequent year. The long-term forecast, F_{LT} , is the forecaster's prediction for the fourth or the fifth calendar year following the year in which the forecaster submitted his prediction, based on data availability. Forecasts of growth refer to non-overlapping periods, and are annualized. Having defined forecast errors as the difference between the forecast and the realized outcomes based on the most recent vintage estimate, HB_{Stable} is the difference between the forecast error at long horizon and the forecast error at short horizon. HB_{Stat} is an alternative metric for horizon bias, that is constructed as the difference between long and short term forecast. In brackets are t-statistic double clustered by forecaster and time. More details on the data are in Sections A .

	(1) F_{ST}	(2) F_{LT}	(3) HB_{Stable}	(4) HB_{Stat}
GDP	1.432	1.979	1.039	0.560
	[13.455]	[44.040]	[7.637]	[5.416]
N	4131	3226	2969	3217
	(1)	(2)	(3)	(4)
UNEMP	9.239	7.979	-1.464	-1.267
	[55.517]	[66.825]	[-6.347]	[-16.054]
	4040	2898	2343	2897

Table A5
Determinants of Time-Series Variation in Horizon Bias: Robustness Checks

Time-series regressions of horizon bias (HB) on a set of explanatory variables measured as of the forecast date. The Table has four panels. Panel A extends the evidence presented in Table 3 to the individual macroeconomic outcomes studied in the paper. Panel B repeats the analysis of Panel A, but measures horizon bias by using stable estimates of macroeconomic outcomes (i.e., estimates as of the most recent vintage date). Panel C performs a similar analysis, but replaces mean forecasts with median forecasts as the left hand side variables in our regressions. Panel D further replicates the main analysis, but adopts an alternative definition of short-term forecasts, in that it uses forecasts of next-quarter outcomes as opposed to nowcasts. Further details are in Section A3 and in Section 5. Inference is based on Newey-West (1987) standard errors with 4 lags (i.e., one year). Forecast data as well as data on ex-post realizations is from the Federal Reserve Survey of Professional Forecasters. The sample period is 1968-2018.

	Panel A:TS Means, Initial Release					Panel B:TS Means, Stable Release				
Variable	(1) GDP	(2) IP	(3) PROF	(4) UNEMP	(5) PC	(1) GDP	(2) IP	(3) PROF	(4) UNEMP	(5) PC
I(REC)	-0.456	-0.764	-0.444	-1.015	-0.373	-0.607	-0.592	-0.515	-1.035	-0.4
	[-0.986]	[-1.467]	[-0.998]	[-3.294]	[-0.747]	[-1.648]	[-1.271]	[-1.125]	[-3.302]	[-0.916]
$N_{badnews}$	-0.104	-0.073	-0.015	0.092	-0.092	-0.066	-0.102	0.052	0.099	-0.08
	[-2.13]	[-1.509]	[-0.365]	[1.78]	[-1.822]	[-1.522]	[-2.28]	[1.319]	[1.908]	[-1.692]
$EG_{t-5,t-1}$	0.02	-0.017	-0.061	-0.057	-0.005	0.024	-0.037	0.059	-0.056	0.029
	[0.317]	[-0.225]	[-0.811]	[-1.144]	[-0.071]	[0.426]	[-0.48]	[1.254]	[-1.129]	[0.527]
$Memory_{MN11}$	-8.211	-6.925	-6.105	6.459	-9.28	-6.225	-9.583	-8.104	6.606	-11.162
	[-1.286]	[-1.071]	[-1.158]	[0.793]	[-1.346]	[-1.081]	[-1.49]	[-1.182]	[0.808]	[-1.544]
σ^Y_{ST}	-7.887	-9.727	-7.727	2.206	-9.542	-6.214	-13.456	-7.592	2.08	-11.138
	[-1.705]	[-1.909]	[-1.683]	[0.499]	[-2.107]	[-1.372]	[-2.494]	[-1.765]	[0.479]	[-2.446]
σ^Y_{LT}	17.016	18.147	13.658	-9.036	19.525	13.678	22.25	11.465	-8.769	20.914
	[2.455]	[2.399]	[2.385]	[-1.376]	[2.919]	[2.032]	[3.156]	[2.032]	[-1.349]	[3.242]
$p(Expansion_{ST})$	-0.001	-0.002	0.001	0	-0.001	-0.003	-0.004	-0.011	0	-0.007
	[-0.137]	[-0.282]	[0.097]	[-0.063]	[-0.136]	[-0.581]	[-0.53]	[-1.923]	[0.059]	[-1.058]
$p(Expansion_{LT})$	0.02	0.024	0.01	-0.023	0.025	0.022	0.026	0.001	-0.022	0.026
	[1.477]	[1.556]	[0.781]	[-2.019]	[1.744]	[1.495]	[1.993]	[0.082]	[-1.918]	[1.914]
N	193	193	194	194	193	193	193	194	194	193
Adj. R^2 (%)	13.491	11.541	2.414	33.418	15.956	8.712	13.933	3.98	34.354	17.516

Table A5
Determinants of Time-Series Variation in Horizon Bias: Robustness Checks (Continued)

Variable	Panel C:TS Medians, Initial Release					Panel D:TS Means (Alternative), Initial Release				
	(1) GDP	(2) IP	(3) PROF	(4) UNEMP	(5) PC	(1) GDP	(2) IP	(3) PROF	(4) UNEMP	(5) PC
I(REC)	-0.439	-0.791	-0.412	-1.021	-0.365	-1.005	-1.358	-0.578	-0.397	-0.848
	[-0.92]	[-1.478]	[-0.954]	[-3.301]	[-0.716]	[-2.137]	[-2.581]	[-1.134]	[-1.007]	[-1.64]
$N_{badnews}$	-0.102	-0.071	-0.013	0.09	-0.091	-0.111	-0.097	-0.034	0.103	-0.105
	[-2.096]	[-1.49]	[-0.333]	[1.747]	[-1.799]	[-2.329]	[-1.962]	[-0.879]	[1.899]	[-2.132]
$EG_{t-5,t-1}$	0.024	-0.013	-0.059	-0.055	-0.001	-0.018	-0.08	-0.098	-0.087	-0.038
	[0.364]	[-0.172]	[-0.779]	[-1.129]	[-0.016]	[-0.365]	[-1.203]	[-1.73]	[-1.68]	[-0.687]
$Memory_{MN11}$	-7.095	-6.238	-4.62	5.875	-8.037	-9.063	-8.263	-7.293	7.043	-9.972
	[-1.121]	[-0.969]	[-0.891]	[0.723]	[-1.171]	[-1.511]	[-1.334]	[-1.226]	[0.876]	[-1.521]
σ^Y_{ST}	-7.765	-9.339	-7.092	2.911	-9.35	-10.709	-11.331	-12.045	3.452	-11.622
	[-1.658]	[-1.828]	[-1.605]	[0.661]	[-2.056]	[-2.663]	[-2.523]	[-2.496]	[0.84]	[-2.726]
σ^Y_{LT}	16.911	17.721	12.857	-10.005	19.395	20.559	19.833	19.378	-10.804	21.618
	[2.418]	[2.345]	[2.326]	[-1.522]	[2.887]	[3.305]	[2.877]	[3.126]	[-1.671]	[3.288]
$p(Expansion_{ST})$	-0.001	-0.002	0.002	0	0	-0.006	-0.008	-0.001	0.007	-0.007
	[-0.089]	[-0.213]	[0.354]	[-0.094]	[-0.011]	[-0.765]	[-1.258]	[-0.275]	[1.154]	[-1.007]
$p(Expansion_{LT})$	0.019	0.022	0.013	-0.022	0.024	0.026	0.028	0.023	-0.026	0.03
	[1.381]	[1.461]	[1.002]	[-1.913]	[1.714]	[2.106]	[1.908]	[1.644]	[-2.153]	[2.281]
N	193	193	194	194	193	193	193	194	194	193
$Adj.R^2(\%)$	13.523	11.303	1.965	33.353	15.876	19.316	21.752	8.937	27.051	20.133

B Horizon Bias and Rational Expectations

B1 Horizon Bias and Strategic Considerations

In this Section we ask whether forecasters' strategic considerations can generate the horizon bias.[39] For instance, Michaely and Womack (2005) describe the compensation and career advancement of sell-side analysts who work in the brokerage departments of the largest investment banks in the U.S. They note that these analysts' compensation does not only depend on the reputation they build by issuing accurate forecasts. Rather, these analysts often receive bonuses and promotions when they systematically issue optimistic forecasts that help the corporate finance division of the bank gain new customers or retain existing ones. Even when analysts aim for accuracy, they can find it optimal to issue a somewhat more optimistic forecast rather than a less optimistic one, as corporate managers reward optimistic forecasters with better access (Francis, Hanna, and Philbrick 1997; Chen and Matsumoto 2006), and punish pessimistic forecasters by "freezing them out".

To see what implications these strategic considerations have for horizon bias, we consider a simple model with a risk-neutral analyst with perfect foresight about the future realization of a firm's profits. The analyst's compensation is based on both his reputation for accuracy and the career benefits that excessively optimistic forecasts of firms' profits entail. The analyst chooses the optimal strategic level of optimism bias in short and long-horizon forecasts, ε^{ST^2} and ε^{LT^2}, respectively, by solving the following problem:

$$\max_{\varepsilon^{ST},\varepsilon^{LT}} E_t\left[R_{ST}\left(1-\alpha_{ST}\varepsilon^{ST^2}\right)+R_{LT}\left(1-\alpha_{LT}\varepsilon^{LT^2}\right)+P_{ST}\left(\varepsilon^{ST}\right)+P_{LT}\left(\varepsilon^{LT}\right)\right]-C_1\varepsilon^{ST^2}-C_2\varepsilon^{LT^2} \tag{B.1}$$

where R_{ST} and R_{LT} capture the reputational benefits of accuracy in short and long-term forecasts, P_{ST} and P_{LT} are the career benefits of issuing positively biased forecasts at short and long horizon, and C_1 and C_2 represent the personal cost of disguising the analyst's actual forecast by issuing biased predictions.

We solve this simple model and obtain:

$$\begin{cases} \varepsilon^{ST^*} = \frac{P_{ST}}{2(C_1+\alpha_{ST}R_{ST})} \\ \varepsilon^{LT^*} = \frac{P_{LT}}{2(C_2+\alpha_{LT}R_{LT})} \end{cases} \tag{B.2}$$

[39] See Scharfstein and Stein (1990), Ehrbeck and Waldmann (1996), and Frankel, Kothari, and Weber (2006) are classical examples of work on strategic considerations affecting forecasts.

Horizon bias arises due to strategic considerations if $\varepsilon^{LT^*} > \varepsilon^{ST^*}$, i.e.,

$$\frac{P_{LT}}{(C_2 + \alpha_{LT} R_{LT})} > \frac{P_{ST}}{(C_1 + \alpha_{ST} R_{ST})} \tag{B.3}$$

Even though it is possible that forecasters' strategic considerations lead to horizon-specific benefits and costs, and thus can generate horizon bias, we argue that such strategic considerations are unlikely to be behind the results we document for the Survey of Professional Forecasters (SPF) in the US and in the Eurozone. First, the forecasters interviewed in these surveys submit their forecasts under the condition of anonymity (e.g., Elliott, Komunier and Timmermann 2005). The survey organizers pride themselves for having maintained this condition intact for many decades (Garcia (2003), Croushore and Stark (2019)). This means that, within the context of the model above, $R_{ST} = R_{LT} = 0$, i.e., these forecasters do not gain reputation benefits from issuing forecasts that cannot be observed by third parties. Moreover, the forecasts issued in these two surveys concern the macroeconomy. As such, expressing optimism in these forecasts does not help forecasters please any firm, nor advance their careers, i.e., $P_{ST} = P_{LT} = 0$. In other words, the forecasters in the surveys that we analyze lack the incentives to issue forecasts strategically. As a result, $\varepsilon^{ST^*} = \varepsilon^{LT^*} = 0$, i.e., it is very unlikely that horizon bias in these surveys is due to strategic considerations.

B2 State-dependent Information Rigidities and Horizon Bias

Can time-varying information rigidities account for the evidence of unconditional horizon bias presented in Table 1? To investigate this formally, we consider a model of sticky information (Mankiw and Reis (2002)) with a time- varying rigidity parameter, λ_t. As in Equation (4), we write the time-t forecast of outcome x_{t+h} to be realized h periods later as:

$$F^{SI}_{t+h|t} = (1-\lambda_t)\sum_{j=0}^{\infty}\lambda_t^j E_{t-j}\pi_{t+h} \tag{B.4}$$

Where information rigidity is time-varying. We assume a standard AR(1) law of motion for process $\{\pi_t\}$,

$$\pi_{t+1} = \mu(1-\rho) + \rho\pi_t + \varepsilon_{t+1} \tag{B.5}$$

where μ is the long-run mean and the process, ρ is the root, and $\varepsilon_{t+1} \sim N(0,\sigma^2)$. Based on the above, one can write horizon bias as follows:

$$\begin{gathered} HB^{SI}_t = \left(F^{SI}_{t+h|t} - \pi_{t+h}\right) - \left(F^{SI}_{t+1|t} - \pi_{t+1}\right) = \\ \lambda_t\left(\rho-\rho^h\right)(\pi_t-\mu) - \lambda_t(1-\lambda_t)\sum_{j=0}^{\infty}\left[(\pi_t-\mu)\left(\rho^{j+2}-\rho^{j+h+1}\right)\right] \end{gathered} \tag{B.6}$$

When λ_t is constant, it is easy to see how Equation (B3) reiterates the result in the paper (Section 4.1.2) that information rigidities cannot generate horizon bias unconditionally, i.e., $E\left[HB^{SI}_t\right] = 0$. On the other hand, when information rigidities are time-varying, horizon bias need not to be equal to zero on average. Having defined $\{\tilde{\pi}_t\}$ as the unconditionally demeaned outcome of interest, one can write

$$E\left[HB^{SI}_t\right] = \left(\rho-\rho^h\right)E\left[\tilde{\pi}_t\lambda_t\right] + \sum_{j=0}^{\infty}E\left[\left(\lambda_t^{j+2}-\lambda_t^{j+1}\right)\widetilde{\pi_{t-1-j}}\left(\rho^{j+2}-\rho^{j+h+1}\right)\right] \tag{B.7}$$

To learn whether horizon bias is unconditionally positive or negative in this model, and how large it is, one needs to specify the covariance structure of λ_t and $\widetilde{x_{t-j}}$ for $j \geq 0$. To this end, we choose to focus on one macroeconomic variable in particular, namely real GDP growth, for which we can rely on insights from Coibion and Gorodnichenko (2015). They show that λ_t is highly negative correlated with macroeconomic uncertainty, measured as the 5 - year trailing standard deviation of real GDP growth in the US (henceforth σ_t). Based on this, we model the information rigidity time-series as

$$\lambda_t = a - b\sigma_t \tag{B.8}$$

where the parameters a and b, both positive, are chosen to match the observed dynamics of λ_t. In particular, we use CG (2015) estimate of the full-sample average value of $\frac{\lambda}{(1-\lambda)}$ in the forecast

of GDP growth (0.5) to back out the average value of the information rigidity parameter in the sample (0.333). We then assume that when σ_t reaches its maximum historical level in the sample period (0.079), rigidities are absent, as λ_t drops to 0. This renders the following equation for λ_t

$$\lambda_t = 0.194 - 6.938\sigma_t \tag{B.9}$$

Using the time-series of real GDP from the Federal Reserve, we can now obtain sample estimates for $E\left[\widetilde{x_{t-j}}\lambda_t\right]$ for all values of the lag parameter j. We then plug them into Equation B.7. This renders a negative estimate of $E\left[HB_t^{SI}\right]$. Thus time-series variation in information rigidities stemming from variation in macroeconomic uncertainty cannot easily explain the evidence of horizon bias in Table 1.[40]

We also consider a second quantification of the unconditional horizon bias generated under time-varying information rigidities. To this end, we rely on another insight from CG (2015), namely that information rigidities progressively decline following the beginning of a recession, to reach a minimum 8 quarters after the recession start, and return to normal level 16 quarters after a recession has begun. We hence propose a second equation for time-series variation in information rigidities:

$$\lambda_t = \max\left(0.457 - 0.457\sum_{j=1}^{16}\frac{j}{8}I\left(\text{Rec}_{\text{Start}}\right)_{t-j} + 0.914\sum_{j=9}^{16}\frac{j-8}{8}I\left(\text{Rec}_{\text{Start}}\right)_{t-j}, 0.001\right). \tag{B.10}$$

where $I\left(\text{Rec}_{\text{Start}}\right)_{t-j}$ is an indicator variable that is equal to 1 if a recession has started less than j quarters ago, and the coefficients 0.457 and 0.914 are chosen to match the unconditional value of information rigidities in forecast of GDP growth documented in CG (2015). Based on this second parametrization of λ_t we estimate again Equation (B4). Here too we find that the expected horizon bias stemming from information rigidities is negative. Overall, it does not appear that an upward sloping term structure of optimism stems from the time-series variation in information rigidities of that has been uncovered in prior literature.[41]

[40] To obtain this estimate, we need to truncate the infinite summation of Equation (B4) to 20 lags (i.e., 5 years). The result that a negative horizon bias obtains is robust to the selection of another macroeconomic uncertainty metric, such as the one proposed by Jurado, Ludvigson, and Ng (2015).

[41] Unreported simulation results indicate that $\text{E}\left[\lambda_t\widetilde{x}_t\right]$ is the dominating element in Equation (B4), thus the sign of $E\left[HB_t^{SI}\right]$ is largely determined by the contemporaneous covariance of x_t and λ_t. The negative horizon bias obtained in the first setting above can hence be explained with the positive, albeit weak, correlation between σ_t and x_t(13%) that is observed in the data, which implies a small negative correlation between λ_t and $\tilde{x}_t$. Similarly, the second setting delivers a negative horizon bias since the rigidity proxy obtained in Equation (B6) is mildly negatively correlated (12%) with the real GDP growth.

C Optimal Expectations and Horizon Bias

D1 Model

In this section, we show that agents will exhibit the horizon bias, or be more optimistic at long horizons relative to short horizons when they invest in the short horizon asset, in an extension of the model proposed by Brunnermeier and Parker (2005).

We define π_s as the true probability of a given state. We define $\hat{\pi}_s$ as the probability an agent assigns to a given state s. The optimal portfolio choice is denoted $\alpha^*.\beta$ is a constant time discount factor. Specifically, we consider the same portfolio choice problem discussed in Brunnermeier and Parker (2005). In period one, the agent chooses her portfolio share, α, such that she maximizes her expected utility. Specifically, the agent solves the following problem

$$\begin{array}{c} \max_{\alpha} \beta \sum_{s=1}^{S} \widehat{\pi}_s U\left(c_s\right) \\ \text{s.t. } \mathrm{c}_s = R + \alpha Z_s \\ c_s \geq 0 \end{array} \tag{C.1}$$

where R is the gross return of the risk-free asset and Z_s is the excess return above the risk-free return in state S. U is an increasing concave function with infinite marginal utility at 0. There are S states. The S states are organized such that for $Z_{s+1} > Z_s, Z_1 < 0 < Z_s$, and $Z_s \neq Z_{s'}$ for $s' \neq s$. Optimal expectations imply that consumption will never equal zero - given that there is infinite marginal utility at zero, the agent will adjust probabilities such that consumption will be nonzero in the associated state. After setting up the Lagrangian we know that the optimal portfolio is characterized by

$$0 = \sum_{s=1}^{S} \widehat{\pi}_s U'\left(R + \alpha^* Z_s\right) Z_s \Rightarrow \alpha^*\left(\{\widehat{\pi}_s\}\right) \tag{C.2}$$

We then consider a model that relies on this optimal portfolio choice. Our model is an extension of Brunnermeier and Parker (2005). Brunnermeier and Parker (2005) consider agents that decide how much to invest in an asset that pays off and is consumed in the 1^{st} period. We add an additional period such that agents decide how much to invest in a period 1 asset that can only be consumed in the 1^{st} period, and a period 2 asset that can only be consumed in the 2^{nd} period. Therefore, the agent's portfolio choice for the 1^{st} period and the agent's portfolio choice for the 2^{nd} period can both be characterized by equation (1.2). For comparison purposes, we assume that the true distribution of the 1^{st} period asset and the true distribution of the 2^{nd} period asset are the same. That is, $\pi_{2,s} = \pi_{1,s} = \pi_s$ and $Z_{2,s} = Z_{1,s} = Z_s$. Brunnermeier and Parker (2005) assume that individuals' well-being is a time-average of felicities in period 0 and period 1. We extend their model such that an individual's well-being is a time-average of felicities in period 0, period 1 and period 2. In

period 0, the agent's felicity is the subjectively expected discounted utility flow in the next two periods. In period 1, the agent's felicity comes from anticipated utility in the 2nd period and from actual consumption in the 1st period. The agent's 2nd period utility flow is based on actual consumption in the 2nd period. In other words, agents look to optimize their well-being (WB) by solving the following problem, where $S_1 = S$ is the total number of states in the 1st period, $S_2 = S$ is the total number of states in the 2nd period, and $\{\widehat{\pi}_a\} = \{\widehat{\pi}_{a,1}, \widehat{\pi}_{a,2}, \ldots, \widehat{\pi}_{a,S}\}$ is the sequence of investor beliefs across all states in period a :

$$\max_{\{\widehat{\pi}_1\},\{\widehat{\pi}_2\}} \frac{1}{3} \left[\begin{array}{l} WB = \beta \sum_{s=1}^{S} \widehat{\pi}_{1,s} U\left(R + \alpha^*\left(\{\widehat{\pi}_1\}\right) Z_s\right) + \beta^2 \sum_{s=1}^{S} \widehat{\pi}_{2,s} U\left(R + \alpha^*\left(\{\widehat{\pi}_2\}\right) Z_s\right) + \\ \beta \sum_{s=1}^{S} \pi_s U\left(R + \alpha^*\left(\{\widehat{\pi}_1\}\right) Z_s\right) + \\ \beta^2 \sum_{s=1}^{S} \widehat{\pi_{2,s}} U\left(R + \alpha^*\left(\{\widehat{\pi}_2\}\right) Z_s\right) + \beta^2 \sum_{s=1}^{S} \pi_s U\left(R + \alpha^*(\{\pi\}) Z_s\right) \end{array} \right] \tag{C.3}$$

In other words, agents maximize their well-being by arriving at expectations that make them happiest in expectation. This hedonic editing of their beliefs involves a trade-off between greater anticipation utility and suboptimal realized utility (from making suboptimal choices). We can rewrite the optimization in (1.3) as two optimization problems since $\{\widehat{\pi}_1\}, \{\widehat{\pi}_2\}$ are disjoint in the maximization problem. Specifically, (1.3) is equivalent to finding the optimal to the following two problems[1]:

$$\max_{\{\widehat{\pi}_1\}} \left[WB_1 = \beta \sum_{s=1}^{S} \widehat{\pi}_{1,s} U\left(R + \alpha^*\left(\{\widehat{\pi}_1\}\right) Z_s\right) + \beta \sum_{s=1}^{S} \pi_s U\left(R + \alpha^*\left(\{\widehat{\pi}_1\}\right) Z_s\right) \right] \tag{C.4}$$

and

$$\max_{\{\widehat{\pi}_2\}} \left[WB_2 = 2\beta^2 \sum_{s=1}^{S} \widehat{\pi}_{2,s} U\left(R + \alpha^*\left(\{\widehat{\pi}_2\}\right) Z_s\right) + \beta^2 \sum_{s=1}^{S} \pi_s U\left(R + \alpha^*\left(\{\widehat{\pi}_2\}\right) Z_s\right) \right] \tag{C.5}$$

We note that in each period there must be a state s' such that the payout in the state $Z_{s'}$ is negative and another state s'' such that the payout in that state $Z_{s''}$ is positive. Otherwise, the agent would short or invest, respectively, as much as possible. This would result in a contradiction from (1.2) since consumption would then equal 0 in the first state or the last state. We also assume that the agent thinks all states have a positive probability. Therefore, we can consider the first-order condition associated with moving $d\hat{\pi}$ from s' to s''.[2] We next

[1]For notational purposes, we do not need a subscript on α^*, because a given probability distribution will yield the same α^* for the long-term asset and the short-term asset. We can see this from the fact that the only thing that will change in (1.1)'s optimization for the long-term asset and the short-term asset is that the objective will be multiplied by a constant.

[2]Another way to think about this is that we're setting the probability of state s' equal to $\widehat{\pi}_{s'} - t$, and setting the probability of state s'' equal to $\widehat{\pi}_{s''} + t$ and examining how α^* changes with t.

show that, for $\alpha^* > 0$, $\frac{d\alpha^*}{d\pi} > 0$. Consider equation (1.2) and consider moving $d\widehat{\pi}$ from s' to s'' It follows that

$$0 = \left(U'\left(R + \alpha^* Z_{s''}\right) Z_{s''} - U'\left(R + \alpha^* Z_{s'}\right) Z_{s'}\right) d\widehat{\pi} + \sum_{s=1}^{S} \pi_s U''\left(R + \alpha^* Z_s\right) Z_s^2 d\alpha^* \tag{C.6}$$

which implies that

$$\frac{d\alpha^*}{d\widehat{\pi}} = \frac{-\left(U'\left(R + \alpha^* Z_{s''}\right) Z_{s''} - U'\left(R + \alpha^* Z_{s'}\right) Z_{s'}\right)}{\sum_{s=1}^{S} \widehat{\pi}_s U''\left(R + \alpha^* Z_s\right) Z_s^2} \tag{C.7}$$

But, since we assume U is concave and increasing, this implies that $\frac{d\alpha^*}{d\widehat{\pi}} > 0$. Specifically, the numerator will be negative since the first derivative of U is positive, and the denominator will be negative since the second derivative of U is negative.

Define $\left\{\widehat{\pi}_1^{1OE}\right\}$ as the sequence of optimal expectations for all states that solve (1.4). Assume $\alpha^*\left(\left\{\widehat{\pi}_1^{1OE}\right\}\right) > 0$. Consider a change at the optimum of moving $d\widehat{\pi}_1$ from s' to s''. At the optimum, we know that $\frac{\partial WB_1}{\partial \widehat{\pi}_1} = 0$. Assume that we have the same belief distribution for the long-term asset, $\left\{\widehat{\pi}_1^{1OE}\right\} = \left\{\widehat{\pi}_2^{1OE}\right\}$ Consider how WB_2 changes at this belief distribution with a movement of $d\widehat{\pi}_2$ from s' to s'' $\cdot\, \widehat{\pi}_{2,s}^{1OE}$ is the perceived probability of the period 2 asset being in state S under the $\left\{\widehat{\pi}_2^{1OE}\right\}$ probability distribution and $\pi_{2,s}$ is the actual probability of the period 2 asset being in state S. since we assume the true probability distribution is the same for the period 1 asset and the period 2 asset, $\pi_{2,s} = \pi_{1,s} = \pi_s$ and $Z_{2,s} = Z_{1,s} = Z_s$. Additionally, since we assume $\left\{\widehat{\pi}_1^{1OE}\right\} = \left\{\widehat{\pi}_2^{1OE}\right\}$, we know that $\widehat{\pi}_{2,s}^{1OE} = \widehat{\pi}_{1,s}^{1OE}$

$$\begin{aligned}
\tfrac{\partial WB_2}{\partial \widehat{\pi}_2}\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right) &= 2\beta^2 \left(\begin{array}{c} U\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s''}\right) - U\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s'}\right) + \\ \sum_{s=1}^{S} \widehat{\pi_{2,s}}^{1OE} U'\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{2,s}\right)Z_{2,s}\tfrac{d\alpha^*}{d\widehat{\pi}_2} \end{array} \right) \\
&\quad +\beta^2 \textstyle\sum_{s=1}^{S} \pi_{2,s} U'\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{2,s}\right)Z_{2,s}\tfrac{d\alpha^*}{d\widehat{\pi}_2} \\
&= \beta^2 \left(\begin{array}{c} U\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s''}\right) - U\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s'}\right) + \\ \sum_{s=1}^{S} \widehat{\pi_{2,s}}^{1OE} U'\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s}\right)Z_{s}\tfrac{d\alpha^*}{d\widehat{\pi}_2} \end{array} \right) \\
&\quad + \left(\begin{array}{c} \beta^2 \left(\begin{array}{c} U\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s''}\right) - U\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s'}\right) + \\ \sum_{s=1}^{S} \widehat{\pi_{2,s}}^{1OE} U'\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s}\right)Z_{s}\tfrac{d\alpha^*}{d\widehat{\pi}_2} \end{array} \right) \\ \beta^2 \textstyle\sum_{s=1}^{S} \pi_s U'\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s}\right)Z_{s}\tfrac{d\alpha^*}{d\widehat{\pi}_2} \end{array} \right) \\
&= \beta^2 \left(\begin{array}{c} U\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s''}\right) - U\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s'}\right) + \\ \tfrac{d\alpha^*}{d\widehat{\pi}_2} \sum_{s=1}^{S} \widehat{\pi_{2,s}}^{1OE} U'\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s}\right)Z_{s} \end{array} \right) + \beta\left(\tfrac{\partial WB_1}{\partial \widehat{\pi}_1}\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)\right) \\
&= \beta^2 \left(U\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s''}\right) - U\left(R+\alpha^*\left(\left\{\widehat{\pi}_2^{1OE}\right\}\right)Z_{s'}\right)\right) > 0
\end{aligned} \tag{C.8}$$

where the last equality follows from (1.2), our belief choice of $\left\{\widehat{\pi}_1^{1OE}\right\} = \left\{\widehat{\pi}_2^{1OE}\right\}$, and the definition of the optimum. The final inequality follows from the fact that U is an increasing function and our assumption that $\alpha^*\left(\left\{\widehat{\pi}_1^{1OE}\right\}\right) > 0$ Define $\alpha_1^{OE} = \alpha^*\left(\left\{\widehat{\pi}_1^{1OE}\right\}\right)$ and $\alpha^*(\pi) = \alpha^{RE}$. If we assume that $\alpha_1^{OE}, \left\{\widehat{\pi}_1^{OE}\right\}$ is a unique local optimum in the positive region for $\alpha^*\left(\widehat{\pi}_a\right)$ such that $0 < \alpha^{RE} < \alpha^*\left(\widehat{\pi}_a\right) < \alpha_1^{OE}$, then it follows that $\frac{\partial WB_1}{\partial \widehat{\pi}} = \frac{\partial WB_1}{\partial \widehat{\pi}_1} > 0$ for all α^* such that $0 < \alpha^{RE} < \alpha^*\left(\widehat{\pi}_a\right) < \alpha_1^{OE}$.[3] Therefore, we know that

$$\frac{\partial WB_1}{\partial \widehat{\pi}_1}\left(\{\widehat{\pi}_a\}\right) = \beta \left(\begin{array}{c} U\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_{s''}\right) - U\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_{s'}\right) + \\ \sum_{s=1}^{S_2} \widehat{\pi}_{a,s} U'\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_{s}\right)Z_{s}\tfrac{d\alpha^*}{d\widehat{\pi}_1} + \sum_{s=1}^{S_2} \pi_s U'\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_{s}\right)Z_{s}\tfrac{d\alpha^*}{d\widehat{\pi}_1} \end{array} \right) > 0$$

$$\begin{aligned}
\Rightarrow U\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_s''\right) - U\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_{s'}\right) + \sum_{s=1}^{S_2} \widehat{\pi}_{a,s} U'\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_{s}\right)Z_{s}\frac{d\alpha^*}{d\pi_1} > \\
-\frac{d\alpha^*}{d\widehat{\pi_1}} \sum_{s=1}^{S_2} \pi_s U'\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_{s}\right)Z_{s}
\end{aligned}$$

But, we know that

[3]From Brunnermeier and Parker (2005), we know that if the investment has a positive expected value, $\alpha^{RE} > 0$ and there exists an equilibrium with $\alpha^{1OE} > \alpha^{RE}$.

$$\begin{array}{c}\sum_{s=1}^{S}\pi_s U'\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_s\right)Z_s=\sum_{s\ni Z_s<0}\pi_s U'\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_s\right)Z_s \\ +\sum_{s\ni Z_s>=0}\pi_s U'\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_s\right)Z_s \\ <\sum_{s\ni Z_s<0}\pi_s U'\left(R+\alpha^{RE}Z_s\right)Z_s+\sum_{s\ni Z_s>=0}\pi_s U'\left(R+\alpha^{RE}Z_s\right)Z_s=0\end{array} \tag{C.9}$$

where the inequality comes from the fact that $0<\alpha^{RE}<\alpha^*\left(\widehat{\pi}_a\right)$. Combining (1.6), (1.8), and (1.9), we know that

$$U\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_{s''}\right)-U\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_{s'}\right)+\sum_{s=1}^{S_2}\widehat{\pi}_s^a U'\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_s\right)Z_s\frac{d\alpha^*}{d\widehat{\pi}}>0 \tag{C.10}$$

$$\begin{array}{l}\text{Calculating } \dfrac{\partial WB_2}{\partial\widehat{\pi}_2}\left(\{\widehat{\pi}_a\}\right)=\dfrac{\partial WB_2}{\partial\widehat{\pi}}\left(\{\widehat{\pi}_a\}\right): \\ \dfrac{\partial WB_2}{\partial\widehat{\pi}_2}\left(\{\widehat{\pi}_a\}\right)=\beta\dfrac{\partial WB_1}{\partial\widehat{\pi}}\left(\{\widehat{\pi}_a\}\right)+\beta^2\left(\begin{array}{l}U\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_{s''}\right)-U\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_{s'}\right)+ \\ \sum_{s=1}^{s_2}\widehat{\pi}_s^a U'\left(R+\alpha^*\left(\{\widehat{\pi}_a\}\right)Z_s\right)Z_s\frac{d\alpha^*}{d\widehat{\pi}}\end{array}\right)> \\ \beta\dfrac{\partial WB_1}{\partial\widehat{\pi}}\left(\{\widehat{\pi}_a\}\right)>0\end{array} \tag{C.11}$$

where the first inequality follows from (1.10) and the fact that β is a positive constant. since WB_2 increased with $d\pi$ from a starting point of $\left\{\widehat{\pi}_1^{OE}\right\}$, and is also increasing for all α^* such that $0<\alpha^{RE}<\alpha^*\left(\widehat{\pi}_a\right)<\alpha_1^{OE}$, it follows that $\alpha_1^{OE}<\alpha_2^{OE}$.[4] This means that when investors allocate a positive amount to the short-term asset, there exists an equilibrium where they will allocate an even greater amount to the longterm asset.[5]

We next show that this implies that investors are more optimistic at long horizons relative to short horizons. From the earlier first order condition (1.2), we know that:

$$\sum_{s=1}^{S}\widehat{\pi}_{1,s}U'\left(R+\alpha^*\left(\{\widehat{\pi}_1\}\right)Z_s\right)Z_s=0 \tag{C.12}$$

This can be rewritten as:

$$\sum_{s\ni Z_s<0}^{S}\widehat{\pi}_{1,s}U'\left(R+\alpha^*\left(\{\widehat{\pi}_1\}\right)Z_s\right)Z_s+\sum_{s\ni Z_s>=0}^{S}\widehat{\pi}_{1,s}U'\left(R+\alpha^*\left(\{\widehat{\pi}_1\}\right)Z_s\right)Z_s=0 \tag{C.13}$$

[4]From Bénabou (2015), we know that there exists an equilibrium with $\alpha_2^{OE}>\alpha^{RE}$.

[5]A similar proof shows that when $\alpha_1^{OE}<0$, there exists an $\alpha_2^{OE}<\alpha_1^{OE}$.

But, we know from before that $\alpha_2^* > \alpha_1^*$. This implies that:

$$\sum_{s \ni Z_s < 0}^{S} \widehat{\pi}_{1,s} U'\left(R + \alpha^*\left(\{\widehat{\pi}_2\}\right) Z_s\right) Z_s + \sum_{s \ni Z_s >= 0}^{S} \widehat{\pi}_{1,s} U'\left(R + \alpha^*\left(\{\widehat{\pi}_2\}\right) Z_s\right) Z_s < 0 \tag{C.14}$$

From the earlier, first order condition, we also know that

$$\sum_{s=1}^{S} \widehat{\pi}_{2,s} U'\left(R + \alpha^*\left(\{\widehat{\pi}_2\}\right) Z_s\right) Z_s = 0 \tag{C.15}$$

This implies that:

$$\sum_{s=1}^{S} \left(\widehat{\pi}_{2,s} - \widehat{\pi}_{1,s}\right) U'\left(R + \alpha^*\left(\{\widehat{\pi}_2\}\right) Z_s\right) Z_s > 0 \tag{C.16}$$

which implies that agents are more optimistic at long horizons relative to short horizons.

D2 Horizon Bias and Skewness

In the previous section, we demonstrated that investors will exhibit the horizon bias when they have a positive investment in the short horizon asset. In this section, we will show that for an asset with a sufficiently negative skewness, the investor will switch from a long position to a short position in the short horizon asset, and the investor will exhibit the opposite of the horizon bias - the investor will be more pessimistic at long horizons relative to short horizons.

Like Brunnermeier and Parker (2005), we consider an example to highlight this intuition. We assume a positive expected excess return to asset Z equal to μ_z. The two states are defined as such:

State	Probability	Excess Payoff
1	$\pi_1 = 1 - \pi_2$	$Z_1 = \mu_z - \sigma_z \sqrt{\frac{\pi_2}{1-\pi_2}}$
2	π_2	$Z_2 = \mu_z + \sigma_z \sqrt{\frac{1-\pi_2}{\pi_2}}$

(C.17)

When the probability of the good state is small, the asset is positively skewed. When the probability of the good state is large, the asset is negatively skewed. We know from the previous section that, if the agent shorts the short-term asset, then the agent shorts the long-term asset to an even greater degree.

We prove that there exists a level of negative skewness for which the agent will short the short-term asset by constructing a lower bound for well-being when shorting the asset, an upper bound for well-being when long the asset and showing that for a sufficiently low level of

negative skewness this lower bound for well-being when short the asset will be higher than the upper bound for well-being when long the asset. We again assume that the true distribution for the short-term asset and the long-term asset are the same. Based on (1.3), an agent's well-being in the described two-state world can be defined as

$$\begin{aligned} &W\left(\widehat{\pi}_1^1, \widehat{\pi}_1^2; \pi_1\right) = \\ &\frac{1}{3}\beta\left[\left(\pi_1 + \widehat{\pi}_1^1\right) U\left(R + \alpha^*\left(\left\{\widehat{\pi}_1^1\right\}\right) Z_1\right) + \left(2 - \pi_1 - \widehat{\pi}_1^1\right) U\left(R + \alpha^*\left(\left\{\widehat{\pi}_1^1\right\}\right) Z_2\right)\right] + \\ &\frac{1}{3}\beta^2\left[\left(\pi_1 + 2\widehat{\pi}_1^2\right) U\left(R + \alpha^*\left(\left\{\widehat{\pi}_1^2\right\}\right) Z_1\right) + \left(3 - \pi_1 - 2\widehat{\pi}_1^2\right) U\left(R + \alpha^*\left(\left\{\widehat{\pi}_1^2\right\}\right) Z_2\right)\right] \end{aligned} \tag{C.18}$$

where $\hat{\pi}_a^b$ represents the agents belief about the likelihood of state a for an asset that pays off in period b and π_a is the true probability of state a. We first assume that the investor is short the asset, and the asset is sufficiently negatively skewed s.t. the investor will also be short the long-term asset. since the investor is short the asset, we first assume an optimistic belief $\hat{\pi}_1' = \hat{\pi}_1^1 = \hat{\pi}_1^2 > \pi_1$. This is not necessarily an optimal belief so $W\left(\widehat{\pi}_1', \widehat{\pi}_1'; \pi_1\right)$ is a lower bound for well-being when short the asset. Taking the limit of (2.1) as $\pi_1 \to 0$, or as skewness goes to negative infinity, we see:

$$\begin{aligned} &\lim_{\pi_1 \to 0} W\left(\widehat{\pi}_1', \widehat{\pi}_1'; \pi_1\right) = \tfrac{1}{3}\beta\left[\left(\widehat{\pi}_1'\right) \lim_{\pi_1 \to 0} U\left(R + \alpha^*\left(\{\widehat{\pi}_1'\}\right) Z_1\right) + \left(2 - \widehat{\pi}_1^1\right) U\left(R + \alpha^*\left(\{\widehat{\pi}_1'\}\right) \mu_z\right)\right] + \\ &\tfrac{1}{3}\beta^2\left[\left(2\widehat{\pi}_1^2\right) \lim_{\pi_1 \to 0} U\left(R + \alpha^*\left(\{\widehat{\pi}_1'\}\right) Z_1\right) + \left(3 - 2\widehat{\pi}_1^2\right) U\left(R + \alpha^*\left(\{\widehat{\pi}_1^2\}\right) \mu_z\right)\right] \to \infty \end{aligned} \tag{C.19}$$

The last statement follows since $Z_1 \to -\infty$ as $\pi_1 \to 0$.

We also consider well-being when the investor is long the asset as skewness approaches negative infinity. If we go long the short-term asset, we know that we will also go long the long-term asset (from the previous section). Additionally, we know that $0 \leq \alpha^* \leq \frac{-R}{Z_1}$ from (1.1). From (2.2), and choosing the optimal $\alpha*$ separately for each individual state, we know that

$$\begin{aligned} &W\left(\widehat{\pi}_1^1, \widehat{\pi}_1^2; \pi_1\right) \leq \tfrac{1}{3}\beta\left[\left(\pi_1 + \widehat{\pi}_1^1\right) U(R) + \left(2 - \pi_1 - \widehat{\pi}_1^1\right) U\left(R - \tfrac{R^* Z_2}{Z_1}\right)\right] + \\ &\tfrac{1}{3}\beta^2\left[\left(\pi_1 + 2\pi_1^2\right) U(R) + \left(3 - \pi_1 - 2\pi_1^2\right) U\left(R - \tfrac{R^* Z_2}{Z_1}\right)\right] \end{aligned} \tag{C.20}$$

Taking the limit as $\pi_1 \to 0$, we can see that

$$\begin{aligned} &\lim_{\pi_1 \to 0} W\left(\widehat{\pi}_1^1, \widehat{\pi}_1^2; \pi_1\right) \leq \tfrac{1}{3}\beta\left[\left(\widehat{\pi}_1^1\right) U(R) + \left(2 - \widehat{\pi}_1^1\right) \lim_{\pi_1 \to 0} U\left(R - \tfrac{R^* Z_2}{Z_1}\right)\right] + \\ &\tfrac{1}{3}\beta^2\left[\left(2\widehat{\pi}_1^2\right) U(R) + \left(3 - 2\widehat{\pi}_1^2\right) \lim_{x_1 \to 0} U\left(R - \tfrac{R^* Z_2}{Z_1}\right)\right] = \tfrac{1}{3}\beta[2U(R)] + \tfrac{1}{3}\beta^2[3U(R)] < \infty \end{aligned} \tag{C.21}$$

This implies that there exists a level of negative skewness such that we will short the short-term asset and be short the long-term asset to an even greater degree.

Finally, we show that this implies agents are more pessimistic at long horizons relative to short horizons. From the earlier first order condition (1.2), we know that:

$$\sum_{s=1}^{S} \widehat{\pi}_{1,s} U' \left(R + \alpha^* \left(\{ \widehat{\pi}_1 \} \right) Z_s \right) Z_s = 0 \tag{C.22}$$

This can be rewritten as:

$$\sum_{s \ni Z_s < 0}^{S} \widehat{\pi}_{1,s} U' \left(R + \alpha^* \left(\{ \widehat{\pi}_1 \} \right) Z_s \right) Z_s + \sum_{s \ni Z_s >= 0}^{S} \widehat{\pi}_{1,s} U' \left(R + \alpha^* \left(\{ \widehat{\pi}_1 \} \right) Z_s \right) Z_s = 0 \tag{C.23}$$

But, we know from before that $\alpha_2^* < \alpha_1^*$. This implies that:

$$\sum_{s \ni Z_s < 0}^{S} \widehat{\pi}_{1,s} U' \left(R + \alpha^* \left(\{ \widehat{\pi}_2 \} \right) Z_s \right) Z_s + \sum_{s \ni Z_s >= 0}^{S} \widehat{\pi}_{1,s} U' \left(R + \alpha^* \left(\{ \widehat{\pi}_2 \} \right) Z_s \right) Z_s > 0 \tag{C.24}$$

From the earlier, first order condition, we also know that

$$\sum_{s=1}^{S} \widehat{\pi}_{2,s} U' \left(R + \alpha^* \left(\{ \widehat{\pi}_2 \} \right) Z_s \right) Z_s = 0 \tag{C.25}$$

This implies that:

$$\sum_{s=1}^{S} \left(\widehat{\pi}_{2,s} - \widehat{\pi}_{1,s} \right) U' \left(R + \alpha^* \left(\{ \widehat{\pi}_2 \} \right) Z_s \right) Z_s < 0 \tag{C.26}$$

which implies that agents are more pessimistic at long horizons relative to short horizons when they are short the short-term asset. The proof to demonstrate that there is a level of positive skewness for which the investor will exhibit horizon bias (from the previous section) is similar.

D Wishful Thinking and Horizon Bias

An agent who lives for three periods derives utility at time t from consumption at time t, c_t, plus the anticipation of consumption at times $t+1$ and $t+2$. Consumption over the next two periods is determined by the current level of consumption and the one-step and two-step ahead per-period stochastic growth rates of consumption, g_{t+1} and g_{t+2}. Consumption is assumed to be strictly positive in all periods.

We define $u(c)$ as the agent's utility from consumption, such that $u(c) > 0 \; \forall c > 0$, $u^{'}(c) > 0 \; \forall c > 0$, and $u^{''}(c) <= 0 \; \forall c > 0$. The wishful thinker's expected utility from current and future consumption is

$$\begin{aligned} U_t =& u(c_t) + \beta \int_{g_{t+1}} u(c_t(1+g_{t+1}))f(g_{t+1})dg_{t+1} + \\ & \beta^2 \int_{g_{t+1}} \int_{g_{t+2}} u(c_t(1+g_{t+1})(1+g_{t+2}))f(g_{t+1}, g_{t+2})dg_{t+2}dg_{t+1} \end{aligned} \tag{D.1}$$

where the functional $f(.)$ denotes the wishful thinker's subjective distribution of future consumption growth, and β is a time-discount coefficient such that $0 \geq \beta \geq 1$. Equation (D.1) suggests that the agent could increase his anticipation of future utility from consumption by selecting a subjective probability distribution of future consumption growth that assigns larger (smaller) probability to states of higher (lower) growth.[1]

To discipline the agent's selection of subjective beliefs, we introduce a cost of belief distortions that is modeled in the spirit of Hansen and Sargent (2008) and Caplin and Leahy (2019), as a Kullback-Leibler divergence of the wishful thinker's chosen distribution f(.), from the econometrician's non-distorted probabilistic assessment, which we denote with the functional $\overline{f}(.)$. Thus, the cost of distorting beliefs takes the following form:

$$\begin{aligned} C_t =& \frac{1}{\theta} \Bigg[\beta \int_{g_{t+1}} f(g_{t+1}) ln \frac{f(g_{t+1})}{\overline{f}(g_{t+1})} dg_{t+1} \\ & + \beta^2 \int_{g_{t+1}} \int_{g_{t+2}} f(g_{t+1}, g_{t+2}) ln \frac{f(g_{t+1}, g_{t+2})}{\overline{f}(g_{t+1}, g_{t+2})} dg_{t+2} dg_{t+1} \Bigg] \end{aligned} \tag{D.2}$$

[1] The model could in principal be extended to incorporate an investment decision that shifts consumption across time and states of the world. However, this addition to the model would not only make it more difficult to provide a solution of the wishful thinker's problem in closed form, but it would also introduce similarities between our analysis here and the analysis of horizon bias under optimal expectations in Appendix 4.3.1. Since here we aim at investigating the specific implications of wishful thinking for horizon bias, we prefer a simpler setting where the only trade-off the agent faces when forming beliefs is the key one in Caplin and Leahy (2019).

The first term in Equation (D.2) captures the cost of distorting the beliefs of one-step ahead consumption growth. The second term of the Equation captures the costs of distorting beliefs 2 periods into the future.[2] The parameter θ determines how costly it is to engage in wishful thinking. θ will be small (i.e., ceteris paribus, a larger C_t) when it is too difficult to engage in practices such as information avoidance or self-deception and denial of incoming information, that help maintain one's optimistic views about the future.

For the purpose of the discussion below, we follow Caplin and Leahy (2019) and assume that the wishful thinker's beliefs are consistent with the laws of probability, and in particular $f(g_{t+1}, g_{t+2}) = f(g_{t+1})f(g_{t+2}|g_{t+1})$. Thus, we can write the wishful thinker's program as follows:

$$\begin{aligned}
&\underset{f(g_{t+1}),f(g_{t+2}|g_{t+1})}{Max} U_t - C_t = \\
&\quad \Bigg\{ u(c_t) + \beta \int_{g_{t+1}} u(c_t(1+g_{t+1}))f(g_{t+1})dg_{t+1} + \\
&\quad \beta^2 \int_{g_{t+1}} \int_{g_{t+2}} u(c_t(1+g_{t+1})(1+g_{t+2}))f(g_{t+1})f(g_{t+2}|g_{t+1})dg_{t+2}dg_{t+1} \\
&\quad - \frac{1}{\theta} \Bigg[\beta \int_{g_{t+1}} f(g_{t+1}) ln \frac{f(g_{t+1})}{\overline{f}(g_{t+1})} dg_{t+1} + \\
&\qquad \beta^2 \int_{g_{t+1}} \int_{g_{t+2}} f(g_{t+1})f(g_{t+2}|g_{t+1}) ln \frac{f(g_{t+1})f(g_{t+2}|g_{t+1})}{\overline{f}(g_{t+1})\overline{f}(g_{t+2}|g_{t+1})} dg_{t+2}dg_{t+1} \Bigg] \Bigg\}
\end{aligned} \tag{D.3}$$

To specialize Equation (D.3) to study how wishful thinking can distort macroeconomic expectations, we now impose some additional structure that is natural in this setting. We assume that the econometrician's model for g_{t+1} and g_{t+2} is as follows:

$$\begin{aligned}
g_{t+1} &= \mu_g + \gamma \tilde{g}_t + \epsilon_{t+1} \\
g_{t+2} &= \mu_g + \gamma \tilde{g_{t+1}} + \epsilon_{t+2}
\end{aligned} \tag{D.4}$$

where $\tilde{g}$ refers to the unconditionally demeaned per-period growth rate,$\epsilon_{t+j} \sim N(0, \sigma_\epsilon^2) \quad \forall j > 0$ and $cov(\epsilon_{t+s}, \epsilon_{t+j}) = 0 \quad \forall j, s$, and $|\gamma| < 1$. In other words, the econometrician believes growth in consumption to evolve as a standard stationary AR(1) process with mean μ_g, persistence γ, and normally distributed and serially uncorrelated innovations.[3] Therefore, We can restate these beliefs in terms of $\overline{f}(g_{t+1})$ and $\overline{f}(g_{t+2}|g_{t+1})$:

[2]Like in Caplin and Leahy (2019) the cost of distorting beliefs concerning outcomes that are realized h periods into the future is expressed as the cost of a sequence of beliefs up to horizon h.

[3]With normally distributed growth innovations, consumption can sometimes become negative. On the other hand, for sufficiently small values of σ_ϵ, the likelihood that this occurs is small.

$$\begin{aligned}\overline{f}(g_{t+1}) &\sim N\left(\mu_g + \gamma\tilde{g}_t, \sigma_\epsilon^2\right)\\ \overline{f}(g_{t+2}|g_{t+1}) &\sim N\left(\mu_g + \gamma\tilde{g_{t+1}}, \sigma_\epsilon^2\right)\end{aligned} \tag{D.5}$$

Next we hypothesize that the wishful thinker believes the law of motion of g_{t+1} and g_{t+2} to be:

$$\begin{aligned}g_{t+1} &= \mu_g + \gamma\tilde{g}_t + B_{ST_t} + \epsilon_{t+1}\\ g_{t+2} &= \mu_g + \gamma\tilde{g_{t+1}} + B_{ST_{t+1}} + \epsilon_{t+2}\end{aligned} \tag{D.6}$$

Like the econometrician, the wishful thinker also believes that consumption growth to have an autoregressive behavior, and agrees on the parameters governing such AR(1) law of motion, as well as the distribution of the innovations in consumption growth.[4] However, the wishful thinker deviates from the econometrician's model due to the presence of terms B_{ST_t} and $B_{ST_{t+1}}$. These two terms reflect the wishful thinker's bias in beliefs of one-step ahead growth at time t and $t+1$ respectively. These are to be determined endogenously as part of the wishful thinker's maximization problem. So, the relevant wishful thinker's probability distributions are

$$\begin{aligned}f(g_{t+1}) &\sim N\left(\mu_g + \gamma\tilde{g}_t + B_{ST_t}, \sigma_\epsilon^2\right)\\ f(g_{t+2}|g_{t+1}) &\sim N\left(\mu_g + \gamma\tilde{g_{t+1}} + B_{ST_{t+1}}, \sigma_\epsilon^2\right)\end{aligned} \tag{D.7}$$

Having imposed this simple, yet reasonable, structure, we are able to restate U_t and C_t in the wishful thinker's decision problem as a function of B_{ST_t} and $B_{ST_{t+1}}$:

[4]In principal, nothing prevents the wishful thinker from selecting from a wide range of possible laws of motion for consumption growth, or using different model parameters. However, deviating entirely from the econometrician's model entails a cost which can be very large. In the wishful thinker's world, the costs of choosing beliefs is linked to how easy it is to refute the wishful thinker's choice. Since the parameters of an autoregressive model are easily estimated with data that is publicly available, the cost of avoiding such data and choosing different parameters can be large. Moreover, the AR(1) law of motion is a rather simple and standard model of macroeconomic growth. Thus, If the wishful thinker chose to believe in an entirely different law of motion and a different probability distribution for the innovations of the growth process, the costs of justifying it to himself or to others could be too high to bear. One way to restate all the above is that, to the extent that experts mostly agree on the law of motion of consumption growth, and use the same data to estimate model parameters, there is little divergence of experts' opinion to allow the wishful thinker to disregard such a united front of expert opinions. Finally, we impose that the wishful thinker believes innovations in consumption growth to be normally distributed for mathematical convenience.

$$
\begin{aligned}
U_t &\simeq u(c_t) + \beta\left[u(\overline{c_{t+1}}) + c_t u^{'}(\overline{c_{t+1}})(\gamma\tilde{g}_t + B_{ST_t})\right] \\
&\quad + \beta^2\left[u(\overline{c_{t+2}}) + \overline{c_{t+1}}u^{'}(\overline{c_{t+2}})(\gamma(1+\gamma)\tilde{g}_t + (1+\gamma)B_{ST_t} + B_{ST_{t+1}})\right] \\
C_t &= \frac{\beta+\beta^2}{2\theta}\left(\frac{B_{ST_t}}{\sigma_\epsilon}\right)^2 + \frac{\beta^2}{2\theta}\left(\frac{B_{ST_{t+1}}}{\sigma_\epsilon}\right)^2
\end{aligned}
\tag{D.8}
$$

where $\overline{c_{t+1}} = c_t(1+\mu_g)$ and $\overline{c_{t+2}} = c_t(1+\mu_g)^2$ and the equation for U_t is obtained after linearizing the wishful thinker's utility function with respect to g_{t+1} and g_{t+2} around the long-run mean of consumption growth, μ_g.

Solving the maximization problem yields:

$$
\begin{aligned}
B^*_{ST_t} &= \frac{\theta\sigma^2_\epsilon}{\beta+\beta^2}c_t\left[\beta u^{'}(\overline{c_{t+1}}) + \beta^2(1+\mu_g)u^{'}(\overline{c_{t+2}})(1+\gamma)\right] \\
B^*_{ST_{t+1}} &= \theta\sigma^2_\epsilon\overline{c_{t+1}}u^{'}(\overline{c_{t+2}})
\end{aligned}
\tag{D.9}
$$

To see under what conditions wishful thinking generates the horizon bias, we now express the wishful thinker's expectations of g_{t+1} and g_{t+2} at time t as a function of $B^*_{ST_t}$ and $B^*_{ST_{t+1}}$. Using Equation (D.6), we obtain:

$$
\begin{aligned}
E^{WT}_t(g_{t+1}) &= \mu_g + \gamma\tilde{g}_t + B^*_{ST_t} \\
E^{WT}_t(g_{t+2}) &= \mu_g + \gamma^2\tilde{g}_t + B^*_{ST_{t+1}} + \gamma B^*_{ST_t}
\end{aligned}
\tag{D.10}
$$

where $E^{WT}(.)$ indicates the wishful thinker's expectations operator. Equation (D.10) nests the econometrician's rational expectations of growth as a special case. Such case arises when $B^*_{ST_t} = B^*_{ST_{t+1}} = 0$, a solution to the wishful thinker's problem that obtains when the costs of wishful thinking are too high (i.e., $\frac{1}{\theta}$ tends to infinity), or there is no uncertainty over future consumption growth, i.e., $\sigma^2_\epsilon = 0$. Based on the above, we can write an equation for horizon bias under wishful thinking:

$$
HB^{WT}_t = \left[\frac{\theta\sigma^2_\epsilon c_{t+1}u'(\overline{c_{t+2}})(1-\gamma)}{1+\beta}\right]\left[\frac{1+\beta}{1-\gamma} - \left(\frac{1}{1+\mu_g}\frac{u'(\overline{c_{t+1}})}{u'(\overline{c_{t+2}})} + \beta(1+\gamma)\right)\right]
\tag{D.11}
$$

Given the assumptions of non-satiation, strictly positive consumption, and stationarity

of the growth process, the first term in brackets in Equation D is positive in all periods. Therefore, what determines the sign of horizon bias is the second term in brackets in Equation D.

Rearranging this second term, we obtain the following condition for a positive horizon bias:

Proposition 1: Under wishful thinking, horizon bias in growth expectations arises if

$$\frac{u'(\overline{c_{t+2}})}{u'(\overline{c_{t+1}})} > \frac{1-\gamma}{(1+\mu_g)(1+\beta\gamma^2)}$$

Proposition 1 is easily satisfied in practice. First note that, empirically, $\mu_g > 0$ i.e., on average economic growth is positive. Given positive long-run economic growth, the left hand side of the inequality in Proposition 1 is bounded to be lower than 1 due to decreasing marginal utility of consumption. Therefore, the model can deliver a positive horizon bias if and only if the right side of the inequality in Proposition 1 is lower than 1. This obtains for $0 < \beta < 1$ and for $1 > \gamma > 0$, i.e., a non-negative persistence of economic growth, which is observed in practice.[5]

Corollary 1: If the condition in Proposition 1 holds, horizon bias grows more positive when consumption growth uncertainty increases, i.e.,

$$\frac{\partial HB^{WT}}{\partial \sigma_\epsilon^2} > 0$$

Corollary 2: If the condition in Proposition 1 holds, horizon bias grows more positive when the cost of wishful thinking declines, i.e.,

$$\frac{\partial HB^{WT}}{\partial \theta} > 0$$

[5]In fact, for $\mu_g > 0$ the range of values of γ for which the horizon bias condition can be satisfied is broader, since the right hand side of the inequality in Proposition 1 is lower than 1 when $\gamma < max(-1, \frac{-1-\sqrt{1-4\beta(1+\mu_g)\mu_g}}{2(1+\mu_g)\beta})$ or $\gamma > min(1, \frac{-1+\sqrt{1-4\beta(1+\mu_g)\mu_g}}{2(1+\mu_g)\beta})$. An inspection of this condition reveals that horizon bias can obtain even for processes with mild negative correlation. Moreover, when μ_g is sufficiently high, horizon bias can also obtain for processes with very large negative autocorrelation.