The Volatility of Inflation Expectations and Interest Rates*

Edoardo Bonaglia†, Daniele d'Arienzo‡, Nunzio Fallico§,
Nicola Gennaioli¶, Luigi Iovino‖

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Abstract

Using the consensus forecasts of major banks during 1989-2022, we link inflation expectations to interest rates in 18 advanced economies. We detect horizon-increasing overreaction: high expected inflation today predicts future inflation overestimation, especially at long horizons, and higher real returns on nominal bonds, especially at long maturities. As a result, high expected inflation today predicts a future redistribution of wealth from borrowers to lenders. To understand the drivers of such redistribution, we offer a learning model where investors overweight states that are salient in memory due to their past frequency or similarity to current inflation. The model endogenizes belief under- and overreaction based on features of the inflation DGP, helping account for observed cross-country variation in belief biases and return predictability.

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†New York University, Department of Economics. E-mail: eb4474@nyu.edu

‡Capital Fund Management, E-mail: daniele.darienzo@cfm.com

§Boston University, Department of Economics. E-mail: fallico@bu.edu

¶Università Bocconi, Department of Finance and IGIER. E-mail: nicola.gennaioli@unibocconi.it

‖Università Bocconi, Department of Economics and IGIER. E-mail: luigi.iovino@unibocconi.it

1 Introduction

Inflation expectations are central to macro-financial dynamics. By the Fisher Equation, the nominal interest rate i is equal to the ex-ante real rate r plus expected inflation π^e:

$$i = r + \pi^e. \tag{1}$$

Classic work on the Fisher Equation adopts rational expectations (Woodford, 2003b; Galí, 2015; Fama, 1975; Mishkin, 1992; Gürkaynak et al., 2010). In this approach, if prices are rigid expected inflation affects resource allocation by shaping the ex-ante real interest rate $r = i - \pi^e$, in part through monetary policy. If instead prices are flexible, money is neutral: changes in π^e affect the nominal rate i one to one, leaving r and resource allocation unchanged.

Contrary to rationality, professional inflation forecasts exhibit predictable errors (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020). Accounting for such errors is important, because they could affect interest rates via Equation (1). First, if prices are rigid they could distort the ex-ante real rate $r = i - \pi^e$ and output. Second, they could drive a wedge between the ex ante real rate and the average ex post one $i - \pi$. By redistributing wealth between borrowers and lenders with different propensities to spend, this wedge could affect output even under flexible prices. Doepke and Schneider (2006) document inflation-driven redistributions, Fisher (1933) famously discussed the cost of debt deflation. Critically, in a rational world such redistributions are random. They instead systematically occur and affect output when beliefs are biased. Do biases in inflation expectations affect interest rates? If so, how?

We address these questions using data on the inflation forecasts of major banks and on interest rates in 18 advanced economies over 1989-2022. We detect excess volatility in expectations that links to excess volatility in interest rates. We present a model of mnemonic learning that illuminates such link and its redistributive effects. Compared to existing models, mnemonic learning produces both under and overreaction to news and ties them to inflation histories, explaining cross-country variation in belief and interest rate volatility.

Section 2 presents our motivating facts. First, consensus inflation forecasts sharply overreact at medium and long horizons, while exhibiting no or reverse bias (underreaction) at short ones. Horizon-increasing overreaction is a broad phenomenon: it has been detected in interest rate forecasts D'Arienzo (2020), in a lab experiment Afrouzi et al. (2023), and in the consensus forecasts of several series Halperin and Mazlish (2025). Second, and critically, belief biases tie to interest rates: high expected inflation today predicts high future real yields to maturity and excess returns on nominal bonds, especially at long maturities. These findings are robust to accounting for Stambaugh bias Boudoukh et al. (2022) and time-varying ex-ante real rates.

Interest rate volatility (Shiller, 1979; Fama and Bliss, 1987) is typically explained with time varying required returns in rational models. Our findings instead point to non-rationality: high

current inflation prompts overestimation of future inflation, especially at long horizons, causing investors to demand too high a nominal rate, especially for long-term bonds. Because future inflation is on average less than anticipated, high returns follow. This mechanism implies that to understand interest rates we must understand belief biases. As we later discuss, existing non-rational models either produce over- or under-reaction, but not the horizon-dependent combination of the two we see in the data.

Section 3 offers a new model of mnemonic learning that accounts for the evidence. The idea is that, when forming beliefs or when making qualitative adjustments to model-based forecasts, investors overweight past states that are salient in memory and underweight non salient ones, consistent with the role of past experiences (Malmendier and Nagel, 2016) also for professionals (Malmendier et al., 2021). Following (Bordalo et al., 2023) we model memory based on regularities in human recall (Kahana, 2012): frequency, similarity and interference. Our key innovation is to allow for the dynamic accumulation of the memory database as the inflation history unfolds, and for its interaction with time-varying cues.

Dynamics prove critical. Seeing current inflation at 3% cues over-weighting of past states similar to 3%, or that followed 3% episodes, promoting forward-looking overreaction. However, the database matters: beliefs swiftly update if the current database contains many 3% episodes, while they stay anchored if it contains many episodes with lower inflation, say at 1%. Thus, biases are state- and database-dependent. Long-run beliefs converge to a stable distortion of the DGP, with similarity promoting overreaction and frequency promoting anchoring to the long-run mean (underreaction). By setting the database, the DGP shapes which of these forces dominates. With AR(1) inflation, for instance, higher persistence promotes underreaction, higher volatility overreaction. Intuitively, in volatile histories many extreme events can be retrieved based on extreme inflation cues, causing swift belief updating.

Going back to the evidence, then, the model produces stronger belief overreaction for longer horizons and reconciles it with under-reaction for short-horizons. It also makes a new prediction: different inflation histories should cause variation in biases and interest rate volatility. Section 4 uses the observable inflation database and cue to estimate two similarity parameters (our only degrees of freedom) by fitting model-implied beliefs to CE forecasts in the pooled sample. The estimated model matches – entirely based on inflation histories – significant cross-country variation in belief extrapolation, which is stronger is more volatile histories. Important, the realistic forecast errors produced by the model produce realistic cross country variation in interest rate volatility, even under constant required returns. The average level of wealth redistribution from borrowers to lenders and its cross country variation are sizable: a 2% higher expected inflation today predicts a higher real repayment cost of about 2% of the value of a 2-year loan, and 12% of that of a 10-year one. In heterogeneous agent models, this redistribution amplify boom-bust cycles if expected inflation is high during booms.

Much work detects excess interest rate volatility (Shiller, 1979; Mankiw and Summers, 1984; Fama and Bliss, 1987; Cochrane and Piazzesi, 2005) and explains it by adding time-varying required returns in rational models (Wachter, 2006; Bansal and Shaliastovich, 2013; Vayanos and Vila, 2021; Cieslak, 2018). Giglio and Kelly (2018) detect excess volatility of long relative to short rates in the U.S., show that it is at odds with these models, and argue that it may be due to beliefs. We are first to link excess volatility in *measured inflation expectations* to interest rates, and to shed light on cross-country variation. We add to work showing that measured beliefs help explain macro-financial volatility (Bordalo et al., 2024b,c). Bianchi et al. (2022) and Nagel (2024) study how rigid household inflation expectations drive low-frequency changes in interest rates by shaping monetary policy, with a focus on the disinflation of the 1980s. We study high-frequency overreaction starting from the 1990s, a period of more stable inflation, and account for cross-country variation in biases and return predictability.

Growing work studies non-rational beliefs. Some models capture overreaction, due to representativeness in diagnostic expectations (DE) (Bordalo et al., 2018; Bianchi et al., 2024b) or to overweighting of recent states in adaptive (Evans and Honkapohja, 2009; Marcet and Nicolini, 2003) or boundedly rational (Afrouzi et al., 2023) learning models. Other models capture rigidity via inattention (Sims, 2003; Woodford, 2003a; Gabaix, 2014), which is used to explain underreaction of short-term inflation forecasts Coibion and Gorodnichenko (2015). These models either produce over or underreaction, ours yields both. (Bordalo et al., 2020) obtain consensus over and underreaction by merging inattention with DE, (Angeletos et al., 2021) by merging it with excess persistence, and (Halperin and Mazlish, 2025) with recency. These models cannot explain underreaction of short-term individual forecasts and over-reaction of long term ones, which Bordalo et al. (2020) detect for US interest rates.

More broadly, memory has two methodological advantages compared to existing approaches. First, it does not rely on "ad hoc" distortions of the DGP but on well established regularities in recall, whose explanatory power has been shown in economics. Bordalo et al. (2024a), Jiang et al. (2024) and Taubinsky et al. (2024) use them to jointly explain data on beliefs and recall in the estimation of novel risks, stock returns, and inflation, respectively. (Gennaioli et al., 2024) show that they can account for US households' inflation expectations. Unlike us, these papers neither allow for learning nor study interest rates and their cross-country variation. The second advantage of memory is that it allows for model free-learning: without knowledge of the "true DGP" it creates forward looking and environment-dependent beliefs (which are thus immune to the Lucas Critique (Lucas, 1972)) solely based on the inflation history. In Section 4 we evaluate adaptive and boundedly rational models of recency bias and show that they cannot produce meaningful cross-country variation in extrapolation. The reason is that, to produce significant overreaction, these models must underweight the past, which limits their explanatory power

across histories.[1]

2 Volatility in Inflation Expectations and Returns

2.1 Data Sources and Sample

Expectations are drawn from Consensus Economics (CE), which surveys macroeconomic forecasts from major financial institutions worldwide. Our main variable is the consensus forecast for year-on-year CPI inflation h calendar years ahead, with $h = 0, 1, 2, 3, 4, 5,$ 6-10. The $h = 0$ forecast pertains to current year inflation; the $h =$ 6-10 forecast pertains to average inflation between 6 to 10 years ahead. We also use CE consensus forecasts of next year's 3-month and 10-year interest rates to proxy for required return variation. Forecasts are reported quarterly after 2014, semiannually before.

Realized year-on-year CPI inflation is from the IMF Data Mapper and the World Development Indicators (WB); when both sources are available, we take the average.[2] We compute interest rates and returns using the prices of bonds with maturities 1-10 from Refinitiv. The 4-year maturity is excluded due to data gaps. We focus on IMF's "advanced economies" with consistent data coverage. For each horizon h, countries are included if they have data on bond yields and forecasts since at least 1999Q4. The sample has 18 countries and ranges from 1989Q4 to 2022Q1. Tables 6 and Table 7 describe the data.[3]

In our sample, average yearly inflation across countries and over time is 4.21% with a standard deviation of 4.29%. CE forecasts do not exhibit systematic bias: the average forecast error at the 1-year horizon is -0.0046 with $p = 0.9507$. Due to relatively stable inflation in our sample period, there is no systematic bias or fear of a "Peso problem". Figure 6 in Appendix A.1 plots in-sample inflation for the 18 countries.

Section (2.2) shows that investors tend to over-estimate future inflation during high inflation states and vice-versa during low states. Section (2.3) connects these biases to excess interest rate volatility based on tests built from the Fisher Equation (1).

2.2 The Volatility of Inflation Expectations

To assess whether investors over- or underestimate future inflation during high inflation states we predict the consensus forecast error for country c at horizon $t + h$ using two proxies. The

[1] Alternative approaches to beliefs include natural expectations (Fuster et al., 2012), level-k thinking (e.g. Iovino and Sergeyev (2023)), and incorrect models (Molavi et al., 2024). Farmer et al. (2024) assume slow learning under an incorrect prior, which may stem from memory of past history.

[2] IMF and World Bank data cover up to 2023; the sources for 2024Q1 data are reported in Table 6.

[3] The UK is excluded from our main sample because its CE coverage starts only in 2004. Results are robust to having all countries, including the UK, at all maturities, see Tables 29 to 32.

first one is the current inflation forecast for h calendar years ahead, $\mathbb{F}_t(\pi_{c,t+hY})$. A high forecast signals a high inflation state at t. Pooling countries and time periods we estimate:

$$\pi_{c,t+hY} - \mathbb{F}_t\left(\pi_{c,t+hY}\right) = \alpha_h + \delta_h \cdot \mathbb{F}_t\left(\pi_{c,t+hY}\right) + \varepsilon_{c,t+hY}. \tag{2}$$

A negative coefficient $\delta_h < 0$ implies that forecasters overestimate future inflation in a high inflation state, and vice-versa in a low state. The opposite occurs if $\delta_h > 0$.

Our second proxy is the average inflation in the two prior years $\overline{\pi}_{c,t} = (\pi_{c,(t-1)Y} + \pi_{c,(t-2)Y})/2$. We observe inflation annually, and take a two-year average because forecasters do not observe the final realized inflation estimate in real time. As a dependent variable, we average the forecast error in year t across quarters. Again, a negative (positive) coefficient detects over- (under-) estimation of future inflation in a high inflation state.

Table 1 reports the estimates, with Panel A using the first proxy and Panel B the second. We denote the forecast error at horizon h by $FE_{c,h} \equiv \pi_{c,t+hY} - \mathbb{F}_t\left(\pi_{c,t+hY}\right)$. All regressions in the paper include country dummies and Driscoll-Kraay standard errors to control for heteroskedasticity and spatio-temporal correlation (including due to averaging in our second proxy).

In Panel A, δ_h is positive but not significant at the shortest horizon. For $h \geq 1$, the coefficient turns negative: high current expected inflation predicts overestimation of future inflation. Critically, the effect is stronger at longer horizons h. These results are robust when estimating equation (2) at the annual frequency (see Appendix Table 23). Panel B confirms the result using our second proxy: high recent inflation predicts overestimation of future inflation, more strongly so at longer horizons. Magnitudes are meaningful. In Panel A, a one standard deviation increase in the current forecast reduces the future forecast error by 0.217 standard deviations at the 1-year horizon, and by 0.826 standard deviations at the 6-10-year horizon. In Panel B, a one standard deviation increase in recent inflation reduces the error by 0.205 standard deviations at the 1-year and by 0.667 at the 6-10-year horizons.

De Silva and Thesmar (2024) show that noise or measurement error in expectations could create a spurious negative coefficient when predicting the forecast error with the current forecast (or its revision). This mechanism cannot explain our results. First, noise or measurement error is dampened by averaging individual analyst forecasts in the consensus. Second, we see negative predictability also in Panel B, using past inflation as a predictor.

A second concern is small sample bias with persistent predictors, which becomes stronger at longer horizon, see Stambaugh (1999). Boudoukh et al. (2022) develop an adjustment for such bias in time-series regressions, which we apply country by country in our panel. Table 28 reports, in the first and third row, the median corrected coefficient of Panel A and B, respectively, and in the second and fourth row the country by country correlation between corrected and non-corrected coefficients. The median corrected coefficients exhibit strong maturity increasing overreaction, suggesting that this pattern holds for most countries. The correlation

Table 1: Predicting the consensus forecast error using the current inflation state

	Panel A					
	(1)	(2)	(3)	(4)	(5)	(6)
	$FE_{c,0}$	$FE_{c,1}$	$FE_{c,2}$	$FE_{c,3}$	$FE_{c,5}$	$FE_{c,6\text{-}10}$
$\mathbb{F}_t(\pi_{c,t+hY})$	0.037	-0.356**	-1.004***	-1.114***	-1.655***	-1.207***
	(0.045)	(0.140)	(0.300)	(0.274)	(0.273)	(0.108)
Country fixed effects	✓	✓	✓	✓	✓	✓
N	1029	1029	1171	1033	1093	656
Adj. R^2	0.020	0.062	0.157	0.176	0.252	0.553
	Panel B					
	(1)	(2)	(3)	(4)	(5)	(6)
	$FE_{c,0}$	$FE_{c,1}$	$FE_{c,2}$	$FE_{c,3}$	$FE_{c,5}$	$FE_{c,6\text{-}10}$
$\overline{\pi}_{c,t}$	-0.041	-0.218*	-0.295**	-0.339**	-0.626***	-0.490***
	(0.039)	(0.119)	(0.141)	(0.127)	(0.189)	(0.074)
Country fixed effects	✓	✓	✓	✓	✓	✓
N	420	420	462	416	462	331
Adj. R^2	-0.002	0.048	0.057	0.088	0.229	0.426

Note. Each column reports the country pooled regression at horizon $h = 0, ..., 6\text{-}10$: the dependent variable is the consensus forecast error $\pi_{c,t+hY} - \mathbb{F}_t(\pi_{c,t+hY})$ at horizon h and country c. The independent variables are: (i) the consensus forecast for country c at horizon h, $\mathbb{F}_t(\pi_{c,t+hY})$ (Panel A, quarterly frequency), and (ii) the average realized inflation of country c over the past two years, $\overline{\pi}_{c,t} = (\pi_{c,(t-1)Y} + \pi_{c,(t-2)Y})/2$ (Panel B, annual frequency). We control for country fixed effects. The sample ranges from 1989Q4 to 2022Q1, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

between non-corrected and corrected coefficient is large, typically above 0.9, so the correction does not alter the cross-country gradient of maturity increasing overreaction. Country by country estimates reveal substantial heterogeneity, including the statistically significant short-term underreaction for some countries, as in Coibion and Gorodnichenko (2015). We return to this heterogeneity later, and show that our model can help account for it.

Having ruled out noise, measurement error and small-sample bias, we explore the behavioral mechanisms driving beliefs. A high inflation state can prompt future inflation overestimation because forecasters overreact to recent "high inflation" news, or because they are too pessimistic following periods during which their forecasts were high, indicating a persistent overreaction to past inflation. Coibion and Gorodnichenko (2015) measure underreaction as a positive correlation between forecast errors and revisions for US short term inflation, Bordalo et al. (2024b) detect overreaction to both news and the lagged state for US earnings growth forecasts. To separate these mechanisms, we follow Bordalo et al. (2024b) and proxy for news using the four-quarter belief revision, $\mathbb{F}_t(\pi_{c,t+hY}) - \mathbb{F}_{t-4}(\pi_{c,t+hY})$, and for past pessimism using the four

quarters ago consensus, $\mathbb{F}_{t-4}(\pi_{c,t+hY})$.[4] We thus estimate:

$$\pi_{c,t+hY} - \mathbb{F}_t(\pi_{c,t+hY}) = \alpha_h + \delta_{1,h} \cdot [\mathbb{F}_t(\pi_{c,t+hY}) - \mathbb{F}_{t-4}(\pi_{c,t+hY})] + \delta_{2,h} \cdot \mathbb{F}_{t-4}(\pi_{c,t+hY}) + \varepsilon_{c,t+hY}. \quad (3)$$

A negative $\delta_{1,h}$ indicates overreaction to recent news; a negative $\delta_{2,h}$ indicates persistent overreaction to past high inflation. Positive coefficients instead indicate underreaction.

Table 2 shows that, at horizons up to one year, $\delta_{1,h}$ is positive, although not statistically significant, suggesting mild underreaction to news. At longer horizons, $\delta_{1,h}$ is significantly negative, indicating overreaction. The lagged forecast coefficient $\delta_{2,h}$ is negative and significant at all horizons, showing persistent overreaction to past inflation. The rigidity of consensus inflation expectations documented by Coibion and Gorodnichenko (2015) is thus a feature of short-term forecasts.[5] At long horizons, consensus beliefs overreact, consistent with non-rational updating. Interestingly, for $h \geq 2$, overreaction to news and past states are comparable: $\delta_{1,h} = \delta_{2,h}$ cannot be rejected at conventional levels. This means that the simpler predictability regression in equation (2), which imposes $\delta_{1,h} = \delta_{2,h}$, captures horizon-increasing overreaction in the data. As we will see, this is the specification entailed by our model.

The results of Table (2) are also robust to correcting for small sample bias, see columns 5-8 in Table 28. Horizon-increasing overreaction is a broad property of beliefs. D'Arienzo (2020) and Afrouzi et al. (2023) show it for professional forecasts of US rates and in a lab experiment, respectively. In contemporaneous work, Halperin and Mazlish (2025) detect it for several macro series. For our purposes the key question is: do the observed biases in inflation forecasts tie to bond market efficiency via the Fisher Equation?

2.3 Belief Overreaction and Bond Returns

Under the expectations hypothesis (Campbell and Shiller, 1991), the ex-ante real rate $r_c^{(h)}$ on a zero-coupon of maturity h in country c is constant and the nominal rate $i_{c,t}^{(h)}$ obeys:

$$i_{c,t}^{(h)} = r_c^{(h)} + \mathbb{E}_t\left(\overline{\pi_{c,t+1,h}}\right), \quad (4)$$

[4] This test is also methodologically more appropriate than merely correlating forecast errors. Such test is well specified if forecasters are rational, the case considered by Coibion and Gorodnichenko (2015), not otherwise. The reason is that with non-rational updating the forecast revision is correlated with the lagged forecast – a pattern that we observe in the data (see Appendix Table 8) – which creates an omitted variable problem if the lagged forecast is not itself used as a predictor.

[5] If we replicate the Coibion and Gorodnichenko (2015) test, regressing the forecast error on the four quarters forecast revision, we see positive predictability at short horizons and negative but not statistically significant predictability at longer horizons, see Appendix Table 9. If we estimate equation (3) using US short-term CPI forecasts in the SPF as in Coibion and Gorodnichenko (2015) and US quarterly realized inflation from the Bureau of Labor Statistics, we obtain no predictability from the revision and negative predictability from the lagged forecast – consistent with our findings in columns (1) and (2) of Table 2; see Appendix Table 10.

Table 2: Predicting consensus error from recent news and past inflation states

	(1)	(2)	(3)	(4)	(5)	(6)
	$FE_{c,0}$	$FE_{c,1}$	$FE_{c,2}$	$FE_{c,3}$	$FE_{c,5}$	$FE_{c,6\text{-}10}$
$\mathbb{F}_t(\pi_{c,t+hY}) - \mathbb{F}_{t-4}(\pi_{c,t+hY})$	0.160	0.215	-0.847*	-1.092***	-1.297***	-1.123***
	(0.098)	(0.240)	(0.448)	(0.411)	(0.257)	(0.110)
$\mathbb{F}_{t-4}(\pi_{c,t+hY})$	-0.105**	-0.625**	-1.232***	-1.318***	-1.765***	-0.988***
	(0.045)	(0.246)	(0.433)	(0.399)	(0.380)	(0.107)
Country fixed effects	✓	✓	✓	✓	✓	✓
N	973	970	1104	969	1008	618
Adj. R^2	0.088	0.103	0.137	0.151	0.183	0.398

Note. Each column reports the country pooled regression at horizon $h = 0, ..., 6\text{-}10$: the dependent variable is the inflation consensus forecast error $\pi_{c,t+hY} - \mathbb{F}_t\left(\pi_{c,t+hY}\right)$ over horizon h and country c. The independent variables are the consensus revision $\mathbb{F}_t\left(\pi_{c,t+hY}\right) - \mathbb{F}_{t-4}\left(\pi_{c,t+hY}\right)$ and the lagged inflation forecast $\mathbb{F}_{t-4}\left(\pi_{c,t+hY}\right)$. We control for country fixed effects. The sample ranges from 1989Q4 to 2022Q1, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

where $\overline{\pi_{c,t+1,h}} = (\pi_{t+1Y} + ... + \pi_{t+hY})/h$ is average inflation between t and $t + hY$, and $\mathbb{E}_t(\cdot)$ denotes market expectations.

Under constant real rates and market efficiency, equation (4) implies that ex-post real bond returns are unpredictable, and are on average equal to the constant $r_c^{(h)}$. If instead markets are inefficient, returns are predictable in a way tied to belief overreaction. We use Equation (4) to derive these predictability implications (all proofs are in the Appendix). We then develop empirical tests that relax the strong assumption of constant ex-ante real rates.

Real yield to maturity. This is the difference between a bond's nominal yield at issuance $i_{c,t}^{(h)}$ and the average realized inflation over its life. From equation (4), for a bond issued at t with maturity h it is equal to:

$$\widetilde{r}_{c,t,t+h}^{(h)} = r_c^{(h)} - \left[\overline{\pi_{c,t+1,h}} - \mathbb{E}_t\left(\overline{\pi_{c,t+1,h}}\right)\right]. \tag{5}$$

If inflation is lower than expected, $[\overline{\pi_{c,t+1,h}} - \mathbb{E}(\overline{\pi_{c,t+1,h}})] < 0$, the real yield exceeds the ex-ante real rate $\widetilde{r}_{c,t,t+h}^{(h)} > r_c^{(h)}$; the opposite holds when inflation is higher than expected. Under rational expectations, inflation surprises are unpredictable and so is the return. This is no longer true if investors overreact.

Prediction 1. *If investors overreact, more strongly so at longer maturities, the regression:*

$$\widetilde{r}_{c,t,t+h}^{(h)} = \theta_{0,h}^r + \theta_h^r \cdot \mathbb{F}_t(\overline{\pi_{c,t+1,h}}) + \varepsilon_{c,t,t+h}^{(h)} \tag{6}$$

should yield a positive coefficient θ_h^r, with its magnitude increasing in h.

In high inflation states, expected inflation and nominal rates are too high, predicting high realized real rates, especially at long maturities. The reverse occurs in low inflation states.

Excess holding period return. This is the one-period return on a bond with maturity $h > 1$ in excess of the short rate. Formally, an investor buying a unit face value bond at price $\ln P_t^{(h)} = -h \cdot i_t^{(h)}$ and selling it at $t+1$ obtains a return $y_{t,t+1}^{(h)} = P_{t+1}^{(h-1)}/P_t^{(h)} - 1$, which is approximately $y_{t,t+1}^{(h)} \approx i_t^{(h)} + (h-1)(i_t^{(h)} - i_{t+1}^{(h-1)})$. The excess return over the short rate $i_t^{(1)}$ is:

$$rx_{t,t+1}^{(h)} = rx^{(h)} - (h-1)\left[\mathbb{E}_{t+1}\left(\overline{\pi_{t+2,h}}\right) - \mathbb{E}_t\left(\overline{\pi_{t+2,h}}\right)\right], \tag{7}$$

where $rx^{(h)} \equiv -(h-1)r^{(h-1)} + hr^{(h)} - r^{(1)}$ is constant. If investors revise beliefs upward at $t+1$, $\mathbb{E}_{t+1}(\overline{\pi_{t+2,h}}) - \mathbb{E}_t(\overline{\pi_{t+2,h}}) > 0$, the nominal rate increases, depressing the bond's resale price and the realized return. A downward revision conversely raises the price and the realized return. Under rationality, future revisions are unpredictable and so are returns. If instead investors overreact, revisions tend to be low following high inflation states and high otherwise. This pattern is indeed in the data (see Table 8), motivating our second prediction.

Prediction 2. *If investors overreact, more strongly so at longer maturities, the regression:*

$$rx_{c,t,t+1}^{(h)} = \theta_{0,h}^{ex} + \theta_h^{ex} \cdot \mathbb{F}_t(\overline{\pi_{c,t+1,h}}) + \varepsilon_{c,t,t+1}^{(h)} \tag{8}$$

should yield a positive coefficients θ_h^{ex}, with its magnitude increasing in h.

Due to horizon-increasing overreaction, nominal rates are excessively high in high-inflation states, especially at long maturities. As a result, bonds appreciate over time, especially long maturity ones. Predictability here originates from belief revisions, not errors.

Predictions 1 and 2 assume a constant real rate $r_c^{(h)}$, embedded in the intercepts $\theta_{0,h}^r$ and $\theta_{0,h}^{ex}$ of equations (6) and (8), respectively. In reality, the real rate $r_c^{(h)}$ can vary over time, due to monetary policy (including in reaction to inflation expectations as in Bianchi et al. (2022); Nagel (2024); Bauer and Rudebusch (2020)), or due to changes in risk aversion or other fundamentals. In this case, market inefficiency can still be detected, but *conditional* on proxies of ex-ante real rates. We thus implement the regressions of Predictions 1 and 2 by controlling for such proxies.

A large body of work on return predictability Duffee (2013) proxies for real rates using current nominal rates. Cieslak and Povala (2015) also use current nominal rate forecasts. We follow both approaches. In our baseline tests, we proxy for the ex-ante real rate at t in country c for horizon h by the current nominal rate at the same maturity minus expected average inflation over the horizon, $i_{c,t}^{(h)} - \mathbb{F}_t(\overline{\pi_{c,t+1,h}})$. As a second proxy, we use CE forecasts of nominal rates in the next 12 months, which are available for short-term (3-months) and long-term (10-years)

bonds. We construct expected real rates by subtracting inflation forecasts over short and long horizons, respectively. These measures directly proxy for real rates (our second proxy indeed reflects real rate forecasts). However, our results are unchanged if we use nominal current or expected rates, without adjusting for expected inflation. We cannot instead infer real rates from inflation-adjusted bonds because these bonds are not available or liquid in many countries in our sample. We use such market based proxies to validate our approach in the US and UK, where inflation-adjusted bonds are present and highly liquid.

Under the rational null, inflation forecasts should not predict returns conditional on real rate proxies. Finding $\theta_h^r, \theta_{0,h}^{ex} > 0$ and increasing in the horizon h instead ties predictability to maturity increasing belief overreaction. Conditional tests are demanding: changes in current or expected nominal rates by definition price-in all required return variation but they also price-in possible biases in investors' inflation expectations, for which CE forecasts are only a noisy proxy. If CE forecasts pass these tests, it must be because they contain genuine information about market beliefs, this information is orthogonal to required returns embedded in equilibrium interest rates, and it is additionally predictive of future returns over and above the yield curve. By comparison, canonical tests of rational models are weak: they *assume* that all variation in the yield curve is due to time-varying real rates without directly measuring them. Thus, these tests cannot rule out that the yield curve may move due to beliefs. By using measured inflation expectations, we can separate different drivers.

To test predictions 1 and 2 we compute nominal rates $i_{c,t}^{(h)}$ and bond returns from the zero-coupon price $P_{c,t}^{(h)}$ using the identity $\ln P_{c,t}^{(h)} = -h \cdot i_{c,t}^{(h)}$. For the (6-10)-year horizon we use the average of the available zero-coupon yields for maturities between 6 and 10 years, excluding missing maturities when unavailable. We compute quarterly rates as averages of monthly rates.

To begin, we compute proxies for real rates and validate them using "market-based measures" inferred from inflation-adjusted bonds (King and Low, 2014) in the US and UK. Our first proxy, the current nominal rate minus expected inflation, is strongly positively correlated with market based measures in these countries, ranging from 87% to 95%, (see Table 13). Our second proxy, the expected future rate minus expected inflation, also exhibits a strong correlation with market based measures, ranging from 87% to 96% (see Table 14). These correlations are very reassuring: they indicate that our proxies for real rates are very good at capturing the market's required real return, so our tests of market efficiency are powerful.

Testing Prediction 1 Following equation (6), we regress the future real yield to maturity $\widetilde{r}_{c,t,t+h}^{(h)}$ on the current forecast $\mathbb{F}_t(\overline{\pi_{c,t+1,h}})$, controlling for our main proxy for the ex ante real rate: the current nominal minus inflation forecast.

Table 3 reports the estimates. Consistent with Prediction 1, higher expected inflation predicts higher ex-post yields that – consistent with horizon-increasing overreaction – become

stronger as h increases.[6] Predictability of real yields does not simply reflect changing expected real rates, which are controlled for in the regression: it also reflects a distorted inflation compensation.

Belief-driven excess volatility is sizable: a one standard deviation increase in the inflation forecast is associated with a 0.127 and 0.380 standard–deviation increase in the ex-post real return at the 1-year and (6–10)-year horizons, respectively.

Table 3: Predicting ex-post real rates using consensus inflation forecast

	(1)	(2)	(3)	(4)	(5)
	$\tilde{r}^{(1)}_{c,t,t+1}$	$\tilde{r}^{(2)}_{c,t,t+2}$	$\tilde{r}^{(3)}_{c,t,t+3}$	$\tilde{r}^{(5)}_{c,t,t+5}$	$\tilde{r}^{(6-10)}_{c,t+6,t+10}$
$\mathbb{F}_t\left(\overline{\pi_{c,t+1,h}}\right)$	0.375***	0.470***	0.579***	0.796***	1.087***
	(0.131)	(0.143)	(0.145)	(0.125)	(0.119)
$r^{(h)}_{c,t}$	1.202***	1.161***	1.098***	1.031***	0.942***
	(0.125)	(0.105)	(0.076)	(0.059)	(0.044)
Country fixed effects	✓	✓	✓	✓	✓
N	972	1163	1019	1080	640
Adj. R^2	0.682	0.736	0.802	0.880	0.945

Note. We predict the real yield to maturity $\tilde{r}^{(h)}_{c,t,t+h}$ using the consensus forecast for average inflation over h years, measured as $\mathbb{F}_t(\overline{\pi_{c,t+1,h}}) = \frac{1}{h}\sum_{h'=1}^{h}\mathbb{F}_t\left(\pi_{c,t+h'Y}\right)$, and the ex-ante real rate proxy $r^{(h)}_{c,t} = i^{(h)}_{c,t} - \mathbb{F}_t(\overline{\pi_{c,t+1,h}})$. We pool countries and control for country-fixed effects. The sample ranges from 1989Q4 to 2022Q1, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Test of Prediction 2 Following Prediction 2, we compute for each quarter the 1-year excess bond return $rx^{(h)}_{c,t,t+1} = i^{(h)}_{c,t} + (h-1)\big(i^{(h)}_{c,t} - i^{(h-1)}_{c,t+1}\big) - i^{(1)}_{c,t}$, where quarterly yields average monthly yields. Results are robust to using annual data. To reduce the influence of short-term price volatility, which is notoriously large, we average excess returns over two years:

$$\overline{rx}^{(h)}_{c,t,t+1} = \frac{rx^{(h)}_{c,t,t+1} + rx^{(h)}_{c,t+1,t+2}}{2}. \tag{9}$$

Table 4, columns (1)-(4), reports estimates of equation (8), controlling for the two key proxies for real rates in the bond return predictability literature (Duffee, 2013): the "level" and "slope" at t of the (real) yield curve: "level" is the 1-year nominal rate minus one year expected inflation, "slope" is the difference between the 10 year real rate (10-year nominal rate minus ten year expected inflation) and the 1-year real rate.

In line with Prediction 2, higher inflation forecasts predict higher excess returns, more strongly so at longer maturities – consistent with horizon-increasing overreaction – and pointing

[6]Results are also robust at the annual frequency (see Table 25). We have fewer data points at the 6-10 maturity because we need ten years of realized inflation to construct the real yield.

Table 4: Predicting realized excess returns using consensus inflation forecasts

	(1)	(2)	(3)	(4)
	$\overline{rx}^{(2)}_{c,t,t+1}$	$\overline{rx}^{(3)}_{c,t,t+1}$	$\overline{rx}^{(5)}_{c,t,t+1}$	$\overline{rx}^{(6-10)}_{c,t,t+1}$
$\mathbb{F}_t\left(\overline{\pi_{c,t+1,h}}\right)$	0.164*	0.306**	1.385***	3.950***
	(0.088)	(0.147)	(0.508)	(0.758)
$r^{(1)}_{c,t}$	0.287***	0.171*	0.876***	0.702***
	(0.036)	(0.092)	(0.135)	(0.225)
$r^{(6-10)}_{c,t} - r^{(1)}_{c,t}$	0.389***	0.344**	1.350***	2.391***
	(0.072)	(0.147)	(0.319)	(0.499)
Country fixed effects	✓	✓	✓	✓
N	938	867	712	583
Adj. R^2	0.392	0.293	0.465	0.387

Note. We predict the smoothed excess return $\overline{rx}^{(h)}_{c,t,t+1} = \frac{rx^{(h)}_{c,t,t+1} + rx^{(h)}_{c,t+1,t+2}}{2}$ using the consensus forecast for average inflation over h years $\mathbb{F}_t(\overline{\pi_{c,t+1,h}}) = \frac{1}{h}\sum_{h'=1}^{h}\mathbb{F}_t\left(\pi_{c,t+h'Y}\right)$. We also control for the ex-ante real level $r^{(1)}_{c,t}$ and ex-ante real slope $r^{(6-10)}_{c,t} - r^{(1)}_{c,t}$ of the yield curve. The ex-ante real rate is defined as $r^{(h)}_{c,t} = i^{(h)}_{c,t} - \mathbb{F}_t(\overline{\pi_{c,t+1,h}})$. The raw one-year excess return is $rx^{(h)}_{c,t,t+1}$ is defined as $i^{(h)}_{c,t} + (h-1)(i^{(h)}_{c,t} - i^{(h-1)}_{c,t+1}) - i^{(1)}_{c,t}$. We pool countries and control for country fixed effects. The sample ranges from 1989Q4 to 2022Q1, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

to inefficiency. The effect is robust to smoothing returns over three years (see Appendix Table 27). Magnitude-wise, a one standard deviation increase in expected inflation predicts a 0.122 standard deviation rise in excess returns at $h = 2$, and a 0.488 rise at $h = 6$–10.

We evaluate whether the evidence for Predictions 1 and 2 is robust to several concerns. The first one is that our proxy for real rates may be imperfect. As a first step, we use our second proxy, constructed as the expected future nominal rate minus expected inflation. Results are strongly robust, see Table 12. As a second alternative strategy, in excess-return regressions we proxy fro real rates using the canonical nominal "level" and "slope" as proxies (this test is redundant for the real yield). Again, our results are strongly confirmed (see Table 15).

A second concern is that our return predictability tests may also be contaminated with small-sample bias due to a persistent predictor Stambaugh (1999). We thus use, also for Predictions 1 and 2, the correction in Boudoukh et al. (2022). Columns 6-9 of Table 28) strongly confirm our results: corrected coefficients show strong, positive, and maturity increasing return predictability, and are strongly positively correlated with non-corrected coefficients across countries, confirming that our results are not spuriously due to persistent predictors.

Overall, then, we detect predictability of excess returns and realized yields across major economies, which is directly tied to maturity-increasing overreaction in inflation expectations.

Starting with Fama and Bliss (1987), many papers show the predictability of excess returns in the US.[7] This evidence is typically explained based on time varying required returns, but without measuring the latter directly. Giglio and Kelly (2018) show that this account is inconsistent with excess volatility of long rates compared to short ones, and argue that non-rational beliefs may play a role. We directly show, using measured inflation forecasts, that excess volatility in beliefs links to interest rates volatility, especially at long maturities. [8] We now study the drivers of belief biases and their economic implications.

3 Selective Memory, Expectations and Interest Rates

The belief biases and return predictability in Section (2) challenge leading theories of inflation expectations. Models of information frictions or inattention (Sims, 2003; Woodford, 2003a), motivated by underreaction of US short-term inflation forecasts (Coibion and Gorodnichenko, 2015), predict consensus underreaction, and *only* to recent news. In equation (3) this means $\delta_{1,h} > 0$ and $\delta_{2,h} = 0$, which is counterfactual: for $h > 1$ we see "full" overreaction, $\delta_{1,h} < 0$ and $\delta_{2,h} < 0$. Diagnostic expectations (DE), (Bordalo et al., 2018; Bianchi et al., 2024a), motivated by individual-forecaster overreaction (Bordalo et al., 2020), predict $\delta_{1,h} < 0$. In formulations with a long look-back period (Bianchi et al., 2024b; Bordalo et al., 2024b), they also predict $\delta_{2,h} < 0$. The same is true for Bayesian learning of AR(1) inflation with a recency bias. Such bias is modeled using a constant gain parameter (Evans and Lewis, 1995; Marcet and Nicolini, 2003), giving a forward-looking version of adaptive expectations (Nerlove, 1958; Cagan, 1956), or using information processing costs Afrouzi et al. (2023). DE and recency bias produce overreaction of inflation expectations, but cannot jointly produce overreaction at long horizons and "no overreaction" or even underreaction at short ones.[9]

To reconcile under and overreaction, Bordalo et al. (2020) combine information frictions with diagnostic expectations. Angeletos et al. (2021) and Halperin and Mazlish (2025) analogously combine frictions with excess persistence and recency bias, respectively. Combined approaches can reconcile over and under reaction in the consensus, but not at the individual forecaster level. Yet, Bordalo et al. (2020) show – close to our current setting – that individual SPF interest rate forecasts underreact at the 3 month maturity and overreact at the 10 year one,

[7] Fama and Bliss (1987) offer early evidence based on the spread between the h-year forward and spot rates. Cochrane and Piazzesi (2005) build a related predictor based on forward rates.

[8] We can also assess excess volatility by estimating a "Fisher Equation" where we proxy for the ex-ante real rate using the expected (future rate - inflation). We could not use our first proxy for this test: its estimated coefficient would be mechanically equal to one. Here excess volatility is detected as a coefficient on inflation forecasts equal to (or above) one. Table 17 shows consistent evidence.

[9] Adaptive expectations cannot also reproduce our findings.The adaptive one-step ahead forecast is $\pi^e_{t+1} = p[\pi_t - \pi^e_{t-1}] + (1-p)\pi^e_{t-1}$. If inflation is AR(1) with persistence ρ, the coefficient on the inflation news is $(\rho - \alpha)$, and the one on the lagged forecast is $(\rho + \alpha - 1)$. Higher α reduces the former coefficient and increases the second; the two coefficients are equal when $\alpha = 0.5$, which entails underreaction for realistic values of ρ.

inconsistent with existing models. In addition, existing models rely on the knowledge of the true DGP, e.g. its AR(1) structure, or on a fixed mis-specified model. This restricts their portability to different settings and also hard-wires belief biases, reducing the ability to explain their variation.

We offer a model of mnemonic learning that accounts for short-term underreaction and long-term overreaction in a unified way. Memory limitations are invoked to justify sophisticated departures from rationality such as recency (Evans and Lewis, 1995; Marcet and Nicolini, 2003), experience effects (Malmendier and Nagel, 2016), or diagnosticity (Bordalo et al., 2018). We explicitly formalize well established regularities in recall, following Bordalo et al. (2023). As discussed in the introduction, these regularities have already been shown to jointly account for beliefs and recall data in economics. Most related to us, Gennaioli et al. (2024) use memory to study US households' inflation expectations. They take the database as given, linearize the model, and test its predictions on cross-cohort belief heterogeneity. Our key innovation is to allow for and characterize learning dynamics for inflation expectations and their link to interest rates within and across countries.[10] We build on Bonaglia and Gennaioli (2025), who formalize a highly general learning structure and study its connection to rational expectations and leading non-rational models. Here we show how this approach can be specified to study inflation expectations and interest rates.

The broad idea of our model is that, when forecasting inflation at t for horizon h, the agent retrieves episodes she frequently experienced or are similar to the current inflation cue. She then overweights these states in the future. Critically, what is retrieved depends on the database of past inflation accumulated up to t, so that mnemonic learning precisely refers to the interaction of time varying cues with the evolving database. Memory overweighting may directly affect beliefs or act on a model output. Due to concerns about misspecification, upon observing an inflation surprise the agent may adjust a model forecast using qualitative judgments that are tainted by states salient in memory.[11] Learning then proves crucial: rather than the time-decaying weights produced by recency or the invariant overreaction bias of DE, the model produces state- and horizon-dependent distortions that allow to account for the evidence in Section 2 but also yield new implications on the cross country variation of inflation expectations and interest rates that we later test.

[10]Compared to Gennaioli et al. (2024) we do not include primacy effects in memory, because we do not know the identity of forecasters (while recency effects are subsumed under similarity). Regarding numerical similarity, we include a semantic component, which is important to capture sophisticated forecasters and investors.

[11]We do not explicitly formalize this process, but without much loss of generality. As we will show, in fact, model-free mnemonic learning implies that beliefs take the form of a distorted version of the true DGP, "as if" the agent distorts an underlying statistical model.

3.1 The Model

An agent has lived through or studied a country's inflation path up to t, which forms her database. Retrieval is driven by robust regularities in human recall (Kahana, 2012): frequency, similarity to cues, and interference. [12] We now formalize these model ingredients.

The Database. At each $t = 0, 1, ...$ the memory database $\Pi_t \equiv \{\pi_k\}_{0 \leq k \leq t-1}$ contains dated realizations of past inflation. In principle, memory traces could encode macroeconomic conditions (e.g., the monetary policy regime, unemployment). In this case, recall can depend on these features, allowing mnemonic beliefs to endogenously produce "partial models": for instance the DM may recall histories that are similar along both inflation and unemployment, creating a multivariate belief structure. For parsimony, we focus on similarity to inflation and assess the explanatory power of this single retrieval feature for measured forecasts and interest rates. Bonaglia and Gennaioli (2025) formalize high dimensional structures.

Cues, Similarity, Retrieval. When forecasting at time t inflation at $t+h$, the agent draws a number of episodes π_k from her database based on a cue q_t, which is a salient signal triggering recall. In our setting the cue is current inflation, $q_t = \pi_t$. Retrieval of episode π_k then depends on its similarity to current inflation π_t. Following multidimensional scaling (Nosofsky, 1992; Torgerson, 1958), similarity decays exponentially with distance along attended to features. We allow for two features. The first is *contextual*: the numerical value of the episode. Similarity of π_k to π_t falls in their discrepancy $|\pi_t - \pi_k|$. This implies that upon seeing 2% inflation, past 2% episodes are easier to retrieve. The second feature is *semantic*. It depends on the forecasting task and captures "cause-effect" logic: when tasked at time t with forecasting two-years-ahead inflation, $h = 2$, current inflation at 3% fosters recall of what typically happened two years after 3%. Formally, the semantic feature of π_k is the numerical inflation π_{k-h} in its h-step antecedent. When forecasting at horizon h, then, semantic similarity between π_k and the cue π_t drops in the discrepancy $|\pi_t - \pi_{k-h}|$. These distances enter an overall discrepancy function $d_h(\pi_k, \pi_t)$. The probability of recalling π_k is equal to

$$r_{t,h}(\pi_k) = \frac{\exp\left[-d_h(\pi_k, \pi_t)\right]}{\sum_{\pi_s \in \Pi_t} \exp\left[-d_h(\pi_s, \pi_t)\right]}. \tag{10}$$

By the numerator, it is easier to retrieve numerical values that are more similar or frequent. A DM who is seeing inflation at 2% or that has experienced inflation at 2% very often is more

[12] In classic experiments, subjects recall words from a studied list. Frequency means that a word, say "apple", is more likely recalled if it is repeated in the list. Similarity has two dimensions: semantic (e.g., the word "wheel" cues "car"), and contextual (e.g., "wheel" may cue "eel" due to similar spelling and phonetics). Interference reflects the competition among memories: frequent or similar items crowd out others.

likely to retrieve this realization. The denominator captures interference: a highly frequent or similar episode π_s hinders recall of π_k for a given cue π_t.

Recall and Beliefs. The agent retrieves a set of episodes with i.i.d probability $r_{t,h}(\pi_k)$, and her expectation is the average retrieved episode. Due to stochasticity in recall, agents with the same database may form different beliefs based on the same cue. Their average forecast will however reflect a systematic bias – our main object of interest. Aggregating across many agents sharing the same database and cue, the consensus mnemonic forecast is equal to:

$$\mathbb{E}_t^m(\pi_{t+h}) = \sum_{\pi_k \in \Pi_t} \pi_k r_{t,h}(\pi_k). \tag{11}$$

Equation (11) implies that a frequent past state, say inflation at 2%, is more likely to be recalled and hence beliefs are more anchored to it. It also implies that current inflation anchors beliefs to similar episodes. By *contextual* similarity, current inflation at 3% prompts recall and overweighting of 3%. By *semantic* similarity, if current inflation is 3% and 3% typically led to 2% in the past, the latter outcome is more accessible and hence overweighted in the future. Critically, cues intereact with the database: the current 3% inflation will have an especially large effect if there are sufficiently many similar episodes in Π_t. As a result, changing cues re-weight recall but the process depends on Π_t, causing beliefs to be state- and database-dependent.

Expectations. Equations (11) and (10) characterize beliefs at every horizon h as a function of: i) the database Π_t, and ii) numerical and semantic distances with the cue π_t, $|\pi_t - \pi_k|$ and $|\pi_t - \pi_{k-h}|$. These objects are observable from a country's inflation history. Beliefs are then pinned down by the similarity "weights" of features, which we later estimate. This shows that mnemonic learning is "model free": belief updating depends solely on the observed history, without the agent having to know the DGP and without needing the econometrician to estimate it. The DGP is useful to mathematically characterize long run mnemonic beliefs, which we do next, building on Bonaglia and Gennaioli (2025). In Section 4 we estimate the model "agnostically", using only inflation histories.

3.2 Long Run Beliefs

To get tractability, we take a second-order approximation of the discrepancy function, so that:

$$d_h(\pi_k, \pi_t) = \alpha(\pi_{k-h} - \pi_t)^2 + \beta(\pi_k - \pi_t)^2, \tag{12}$$

where $\alpha \geq 0$ and $\beta \geq 0$ are the weights of semantic and contextual features, respectively.

Given the DGP $(\pi_t)_{t\in\mathbb{N}}$, the expectation $\mathbb{E}_t^m(\pi_{t+h})$ in equation (11) is a stochastic process that depends on the cue π_t and the database Π_t. We say that this process has a long-run approximation $\mathbb{E}_t^\infty(\pi_{t+h})$ if, fixing $\epsilon > 0$ arbitrarily, the probability of the event $\{|\mathbb{E}_t^m(\pi_{t+h}) - \mathbb{E}_t^\infty(\pi_{t+h})| > \epsilon\}$ tends to zero under the DGP as $t \to \infty$. Under general assumptions described in the appendix, $\mathbb{E}_t^m(\pi_{t+h})$ admits a long-run approximation, which we now characterize.

Proposition 1 *Let $(\pi_t)_{t\in\mathbb{N}}$ be zero-mean, stationary, ergodic and Gaussian. Then, under the discrepancy in equation (12), there is a coefficient $\phi(\alpha, \beta, h) \in \mathbb{R}$ such that the expectation $\mathbb{E}_t^m(\pi_{t+h})$ admits the long-run approximation:*

$$\mathbb{E}_t^\infty(\pi_{t+h}) := \phi(\alpha, \beta, h)\pi_t.$$

We call "mnemonic expectation" the approximation above. Mnemonic learning causes beliefs to take the form of a possibly distorted model that relies on the attended to similarity features with weights α and β, and on the true parameters of the data generating process through the database Π_t. With the discrepancy in equation (12) such model is akin to an AR(1): it loads on current inflation with a proportionality coefficient $\phi(.)$.[13]

We characterize the role of similarity weights, of the database, and their interaction.

Proposition 2 *The mnemonic expectation obeys the following limit cases:*

$$\begin{aligned}
&\lim_{\alpha\to\infty,\ \beta\to 0} \phi(\alpha, \beta, h) = \frac{cov(\pi_{t+h}, \pi_t)}{var(\pi_t)}, && \textit{(Least Squares)}\\
&\lim_{\alpha\to 0,\ \beta\to\infty} \phi(\alpha, \beta, h) = 1, && \textit{(Adaptive)}\\
&\lim_{\alpha\to 0,\ \beta\to 0} \phi(\alpha, \beta, h) = 0. && \textit{(Frequentist)}
\end{aligned}$$

If $cov(\pi_{t+h}, \pi_t) > 0$ converges to zero as $h \to \infty$ and $\beta > 0$, there is a horizon $\tilde{h}$ such that, for all horizons $h \geq \tilde{h}$, the mnemonic expectation overreacts:

$$\phi(\alpha, \beta, h) > \frac{cov(\pi_{t+h}, \pi_t)}{var(\pi_t)}.$$

Semantic similarity fosters forward-looking beliefs. If this force dominates ($\alpha \to \infty$ and $\beta \to 0$), the forecast is a least square projection of future inflation on π_t. Expectations are rational if the DGP is AR(1). They select the best AR(1) fit otherwise, as in natural expectations (Fuster et al., 2012). Semantic similarity can thus capture the use of a statistical model.

Numerical similarity causes instead anchoring to the present. If this force dominates ($\alpha \to 0$ and $\beta \to \infty$), the agent expects π_t to persist at any future horizon, promoting overreaction.

[13] In a finite sample, the mnemonic forecast will not load on current inflation but on the most similar inflation episodes experienced in the past.

Critically, this is not a recency effect: if $\beta < \infty$ the cue π_t is more potent if the frequency of similar episodes in Π_t is larger. An inflation surge will not change beliefs much if similar episodes were rare in the past. This property is a key consequence of mnemonic learning.

Finally, frequency causes overweighting of the zero long-run mean around which inflation fluctuates. If this force dominates ($\alpha, \beta \to 0$), the agent expects immediate reversal to such mean. If the DGP exhibits any serial correlation, this force promotes underreaction to π_t.

Consider next the interaction between the database and retrieval cues. It depends on the DGP, which shapes the database. If the stationary DGP exhibits positive short-run autocorrelation, the mnemonic expectation moves in the right direction but – due to numerical similarity β – it exhibits long-run overreaction: by overweighting future scenarios that resemble the present, it causes neglect of mean reversion. To characterize more sharply this interaction, and in particular whether forecasts under- or overreact, we must pin down the long run database $\lim_{t\to\infty} \Pi_t$. To do so, we assume that inflation is AR(1):

$$\pi_k = \rho \cdot \pi_{k-1} + \sigma \cdot \epsilon_k, \tag{13}$$

with persistence $\rho \in (0, 1)$ and volatility $\sigma > 0$. We obtain the following result.

Proposition 3 *Let $\sigma_\pi^2 \equiv \sigma^2/(1-\rho^2)$. Expected inflation at t for $t+h$ is equal to*

$$\mathbb{E}_t^\infty(\pi_{t+h}) = \frac{\alpha\rho^h + \beta + 2\alpha\beta\sigma_\pi^2\left(1-\rho^{2h}\right)}{\alpha + \beta + 2\alpha\beta\sigma_\pi^2\left(1-\rho^{2h}\right) + \frac{1}{2\sigma_\pi^2}}\pi_t. \tag{14}$$

The mnemonic expectation extrapolates from current inflation by distorting the AR(1) persistence parameter. Critically, the interaction between cues and the database causes the degree of extrapolation to increase in true volatility σ and persistence ρ. When σ is large, the agent has experienced many high and low inflation states. By similarity, these states are selectively retrieved when π_t is high or low, so extrapolation is strong. If $\sigma \to \infty$ the mnemonic expectation fully projects the present into any future horizon, $\mathbb{E}_t^\infty(\pi_{t+h}) \to \pi_t$. Stable inflation (low σ) instead promotes belief rigidity through overweighting of the long-run mean. When $\sigma \to 0$ we have $\mathbb{E}_t^\infty(\pi_{t+h}) \to 0$. This is a second novel property of mnemonic learning: under and over-reaction are rationalized based on the frequency of different experiences in the database, which affects updating based on changing cues.

Higher persistence ρ increases extrapolation in two ways: it increases volatility, but it also increases semantically-retrieved persistence from the past. If persistence is maximal $\rho \to 1$ the mnemonic expectation is rational for any similarity parameters, $\mathbb{E}_t^\infty(\pi_{t+h}) \to \pi_t$. If persistence is zero, the mnemonic expectation overreacts at any $\beta > 0$.

Whether belief under- or overreact depends on the balancing of these forces. By equation

(14), the short-run forecast (i.e., $h = 1$) overreacts, $\phi(\cdot) > \rho$, if and only if

$$\rho\,(1+\rho) < 2\beta\sigma^2\left(1+2\alpha\sigma^2\right). \tag{15}$$

Overreaction occurs when cues are strong enough, α and β are large, volatility σ is high, and persistence ρ is low. At high volatility, higher inflation retrieves many similar past episodes, fostering overreaction. At low persistence, even a small amount of numerical anchoring causes overreaction. At high persistence a sufficient weight on frequency (i.e., low enough similarity weights) causes excess anchoring to the long-run mean and thus underreaction.

Mnemonic learning thus reconciles models featuring excess AR(1) persistence such as Gabaix (2019), Angeletos et al. (2021)) or DE with long look-back period ($J \to \infty$ in Bianchi et al. (2024b)), with models featuring rigidity (Sims, 2003; Woodford, 2003a). Critically, which of these forces prevails, and hence the direction and strength of biases, depends on the inflation DGP and the horizon h, rationalizing our findings and yielding new predictions.

3.3 Implications of Selective Memory

Consider the predictability of forecast errors from the forecast revision and lagged forecast – the counterpart of regression (3). the mnemonic expectation obeys the property below.

Proposition 4 *Under equation (14) the mnemonic revision at t and the mnemonic expectation at $t-1$ predict the forecast error at $t+h$ with coefficients:*

$$\delta_{1,h} = \delta_{2,h} = \delta_h \equiv \rho^h \frac{\alpha+\beta+2\alpha\beta\sigma_\pi^2(1-\rho^{2h})+1/2\sigma_\pi^2}{\alpha\rho^h+\beta+2\alpha\beta\sigma_\pi^2(1-\rho^{2h})} - 1. \tag{16}$$

If $\beta > 0$ the predictability coefficient δ_h monotonically decreases in the forecast horizon h and exhibits long-term overreaction: $\lim_{h\to\infty}\delta_h = -1$.

Consistent with Table 2, there is horizon-increasing overreaction to news and the lagged forecast: $\delta_{1,h}$ and $\delta_{2,h}$ decrease with the horizon h. At short horizons, underreaction may prevail, depending on parameter values, as shown in equation (15). At longer horizons, overreaction eventually prevails if $\beta > 0$. Consistent with Table 2, under an AR(1) DGP, $\delta_{1,h} = \delta_{2,h}$.

With respect to the AR(1) parameters, our discussion of extrapolation suggests that we should expect overreaction to be stronger (and short-term underreaction to be less likely to arise) when inflation is more volatile and less persistent, i.e., σ is higher or ρ is lower. The comparative static on σ is easily proved analytically, the one on ρ is more complicated but our simulations show that it generally holds. Specifically, if beliefs overreact at a certain ρ, then under most parameter values overreaction becomes weakens as ρ increases (and δ_h may even shift from negative to positive when ρ becomes large enough, consistent with underreaction

in equation (15)). If however β is large or the forecast horizon is long, the model produces overreaction even at high persistence, but such overreaction decreases monotonically in ρ.[14]

Consider return predictability. It can be analytically studied under the expectations hypothesis if the DGP is AR(1), giving the mnemonic counterparts of equations (5) and (7).

Proposition 5 *If $\beta > 0$, the mnemonic expectation $\mathbb{E}_t^{\infty}(\overline{\pi_{t+1,h}})$ predicts the ex-post real yield to maturity h with coefficient*

$$\theta_h^r = -\sum_{j=1}^{h} \delta_j w_j, \tag{17}$$

where weights $(w_j)_{1\leq j\leq h}$ are positive and sum to one. If $\alpha = 0$, this simplifies to $\theta_h^r = 1 - \frac{\rho(1+2\beta-\rho^2)(1-\rho^h)}{2h\beta(1-\rho)}$, which is increasing in h and positive for sufficiently large h.

The same expectation also predicts the excess return on a maturity h bond with coefficient:

$$\theta_h^{rx} = h[\theta_h^r(1-\rho) + \delta_1 w_1 - \rho\delta_h w_h]. \tag{18}$$

When $\alpha = 0$, this simplifies to $\theta_h^{rx} = (h-1)(1-\rho)$, implying positive and maturity-increasing predictability of excess returns.

Numerical similarity ($\beta > 0$) causes nominal rates to increase excessively with higher π_t. As a result, future inflation is systematically below expectations and real yields to maturity are abnormally high. This effect drives the positive and maturity-increasing values of θ_h^r. In equation (17) predictability at maturity h is inversely related to the forecast error coefficient δ_h, averaged across the relevant horizons.

For excess returns, the link with error predictability is more complex: overreaction of long-term beliefs, captured in equation (18) by $\theta_h^r > 0$, can be offset by biased shifts in short-term beliefs, captured by δ_1. The balance between these forces depends on α: when the agent is very forward-looking (i.e., α is high), long-term rates respond less than short-term ones in absolute terms, potentially causing negative predictability; the opposite occurs when α is low. If $\alpha = 0$, we obtain positive maturity-increasing predictability of excess returns as in the data.

Crucially, the direction and strength of forecast errors and return predictability should depend on similarity weights and the DGP. We test these implications by estimating the model.

4 The Explanatory Power of the Model

Section 4.1 estimates the model. Sections 4.2, 4.3 and 4.4 assess key new implications of the memory approach: its ability to produce realistic variation in the degrees of under and

[14]The mapping between ρ and δ_h is non-monotonic if beliefs exhibit substantial underreaction at intermediate values of ρ, which can happen at short horizons. In this case, as ρ approaches one the predictability coefficient δ_h decreases toward zero.

overreaction and return predictability across countries solely based on inflation histories. Due to the "model free" nature of mnemonic learning, we do not need to assume a DGP for inflation. We only need to keep track of the evolution inflation which sets the cue and the database.

4.1 The Database and Similarity Weights

We implement mnemonic beliefs by applying equation (11) to the database of past annual inflation. For the generic time t and country c, the database is $\Pi_{c,t} = \{\pi_{c,t}\}_{k=t_{c,0},\dots t-1}$, where $t_{c,0}$ is the first available inflation episode for c (ranging from 1960 to 1996, see Table 6). The probability $r_{t,h}(\pi_{c,k})$ is computed using the discrepancy function:

$$d_h(\pi_{c,k}, \pi_{c,t}) = \alpha(\pi_{c,k-h} - \pi_{c,t})^2 + \beta(\pi_{c,k} - \pi_{c,t})^2 \quad \text{for } \pi_{c,k} \in \Pi_{c,t}. \tag{19}$$

For given weights (α, β), retrieval from the evolving database pins down the model implied forecast $\mathbb{E}_t^m(\pi_{c,t+h}|\alpha, \beta)$. We estimate (α, β) by matching this forecast with CE forecasts for all t, c, h. (α, β) is constant across time, space and horizon. As a result, the model's explanatory power for horizon and country variation stems *entirely* from temporal and cross-sectional differences in databases.

We build a grid of more than 10,000 points $(\alpha, \beta) \in [0, 1]^2$ with a step size of 0.01, each yielding a panel of model-implied forecasts. We then select (α, β) to minimize the total absolute deviation between CE and model-implied forecasts:

$$\min_{\alpha,\beta} \sum_{c,t,h} |\mathbb{F}_t(\pi_{c,t+h}) - \mathbb{E}_t^m(\pi_{c,t+h}|\alpha, \beta)|,$$

where $\mathbb{F}_t(\pi_{c,t+h})$ is the CE forecast (see Appendix B.3 for details). The point estimates and 99% confidence intervals are:[15]

$$\widehat{\alpha} = 0.07 \pm 0.006 \quad \text{and} \quad \widehat{\beta} = 0.18 \pm 0.015.$$

These estimates reveal that contextual similarity matters, $\widehat{\beta} = 0.18$, producing overreaction. Semantic similarity receives a smaller weight, $\widehat{\alpha} = 0.07$, generating a forward-looking component. Finally, the fairly low magnitude of the weights implies that anchoring to frequent outcomes is also sizable. All mnemonic forces are thus active in the data. Hereafter, we refer to

[15] We perform a case-resampling bootstrap on the panel of model-generated inflation expectations for each country over the in-sample period 1989–2022, drawing $N = 1000$ bootstrap samples by sampling with replacement a multiset of length 34 (the number of in-sample years). For each sample, we reconstruct the bootstrapped series for each (α, β) pair, adjust for country-specific start dates, and estimate (α, β) by minimizing the sum of absolute deviations between simulated and observed CPI from CE. See Appendix B.4 for details. Confidence intervals are 99% symmetric percentile bootstrap confidence intervals, which have the advantage of being robust under model misspecification (Kolesár, 2025).

the predicted belief at the above point estimates as the "mnemonic forecast". Model fit is good: with only two parameters, mnemonic forecasts exhibit a correlation of 0.60 with CE forecasts, capturing a sizable share of variation across countries, time periods, and horizons.

With these estimates in hand, we evaluate the model's explanatory power. For understanding the volatility of beliefs and interest rates, three key metrics must be considered. The first is the strength with which inflation expectations extrapolate from recent inflation. In mechanical models such strength is fixed, under mnemonic learning it depends on history. History dependence is key to assess the ability of the model to produce different degrees of over or under reaction across economic and policy contexts, also addressing the Lucas critique (Lucas, 1972). The second and third metrics instead directly follow from Section 2: the extent of forecast error predictability (Tables 1 and 2), and the extent of return predictability (Tables 3 and 4). Also in this case, we evaluate the model's ability to explain cross country variation in these phenomena, which is entirely un-targeted in our estimation.

4.2 Strength of Extrapolation

The strength of extrapolation refers to the sensitivity of forecasts to the inflation level recently observed by forecasters. We measure this strength by estimating the following regression separately for CE and mnemonic forecasts:

$$\mathbb{F}^i_t(\pi_{c,t+h}) = \alpha^i_{c,h} + \chi^i_{c,h} \cdot \overline{\pi}_{c,t} + \varepsilon^i_{c,t,t+h}, \tag{20}$$

where $i = \text{CE}$ and $i = m$ denote CE and mnemonic forecasts, respectively. The coefficient $\chi^i_{c,h}$ captures the sensitivity of forecasts to the inflation state in country c at horizon h. Following Section (2), the inflation state is $\overline{\pi}_{c,t} = (\pi_{c,t-1} + \pi_{c,t-2})/2$.

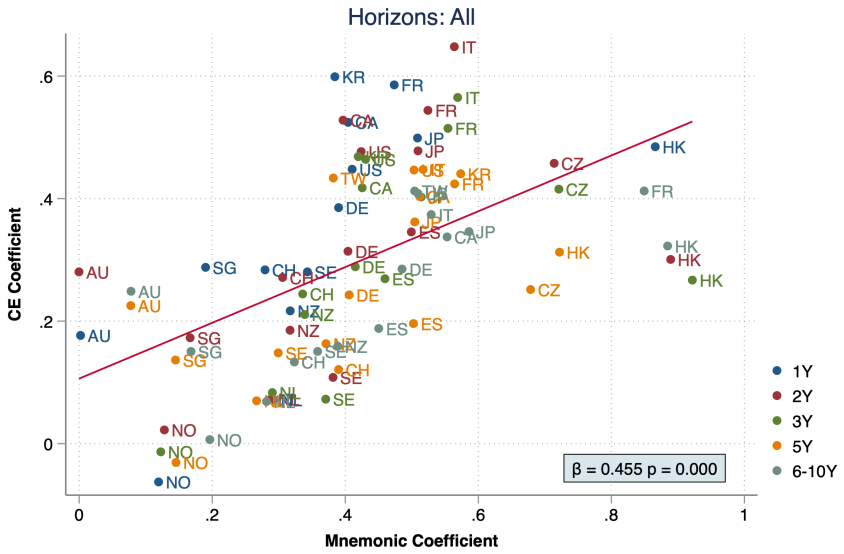
CE-based estimates reveal strong heterogeneity in the extent of extrapolation $\chi^{CE}_{c,h}$ across countries and horizons (see the boxplot in Appendix Figure 7, Panel A, for details). At the shortest horizon, the median coefficient $\chi^{CE}_{c,1}$ is about 0.34 with an inter-quartile range of $[0.22, 0.50]$. At the longest horizon, the median $\chi^{CE}_{c,\text{6-10}}$ is about 0.27 with an inter-quartile range of $[0.15, 0.36]$. Short-run forecasts extrapolate more than long-run ones: forecasters internalize mean reversion. Crucially, at each horizon we observe systematic cross-country variation in extrapolation: the equality of $\chi^{CE}_{c,h}$ across countries is strongly rejected.[16] To assess whether our model reproduces this variation, Figure 1 plots the coefficients $\chi^{CE}_{c,h}$ estimated using CE forecasts (y-axis) against those estimated using mnemonic forecasts $\chi^{m}_{c,h}$ (x-axis).

Our model captures a significant share of variation: the correlation between the two coefficients is 0.42. To isolate cross-country variation, let $\overline{\chi}^{CE}_{c}$ be the average strength of extrapo-

[16] Formally, we estimate a pooled regression in which the inflation state is interacted with country dummies. The p-values of the F-test are 0.0000 for all horizons $h = 1, 2, 3, 5, 6\text{-}10$.

lation in country c across horizons h. Figure 2 reports this coefficient estimated from CE data (y-axis) against its mnemonic counterpart (x-axis). The association is strong: the regression beta is 0.426 ($p = 0.045$), the R^2 is 0.23 and the correlation is 0.48. Mnemonic learning can generate realistic belief functions – and, as we will see, distortions – based on histories.

Figure 1: Degree of Extrapolation

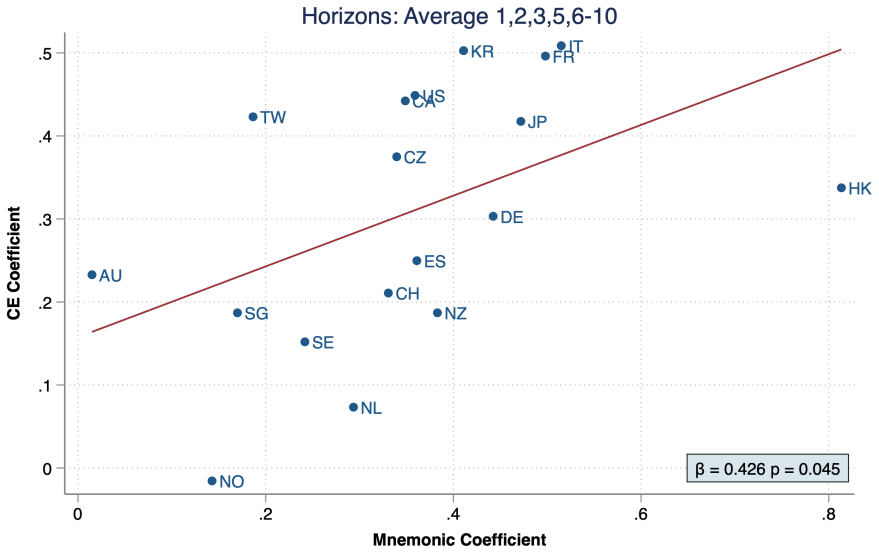


Note. The figure displays extrapolation coefficients estimated using CE forecasts (y-axis) against the those estimated using mnemonic ones (x-axis). The line shows the fit between the two. Pooled (across countries and horizons) slope and pvalue are reported in the blue box in the graph. Each data point is identified by the ISO 3166-2 country abbreviation.

We compare the explanatory power of mnemonic forecasts to standard models of inflation expectations, which are adaptive learning systems featuring a recency bias. The conventional specification is constant-gain learning (Evans and Honkapohja, 2009), but we also consider the bounded rational version in Afrouzi et al. (2023). In the first model, the agent infers the long-run mean and persistence of AR(1) inflation with gain parameter $\gamma > 0$. When matching CE forecasts, we find $\gamma \approx 0.02$, in line with standard estimates (Nagel, 2024) (see Appendix B.5 for details). In the second model, learning is subject to a cost of using past data, leading to overweighting of recent data (in a similar vein Azeredo da Silveira and Woodford (2019) assume costly retrieval of the prior). We calibrate this model following Halperin and Mazlish (2025) (see Appendix B.6 for details).

Figure 3 shows, in Panels A and B, that neither model can reproduce meaningful cross-country variation in extrapolation. For the constant gain model, the estimated coefficient $\overline{\chi}_c$ is low (0.385) and insignificant ($p = 0.167$) and has a small R^2 of 0.11, and the same is true for the bounded rationality model (whose estimated slope is 0.143, $p = 0.463$, and

Figure 2: Country-wise Degree of Extrapolation, Mnemonic Learning



Note. The figure displays the country specific, averaged across horizons, coefficients from the simulated (x-axis) against the CE (y-axis) datasets. The line indicates the fit between the two. Pooled (across countries) slope and pvalue are reported in the blue box in the graph. The identifier for each data point corresponds to the ISO 3166-2 country abbreviation.

$R^2 = 0.03$).[17] Intuitively, recency bias produces extrapolation from current conditions, but not history dependence. Mnemonic learning instead produce overreaction from the interaction of cues and the database, so it exhibits history dependence.

Having shown that the model reproduces variation in the degree of extrapolation across countries, we now see whether the same force can reproduce the belief and interest rates puzzles of Section 2, and whether the model explains their cross country variation, also based on intuitive features of inflation histories.

4.3 Strength of Overreaction

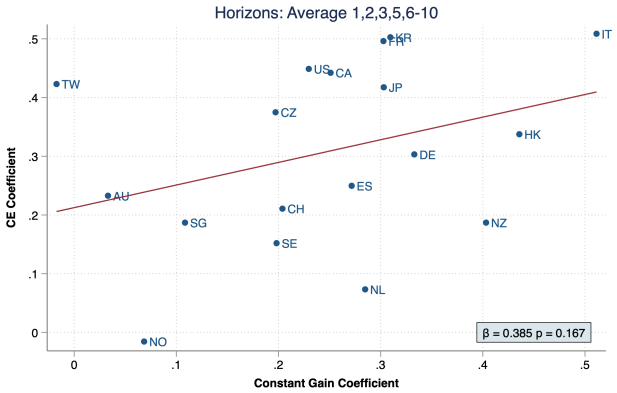
We predict the forecast error using the current forecast as in equation (2). Because the memory model produces annual forecasts, we benchmark the model's explanatory power to annual CE-based estimates. Consider pooled estimates as in Section 2 first (displayed for CE data at annual frequency in Panel A of Table 23). The model successfully captures horizon-increasing overreaction. The coefficients δ_h estimated from mnemonic forecasts are in fact statistically indistinguishable from their CE-based counterparts (see Table 20).[18]

[17] As reported in B.6, we also calibrate the model to match CE forecasts. In that case, the estimated slope is 0.232 ($p = 0.295$) with an $R^2 = 0.07$, again indicating no significant explanatory power.

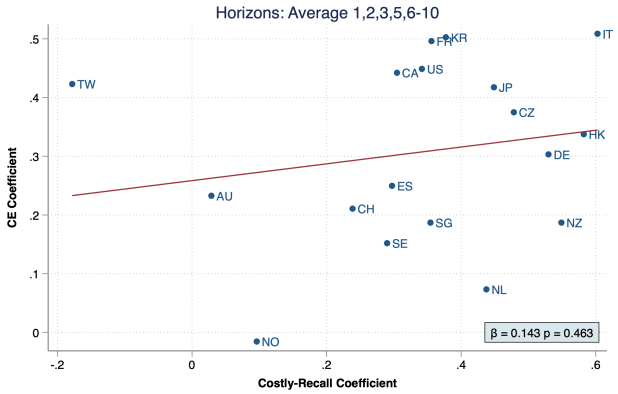
[18] We repeat this exercise for the error predictability specification in equation (3). Our model also matches the coefficients capturing overreaction to news $\delta_{1,h}$ and the lagged forecast $\delta_{2,h}$ (see Table 19). Notably, mnemonic

Figure 3: Country-wise Degree of Extrapolation - Recency

Panel A: Evans and Honkapohja (2009)'s Model



Panel B: Afrouzi et al. (2023)'s Model



Note. The figure displays the country specific, averaged across horizons, coefficients from the two simulated models (Panel A: (Evans and Honkapohja, 2009)'s Model; Panel B: Afrouzi et al. (2023)'s Model) (x-axis) against the CE (y-axis) datasets. The line indicates the fit between the two. Pooled (across countries) slopes and pvalues are reported in the blue boxes in the graphs. The identifier for each data point corresponds to the ISO 3166-2 country abbreviation.

Critically, let us turn to the ability of the model to reproduce also cross country variation. We estimate the specification of Equation (2) separately for each country and horizon. Using CE data, we detect sizable variation in error predictability coefficients $\delta^{CE}_{c,h}$ (see Figure 7, Panel B). At the shortest horizon, the median $\delta^{CE}_{c,0}$ is about 0.14 with an inter-quartile range of $[0.1, 0.19]$, indicating a tendency toward underreaction. At the longest horizon, the median $\delta^{CE}_{c,6\text{-}10}$ is -1.03 with an inter-quartile range of $[-1.3, -0.74]$, pointing to sharp overreaction. Cross-country differences in overreaction are significant.[19]

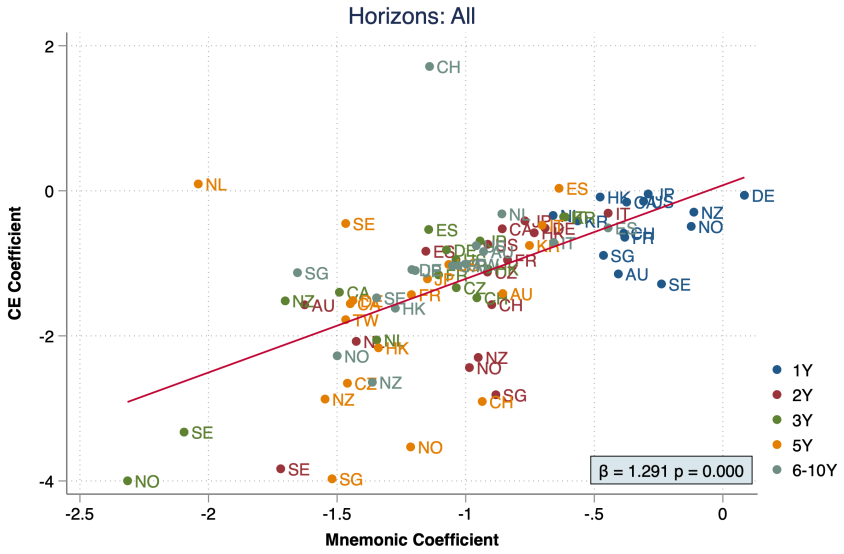
Figure 4, plots the estimated $\delta_{c,h}$ from CE data (y-axis) against their mnemonic counterparts (x-axis). Due to annual frequency, we cannot simulate within year model forecasts, so the figure reports maturities $h \geq 1$. Our model captures significant country and horizon variation in belief biases, achieving a 59% correlation with CE-based coefficient estimates.

To assess the extent of cross-country variation, we regress the estimates of $\delta^{CE}_{c,h}$ on forecast-horizon dummies. The R^2 of this regression is 0.16. Adding the mnemonic coefficient $\delta^{m}_{c,h}$ to the regression yields an R^2 of 0.39 (see Table 18, columns (1) and (2)). The explanatory power more than doubles: our model reproduces significant cross-country variation in overreaction. By comparison, recency models exhibits significantly less explanatory power: the constant gain model has an R^2 of 0.23, while the bounded rationality model of 0.29, which are sensibly smaller than the R^2 of our model.

forecasts can also reconcile the absence of significant overreaction to news at $h = 1$, $\delta_{1,h} = 0$, with significant overreaction to the lagged forecast at the same horizon, $\delta_{2,h} < 0$.

[19]Estimating a pooled error predictability regression in which expected inflation is interacted with country dummies, the F-test rejects coefficient equality at all horizons at standard confidence levels (with p-values of 0.0003 for $h = 1$, 0.0000 for $h = 2$, 0.0000 for $h = 3$, 0.0000 for $h = 5$, and 0.0000 for $h =$ 6-10).

Figure 4: Performance for Forecast Errors Predictability



Note. The figure displays the country specific coefficients from the simulated (x-axis) against the CE (y-axis) datasets across horizons. The line indicates the fit between the two. Pooled (across countries and horizons) slope and pvalue are reported in the blue box in the graph. The identifier for each data point corresponds to the ISO 3166-2 country abbreviation.

One interesting question is whether the model's explanatory power, captured by the fitted values $\hat{\delta}^{CE}_{c,h}$ in Figure 4, is linked to intuitive features of inflation databases. The AR(1) model suggests that two such features may be the historical volatility and persistence of inflation. In volatile environments, seeing high inflation today recalls many high inflation episodes from the past and vice-versa seeing low inflation, fostering overreaction to the current inflation state. Persistence matters because, due to frequency, the agent stays excessively anchored to average inflation in her database, so she will tend to overreact less when actual inflation is more persistent. Of course, the inflation DGP is hardly AR(1) in all countries, but its analysis offers clues as to which historical features to look at.

We regress $\pi_{c,t+h}$ on $\pi_{c,t}$ for country c and horizon h. We take the slope $\rho_{c,h}$ as a measure of persistence and the standard deviation of the residuals $\sigma_{c,h}$ as a proxy for volatility. The AR(1) intuition then suggests that higher persistence $\rho_{c,h}$ is associated with higher $\delta_{c,h}$ (less overreaction), while higher volatility $\sigma_{c,h}$ is associated with lower $\delta_{c,h}$ (more overreaction). This is indeed what we find when regressing $\hat{\delta}^{CE}_{c,h}$ on these statistics:

$$\hat{\delta}^{CE}_{c,h} = \underset{(0.091)}{-1.152^{***}} - \underset{(0.057)}{0.163^{***}} \cdot \sigma_{c,h} + \underset{(0.134)}{1.864^{***}} \cdot \rho_{c,h} + \varepsilon_{c,h}. \tag{21}$$

Countries where inflation is less persistent and more volatile indeed exhibit more overreaction. The role of $\sigma_{c,h}$ is in line with the intuition that in countries with more volatile histories,

extreme inflation cues prompt recall of more extreme past episodes, boosting excess belief volatility. The regression's adjusted R^2 is 0.714, so these two statistic capture the bulk of the model's explanatory power. Mnemonic learning can capture sizable variation in belief biases based on the historical volatility and persistence of inflation.

4.4 Explanatory Power for Bond Returns

To study variation in market efficiency, following Section 2.3, we compute expected average inflation from t to $t+h$ using CE and mnemonic beliefs. We then use these measures to predict the real yield to maturity and excess bond returns observed in the data. We then obtain estimates for the return predictability coefficients $\theta^r_{c,h}$ and $\theta^{ex}_{c,h}$, for CE and mnemonic forecasts.

The CE data show substantial heterogeneity in return predictability. For the real yield (see Figure 7, Panel E), the median coefficient at one year is 1.96 with an inter-quartile range of $[-0.57, 2.62]$. At 6-10 years, the median rises to 2.64 with an inter-quartile range of $[1.52, 3.12]$. The same emerges for excess bond returns (see Figure 7, Panel F). At the $h = 2$ horizon, the median coefficient is 0.93 with interquartile range of $[0.27, 1.79]$; at 6-10 years, the median rises to 5.83 with interquartile range $[4.02, 17.18]$. Maturity-increasing return predictability varies systematically across countries, pointing to differences in market efficiency.[20][21]

To assess whether mnemonic forecasts capture variation in return predictability, Figure 5 reports, in Panel A, the real yield coefficients $\theta^r_{c,h}$ estimated from CE (y-axis) and mnemonic forecasts (x-axis). Panel B reports the excess return coefficients $\theta^{ex}_{c,h}$ estimated from CE (y-axis) and mnemonic forecasts (x-axis).

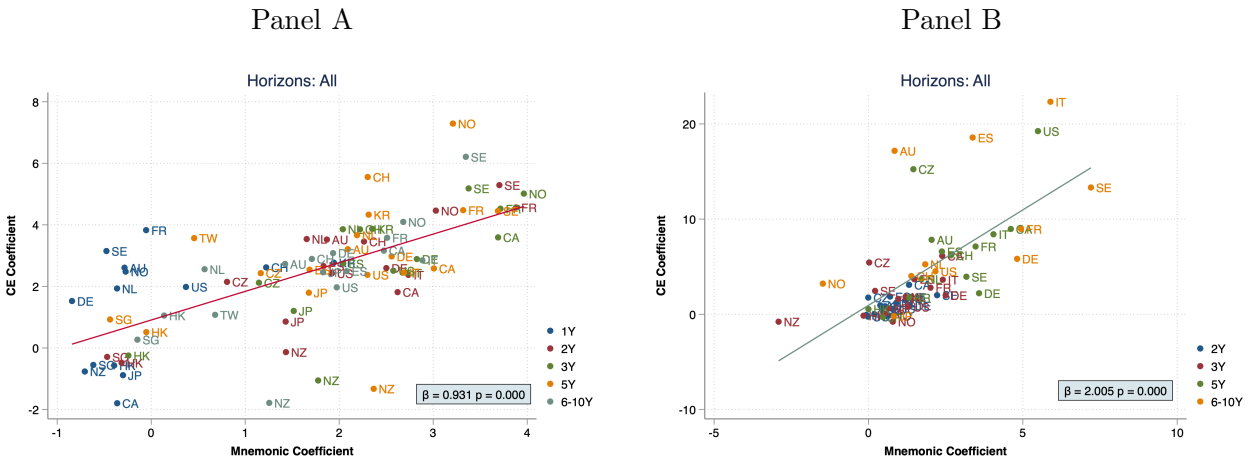
The model captures sizable variation in market inefficiency. The correlation between CE and mnemonic coefficients is 67% for real yields and 68% for excess returns. A significant share of this explanatory power is tied to cross-country variation: for real yields, the R^2 for CE-based coefficients rises from 9.5% to 48% when adding the mnemonic estimates of $\theta^r_{c,h}$ to horizon dummies; for excess returns, it rises from 38% to 55% when adding the mnemonic estimates of $\theta^{ex}_{c,h}$ (see Table 18, columns (3), (4), (5) and (6)). In sum, selective recall applied to different databases accounts for significant variation in interest rate volatility and market inefficiency. Selective memory can have significant economic implications, as we discuss next.

We can also evaluate the ability of mnemonic beliefs to produce sizable return predictability under the assumption of constant required return. This is a useful exercise because it allows to test, in a fully controlled envrionment, whether volatility in systematic forecast errors and revisions can account for the degree of return predictability in the data

[20] Our F-test strongly rejects coefficient equality at all horizons. For real yields, the p-values are 0.0000 for all horizons $h = 1, 2, 3, 5$, 6-10. For excess returns, they are 0.0000 for all horizons $h = 2, 3, 5$, 6-10.

[21] The model reproduces pooled predictability estimates in CE. For the real yield, CE-based estimates are from Columns (1)-(5) of Table 25, mnemonic estimates are from Table 21. Both use annual data and give similar coefficients. For excess returns, mnemonic and CE estimates are in Table 22, which are again similar.

Figure 5: Performance for Real Yield to Maturity and Excess Returns



Note. Panel A plots the return predictability coefficients $\theta^{r}_{c,h}$ from the CE dataset at annual frequency (y-axis) against the simulated dataset (x-axis). Panel B plots the excess return predictability coefficients $\theta^{ex}_{c,h}$ from the CE dataset at annual frequency (y-axis) against the simulated dataset (x-axis). Coefficients in both figures are country- and maturity-specific. The lines indicate the fit between the two datasets' coefficients. Pooled (across countries and horizons) slopes and pvalues are reported in the blue boxes in the graphs. The identifier for each data point corresponds to the ISO 3166-2 country abbreviation.

To do so, we imputed a constant ex-ante required return for each country c and maturity h, set to match the average ex-ante real interest rate in each country (where such ex ante real rate is computed using our first proxy from Section 2). Using this time-constant rate, we then obtain "artificial" nominal rates at each t by adding model-implied expectations in the same period to the constant real rate, following the Fisher Equation. Using these model-based nominal rates, which by definition only move due to model-predicted inflation expectations - we can compute realized yield and excess bond returns. We can then reproduce our country by country bond return predictability regressions, which are now by definition unaffected by any required return variation. We then compare these model-based predictability coefficients to those estimated using CE data and market interest rates. We find that a strong association between the two, confirming that model-implied return predictability captures substantial variation in the data, with correlations of 45% and 53% with real yield and excess return predictability, respectively. This implies that mnemonic learning produces not only realistic belief volatility, but also an associated realistic degree of bond market inefficient and its variation across countries, based on different inflation histories. The results are in Appendix A.8.

4.5 Economic Implications

Via return predictability, high expected inflation today causes a future redistribution of wealth from borrowers to lenders, and vice-versa for low expected inflation. In heterogeneous-agent models such effects can affect output, because borrowers typically have a higher propensity to

spend than lenders (Auclert, 2019; Sterk and Tenreyro, 2018). We now assess the magnitude of such redistributions. We first offer an illustrative quantification for the partial equilibrium effects on a single borrower based on facts from Section 2. We then quantify the effect in an equilibrium model with two types of agents, a borrower and a lender. Here we also directly evaluate the role of mnemonic belief distortions estimates in this section, on average and across countries with different inflation histories.

Partial Equilibrium Effects. Consider a borrower who takes a simple loan with maturity h^* years. The payment is constant in real terms (i.e., in $t = 0$ dollars) and equal to $P^{(h^*)}$. Expected inflation is π^e for all future periods. Thus, the contractually stipulated nominal payment is $P^{(h^*)} \cdot p_s^e$, where p_s^e is the expected price level at time s. We denote the ex-ante real rate at time s by $r_s(\pi^e)$, which we allow to increase with expected inflation, consistent with our data. The ex-ante real rate is indeed another channel through which belief biases can affect output, which has been studied theoretically (Bianchi et al., 2024b; L'Huillier et al., 2024) and empirically (Nagel, 2024). Given these parameters, the real value of the borrower's future payments is on average equal to

$$\hat{L}^{(h^*)} \equiv \sum_{h=1}^{h^*} \prod_{s=1}^{h} \frac{P^{(h^*)}}{1 + r_s(\pi^e)} \cdot \frac{p_s^e}{p_s} \approx \sum_{h=1}^{h^*} \prod_{s=1}^{h} \frac{P^{(h^*)}}{(1 + r_s(\pi^e))(1 + \pi_s - \pi^e)}, \tag{22}$$

where p_s is the price level realized on average at s, and π_s is average inflation in the same period (we work under a certainty equivalent approximation). An increase in expected inflation π^e matters in two ways. First, it leads to a higher ex-ante rate $r_s(\pi^e)$, as shown by the above-one slope coefficients of Table 17, reducing the amount the agent can borrow. This effect is not necessarily causal: it may reflect fundamental shocks to which π^e responds. Second, higher expected inflation causes higher ex-post real payments because average future inflation is below expectations, $\pi_s - \pi^e < 0$, as shown in Panel A of Table 1. This effect, due to belief overreaction, reduces the borrower's future resources and hence spending.

Using our estimated coefficients we can evaluate the effect of an increase in π^e, starting from a scenario in which expected and realized inflation are equal to zero. We distinguish between a pure ex-ante effect – in which we allow the ex-ante real rate to change but set future forecast errors to zero – and a pure ex-post effect – where we allow for predictable forecast errors but keep the ex-ante loan amount constant. The ex-post effect is novel and directly ties to beliefs, the ex-ante effect is a useful benchmark. The top of Table (5) reports two costs: the ex-ante percent loan reduction after a 1 percentage point increase in expected inflation (first row), and the ex-post increase in real payments caused by the same event, again as a percentage of the initial loan amount (second row).

The two costs are sizable and comparable. For a 2-year loan, higher expected inflation is

Table 5: A simple quantification of the redistribution from borrowers to savers

	Loan Maturity				
	1	2	3	5	10
$-\Delta \log L^{(h^*)}$	0.09	1.19	2.10	4.18	8.21
$\Delta \log \hat{L}^{(h^*)}$	0.36	0.86	1.39	2.77	6.04
$L^{(h^*)}$	$\$100,000$	$\$100,000$	$\$100,000$	$\$100,000$	$\$100,000$
$P^{(h^*)}$	$\$100,090$	$\$50,069$	$\$33,540$	$\$20,365$	$\$10,263$
$-\Delta L^{(h^*)}$	\$90	$\$1,187$	$\$2,100$	$\$4,181$	$\$8,206$
$\Delta \hat{L}^{(h^*)}$	\$356	\$857	$\$1,387$	$\$2,772$	$\$6,038$

Note. The top rows report the semi-elasticity of the ex-ante loan value and the ex-post additional cost to a parallel shift in inflation expectations. The lower rows quantify the effects based on an loan of \$100,000 across various maturities, reporting also the repayment amount as well as the absolute ex-ante and ex-post changes resulting from a 1 p.p. parallel increase in inflation expectations. Computations are based on the estimates from Tables 1 and 17.

associated with lower current and future resources of about 1% of the loan amount each. Consistent with horizon-increasing overreaction, for a 10-year loan the costs increase, respectively, to 8% and 6%, adding to a hefty 14%. If the increase in expected inflation is 2%, the effects reach 16% and 12% at the 10-year maturity.[22]

To see the ex-post redistribution in dollars, consider a \$100.000 loan. An extra 1% expected inflation raises the future real repayment by approximately $\$6,038$, while an extra 2% expected inflation entails a $\$12,076$ cost in real (i.e., $t = 0$ dollars) terms, which is significant. Ex-ante, the same events are associated with reductions in the value of the loan of $\$8,206$ and $\$16,412$, respectively. These costs, which obviously scale with the loan amount, show the sizable real costs associated with higher expected inflation.[23]

General Equilibrium Effects. The above analysis relies on an exogenous loan, interest rate, and does not allow the borrower to re-optimize after being adversely hit by lower than expected inflation. We now relax these conditions by formalizing a equilibrium model of intertemporal

[22]This variation in inflation expectations is realistic. A one-percent increase in expected inflation corresponds, in our zero-inflation benchmark, to a forecast error of 1%. By our estimates, this error is fairly common: at the 10-year horizon, it is attained from an increase in expected inflation equal to 1%. This follows from dividing a forecast error of 1% by taking an average coefficient of -1 across maturities from Panel A of Table 1.

[23]In the Survey of Consumer Finances (SCF, 2022 wave) a 40-year-old household has a nominal net position of roughly $-\$100,000$. Nominal assets comprise transaction accounts, certificates of deposit, investment funds (except stock mutual funds), savings bonds, directly held bonds, and cash value of whole life insurance; nominal liabilities comprise debt secured by primary residence, debt secured by other residential property, other lines of credit, credit card balances, installment loans (e.g., education and vehicle loans), other types of debt.

exchange. The model is standard except for mnemonic expectations. To focus on redistributions, we consider a pure exchange economy in which output is exogenous, but we later discuss how the model could be modified to allow redistributions to affect output.

[TO BE COMPLETED]

Adding standard friction to this simple model allows overreaction to reduce output via several channels. Households taking a long-term fixed rate mortgage during times of high expected inflation will have to cut consumption as inflation drops in the future. with price rigidities or endogenous labor supply this can reduce output. Another channel entails indebted firms, especially if facing tight borrowing constraints. As shown by Gomes et al. (2016), a systematic higher repayment due to lower than expected inflation can sharply reduce investment. Real appreciation of borrowers' assets may soften these costs, but this force is limited because households and firms hold many illiquid assets, consistent with the costs of debt deflation. In a similar vein, the drop in inflation can raise the debt burden for banks that finance illiquid real investments using nominal liabilities (Brunnermeier and Sannikov, 2016), and hurt governments issuing long-term nominal debt during high inflation states. If expected inflation is demand-driven, so that investors expect higher inflation during economic expansions, these adverse forces materialize after booms, amplifying the business cycle.

5 Conclusion

The consensus inflation forecasts of major banks in 18 advanced economies exhibit horizon-increasing overreaction. This is associated with maturity-increasing excess volatility of nominal rates, creating a systematic and sizable redistribution of wealth from borrowers to lenders after high expected inflation states. These patterns are at odds with leading models. We explain them using a model of mnemonic learning in which which forecasters overweight events that are salient due to their past frequency or similarity to current inflation. The model endogenizes belief biases based on features of the inflation DGP, making new predictions – supported in the data – on how these biases and return predictability should vary across countries.

We offer some concluding thoughts on the macro-financial implications of selective memory. Overreaction of long-run inflation expectations can affect macroeconomic volatility at business cycle frequencies. By creating a predictable redistribution from borrowing households, firms or governments to lenders, high expected inflation can cause a future reduction in aggregate demand. In general equilibrium, such systematic deflation "surprise" can generate a persistent recession, putting downward pressure on prices and feeding into further deflation. Work on news and sentiment (Lorenzoni, 2009; Angeletos and La'O, 2010, 2013; Angeletos et al., 2018) emphasizes how shifts in expectations about future real variables can generate demand-driven fluctuations without changes in current fundamentals. Mnemonic learning produces

these shocks as a by-product of belief errors. First, a pure nominal shock such as an increase in inflation can cause, through excessively high expected inflation, a predictable future redistribution that has real effects. Second, real shocks can induce shifts in non-rational beliefs via general equilibrium channels, which will create seeming future belief "shocks" through the reversal of expectations, even absent contemporaneous disturbances.

Mnemonic beliefs may also throw new light on historical variation in the cost of disinflation. In the late 1970s and early 1980s, US inflation was high and volatile, and the Fed Chairman Volcker reduced it at a considerable employment cost (Ball, 1994). In contrast, the post pandemic inflation spike has been curbed relatively quickly and painlessly. In an NK model, such variation in the cost of disinflation can be due to shocks having different volatility or persistence or to changes in monetary policy conduct – such as a Taylor rule that responds more aggressively to inflation surges. Mnemonic beliefs can account for these episodes through the historical salience of different inflation scenarios. In the early 1980s, agents drew on a database dominated by high and volatile inflation, causing overweighting of high inflation states. This required a persistent and aggressive policy response. In the recent period, instead, the database was shaped by decades of low and stable inflation, which created, by similarity, a strong force toward rapid re-anchoring after the inflation spike subsided (Gennaioli et al. (2024) document re-anchoring by US households). Similarity is key to allow for such state- and history-dependent speed of belief updating.

This logic can also shed light on the limited effectiveness of forward guidance. Following the financial crisis of 2008, nominal interest rates were constrained by the zero lower bound, prompting central banks to stimulate output by promising to generate higher inflation in the future (Eggertsson et al., 2003; Campbell et al., 2012; Del Negro et al., 2023). These announcements failed to raise expected inflation as intended, undermining their effectiveness, and challenging the predictions of standard NK models (Coibion et al., 2020; Del Negro et al., 2023). Several papers try to explain this phenomenon by departing from full-information rational-expectations (Angeletos and Lian, 2018; Farhi and Werning, 2019). Our model offers a different explanation: beliefs are shaped by similar inflation states. In the aftermath of the crisis, both the inflation database and the inflation cue rendered low inflation salient, making it difficult for agents to envision high-inflation scenarios – even if such scenarios were promised by central banks.

Finally, these memory forces offer a new perspective on optimal monetary policy. On the one hand, belief overreaction justifies gradualism, because an extreme cue may cause agents to overweight similarly extreme future events. On the other hand, memory implies that the level of beliefs is also shaped by historical experience. Ceteris paribus, this latter mechanism calls for aggressive policy: by responding swiftly to an inflation surge, the central bank prevents high-inflation states from accumulating in the database, thereby anchoring expected inflation at low levels, in the present and the future. The tradeoff between influencing memory cues and

the database may offer new insights into the design of optimal policy.

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A Additional Material

A.1 The Data

Table 6: Description of Data Sources

Variable	Data Source	Series Identifier	Sample Period	Coverage Notes
Bond Yields	LSEG	RF *COUNTRY* GVT BMK BID YLD hY - RED. YIELD	1962m2–2022m10	$h = 1, 2, ..., 10$. Further information available upon request.
Realized CPI inflation	IMF Data Mapper	PCPIPCH	1980–2023	CZ from 1996. AU and NZ up to 2022. NL missing in 1980 and 1986.
Realized CPI inflation	World Bank's WDI	FP.CPI.TOTL.ZG	1960–2023	CZ from 1992, HK from 1982, SG from 1961. TW not covered.
Realized CPI inflation	Statistics Bureau	2020-Base Consumer Price Index	2024M1–2024M3	JP only.
Realized CPI inflation	OECD	Consumer price indices (CPIs, HICPs), COICOP 1999	2024Q1	HK, JP, SG, and TW not covered.
Realized CPI inflation	Census and Statistics Dept.	Table 510-60001	2024M1–2024M3	HK only.
Realized CPI inflation	Dept. of Stat., Directorate General of Budget, Accounting & Statistics	Price Indices	2024M1–2024M3	TW only.
Realized CPI inflation	Department of Statistics	Consumer Price Index	2024Q1	SG only.
Realized CPI inflation	Bureau of Labor Statistics	CUSR0000SA0	1947M1–2024M7	US only.

Note. the two-letter identifier in the coverage notes corresponds to the ISO 3166-2 country abbreviation.

Table 6: Description of Data Sources

Variable	Data Source	Series Identifier	Sample Period	Coverage Notes
Forecasted Bond Yields	Consensus Economics	3-month interest rate (12-month period)	1989m10–2022m1	NL, ES, SE, and CH from 1989m11. AU and NZ from 1990m1. SG from 1990m11. HK from 1990m12. KR and TW from 1994m12. CZ from 1998m5. NO from 1998m6. NZ missing from 1991m4 to 1991m12 and from 1993m1 to 1994m11.
Forecasted Bond Yields	Consensus Economics	Prime Lending Rate (12-month period)	1989m10–2022m1	AU from 1990m11. NZ, SG, and KR from 1994m12. NL, ES, and SE from 1995m1. NO and CH from 1998m6. CZ and TW from 2006m3. HK not covered.
Forecasted CPI Inflation	Consensus Economics	Consumer Prices	1989Q4–2022Q1	AU from 1991q2. HK, NL, NZ, SG, KR, ES, SE, and TW from 1995q2. NO and CH from 1998q4. Semiannual data, quarterly after 2014q2
Forecasted CPI Inflation	Survey of Professional Forecasters	CPIh, $h = 1, \ldots 6$	1981Q3–2024Q2	US only. $h = 1$ denotes the "forecast" for the previous quarter, $h = 2$ denotes the forecast for the current quarter, $h = 3, ..6$ denote forecasts for the four quarters succeeding the current. Missing in 1969Q1-1969Q3 and 1970Q1 for $h = 6$.

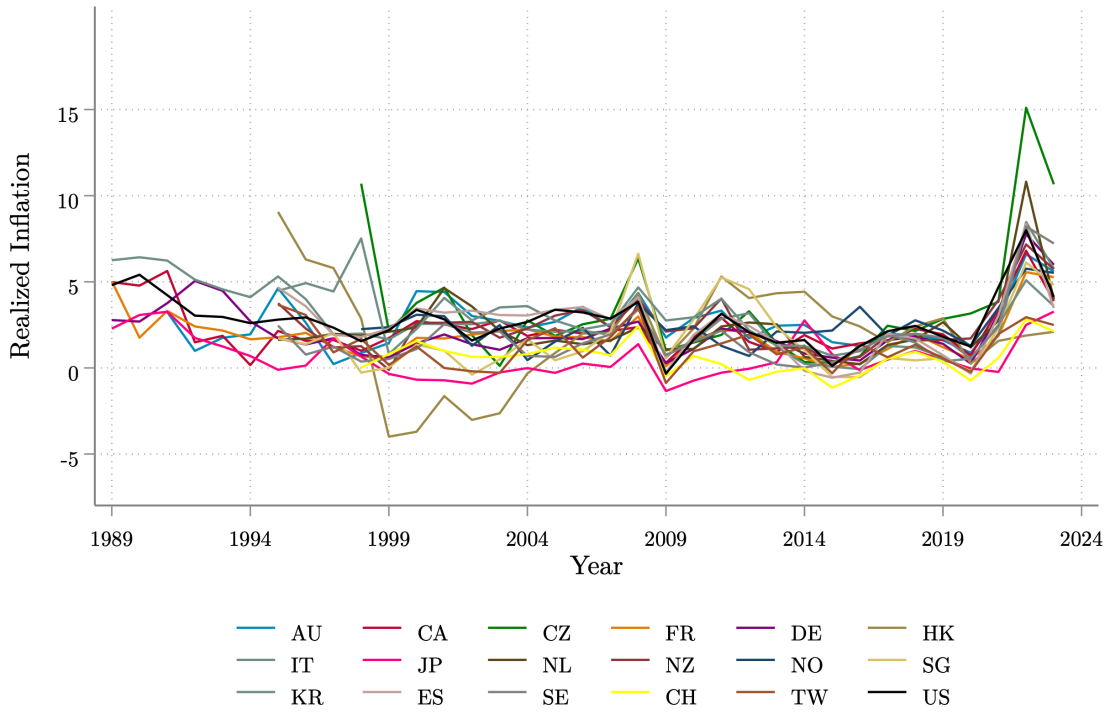
Note. the two-letter identifier in the coverage notes corresponds to the ISO 3166-2 country abbreviation.

Table 7: Composition of samples across different maturities

Country	**Samples**					
	Cumulative	By Maturity				
		H:0Y and H:1Y	H:2Y	H:3Y	H:5Y	H:(6-10)Y
Australia	✓	✓	✓		✓	✓
Canada	✓	✓	✓	✓	✓	✓
Czech Republic	✓		✓	✓	✓	
France	✓	✓	✓	✓	✓	✓
Germany	✓	✓	✓	✓	✓	✓
Hong Kong	✓	✓	✓	✓	✓	✓
Italy	✓		✓	✓	✓	✓
Japan	✓	✓	✓	✓	✓	✓
Netherlands	✓	✓	✓	✓	✓	✓
New Zealand	✓	✓	✓	✓	✓	✓
Norway	✓	✓	✓	✓	✓	✓
Singapore	✓	✓	✓		✓	✓
South Korea	✓	✓		✓	✓	
Spain	✓		✓	✓	✓	✓
Sweden	✓	✓	✓	✓	✓	✓
Switzerland	✓	✓	✓	✓	✓	✓
Taiwan	✓				✓	✓
United States	✓	✓	✓	✓	✓	✓

A.2 Additional Figures

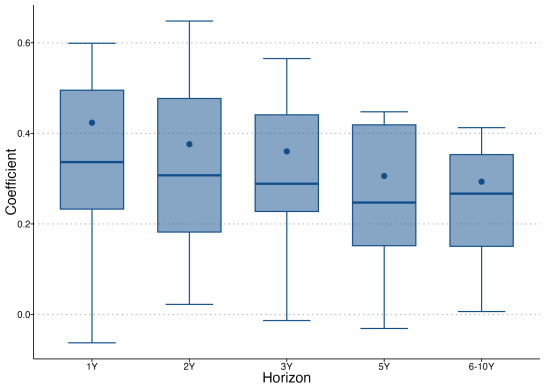
Figure 6: Realized Inflation over the sample



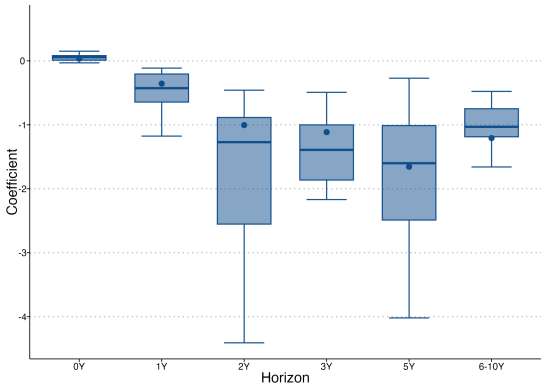
Note. Annual realized inflation for the 18 countries in our sample, from 1989 to 2023. Sample varies according to Table 6. The identifier for each series corresponds to the ISO 3166-2 country abbreviation.

Figure 7: Boxplots of country-specific coefficients

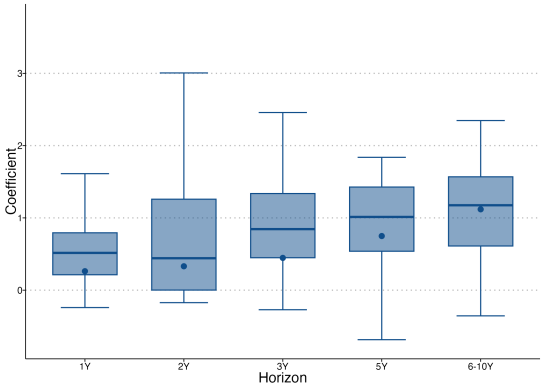
Panel A: Boxplots of Figure 1.



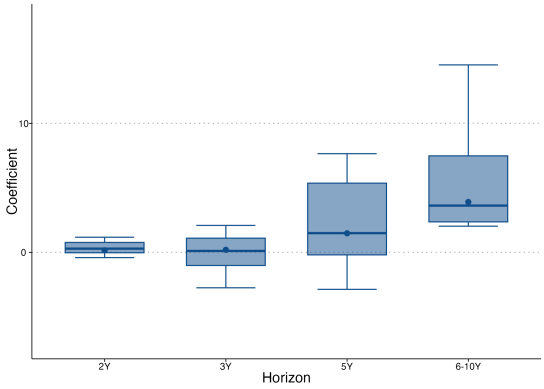
Panel B: Boxplots of Table 1 Panel A.



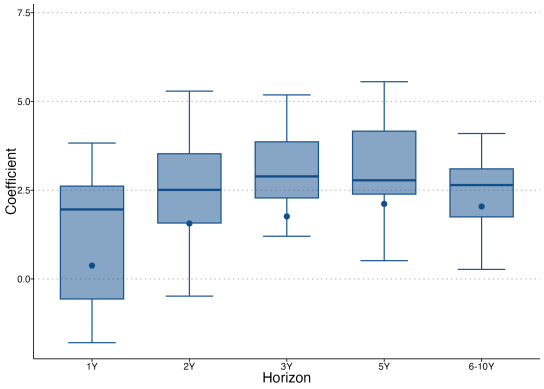
Panel C: Boxplots of Table 3.



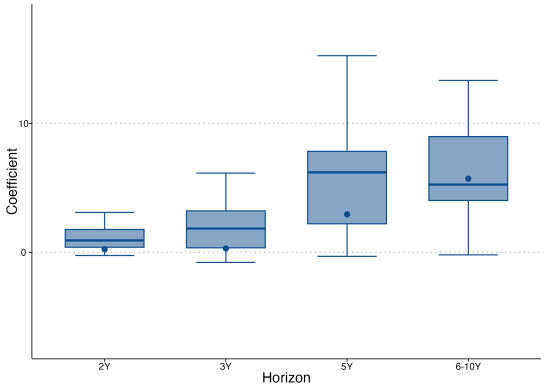
Panel D: Boxplots of Table 4.



Panel E: Boxplots of Figure 5 Panel A.



Panel F: Boxplots of Figure 5 Panel B.



Note. The figure displays the boxplots and the pooled estimates from each Figure or Table according to each subtitle. The y-axis measures the magnitude of the estimated coefficients, while the x-axis identifies the horizons $h = 0, 1, 2, 3, 5, 6\text{-}10$ for which estimates were computed. For each horizon, the sample varies according to Table 7. The boxplots illustrates the distribution of the country-specific coefficients. The boxes represents the interquartile (IQR) range, with the median indicated by the line inside the box. The whiskers extend to 1.5 times the IQR above the upper quartile and below the lower quartile. Points beyond the whiskers are considered outliers and are removed from the boxplots. The plot also displays the respective country-pooled estimates (dots) for each horizon and every specification. All the estimations (boxes and dots) are computed using annual data.

A.3 Additional Tables

Table 8: Forecast revision predictability regressions by horizon

	(1)	(2)	(3)	(4)
	$FR_{c,2}$	$FR_{c,3}$	$FR_{c,5}$	$FR_{c,6-10}$
$\mathbb{F}_{\mathrm{t}}\left(\pi_{\mathrm{c,t+hY}}\right)$	-0.236**	-0.355***	-0.819***	-0.974***
	(0.090)	(0.097)	(0.131)	(0.150)
Country fixed effects	✓	✓	✓	✓
N	1107	973	1021	847
Adj. R^2	0.145	0.213	0.462	0.536

Note. We predict inflation consensus forecast revision from the current inflation state. Each column reports the country pooled regression at horizon $h = 2, 3, 5$, 6-10: the dependent variable is the inflation consensus forecast revision $\mathbb{F}_{t+h-1}\left(\pi_{c,t+hY}\right) - \mathbb{F}_t\left(\pi_{c,t+hY}\right)$ over horizon h and country c. The current inflation state is the consensus forecast for country c and horizon h $\mathbb{F}_t\left(\pi_{c,t+hY}\right)$. We control for country fixed effects. The sample ranges from 1989 to 2021, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 9: Forecast errors on inflation forecast revision

	(1)	(2)	(3)	(4)	(5)	(6)
	$FE_{\mathrm{c},0}$	$FE_{\mathrm{c},1}$	$FE_{\mathrm{c},2}$	$FE_{\mathrm{c},3}$	$FE_{\mathrm{c},5}$	$FE_{\mathrm{c},6-10}$
$\mathbb{F}_{\mathrm{t}}(\pi_{\mathrm{c,t+hY}}) - \mathbb{F}_{\mathrm{t-4}}(\pi_{\mathrm{c,t+hY}})$	0.173*	0.470*	-0.175	-0.256	0.242	-0.240
	(0.102)	(0.262)	(0.295)	(0.338)	(0.414)	(0.149)
Country fixed effects	✓	✓	✓	✓	✓	✓
N	973	970	1104	969	1008	618
Adj. R^2	0.072	0.046	0.033	0.049	0.057	0.149

Note. We predict the inflation consensus forecast error from consensus revision (recent news). Each column reports the country pooled regression at horizon $h = 0, ...,$ 6-10: the dependent variable is the inflation consensus forecast error $\pi_{c,t+hY} - \mathbb{F}_t\left(\pi_{c,t+hY}\right)$ over horizon h and country c. The consensus revision is $\mathbb{F}_t\left(\pi_{c,t+hY}\right) - \mathbb{F}_{t-4}\left(\pi_{c,t+hY}\right)$. We control for country fixed effects. The sample ranges from 1989 to 2022, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 10: Inflation forecast error on inflation forecast revision from inflation forecast revision and lagged inflation forecast at the quarter horizon.

	(1)
	$\pi_{t+4} - \mathbb{F}_t^{SPF}(\pi_{t,t+4})$
$\mathbb{F}_t^{SPF}(\pi_{t+4}) - \mathbb{F}_{t-1}^{SPF}(\pi_{t+3})$	0.017
	(0.407)
$\mathbb{F}_{t-1}^{SPF}(\pi_{t+3})$	-0.463***
	(0.103)
α	1.304***
	(0.322)
N	168
Adj. R^2	0.111

Notes. We predict the inflation consensus forecast error from consensus revision (recent news) and past inflation state. Column (1) reports the regression for the US at horizon $h = 4$, where h here denote quarters: the dependent variable is the CPI inflation SPF forecast error $\pi_{t+4} - \mathbb{F}_t^{SPF}(\pi_{t+4})$. The consensus revision is $\mathbb{F}_t^{SPF}(\pi_{t+4}) - \mathbb{F}_{t-1}^{SPF}(\pi_{t+3})$, while past inflation state is $\mathbb{F}_{t-1}^{SPF}(\pi_{t+3})$. The sample ranges from 1981Q4 to 2023Q3, coverage varies according to Tables 6. Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 11: Nominal yields and consensus inflation forecast

	(1)	(2)	(3)	(4)	(5)
	$i_{c,t}^{(1)}$	$i_{c,t}^{(2)}$	$i_{c,t}^{(3)}$	$i_{c,t}^{(5)}$	$i_{c,t}^{(6-10)}$
$\mathbb{F}_t\left(\overline{\pi_{c,t+1,h}}\right)$	1.047***	1.170***	1.377***	1.194***	1.291***
	(0.042)	(0.043)	(0.081)	(0.054)	(0.065)
$\mathbb{F}_t[i_{c,t+1}^{(3M)}] - \mathbb{F}_t\left(\pi_{c,t+1}\right)$	1.108***	0.833***	0.617***	0.458***	0.205***
	(0.035)	(0.056)	(0.058)	(0.046)	(0.037)
$\mathbb{F}_t[i_{c,t+1}^{(10Y)}] - \mathbb{F}_t\left(\overline{\pi_{c,t+1,t+(6-10)}}\right)$	-0.142***	0.200***	0.319***	0.607***	0.799***
	(0.035)	(0.063)	(0.065)	(0.055)	(0.043)
Country fixed effects	✓	✓	✓	✓	✓
N	829	987	910	1071	1034
Adj. R^2	0.965	0.974	0.944	0.980	0.973

Note. Each column reports a pooled regression at horizon $h = 1, ..., 6\text{-}10$ whose dependent variable is the nominal yield at t to maturity h in country c. The independent variables are: the consensus forecast for average inflation over h years in the same country and time, computed as $\mathbb{F}_t\left(\overline{\pi_{c,t+1,h}}\right) = \frac{1}{h}\sum_{h'=1}^{h}\mathbb{F}_t\left(\pi_{c,t+h'Y}\right)$; the short-term expected real rate $\mathbb{F}_t[i_{c,t+1}^{(3M)}] - \mathbb{F}_t\left(\pi_{c,t+1}\right)$; the long-term expected real rate $\mathbb{F}_t[i_{c,t+1}^{(10Y)}] - \mathbb{F}_t\left(\overline{\pi_{c,t+1,t+(6-10)}}\right)$. We control for country fixed effects. The sample ranges from 1989Q4 to 2022Q1, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 12: Predicting ex-post real rates using consensus inflation forecast

	(1)	(2)	(3)	(4)	(5)
	$\tilde{r}^{(1)}_{c,t,t+1}$	$\tilde{r}^{(2)}_{c,t,t+2}$	$\tilde{r}^{(3)}_{c,t,t+3}$	$\tilde{r}^{(5)}_{c,t,t+5}$	$\tilde{r}^{(6-10)}_{c,t+6,t+10}$
$\mathbb{F}_t\left(\overline{\pi_{c,t+1,h}}\right)$	0.398***	0.639***	0.828***	0.690***	1.045***
	(0.129)	(0.156)	(0.167)	(0.099)	(0.123)
$\mathbb{F}_t[i^{(k)}_{c,t+1}] - \mathbb{F}_t\left(\overline{\pi_{c,t+1,t+h}}\right)$	1.218***	1.210***	1.077***	1.164***	1.015***
	(0.139)	(0.110)	(0.084)	(0.080)	(0.069)
Country fixed effects	✓	✓	✓	✓	✓
N	972	1101	959	879	560
Adj. R^2	0.684	0.764	0.783	0.897	0.926

Note. We predict the real yield to maturity $\tilde{r}^{(h)}_{c,t,t+h}$ using the consensus forecast for average inflation over h years, measured as $\mathbb{F}_t(\overline{\pi_{c,t+1,h}}) = \frac{1}{h}\sum_{h'=1}^{h}\mathbb{F}_t\left(\pi_{c,t+h'Y}\right)$. In column (1)-(3), we control for the short-term expected real rate $\mathbb{F}_t[i^{(3M)}_{c,t+1}] - \mathbb{F}_t\left(\pi_{c,t+1}\right)$; In column (4)-(5), we control for the long-term expected real rate $\mathbb{F}_t[i^{(10Y)}_{c,t+1}] - \mathbb{F}_t\left(\overline{\pi_{c,t+1,t+(6-10)}}\right)$. We pool countries and control for country-fixed effects. The sample ranges from 1989Q4 to 2022Q1, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 13: Correlation between CE ex-ante real yields and actual (FED or BoE) real yields - using inflation forecast

	United Kingdom			
	$h = 2$	$h = 3$	$h = 5$	$h = 6 - 10$
ρ	NA	.9183***	.9365***	.9522***
N	NA	48	51	51
	United States			
	$h = 2$	$h = 3$	$h = 5$	$h = 6 - 10$
ρ	.8723***	.9078***	.9331***	.9319***
N	62	62	62	62

Note. For UK data, we use the "real spot rate" published by the Bank of England, i.e., the rate for a "index-linked zero coupon bond" having " its value linked to movements in a suitable price index to prevent inflation eroding its purchasing power" (see `https://www.bankofengland.co.uk/statistics/yield-curves/terminology-and-concepts`). We use the series at daily frequency, from 1999M1 to 2024M6, and aggregate it at quarterly frequency taking the simple average in order to make it comparable with the data we use in the rest of the analysis. To be consistent with CE data, we take the average of the available rates for the horizons 6- to 10-year ahead (mean across available maturities between 6 and 10 years). For US data, we use "TIPS yields" by the Federal Reserve Board following the methodology of Gürkaynak et al. (2010) (see `https://www.federalreserve.gov/data/tips-yield-curve-and-inflation-compensation.htm`). We used the series of zero-coupon inflation protected treasuries. We use the series at daily frequency, from 1999M1 to 2024M7, and then aggregate it at quarterly frequency taking the simple average in order to make it comparable with the data we use in the rest of the analysis. To be consistent with CE data, we take the average of the rates for the (available) horizons 6- to 10-year ahead. The CE variable for horizon h is defined as $i^h_{c,t} - \mathbb{F}_{\mathrm{t}}\left(\overline{\pi}_{\mathrm{c,t+1,t+h}}\right)$ for all the horizons. Sample sizes and correlation coefficients vary with the horizons. ***, **, and * indicate significance at the 1, 5, and 10 percent levels respectively.

Table 14: Correlation between CE ex-ante real yields and actual (FED or BoE) real yields - using both rates and inflation forecasts

United Kingdom				
	$h=2$	$h=3$	$h=5$	$h=6-10$
ρ	NA	.9145***	.947***	.9567***
N	NA	48	51	51
United States				
	$h=2$	$h=3$	$h=5$	$h=6-10$
ρ	.8713***	.8923***	.8689***	.912***
N	62	62	62	62

Note. For UK data, we use the "real spot rate" published by the Bank of England, i.e., the rate for a "index-linked zero coupon bond" having " its value linked to movements in a suitable price index to prevent inflation eroding its purchasing power" (see `https://www.bankofengland.co.uk/statistics/yield-curves/terminology-and-concepts`). We use the series at daily frequency, from 1999M1 to 2024M6, and aggregate it at quarterly frequency taking the simple average in order to make it comparable with the data we use in the rest of the analysis. To be consistent with CE data, we take the average of the available rates for the horizons 6- to 10-year ahead (mean across available maturities between 6 and 10 years). For US data, we use "TIPS yields" by the Federal Reserve Board following the methodology of Gürkaynak et al. (2010) (see `https://www.federalreserve.gov/data/tips-yield-curve-and-inflation-compensation.htm`). We used the series of zero-coupon inflation protected treasuries. We use the series at daily frequency, from 1999M1 to 2024M7, and then aggregate it at quarterly frequency taking the simple average in order to make it comparable with the data we use in the rest of the analysis. To be consistent with CE data, we take the average of the rates for the (available) horizons 6- to 10-year ahead. CE ex-ante real yields are constructed using both forecasts of rates and inflation. The CE variable for horizon h is defined as $\mathbb{F}_t[i^{(3M)}_{c,t+1}] - \mathbb{F}_t\left(\overline{\pi_{c,t+1,t+h}}\right)$ for horizons between 2 and 4 years; whereas it is defined as $\mathbb{F}_t[i^{(10Y)}_{c,t+1}] - \mathbb{F}_t\left(\overline{\pi_{c,t+1,t+h}}\right)$ for the horizons 5 and 6-10 years. Sample sizes and correlation coefficients vary with the horizons. ***, **, and * indicate significance at the 1, 5, and 10 percent levels respectively.

Table 15: Predicting realized excess returns using consensus inflation forecasts

	(1)	(2)	(3)	(4)
	$\overline{rx}^{(2)}_{c,t,t+1}$	$\overline{rx}^{(3)}_{c,t,t+1}$	$\overline{rx}^{(5)}_{c,t,t+1}$	$\overline{rx}^{(6-10)}_{c,t,t+1}$
$\mathbb{F}_t\left(\overline{\pi_{c,t+1,h}}\right)$	0.097	0.409***	0.926**	3.810***
	(0.072)	(0.149)	(0.407)	(0.746)
$i^{(1)}_{c,t}$	0.270***	0.137	0.867***	0.643***
	(0.036)	(0.089)	(0.137)	(0.221)
$i^{(6-10)}_{c,t} - i^{(1)}_{c,t}$	0.381***	0.349**	1.458***	2.219***
	(0.081)	(0.148)	(0.234)	(0.446)
Country fixed effects	✓	✓	✓	✓
N	941	871	712	583
Adj. R^2	0.417	0.300	0.516	0.391

Note. We predict the smoothed excess return $\overline{rx}^{(h)}_{c,t,t+1} = \dfrac{rx^{(h)}_{c,t,t+1} + rx^{(h)}_{c,t+1,t+2}}{2}$ using the consensus forecast for average inflation over h years $\mathbb{F}_t(\overline{\pi_{c,t+1,h}}) = \frac{1}{h}\sum_{h'=1}^{h} \mathbb{F}_t\left(\pi_{c,t+h'Y}\right)$. We control for the nominal level $i^{(1)}_{c,t}$ and nominal slope $i^{(10)}_{c,t} - i^{(1)}_{c,t}$ of the yield curve. The raw one-year excess return is $rx^{(h)}_{c,t,t+1}$ is defined as $i^{(h)}_{c,t} + (h-1)\left(i^{(h)}_{c,t} - i^{(h-1)}_{c,t+1}\right) - i^{(1)}_{c,t}$. We pool countries and control for country fixed effects. The sample ranges from 1989Q4 to 2022Q1, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 16: Predicting realized excess returns using consensus inflation forecasts

	(1)	(2)	(3)	(4)
	$\overline{rx}^{(2)}_{c,t,t+1}$	$\overline{rx}^{(3)}_{c,t,t+1}$	$\overline{rx}^{(5)}_{c,t,t+1}$	$\overline{rx}^{(6-10)}_{c,t,t+1}$
$\mathbb{F}_t\left(\overline{\pi_{c,t+1,h}}\right)$	0.380***	0.855***	2.247***	3.334***
	(0.111)	(0.223)	(0.547)	(0.819)
$\hat{r}^{(1)}_{c,t}$	0.276***	-0.005	0.934***	0.672***
	(0.037)	(0.097)	(0.139)	(0.214)
$\hat{r}^{(6-10)}_{c,t} - \hat{r}^{(1)}_{c,t}$	0.229**	0.427**	1.215***	2.511***
	(0.091)	(0.187)	(0.307)	(0.526)
Country fixed effects	✓	✓	✓	✓
N	803	747	614	583
Adj. R^2	0.383	0.324	0.526	0.416

Note. We predict the smoothed excess return $\overline{rx}^{(h)}_{c,t,t+1} = \frac{rx^{(h)}_{c,t,t+1} + rx^{(h)}_{c,t+1,t+2}}{2}$ using the consensus forecast for average inflation over h years $\mathbb{F}_t(\overline{\pi_{c,t+1,h}}) = \frac{1}{h}\sum_{h'=1}^{h}\mathbb{F}_t\left(\pi_{c,t+h'Y}\right)$. We control for the expected real level $\hat{r}^{(1)}_{c,t}$ and expected real slope $\hat{r}^{(6-10)}_{c,t} - \hat{r}^{(1)}_{c,t}$ of the yield curve. The expected real level is defined as $\hat{r}^{(1)}_{c,t} = \mathbb{F}_t[i^{(3M)}_{c,t+1}] - \mathbb{F}_t\left(\pi_{c,t+1}\right)$. The expected real slope is defined as $\hat{r}^{(6-10)}_{c,t} - \hat{r}^{(1)}_{c,t} = \left(\mathbb{F}_t[i^{(10Y)}_{c,t+1}] - \mathbb{F}_t\left(\overline{\pi_{c,t+1,t+(6-10)}}\right)\right) - \left(\mathbb{F}_t[i^{(3M)}_{c,t+1}] - \mathbb{F}_t\left(\pi_{c,t+1}\right)\right)$. The raw one-year excess return is $rx^{(h)}_{c,t,t+1}$ is defined as $i^{(h)}_{c,t} + (h-1)\left(i^{(h)}_{c,t} - i^{(h-1)}_{c,t+1}\right) - i^{(1)}_{c,t}$. We pool countries and control for country fixed effects. The sample ranges from 1989Q4 to 2022Q1, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 17: Nominal yields and consensus forecasts

	(1)	(2)	(3)	(4)	(5)
	$i^{(1)}_{c,t}$	$i^{(2)}_{c,t}$	$i^{(3)}_{c,t}$	$i^{(5)}_{c,t}$	$i^{(6-10)}_{c,t}$
$\mathbb{F}_t\left(\overline{\pi_{c,t+1,h}}\right)$	1.021***	1.195***	1.345***	1.230***	1.318***
	(0.028)	(0.026)	(0.055)	(0.071)	(0.072)
$\mathbb{F}_t[i^{(k)}_{c,t+1}] - \mathbb{F}_t\left(\overline{\pi_{c,t+1,t+h}}\right)$	0.982***	1.018***	0.946***	1.013***	0.980***
	(0.018)	(0.017)	(0.024)	(0.034)	(0.026)
Country fixed effects	✓	✓	✓	✓	✓
N	972	1101	1015	1071	1034
Adj. R^2	0.962	0.970	0.939	0.965	0.970

Note. Each column reports a pooled regression at horizon $h = 1, ..., 6\text{-}10$ whose dependent variable is the nominal yield at t to maturity h in country c. The independent variables are: the consensus forecast for average inflation over h years in the same country and time, computed as $\mathbb{F}_t\left(\overline{\pi_{c,t+1,h}}\right) = \frac{1}{h}\sum_{h'=1}^{h}\mathbb{F}_t\left(\pi_{c,t+h'Y}\right)$; in column (1)-(3), we control for the short-term expected real rate $\mathbb{F}_t[i^{(3M)}_{c,t+1}] - \mathbb{F}_t\left(\pi_{c,t+1}\right)$; In column (4)-(5), we control for the long-term expected real rate $\mathbb{F}_t[i^{(10Y)}_{c,t+1}] - \mathbb{F}_t\left(\overline{\pi_{c,t+1,t+(6-10)}}\right)$. The sample ranges from 1989Q4 to 2022Q1, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 18: Inflation forecast error predictability coefficients from Specifications (2), (6), and (8) on horizon dummies and simulated coefficients

	(1)	(2)	(3)	(4)	(5)	(6)
	$\delta_{\text{h,c}}$	$\delta_{\text{h,c}}$	$\theta^r_{\text{h,c}}$	$\theta^r_{\text{h,c}}$	$\theta^{ex}_{\text{h,c}}$	$\theta^{ex}_{\text{h,c}}$
$\Delta^m_{\text{h,c}}$		1.453***		1.106***		1.471***
		(0.273)		(0.152)		(0.328)
α	-0.470*	0.018	1.310***	1.399***	1.040	-0.058
	(0.259)	(0.240)	(0.485)	(0.372)	(1.098)	(0.971)
Horizon fixed effects	✓	✓	✓	✓	✓	✓
N	79	79	79	79	56	56
R^2	0.158	0.393	0.095	0.477	0.376	0.552

Notes. We study the relation between the actual and model-implied coefficients estimated for Specifications (2), (6), and (8). Columns (1), (3), and (5) report the regression of country- and horizon-specific coefficients on horizon dummies, while in Columns (2), (4), and (6) we control also for the model-implied coefficient, $\Delta^m_{c,h}$. $\Delta^m_{c,h} = \delta^m_{c,h}$ in column (2), $\Delta^m_{c,h} = \theta^{r,m}_{c,h}$ in column (4), and $\Delta^m_{c,h} = \theta^{ex,m}_{c,h}$ in column (6). Table 7 reports the countries available at each horizon $h = 1, \ldots,$ 6-10. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. Annual frequency.

Table 19: Inflation forecast error predictability coefficients from Specification (3) on horizon dummies and simulated coefficients

	(1)	(2)	(3)	(4)
	$\delta_{1,\text{h,c}}$	$\delta_{1,\text{h,c}}$	$\delta_{2,\text{h,c}}$	$\delta_{2,\text{h,c}}$
$\delta^m_{\text{i,h,c}}$		1.263***		1.234***
		(0.446)		(0.213)
α	0.445	0.702	-1.132***	-0.313
	(0.494)	(0.481)	(0.426)	(0.382)
Horizon fixed effects	✓	✓	✓	✓
N	79	79	79	79
R^2	0.160	0.244	0.044	0.345

Notes. We study the relation between the actual and model-implied coefficients estimated for Specification (3). Columns (1) and (3) report the regression of country- and horizon-specific coefficients on horizon dummies, while in Columns (2) and (4) we control also for the model-implied coefficient, $\delta^m_{i,c,h}$. $\delta^m_{i,c,h} = \delta^m_{1,c,h}$ in column (2) and $\delta^m_{i,c,h} = \delta^m_{2,c,h}$ in column (4). Table 7 reports the countries available at each horizon $h = 1, \ldots,$ 6-10. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. Annual frequency.

Table 20: Predicting the mnemonic inflation forecast error using mnemonic inflation forecasts

	(1)	(2)	(3)	(4)	(5)
	$FE^m_{c,1}$	$FE^m_{c,2}$	$FE^m_{c,3}$	$FE^m_{c,5}$	$FE^m_{c,6-10}$
$\mathbb{F}^m_{\mathrm{t}}\left(\pi_{\mathrm{c,t+hY}}\right)$	-0.410***	-0.823***	-0.965***	-1.237***	-1.184***
	(0.082)	(0.183)	(0.165)	(0.174)	(0.059)
Country fixed effects	✓	✓	✓	✓	✓
N	420	462	416	462	331
Adj. R^2	0.095	0.203	0.292	0.365	0.779

Note. We predict mnemonic inflation forecast error from the mnemonic inflation forecast. Each column reports the country pooled regression at horizon $h = 1, ..., 6\text{-}10$: the dependent variable is the mnemonic inflation forecast error $\pi_{c,t+hY} - \mathbb{F}^m_t\left(\pi_{c,t+hY}\right)$ over horizon h and country c. The consensus forecast for country c and horizon h is $\mathbb{F}_t\left(\pi_{c,t+hY}\right)$. We control for country fixed effects. The sample ranges from 1989 to 2022, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. Sample varies with the horizons according to Table 7.

Table 21: Ex-post real returns on mnemonic average forecast for inflation

	(1)	(2)	(3)	(4)	(5)
	$\tilde{r}^{(1)}_{\mathrm{c,t,t+1}}$	$\tilde{r}^{(2)}_{\mathrm{c,t,t+2}}$	$\tilde{r}^{(3)}_{\mathrm{c,t,t+3}}$	$\tilde{r}^{(5)}_{\mathrm{c,t,t+5}}$	$\tilde{r}^{(6-10)}_{\mathrm{c,t,t+6.t+10}}$
$\mathbb{F}^m_{\mathrm{t}}\left(\overline{\pi_{\mathrm{c,t+1,h}}}\right)$	-0.259	0.806*	1.015**	1.018**	0.812**
	(0.289)	(0.399)	(0.407)	(0.374)	(0.313)
Country fixed effects	✓	✓	✓	✓	✓
N	390	458	409	456	324
Adj. R^2	0.049	0.132	0.226	0.251	0.310

Notes. We study the association between ex-post real rates to maturity h and the mnemonic forecast for the average inflation over h years. Each column reports the country pooled regression at horizon $h = 1, ..., 6\text{-}10$. The mnemonic forecast for the average inflation over h years for country c, $\mathbb{F}_{\mathrm{t}}\left(\overline{\pi_{\mathrm{c,t+1,h}}}\right)$, is computed as: $\frac{1}{h}\sum_{h'=1}^{h}\mathbb{F}_{\mathrm{t}}\left(\pi_{c,t+h'Y}\right)$. We control for country fixed effects. The sample ranges from 1989 to 2022, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 22: Bond excess returns (smoothed over two years) on mnemonic and consensus inflation forecasts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\overline{rx}^{(2)}_{c,t,t+1}$	$\overline{rx}^{(3)}_{c,t,t+1}$	$\overline{rx}^{(5)}_{c,t,t+1}$	$\overline{rx}^{(6-10)}_{c,t,t+1}$	$\overline{rx}^{(2)}_{c,t,t+1}$	$\overline{rx}^{(3)}_{c,t,t+1}$	$\overline{rx}^{(5)}_{c,t,t+1}$	$\overline{rx}^{(6-10)}_{c,t,t+1}$
$\mathbb{F}^i_t\left(\overline{\pi_{c,t+1,h}}\right)$	0.142	0.082	1.898***	2.924**	0.244**	0.298*	2.941***	5.710***
	(0.092)	(0.138)	(0.507)	(1.052)	(0.102)	(0.157)	(0.836)	(1.871)
Country fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
N	371	342	269	226	371	342	269	226
Adj. R^2	0.085	0.145	0.233	0.177	0.088	0.152	0.173	0.142

Note. We predict one-year holding period realized bond excess returns with maturity h from forecast of the average inflation over h years, both from mnemonic forecasts, Columns (1)-(4), and from consensus forecasts at annual frequency, Columns (5)-(8). Each column reports the country pooled regression at horizon $h = 2, 3, 5$, 6-10: the dependent variable is the smoothed one-year holding period excess returns over horizon h and country c, defined as $\overline{rx}^{(h)}_{c,t,t+1} = \dfrac{rx^{(h)}_{c,t,t+1} + rx^{(h)}_{c,t+1,t+2}}{2}$. The raw one-year holding period excess returns $rx^{(h)}_{c,t,t+1}$ is defined as $i^{(h)}_{c,t} + (h-1)\left(i^{(h)}_{c,t} - i^{(h-1)}_{c,t+1}\right) - i^{(1)}_{c,t}$. The forecast for the average inflation over h years for country c, $\mathbb{F}^i_t\left(\overline{\pi_{c,t+1,h}}\right)$, with i indicating mnemonic or consensus forecasts, is computed as: $\frac{1}{h}\sum_{h'=1}^{h}\mathbb{F}^i_t\left(\pi_{c,t+h'Y}\right)$. We control for country fixed effects. The sample ranges from 1989 to 2020, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

A.4 Robustness: Annual Frequency

Table 23: Predicting the consensus forecast error using consensus inflation forecast - Annual Frequency

	(1)	(2)	(3)	(4)	(5)	(6)
	$FE_{c,0}$	$FE_{c,1}$	$FE_{c,2}$	$FE_{c,3}$	$FE_{c,5}$	$FE_{c,6-10}$
$\mathbb{F}_t(\pi_{c,t+hY})$	0.111	-0.271*	-0.763**	-0.937***	-1.549***	-1.211***
	(0.075)	(0.151)	(0.286)	(0.275)	(0.297)	(0.123)
Country fixed effects	✓	✓	✓	✓	✓	✓
N	420	420	462	416	462	331
Adj. R^2	0.022	0.036	0.117	0.154	0.268	0.545

Note. Each column reports the country pooled regression at horizon $h = 0, ..., 6\text{-}10$: the dependent variable is the consensus forecast error $\pi_{c,t+hY} - \mathbb{F}_t(\pi_{c,t+hY})$ at horizon h and country c. The independent variables are: (i) the consensus forecast for country c at horizon h, $\mathbb{F}_t(\pi_{c,t+hY})$ (Panel A), and (ii) the average realized inflation of country c over the past two years, $\overline{\pi}_{c,t} = (\pi_{c,(t-1)Y} + \pi_{c,(t-2)Y})/2$ (Panel B). We control for country fixed effects. The sample ranges from 1989Q4 to 2022Q1, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 24: Forecast errors on inflation forecast revision and lagged inflation forecast - Annual Frequency

	(1)	(2)	(3)	(4)	(5)	(6)
	$FE_{c,0}$	$FE_{c,1}$	$FE_{c,2}$	$FE_{c,3}$	$FE_{c,5}$	$FE_{c,6\text{-}10}$
$\mathbb{F}_t(\pi_{c,t+hY}) - \mathbb{F}_{t-4}(\pi_{c,t+hY})$	0.324	0.481**	-0.434	-0.635	-1.265***	-1.115***
	(0.199)	(0.232)	(0.356)	(0.378)	(0.313)	(0.137)
$\mathbb{F}_{t-4}(\pi_{c,t+hY})$	-0.091	-0.426*	-0.923**	-1.051**	-1.588***	-1.015***
	(0.055)	(0.235)	(0.421)	(0.405)	(0.359)	(0.120)
Country fixed effects	✓	✓	✓	✓	✓	✓
N	406	405	445	400	437	314
Adj. R^2	0.137	0.092	0.091	0.114	0.165	0.389

Note. We predict the inflation consensus forecast error from consensus revision (recent news) and past inflation state. Each column reports the country pooled regression at horizon $h = 0, ..., 6\text{-}10$: the dependent variable is the inflation consensus forecast error $\pi_{c,t+hY} - \mathbb{F}_t(\pi_{c,t+hY})$ over horizon h and country c. The consensus revision is $\mathbb{F}_t(\pi_{c,t+hY}) - \mathbb{F}_{t-4}(\pi_{c,t+hY})$, while past inflation state is $\mathbb{F}_{t-4}(\pi_{c,t+hY})$. We control for country fixed effects. The sample ranges from 1989 to 2022, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 25: Predicting ex-post real rates using consensus inflation forecast - Annual frequency

	(1)	(2)	(3)	(4)	(5)
	$\tilde{r}^{(1)}_{\mathrm{c,t,t+1}}$	$\tilde{r}^{(2)}_{\mathrm{c,t,t+2}}$	$\tilde{r}^{(3)}_{\mathrm{c,t,t+3}}$	$\tilde{r}^{(5)}_{\mathrm{c,t,t+5}}$	$\tilde{r}^{(6-10)}_{\mathrm{c,t+6,t+10}}$
$\mathbb{F}_{\mathrm{t}}\left(\overline{\pi_{\mathrm{c,t+1,h}}}\right)$	0.262*	0.331**	0.446***	0.749***	1.119***
	(0.136)	(0.134)	(0.142)	(0.147)	(0.128)
$r^{(h)}_{\mathrm{c,t}}$	1.183***	1.146***	1.081***	1.010***	0.935***
	(0.135)	(0.119)	(0.081)	(0.066)	(0.051)
Country fixed effects	✓	✓	✓	✓	✓
N	390	458	409	456	324
Adj. R^2	0.706	0.773	0.831	0.883	0.941

Note. We predict the real yield to maturity $\tilde{r}^{(h)}_{c,t,t+h}$ using the consensus forecast for average inflation over h years, measured as $\mathbb{F}_{\mathrm{t}}(\overline{\pi_{\mathrm{c,t+1,h}}}) = \frac{1}{h}\sum_{h'=1}^{h}\mathbb{F}_{\mathrm{t}}\left(\pi_{c,t+h'Y}\right)$, and the ex-ante real rate proxy $r^{(h)}_{\mathrm{c,t}} = i^{(h)}_{\mathrm{c,t}} - \mathbb{F}_{\mathrm{t}}(\overline{\pi_{\mathrm{c,t+1,h}}})$. We pool countries and control for country-fixed effects. The sample ranges from 1989Q4 to 2022Q1, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 26: Predicting realized excess returns using consensus inflation forecasts - Annual frequency

	(1)	(2)	(3)	(4)
	$\overline{rx}^{(2)}_{c,t,t+1}$	$\overline{rx}^{(3)}_{c,t,t+1}$	$\overline{rx}^{(5)}_{c,t,t+1}$	$\overline{rx}^{(6-10)}_{c,t,t+1}$
$\mathbb{F}_{\mathrm{t}}\left(\overline{\pi_{\mathrm{c,t+1,h}}}\right)$	0.159*	0.198	1.478**	3.904***
	(0.084)	(0.127)	(0.601)	(0.960)
$r^{(1)}_{\mathrm{c,t}}$	0.272***	0.192**	0.782***	0.569**
	(0.027)	(0.087)	(0.116)	(0.214)
$r^{(6-10)}_{\mathrm{c,t}} - r^{(1)}_{\mathrm{c,t}}$	0.369***	0.349**	1.149***	2.134***
	(0.085)	(0.160)	(0.389)	(0.511)
Country fixed effects	✓	✓	✓	✓
N	370	341	269	226
Adj. R^2	0.340	0.185	0.399	0.328

Note. We predict the smoothed excess return $\overline{rx}^{(h)}_{c,t,t+1} = \dfrac{rx^{(h)}_{c,t,t+1} + rx^{(h)}_{c,t+1,t+2}}{2}$ using the consensus forecast for average inflation over h years $\mathbb{F}_{\mathrm{t}}(\overline{\pi_{\mathrm{c,t+1,h}}}) = \frac{1}{h}\sum_{h'=1}^{h}\mathbb{F}_{\mathrm{t}}\left(\pi_{c,t+h'Y}\right)$. We also control for the ex-ante real level $r^{(1)}_{c,t}$ and ex-ante real slope $r^{(6-10)}_{c,t} - r^{(1)}_{c,t}$ of the yield curve. The ex-ante real rate is defined as $r^{(h)}_{c,t} = i^{(h)}_{\mathrm{c,t}} - \mathbb{F}_{\mathrm{t}}(\overline{\pi_{\mathrm{c,t+1,h}}})$. The raw one-year excess return is $rx^{(h)}_{c,t,t+1}$ is defined as $i^{(h)}_{c,t} + (h-1)\left(i^{(h)}_{c,t} - i^{(h-1)}_{c,t+1}\right) - i^{(1)}_{c,t}$. We pool countries and control for country fixed effects. The sample ranges from 1989Q4 to 2022Q1, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

A.5 Robustness: Smoothing excess returns over three years

Table 27: Predicting realized excess returns using consensus inflation forecasts

	(1)	(2)	(3)	(4)
	$\overline{rx}^{(2)}_{c,t,t+1}$	$\overline{rx}^{(3)}_{c,t,t+1}$	$\overline{rx}^{(5)}_{c,t,t+1}$	$\overline{rx}^{(6-10)}_{c,t,t+1}$
$\mathbb{F}_t\left(\overline{\pi_{c,t+1,h}}\right)$	0.132	0.252**	1.047**	3.162***
	(0.091)	(0.123)	(0.435)	(0.772)
$r^{(1)}_{c,t}$	0.269***	0.148*	0.823***	0.726***
	(0.029)	(0.074)	(0.104)	(0.197)
$r^{(6-10)}_{c,t} - r^{(1)}_{c,t}$	0.305***	0.161	1.089***	1.812***
	(0.082)	(0.149)	(0.361)	(0.477)
Country fixed effects	✓	✓	✓	✓
N	874	807	656	539
Adj. R^2	0.421	0.330	0.530	0.427

Note. We predict the smoothed excess return $\overline{rx}^{(h)}_{c,t,t+1} = \frac{rx^{(h)}_{c,t,t+1} + rx^{(h)}_{c,t+1,t+2} + rx^{(h)}_{c,t+2,t+3}}{3}$. using the consensus forecast for average inflation over h years $\mathbb{F}_t(\overline{\pi_{c,t+1,h}}) = \frac{1}{h}\sum_{h'=1}^{h}\mathbb{F}_t\left(\pi_{c,t+h'Y}\right)$. We also control for the ex-ante real level $r^{(1)}_{c,t}$ and ex-ante real slope $r^{(6-10)}_{c,t} - r^{(1)}_{c,t}$ of the yield curve. The ex-ante real rate is defined as $r^{(h)}_{c,t} = i^{(h)}_{c,t} - \mathbb{F}_t(\overline{\pi_{c,t+1,h}})$. The raw one-year excess return is $rx^{(h)}_{c,t,t+1}$ is defined as $i^{(h)}_{c,t} + (h-1)\left(i^{(h)}_{c,t} - i^{(h-1)}_{c,t+1}\right) - i^{(1)}_{c,t}$. We pool countries and control for country fixed effects. The sample ranges from 1989Q4 to 2022Q1, Table 7 reports the countries available at each maturity. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

A.6 Robustness: Stambaugh bias

We address the potential Stambaugh (1999) bias that can arise when predicting variables with highly persistent regressors. This concern applies to all our empirical analyses, namely Tables 1, 2, 3, and 4. Boudoukh et al. (2022) show that such bias becomes more severe at longer horizons, which is relevant for our analysis of maturity-increasing overreaction, and develop a bias-correction formula. We therefore re-estimate all univariate and multivariate predictive regressions using the Boudoukh et al. (2022) adjustment. The correction accounts for the small-sample bias that emerges when predictors are persistent. Because our setting is a panel (whereas Boudoukh et al. (2022) develop their approach for time-series regressions), we apply the correction separately by country and report the median OLS and bias-adjusted coefficients. The results confirm that our main findings are robust to this adjustment.

To see the idea, consider the univariate predictive regression of the 1-period ahead excess bond return onto a regressor X_t, namely:

$$rx_{t,t+1} = \alpha + \beta X_t + u_{t+1}. \tag{23}$$

Stambaugh (1999) showed that with a persistent predictor

$$X_{t+1} = \omega + \rho X_t + v_{t+1}, \tag{24}$$

the OLS estimate β^{OLS} exhibits a small–sample distortion, because the innovation v_t may be contemporaneously correlated with the return error u_t. Stambaugh (1999) further shows that, to a first order approximation in $1/T$:

$$\mathbb{E}[\hat{\beta}^{\text{OLS}}] = \beta - \frac{1}{T}(1+\rho)\frac{\sigma_{uv}}{\sigma_v^2}, \tag{25}$$

where T is the sample length and σ_{uv} is the covariance between the error terms. Boudoukh et al. (2022) show that that in the case of multi-horizon predictions, for overlapping returns (and hence relevant to our long horizon regressions), the OLS estimate is biased as:

$$\mathbb{E}[\hat{\beta}^{\text{OLS}}] = \beta - \frac{1}{T}K\frac{\sigma_{uv}}{\sigma_v^2}, \tag{26}$$

where

$$K = h\big(1+\rho\big) + 2\rho\frac{1-\rho^h}{1-\rho}. \tag{27}$$

We adapt this correction for our univariate tests, and also use the multivariate correction in Boudoukh et al. (2022) for the specification where we also control for time varying return

proxies. In general, we assume that predictors $X_t = (X_{1t}, \ldots, X_{kt})^\top$ follow $AR(1)$ processes with possibly correlated innovations $v_t \sim (0, \Sigma_{vv})$. The vector of OLS slope coefficients then satisfies:

$$\mathbb{E}[\hat{\beta}^{\text{OLS}}] = \beta - \frac{1}{T}\Sigma_{uv}\Sigma_{vv}^{-1}K, \tag{28}$$

with $K = \text{diag}(K_1, \ldots, K_k)$ and K_j defined as

$$K_j = \; h\big(1 + \rho_j\big) + 2\rho_j \frac{1 - \rho_j^h}{1 - \rho_j}. \tag{29}$$

Hence, our bias-adjusted estimator is

$$\hat{\beta}^{\text{BIR}} = \hat{\beta}^{\text{OLS}} + \frac{1}{T}\,\hat{\Sigma}_{uv}\,\hat{\Sigma}_{vv}^{-1}\,\hat{K},$$

which removes the leading $1/T$ bias simultaneously for all (correlated) regressors.

As evident from Table 28 (which reports the median [across countries] Stambaugh-adjusted coefficients and its correlation with the OLS counterpart for each horizon), our finding of maturity-increasing predictability is robust to the Boudoukh et al. (2022) adjustment. The OLS and the bias-adjusted coefficients are generally also close to each other (and with a correlation close to one), suggesting that the bias is small.

Table 28: Stambaugh-adjusted coefficients

	Horizon (h)					
	0	1	2	3	5	6
$\delta_{\mathrm{h}}^{A,STMB}$	0.099	-0.328	-1.085	-1.215	-2.140	-1.734
$\rho\left(\delta_{\mathrm{h}}^{A,STMB}, \delta_{\mathrm{h}}^{A,OLS}\right)$	0.998	0.978	0.990	0.960	0.906	0.857
$\delta_{\mathrm{h}}^{B,STMB}$	-0.043	-0.251	-0.386	-0.405	-0.557	-0.696
$\rho\left(\delta_{\mathrm{h}}^{B,STMB}, \delta_{\mathrm{h}}^{B,OLS}\right)$	0.996	0.991	0.889	0.738	0.906	0.832
$\delta_{1,\mathrm{h}}^{STMB}$	0.206	0.142	-1.751	-1.875	-1.214	-1.773
$\rho\left(\delta_{1,\mathrm{h}}^{STMB}, \delta_{1,\mathrm{h}}^{OLS}\right)$	0.999	0.994	0.999	0.988	0.974	0.936
$\delta_{2,\mathrm{h}}^{STMB}$	-0.161	-1.120	-1.215	-1.272	-3.292	-1.895
$\rho\left(\delta_{2,\mathrm{h}}^{STMB}, \delta_{2,\mathrm{h}}^{OLS}\right)$	0.981	0.991	0.967	0.953	0.886	0.769
$\theta_{\mathrm{h}}^{r,STMB}$		0.484	0.289	0.563	0.749	1.678
$\rho\left(\theta_{\mathrm{h}}^{r,STMB}, \theta_{\mathrm{h}}^{r,OLS}\right)$		0.995	0.987	0.989	0.976	0.856
$\theta_{\mathrm{h}}^{ex,STMB}$			0.261	0.533	1.728	3.140
$\rho\left(\theta_{\mathrm{h}}^{ex,STMB}, \theta_{\mathrm{h}}^{ex,OLS}\right)$			0.984	0.989	0.985	0.951

Note. The table reports, in each cell and for each horizon, the median (across countries) Stambaugh-adjusted coefficients (first row of each cell) and the correlation between the Stambaugh-adjusted and OLS estimates (second row of each cell). Coefficients are estimated separately for each country. The first two coefficients correspond to Panel A and Panel B of Table 1; the third and fourth to Table 2; the fifth to Table 3; and the sixth to Table 4. Only the available horizons are included, and the sample composition varies across horizons. Table 7 reports the list of countries available at each horizon.

A.7 Robustness: Including all countries and UK

Table 29: Predicting the consensus forecast error using the current inflation state - Cumulative Sample, including UK

	Panel A					
	(1)	(2)	(3)	(4)	(5)	(6)
	$FE_{c,0}$	$FE_{c,1}$	$FE_{c,2}$	$FE_{c,3}$	$FE_{c,5}$	$FE_{c,6-10}$
$\mathbb{F}_t(\pi_{c,t+hY})$	0.039	-0.406**	-0.984***	-1.201***	-1.671***	-1.146***
	(0.054)	(0.155)	(0.286)	(0.279)	(0.277)	(0.110)
Country fixed effects	✓	✓	✓	✓	✓	✓
N	1366	1366	1361	1285	1131	745
Adj. R^2	0.018	0.066	0.160	0.187	0.249	0.483
	Panel B					
	(1)	(2)	(3)	(4)	(5)	(6)
	$FE_{c,0}$	$FE_{c,1}$	$FE_{c,2}$	$FE_{c,3}$	$FE_{c,5}$	$FE_{c,6-10}$
$\overline{\pi}_{c,t}$	-0.065	-0.265*	-0.298**	-0.340**	-0.638***	-0.428***
	(0.043)	(0.130)	(0.141)	(0.125)	(0.193)	(0.069)
Country fixed effects	✓	✓	✓	✓	✓	✓
N	554	554	534	515	477	376
Adj. R^2	0.002	0.057	0.065	0.086	0.232	0.348

Note. Each column reports the country pooled regression at horizon $h = 0, ...,$ 6-10: the dependent variable is the consensus forecast error $\pi_{c,t+hY} - \mathbb{F}_t(\pi_{c,t+hY})$ at horizon h and country c. The independent variables are: (i) the consensus forecast for country c at horizon h, $\mathbb{F}_t(\pi_{c,t+hY})$ (Panel A), and (ii) the average realized inflation of country c over the past two years, $\overline{\pi}_{c,t} = (\pi_{c,(t-1)Y} + \pi_{c,(t-2)Y})/2$ (Panel B). We control for country fixed effects. The sample ranges from 1989Q4 to 2022Q1. The sample ranges from 1989Q4 to 2022Q1. For each horizon, we include all of the countries listed in the cumulative sample of Table 7, as well as United Kingdom. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 30: Predicting consensus error from recent news and past inflation states - Cumulative Sample, including UK

	(1)	(2)	(3)	(4)	(5)	(6)
	$FE_{\mathrm{c},0}$	$FE_{\mathrm{c},1}$	$FE_{\mathrm{c},2}$	$FE_{\mathrm{c},3}$	$FE_{\mathrm{c},5}$	$FE_{\mathrm{c},6-10}$
$\mathbb{F}_{\mathrm{t}}(\pi_{\mathrm{c,t+hY}}) - \mathbb{F}_{\mathrm{t-4}}(\pi_{\mathrm{c,t+hY}})$	0.193	0.299	-0.840*	-1.235***	-1.299***	-1.155***
	(0.122)	(0.317)	(0.425)	(0.438)	(0.272)	(0.125)
$\mathbb{F}_{\mathrm{t-4}}(\pi_{\mathrm{c,t+hY}})$	-0.108***	-0.612**	-1.181***	-1.427***	-1.805***	-0.952***
	(0.040)	(0.246)	(0.393)	(0.408)	(0.392)	(0.131)
Country fixed effects	✓	✓	✓	✓	✓	✓
N	1290	1286	1282	1205	1042	701
Adj. R^2	0.108	0.108	0.141	0.163	0.185	0.339

Note. Each column reports the country pooled regression at horizon $h = 0, ..., 6$-10: the dependent variable is the inflation consensus forecast error $\pi_{c,t+hY} - \mathbb{F}_t\left(\pi_{c,t+hY}\right)$ over horizon h and country c. The independent variables are the consensus revision $\mathbb{F}_t\left(\pi_{c,t+hY}\right) - \mathbb{F}_{t-4}\left(\pi_{c,t+hY}\right)$ and the lagged inflation forecast $\mathbb{F}_{t-4}\left(\pi_{c,t+hY}\right)$. We control for country fixed effects. The sample ranges from 1989Q4 to 2022Q1. For each horizon, we include all of the countries listed in the cumulative sample of Table 7, as well as United Kingdom. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 31: Predicting ex-post real rates using consensus inflation forecast - Cumulative Sample, including UK

	(1)	(2)	(3)	(4)	(5)
	$\tilde{r}^{(1)}_{\mathrm{c,t,t+1}}$	$\tilde{r}^{(2)}_{\mathrm{c,t,t+2}}$	$\tilde{r}^{(3)}_{\mathrm{c,t,t+3}}$	$\tilde{r}^{(5)}_{\mathrm{c,t,t+5}}$	$\tilde{r}^{(6-10)}_{\mathrm{c,t+6,t+10}}$
$\mathbb{F}_{\mathrm{t}}\left(\overline{\pi_{\mathrm{c,t+1,h}}}\right)$	0.308**	0.502***	0.621***	0.809***	1.090***
	(0.142)	(0.150)	(0.150)	(0.124)	(0.111)
$r^{(h)}_{\mathrm{c,t}}$	1.200***	1.151***	1.087***	1.026***	0.942***
	(0.136)	(0.108)	(0.079)	(0.060)	(0.043)
Country fixed effects	✓	✓	✓	✓	✓
N	1146	1325	1111	1118	714
Adj. R^2	0.615	0.726	0.799	0.880	0.941

Note. We predict the real yield to maturity $\widetilde{r}^{(h)}_{c,t,t+h}$ using the consensus forecast for average inflation over h years, measured as $\mathbb{F}_{\mathrm{t}}(\overline{\pi_{\mathrm{c,t+1,h}}}) = \frac{1}{h}\sum_{h'=1}^{h}\mathbb{F}_{\mathrm{t}}\left(\pi_{c,t+h'Y}\right)$, and the ex-ante real rate proxy $r^{(h)}_{\mathrm{c,t}} = i^{(h)}_{\mathrm{c,t}} - \mathbb{F}_{\mathrm{t}}(\overline{\pi_{\mathrm{c,t+1,h}}})$. We pool countries and control for country-fixed effects. The sample ranges from 1989Q4 to 2022Q1. For each horizon, we include all of the countries listed in the cumulative sample of 7, as well as United Kingdom. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table 32: Predicting realized excess returns using consensus inflation forecasts - Cumulative Sample, including UK

	(1)	(2)	(3)	(4)
	$\overline{rx}^{(2)}_{c,t,t+1}$	$\overline{rx}^{(3)}_{c,t,t+1}$	$\overline{rx}^{(5)}_{c,t,t+1}$	$\overline{rx}^{(6-10)}_{c,t,t+1}$
$\mathbb{F}_t\left(\overline{\pi_{c,t+1,h}}\right)$	0.147*	0.307**	1.359**	3.772***
	(0.084)	(0.150)	(0.514)	(0.750)
$r^{(1)}_{c,t}$	0.284***	0.193**	0.861***	0.770***
	(0.039)	(0.097)	(0.157)	(0.249)
$r^{(6-10)}_{c,t} - r^{(1)}_{c,t}$	0.386***	0.378**	1.448***	2.653***
	(0.071)	(0.154)	(0.324)	(0.521)
Country fixed effects	✓	✓	✓	✓
N	1035	958	758	666
Adj. R^2	0.389	0.293	0.461	0.396

Note. We predict the smoothed excess return $\overline{rx}^{(h)}_{c,t,t+1} = \frac{rx^{(h)}_{c,t,t+1} + rx^{(h)}_{c,t+1,t+2}}{2}$ using the consensus forecast for average inflation over h years $\mathbb{F}_t(\overline{\pi_{c,t+1,h}}) = \frac{1}{h}\sum_{h'=1}^{h}\mathbb{F}_t\left(\pi_{c,t+h'Y}\right)$. We also control for the ex-ante real level $r^{(1)}_{c,t}$ and ex-ante real slope $r^{(6-10)}_{c,t} - r^{(1)}_{c,t}$ of the yield curve. The ex-ante real rate is defined as $r^{(h)}_{c,t} = i^{(h)}_{c,t} - \mathbb{F}_t(\overline{\pi_{c,t+1,h}})$. The raw one-year excess return is $rx^{(h)}_{c,t,t+1}$ is defined as $i^{(h)}_{c,t} + (h-1)\left(i^{(h)}_{c,t} - i^{(h-1)}_{c,t+1}\right) - i^{(1)}_{c,t}$. We pool countries and control for country fixed effects. The sample ranges from 1989Q4 to 2022Q1. For each horizon, we include all of the countries listed in the cumulative sample of Table 7, as well as United Kingdom. Standard errors in parenthesis are Driscoll-Kraay. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

A.8 Robustness: Artificial Rates

Variable Construction

We first define the following measures, computed using model-implied forecast data (superscript m):

- $r_{c,t}^{(h),m} = i_{c,t}^{(h)} - \mathbb{F}_t^m(\overline{\pi_{c,t+1,h}})$ for $h = 1, 2, 3, 5, 6-10$, ex ante real rate, model implied;
- $r_c^{(h),m} = \frac{1}{T_c}\sum_{t=T_{\text{start},c}}^{T_{\text{end},c}}\left(r_{c,t}^{(h),m}\right)$ for $h = 1, 2, 3, 5, 6-10$, average ex ante real rate over the period in which CE forecast data is available, model implied;
- $i_{c,t}^{*(h),m} = r_{c,t}^{(h),m} + \mathbb{F}_t^m(\overline{\pi_{c,t+1,h}})$ for $h = 1, 2, 3, 5, 6-10$, ex ante nominal rate, model implied;
- $rx_{c,t,t+1}^{(h),m} = -(h-1)\, i_{c,t+1}^{*(h-1),m} + h\, i_{c,t}^{*(h),m} - i_{c,t}^{*(1),m}$ for $h = 1, 2, 3, 5, 6-10$, one-year excess return, model implied;[24]
- $\overline{rx}_{c,t,t+1}^{(h),m} = \frac{1}{2}\left(rx_{c,t,t+1}^{(h),m} + rx_{c,t+1,t+2}^{(h),m}\right)$ for $h = 1, 2, 3, 5, 6-10$, smoothed (over two years) excess returns, model implied.

Results

For each country c, and for each horizon h, we estimate:

$$r_{\text{c,t}}^{(h),i} = \alpha_{c,h}^i + \theta_{c,h}^{r,i}\, \mathbb{F}_{\text{t}}^i\left(\overline{\pi_{\text{c,t+1,h}}}\right) + \epsilon_{c,t}^{(h),i}$$

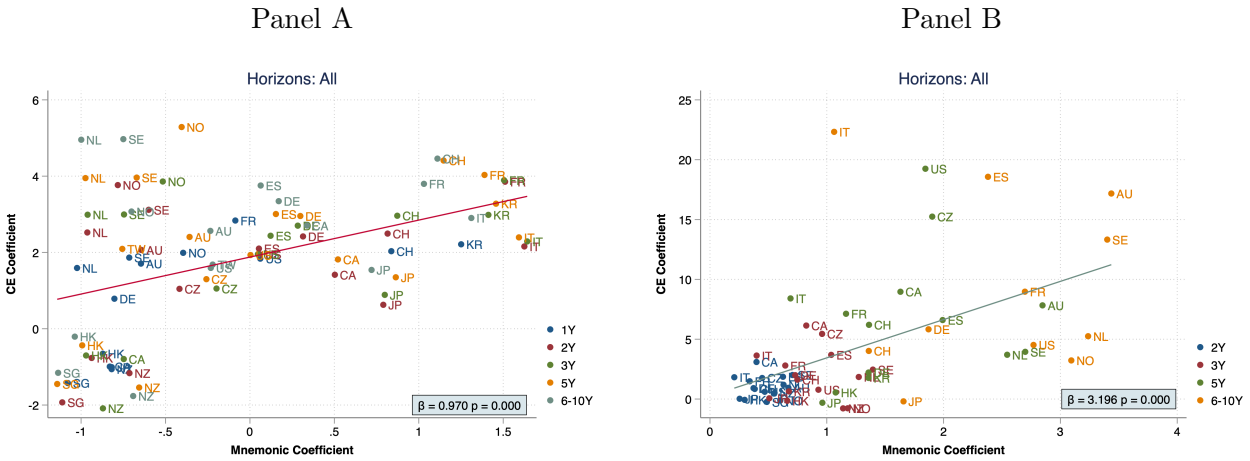
$$\overline{rx}_{c,t,t+1}^{(h),i} = \alpha_{c,h}^i + \theta_{c,h}^{ex,i}\, \mathbb{F}_{\text{t}}^i\left(\overline{\pi_{\text{c,t+1,h}}}\right) + \epsilon_{c,t,t+1}^{(h),i}$$

for $i = CE$ when using the CE dataset and actual Refinitiv rates, and $i = m$ when using the mnemonic dataset and artificial rates.

The estimated coefficients $\theta_{c,h}^{r,i}$ and $\theta_{c,h}^{ex,i}$ are then compared across datasets, as illustrated in the scatterplots in Figure 8 below.

[24] For the (6–10) horizon, the one-year excess return is computed directly using the above formula, since the underlying variables already incorporate the average over horizons (6–10).

Figure 8: Performance for Real Yield to Maturity and Excess Returns - Comparison with Artificial Rates



Note. Panels A and B plot, respectively, the real-rate and excess-return predictability coefficients $\theta_{c,h}^{r,i}$ and $\theta_{c,h}^{ex,i}$ from the CE dataset (y-axis) against those from the artificial (mnemonic) dataset (x-axis). Coefficients in both figures are country- and maturity-specific. The lines indicate the fit between the two datasets' coefficients. Pooled (across countries and horizons) slopes and pvalues are reported in the blue boxes in the graphs. Panel A: $R^2 = 0.20$, correlation $= 0.45$; Panel B: $R^2 = 0.28$, correlation $= 0.55$. The identifier for each data point corresponds to the ISO 3166-2 country abbreviation.

B Formal Analysis and Simulations

B.1 Derivation of Economic Implications

We are interested in how the ex-ante loan value, $L^{(h^*)}$, and ex-post loan value, $\hat{L}^{(h^*)}$, respond to changes in expected inflation π_j^e through changes in the ex-ante real rate and predictable forecast errors. Formally, $L^{(h^*)}$ is defined as

$$L^{(h^*)} := \sum_{h=1}^{h^*} \prod_{s=1}^{h} \frac{P^{(h^*)} p_s^e}{1 + r_s(\pi^e)}, \tag{30}$$

while the definition of $\hat{L}^{(h^*)}$ is given by equation (22).

Note that $\hat{L}^{(h^*)}$ is affected by both changes in the ex-ante real rate and by the predictable forecast errors, whereas $L^{(h^*)}$ responds only to variations in the ex-ante real rate. In addition, since we focus on an approximation around the point where $\pi_s = \pi_s^e$, the impact of a change in π_s^e on $L^{(h^*)}$ is a special case of its effect on $\hat{L}^{(h^*)}$. Therefore, in the derivations that follow, we focus on $\hat{L}^{(h^*)}$.

Formally, if we let $Q^{(h^*)} := \hat{L}^{(h^*)}/P^{(h^*)}$, then

$$\frac{\partial \hat{L}^{(h^*)}}{\partial \pi_j^e} = P^{(h^*)} \frac{\partial Q^{(h^*)}}{\partial \pi_j^e}$$

or, using the definition of $Q^{(h^*)}$,

$$\frac{1}{\hat{L}^{(h^*)}} \cdot \frac{\partial \hat{L}^{(h^*)}}{\partial \pi_j^e} = \frac{1}{Q^{(h^*)}} \cdot \frac{\partial Q^{(h^*)}}{\partial \pi_j^e}.$$

Note that the left-hand side captures the semi-elasticity of $\hat{L}^{(h^*)}$ to a change in expectations: $\partial \log \hat{L}^{(h^*)}/\partial \pi_j^e$.

More specifically, we will consider a parallel change of inflation expectations at all horizons, that is we assume $\pi_s^e = \tilde{\pi}_s^e + \pi^e$ and compute the derivative with respect to π^e. We have

$$\begin{aligned}
\frac{1}{Q^{(h^*)}} \cdot \frac{\partial Q^{(h^*)}}{\partial \pi^e} =& \frac{1}{Q^{(h^*)}} \cdot \frac{\partial}{\partial \pi^e} \sum_{h=1}^{h^*} \prod_{s=1}^{h} \frac{1}{(1+r_s)(1+\pi_s - \pi_s^e)} \\
=& -\frac{1}{Q^{(h^*)}} \left[\frac{1}{(1+r_1)(1+\pi_1 - \pi_1^e)} \left(\frac{1}{1+r_1} \cdot \frac{\partial r_1}{\partial \pi^e} + \frac{1}{1+\pi_1 - \pi_1^e} \cdot \frac{\partial (\pi_1 - \pi_1^e)}{\partial \pi^e} \right) + ... \right. \\
& \left. + \prod_{s=1}^{h^*} \frac{1}{(1+r_s)(1+\pi_s - \pi_s^e)} \sum_{j=1}^{h^*} \frac{1}{1+r_j} \cdot \frac{\partial r_j}{\partial \pi^e} + \frac{1}{1+\pi_j - \pi_j^e} \cdot \frac{\partial (\pi_j - \pi_j^e)}{\partial \pi^e} \right].
\end{aligned}$$

We can further simplify the expression by approximating one-period inflation with average inflation over the loan duration. Similarly, the real rate at time s can be approximated with the average real rate over the loan duration:

$$r_s \approx r^{(h)} := \frac{1}{h}\sum_{j=1}^{h} r_s, \ \forall s.$$

Finally, we consider a change in expectations around the point where inflation and inflation expectations are both equal to zero: $\pi_s - \pi_s^e \approx 0, \ \forall s$. As a result,

$$\frac{1}{Q^{(h^*)}} \cdot \frac{\partial Q^{(h^*)}}{\partial \pi^e} = -\frac{1}{Q^{(h^*)}} \sum_{h=1}^{h^*} \frac{1}{(1+r^{(h)})^h} \left(\frac{h}{1+r^{(h)}} \cdot \frac{\partial r^{(h)}}{\partial \pi^e} + \sum_{j=1}^{h} \frac{\partial(\pi_j - \pi_j^e)}{\partial \pi^e} \right).$$

Therefore,

$$\frac{\partial \log \hat{L}^{(h^*)}}{\partial \pi^e} = \underbrace{-\frac{1}{Q^{(h^*)}} \sum_{h=1}^{h^*} \frac{h}{(1+r^{(h)})^{h+1}} \cdot \frac{\partial r^{(h)}}{\partial \pi^e}}_{\frac{\partial \log L^{(h^*)}}{\pi^e}} \underbrace{-\frac{1}{Q^{(h^*)}} \sum_{h=1}^{h^*} \frac{1}{(1+r^{(h)})^h} \sum_{j=1}^{h} \frac{\partial(\pi_j - \pi_j^e)}{\partial \pi^e}}_{\frac{\partial \log \hat{L}^{(h^*)}}{\pi^e} - \frac{\partial \log L^{(h^*)}}{\pi^e}}.$$

The first term in the round bracket is the change in ex-ante real rate over horizon h. Equation (4) estimates the sensitivity of the h-period nominal rate to a change in the average inflation expectation. Using the notation of this section, we can rewrite equation (4) as

$$i^{(h)} = \alpha_h + \lambda_h \left(\frac{1}{h} \sum_{j=1}^{h} \pi_j^e \right) + \varepsilon^{(h)}.$$

Then, using our assumption that $\pi_j^e = \tilde{\pi}_j^e + \pi^e$ for all $j = 1, ..., h$, it follows that $\frac{\partial}{\partial \pi^e} \sum_{j=1}^{h} (i_{j-1} - \pi_j^e) = \lambda_h - 1$ and, as a result,

$$\frac{\partial \log L^{(h^*)}}{\pi^e} = -\frac{1}{Q^{(h^*)}} \sum_{h=1}^{h^*} \frac{h(\lambda_h - 1)}{(1+r^{(h)})^{h+1}}.$$

Finally, the sum $\sum_{j=1}^{h} (\pi_j - \pi_j^e)$ is the cumulative forecast error over horizon h, thus, $\frac{\partial}{\partial \pi^e} \sum_{j=1}^{h} (\pi_j - \pi_j^e)$ captures the change in the cumulative forecast error following from a parallel change in expectations over the loan duration. Equation (2) estimates the sensitivity of the h-period-ahead forecast error to a change in the average inflation expectation. Using the notation of this section, we can rewrite equation (2) as

$$\pi_h - \pi_h^e = \alpha_h + \delta_h \pi_h^e + \varepsilon^{(h)}.$$

Then, using our assumption that $\pi_j^e = \tilde{\pi}_j^e + \pi^e$ for all h, it follows that

$$\frac{\partial \log \hat{L}^{(h^*)}}{\pi^e} - \frac{\partial \log L^{(h^*)}}{\pi^e} = -\frac{1}{Q^{(h^*)}} \sum_{h=1}^{h^*} \frac{\sum_{j=1}^{h} \delta_j}{(1+r^{(h)})^h}.$$

B.2 Proofs

Proof of Proposition 1 We apply the same line of reasoning used in Bonaglia and Gennaioli (2025) to prove more general convergence results. First we state some preliminary notation. We consider a generic horizon h. Under the assumptions of stationary, gaussian and zero mean DGP and with similarity specification described in (12), we sum up the model in three essential ingredients:

- A probability space $(\mathbb{R}^\infty, \mathcal{B}(\mathbb{R}^\infty), \mathcal{P})$ where $\mathcal{P}$ is the Kolmogorov extension law induced by the ergodic, stationary, gaussian, zero-mean, stochastic process $(X_t)_t$ whose time t realization is denoted by $\pi_t \in \mathbb{R}$ and $\mathcal{B}(\mathbb{R}^\infty)$ is the cylinder sigma algebra. We indicate by $\omega := (\pi_1, \pi_2, ...) \in \mathbb{R}^\infty$ any sequence of real numbers.

- A sequence of (random) mnemnonic expectations over the horizon h, $(\mathbb{E}_t^m)_{t\in\mathbb{N}}$, such that

$$\mathbb{E}_t^m : \omega \mapsto \frac{\sum_{k=h}^{t-1} \pi_k e^{-\alpha(\pi_t - \pi_{k-h})^2 - \beta(\pi_t - \pi_k)^2}}{\sum_{k=h}^{t-1} e^{-\alpha(\pi_t - \pi_{k-h})^2 - \beta(\pi_t - \pi_k)^2}}$$

  which is Borel measurable by standard arguments.

Proof. Fix $x \in \mathbb{R}$. For all $t \in \mathbb{N}$, consider the x-parameterized (random) mnemnonic expectation

$$\mathbb{E}_t^{m,x} : \omega \mapsto \frac{\sum_{k=h}^{t-1} \pi_k e^{-\alpha(x - \pi_{k-h})^2 - \beta(x - \pi_k)^2}}{\sum_{k=h}^{t-1} e^{-\alpha(x - \pi_{k-h})^2 - \beta(x - \pi_k)^2}}$$

We first show that for each $\mathbb{E}_t^{m,x}$ converges almost surely to some $\Lambda(x)$ and we algebraically characterize the limit $\Lambda(x)$. Then we we will prove that $\Lambda(X_t)$ is the p-lim of $(\mathbb{E}_t^m)_{t\in\mathbb{N}}$, namely

$$\lim_{t\to\infty} \mathcal{P}(\{|\mathbb{E}_t^m - \Lambda(X_t)| < \epsilon\}) = 1$$

for all $\epsilon > 0$.

P-lim characterization: Consider the numerator of $\mathbb{E}_t^{m,x}(\omega)$. We know that the map

$$S_x \circ T \circ ... \circ T : \omega \mapsto \pi_t e^{-\alpha(x - \pi_{t-h})^2 - \beta(x - \pi_t)^2}$$

when the shift operator T is applied t times is bounded and $\mathbb{R}^2$-Borel measurable for each t (hence integrable with respect to any probability measure). Hence the Pointwise Bierkoff

Ergodic Theorem applies with respect to the shift operator which a well-known measure preserving and ergodic transformation of the probability measure $\mathcal{P} \in \Delta(\mathbb{R}^{\infty})$ whose marginals for all $t \in \mathbb{N}$ coincides with the stationary distribution of $(X_t)_t$. We conclude that,

$$\lim_{t\to\infty} \frac{\sum_{k=h}^{t-1} \pi_k e^{-\alpha(x-\pi_{k-h})^2-\beta(x-\pi_k)^2}}{t} = \int \tilde{\pi} e^{-\alpha(x-\tilde{\pi}_{-h})^2-\beta(x-\tilde{\pi})^2} d\tau(\tilde{\pi}, \tilde{\pi}_{-h}) \tag{31}$$

$\mathcal{P}$-almost surely, where τ is the unique stationary probability measure for the process (X_{t-h}, X_t) with realizations (π_{t-h}, π_t). An analogous reasoning applies to the denominator. Hence we conclude that

$$\lim_{t\to\infty} \frac{\sum_{k=h}^{t-1} e^{-\alpha(x-\pi_{k-h})^2-\beta(x-\pi_k)^2}}{t} = \int e^{-\alpha(x-\tilde{\pi}_{-h})^2-\beta(x-\tilde{\pi})^2} d\tau(\tilde{\pi}, \tilde{\pi}_{-h}) \tag{32}$$

almost surely. By properties of the exponential function, we know that the denominator is strictly positive almost surely. Consequently we infer that

$$\lim_{t\to\infty} \mathbb{E}_t^{m,x} = \Lambda(x) := \frac{\int \tilde{\pi} e^{-\alpha(x-\tilde{\pi}_{-h})^2-\beta(x-\tilde{\pi})^2} d\tau(\tilde{\pi}, \tilde{\pi}_{-h})}{\int e^{-\alpha(x-\tilde{\pi}_{-h})^2-\beta(x-\tilde{\pi})^2} d\tau(\tilde{\pi}, \tilde{\pi}_{-h})} = \phi(\alpha, \beta, h)x \quad \mathcal{P} - a.e \tag{33}$$

where $\phi(\alpha, \beta, h)$ is the functional representation obtained by performing the algebra inside the integrals.[25] We said that τ is the stationary probability measure for the stochastic process (X_{t-h}, X_t). Denote by Y the bivariate normal having marginals X_{-h}, X distributed identically to the limit distribution of the one dimensional original stochastic process. Next, we prove that $\Lambda(X_t) = \mathbb{E}_t^{\infty}(\pi_{t+h})$, i.e that it characterizes the mnemonic long-run approximation of $\mathbb{E}_t^m(\pi_{t+h})$ of (11).

Convergence in Probability: We want to show that

$$\lim_{t\to\infty} \mathcal{P}(\{\ |\mathbb{E}_t^m - \Lambda(X_t)| \geq \epsilon\}) = 0$$

for all $\epsilon > 0$. Note that, for all $t \in \mathbb{N}$ and for all $B > 0$,

$$\mathcal{P}(\{\ |\mathbb{E}_t^m - \Lambda(X_t)| \geq \epsilon\}) \leq \mathcal{P}\left(\{X_t \in [-B, B]^c\}\right) + \mathcal{P}(\{\ |\mathbb{E}_t^m - \Lambda(X_t)| \cdot 1_{[X_t \in [-B,B]]} \geq \epsilon\}\big). \tag{34}$$

Fix $\delta > 0$ and pick $B > 0$ large enough so that, if $\mathbf{X}$ is distributed according to the stationary distribution, $\mathcal{P}\left(\{\mathbf{X} \in [-B, B]^c\}\right) < \delta$. Let us now focus on $\mathcal{P}(\{\ |\mathbb{E}_t^m - \Lambda(X_t)| \cdot 1_{[X_t \in [-B,B]]} \geq \epsilon\})$;

[25] See the proof of Proposition 2 for an explicit characterization.

in particular, let us prove that

$$\lim_{t\to\infty} |\mathbb{E}_t^m - \Lambda(X_t)| \cdot 1_{[X_t\in[-B,B]]} = 0 \quad \mathcal{P}-a.s.$$

Clearly, for all $\omega \in \{X_t \in [-B,B]^c, \text{ ultimately}\}$, the convergence holds. Hence let us focus on the event $\{X_t \in [-B,B], \text{ infinitely often}\}$. Pick $\omega \in \{X_t \in [-B,B], \text{ infinitely often}\}$. Clearly,

$$\limsup_{t\to\infty} |\mathbb{E}_t^m(\omega) - \Lambda(X_t(\omega))| \cdot 1_{[X_t\in[-B,B]]} \geq \lim_{t\to\infty} |\mathbb{E}_t^m(\omega) - \Lambda(X_t(\omega))| \cdot 1_{[X_t\in[-B,B]]},$$

hence let us prove that the LHS converges to zero. Let $(t_k)_k$ the subsequence where the limsup value is attained in the limit. Now, being $[-B,B]$ compact, $(X_{t_k}(\omega))$ has a convergent subsequence, say convergent to some $x \in [-B,B]$. Now, we claim that $S_{t_k} : (y_1,y_2) \mapsto \exp[-\alpha(X_{t_k}(\omega)-y_1)^2 - \beta(X_{t_k}(\omega)-y_1)^2]$ converges uniformly to $S_x : (y_1,y_2) \mapsto \exp[-\alpha(x-y_1)^2 - \beta(x-y_1)^2]$. This follows from the fact that the derivative of the negative exponential is always bounded by some arbitrarily large K, hence

$$||\exp[-\alpha(X_{t_k}(\omega)-y_1)^2] - \exp[-\alpha(x-y_1)^2]||_\infty \leq K|X_{t_k}(\omega)-x| \to 0,$$

$$||\exp[-\beta(X_{t_k}(\omega)-y_2)^2] - \exp[-\beta(x-y_2)^2]||_\infty \leq K|X_{t_k}(\omega)-x| \to 0,$$

whence

$$||\exp[-\alpha(X_{t_k}(\omega)-y_1)^2 - \beta(X_{t_k}(\omega)-y_2)^2] - \exp[-\alpha(x-y_1)^2 - \beta(x-y_2)^2]||_\infty \to 0,$$

as claimed. Now, by construction,

$$\mathbb{E}_t^m(\omega) = \frac{\int y_2 S_{t_k}((y_1,y_2))\ dm_e(y_1,y_2|\omega)}{\int S_{t_k}((y_1,y_2))\ dm_e(y_1,y_2|\omega)},$$

where $m_e(\cdot|\omega) \in \Delta(\mathbb{R}^2)$ is the empirical measure generated by ω at time t_k. Since the process is ergodic and stationary, a standard implication of Bierkoff-Ergodic theorem in polish spaces (over which we are operating) is that m_e weakly converges to τ, $\mathcal{P}$-ae. WLOG we can assume that $\omega \in \{m_e \to \tau\}$, being $\{m_e \to \tau\}$ a full measure event. By combining the facts that $||S_{t_k}(\cdot) - S_x(\cdot)||_\infty \to 0$ and $m_e(\cdot|\omega) \to \tau$ weakly, we infer that

$$\lim_{k\to\infty} \mathbb{E}_{t_k}^m(\omega) = \lim_{k\to\infty} \frac{\int y_2 S_{t_k}((y_1,y_2))\ dm_e(\cdot|\omega)}{\int S_{t_k}((y_1,y_2))\ dm_e(\cdot|\omega)} = \frac{\int y_2 S_x((y_1,y_2))d\tau}{\int S_x((y_1,y_2))d\tau} = \lim_{k\to\infty} \Lambda(X_{t_k}(\omega)). \quad (35)$$

Because of (35) and (33), and by the definition of t_k, we deduce that

$$\limsup_{t\to\infty} |\mathbb{E}_t^m(\omega) - \Lambda(X_t(\omega)| \cdot 1_{[X_t(\omega)\in[-B,B]]} = 0,$$

but since ω is a generic element belonging to of a full measure event, our almost sure convergence claim holds. Plugging this result in (34) and recalling that almost sure convergence implies convergence in probability, we deduce also that

$$\lim_{t\to\infty} \mathcal{P}(\{\ |\mathbb{E}_t^m - \Lambda(X_t)| \geq \epsilon\}) \leq \lim_{t\to\infty} \mathcal{P}\left(\{X_t \in [-B,B]^c\}\right) + 0. \tag{36}$$

Being $(X_t)_t$ stationary, the distribution of X_t weakly converges to the distribution of $\mathbf{X}$. Since the boundary set of $[-B,B]$ has zero measure, Portmanteau Theorem yields that

$$\lim_{t\to\infty} \mathcal{P}(\{\ |\mathbb{E}_t^m - \Lambda(X_t)| \geq \epsilon\}) \leq \lim_{t\to\infty} \mathcal{P}\left(\{X_t \in [-B,B]^c\}\right) = \mathcal{P}\left(\{\mathbf{X} \in [-B,B]^c\}\right) < \delta.$$

Since $\delta > 0$ is arbitrary, the claim follows. ■

Proof of proposition 2 **Proof.** Reasoning as in the first step of proposition 1, we infer that $\mathbb{E}_t^\infty(\pi_{t+h}) = \dfrac{\int \tilde{\pi} e^{-\alpha(\pi_t-\tilde{\pi}_{-h})^2-\beta(\pi_t-\tilde{\pi})^2} d\tau(\tilde{\pi},\tilde{\pi}_{-h})}{\int e^{-\alpha(\pi_t-\tilde{\pi}_{-h})^2-\beta(\pi_t-\tilde{\pi})^2} d\tau(\tilde{\pi},\tilde{\pi}_{-h})}$, By applying the Radon-Nikodym Theorem and reformulating the RHS of (31) using quadratic forms we get

$$\mathbb{E}_t^\infty(\pi_{t+h}) = \frac{\int_{\mathbb{R}^2} \pi \exp\left(-0.5(\pi_{-h},\pi)^\top \Sigma_1^{-1}(\pi_{-h},\pi) - 0.5(\pi_{-h}-x,\pi-\pi_t)^\top \Sigma_2^{-1}(\pi_{-h}-\pi_t,\pi-\pi_t)\right) d(\pi_{-h},\pi)}{\int_{\mathbb{R}^2} \exp\left(-0.5(\pi_{-h},\pi)^\top \Sigma_1^{-1}(\pi_{-h},\pi) - 0.5(\pi_{-h}-\pi_t,\pi-\pi_t)^\top \Sigma_2^{-1}(\pi_{-h}-\pi_t,\pi-\pi_t)\right) d(\pi_{-h},\pi)}$$

Where one can note that the denominator is just the normalizing constant. By the characterization of the product of two bivariate Gaussian densities, we know it is normal $\mathcal{N}^*(\mathbf{m},\mathbf{\Sigma_3})$ such that:

$$\mathbf{\Sigma_3} = \left(\begin{bmatrix} \mathrm{Var}(X_t) & \mathrm{Cov}(X_{t+h},X_t) \\ \mathrm{Cov}(X_{t+h},X_t) & \mathrm{Var}(X_t) \end{bmatrix}^{-1} + \begin{bmatrix} 2\alpha & 0 \\ 0 & 2\beta \end{bmatrix} \right)^{-1}$$

$$\mathbf{m} = \mathbf{\Sigma_3} \begin{bmatrix} 2\alpha & 0 \\ 0 & 2\beta \end{bmatrix} \begin{pmatrix} \pi_t \\ \pi_t \end{pmatrix}.$$

Now, since the second component of $\mathbf{m}$ coincides with the definition of $\mathbb{E}_t^\infty(\pi_{t+h})$, by performing the algebra,

$$\mathbb{E}_t^{\infty}(\pi_{t+h}) = \frac{2\pi_t \operatorname{Cov}(X_t, X_{t+h})\,\alpha\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)}{\left(\operatorname{Var}(X_t) + 2\alpha\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)\right)\left(\operatorname{Var}(X_t) + 2\beta\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)\right) - \operatorname{Cov}(X_t, X_{t+h})^2}$$
$$+ \frac{2\pi_t\,\beta\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)\left(\operatorname{Var}(X_t) + 2\alpha\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)\right)}{\left(\operatorname{Var}(X_t) + 2\alpha\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)\right)\left(\operatorname{Var}(X_t) + 2\beta\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)\right) - \operatorname{Cov}(X_t, X_{t+h})^2}$$

Not, given this expression, standard algebraic manipulations yield that

$$\lim_{\alpha\to\infty,\ \beta\to 0} \mathbb{E}_t^{\infty}(\pi_{t+h}) = \frac{\operatorname{cov}(X_{t+h}, X_t)}{\operatorname{var}(X_t)}\pi_t, \qquad \text{(Least Square)}$$
$$\lim_{\alpha\to 0,\ \beta\to\infty} \mathbb{E}_t^{\infty}(\pi_{t+h}) = \pi_t, \qquad \text{(Adaptive)}$$
$$\lim_{\alpha\to 0,\ \beta\to 0} \mathbb{E}_t^{\infty}(\pi_{t+h}) = 0. \qquad \text{(Frequentist).}$$

Finally, In order to deduce overreaction for long enough horizons, let us focus on the coefficient that multiplies X_t. Letting $h \to \infty$, by relying on the vanishing auto-covariance hypothesis, we get that the first addendum divided by π_t goes to zero, while coefficient of the second one divided by π_t converges to

$$\frac{2\beta[\operatorname{Var}(X_t)]^2\left[2\alpha[\operatorname{Var}(X_t)]^2 + \operatorname{Var}(X_t)\right]}{[\operatorname{Var}(X_t) + 2\alpha\operatorname{Var}(X_t)^2][\operatorname{Var}(X_t) + 2\beta\operatorname{Var}(X_t)^2]} = \frac{2\beta\operatorname{Var}(X_t)^2}{\operatorname{Var}(X_t) + 2\beta\operatorname{Var}(X_t)^2} > 0 = \lim_{h\to\infty}\frac{\operatorname{Cov}(X_{t+h}, X_t)}{\operatorname{Var}(X_t)},$$

proving the desired claim.

■

Proof of Proposition 3 By relying on the general characterization for gaussian, ergodic, stationary processes, we use the stationary distribution of AR(1) to explicitly write the stationary distribution as a function of the parameter $\rho, \sigma \in \mathbb{R}$.

Proof. The claim follows by simple and immediate algebraic manipulations. Indeed by taking the general expression

$$\mathbb{E}_t^{\infty}(\pi_{t+h}) = \frac{2\pi_t \operatorname{Cov}(X_t, X_{t+h})\,\alpha\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)}{\left(\operatorname{Var}(X_t) + 2\alpha\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)\right)\left(\operatorname{Var}(X_t) + 2\beta\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)\right) - \operatorname{Cov}(X_t, X_{t+h})^2}$$
$$+ \frac{2\pi_t\,\beta\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)\left(\operatorname{Var}(X_t) + 2\alpha\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)\right)}{\left(\operatorname{Var}(X_t) + 2\alpha\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)\right)\left(\operatorname{Var}(X_t) + 2\beta\left(\operatorname{Var}(X_t)^2 - \operatorname{Cov}(X_t, X_{t+h})^2\right)\right) - \operatorname{Cov}(X_t, X_{t+h})^2}$$

and by plugging in the variance and covariance under the stationary distribution of the AR(1) process, we obtain that

$$\mathbb{E}_t^{\infty}(\pi_{t+h}) = \frac{\alpha\rho^h + \beta + 2\alpha\beta\sigma_\pi^2(1-\rho^{2h})}{\alpha + \beta + 2\alpha\beta\sigma_\pi^2(1-\rho^{2h}) + \frac{1}{2\sigma_\pi^2}}\pi_t.$$

■

Proof of Proposition 4. We first derive the expressions for the coefficients in the theoretical counterpart of the OLS regression (3), i.e.,

$$\pi_{t+h} - \mathbb{E}_t^m(\pi_{t+h}) = \alpha_h + \delta_{1,h}\left(\mathbb{E}_t^m(\pi_{t+h}) - \mathbb{E}_{t-1}^m(\pi_{t+h})\right) + \delta_{2,h}\mathbb{E}_{t-1}^m(\pi_{t+h}) + \varepsilon_{t+h}. \tag{37}$$

From (14), $e_h \equiv \mathbb{E}_t^m(\pi_{t+h})/\pi_t$ is independent of π_t. We can then define the forecast error $FE_{t,t+h} \equiv \pi_{t+h} - \mathbb{E}_t^m(\pi_{t+h}) = \pi_{t+h} - e_h\pi_t$ and the forecast revision $FR_{t,t+h} \equiv \mathbb{E}_t^m(\pi_{t+h}) - \mathbb{E}_{t-1}^m(\pi_{t+h}) = e_h\pi_t - e_{h+1}\pi_{t-1}$. To obtain the OLS coefficients, we use (37) and the assumption of orthogonality of ε_{t+h}, to obtain

$$\begin{aligned}
&Cov(FE_{t,t+h}, FR_{t,t+h}) = \delta_{1,h}Var(FR_{t,t+h}) + \delta_{2,h}Cov(FR_{t,t+h}, \mathbb{E}_{t-1}^m(\pi_{t+h})),\\
&Cov(FE_{t,t+h}, \mathbb{E}_{t-1}^m(\pi_{t+h})) = \delta_{1,h}Cov(FR_{t,t+h}, \mathbb{E}_{t-1}^m(\pi_{t+h})) + \delta_{2,h}Var(\mathbb{E}_{t-1}^m(\pi_{t+h})).
\end{aligned}$$

Solving for $\delta_{1,h}$ and $\delta_{2,h}$ yields

$$\delta_{1,h} = \frac{Cov(FE_{t,t+h}, FR_{t,t+h})Var(\mathbb{E}_{t-1}^m(\pi_{t+h})) - Cov(FE_{t,t+h}, \mathbb{E}_{t-1}^m(\pi_{t+h}))Cov(\mathbb{E}_{t-1}^m(\pi_{t+h}), FR_{t,t+h})}{Var(FR_{t,t+h})Var(\mathbb{E}_{t-1}^m(\pi_{t+h})) - Cov(FR_{t,t+h}, \mathbb{E}_{t-1}^m(\pi_{t+h}))^2},$$

$$\delta_{2,h} = \frac{Cov(FE_{t,t+h}, \mathbb{E}_{t-1}^m(\pi_{t+h}))Var(FR_{t,t+h}) - Cov(FE_{t,t+h}, FR_{t,t+h})Cov(FR_{t,t+h}, \mathbb{E}_{t-1}^m(\pi_{t+h}))}{Var(FR_{t,t+h})Var(\mathbb{E}_{t-1}^m(\pi_{t+h})) - Cov(FR_{t,t+h}, \mathbb{E}_{t-1}^m(\pi_{t+h}))^2}.$$

We compute each of the theoretical moments of interests:

$$\begin{aligned}
&Var(FR_{t,t+h}) = (e_h^2 + e_{h+1}^2 - 2\rho e_h e_{h+1})Var(\pi_t),\\
&Var(\mathbb{E}_{t-1}^m(\pi_{t+h})) = e_{h+1}^2 Var(\pi_{t-1}),\\
&Cov(FR_{t,t+h}, \mathbb{E}_{t-1}^m(\pi_{t+h})) = (\rho e_h e_{h+1} - e_{h+1}^2)Var(\pi_{t-1}),\\
&Cov(FE_{t,t+h}, \mathbb{E}_{t-1}^m(\pi_{t+h})) = (\rho^{h+1}e_{h+1} - \rho e_h e_{h+1})Var(\pi_{t-1}),\\
&Cov(FE_{t,t+h}, FR_{t,t+h}) = (\rho^h e_h - \rho^{h+1}e_{h+1} - e_h^2 + \rho e_h e_{h+1})Var(\pi_t).
\end{aligned}$$

Substituting the above moments into the expression for $\delta_{1,h}$ yields

$$\begin{aligned}
\delta_{1,h} &= \frac{(\rho^h e_h - \rho^{h+1}e_{h+1} - e_h^2 + \rho e_h e_{h+1})e_{h+1}^2 - (\rho^{h+1}e_{h+1} - \rho e_h e_{h+1})(\rho e_h e_{h+1} - e_{h+1}^2)}{(e_h^2 + e_{h+1}^2 - 2\rho e_h e_{h+1})e_{h+1}^2 - (\rho e_h e_{h+1} - e_{h+1}^2)^2}\\
&= \frac{\rho^h(1-\rho^2)e_h e_{h+1}^2 - (1-\rho^2)e_h^2 e_{h+1}^2}{(1-\rho^2)e_h^2 e_{h+1}^2}\\
&= \frac{\rho^h}{e_h} - 1.
\end{aligned}$$

Using the definition of e_h, together with (14), gives $\delta_{1,h} = \delta_h$, where δ_h is given by (16).

Analogous steps prove that $\delta_{2,h} = \delta_h$.

Part (i). Differentiating (16) with repsect to h,

$$\begin{aligned}\frac{\partial \delta_h}{\partial h} =& \frac{\rho^h \log \rho}{2\sigma_\pi^2[\alpha\rho^h + \beta + 2\alpha\beta\sigma_\pi^2(1-\rho^{2h})]^2} \times \\ & \big([2\sigma_\pi^2(\alpha+\beta) + 4\alpha\beta(\sigma_\pi^2)^2(1-3\rho^{2h}) + 1][\alpha\rho^h + \beta + 2\alpha\beta\sigma_\pi^2(1-\rho^{2h})] \\ & -[2\sigma_\pi^2(\alpha+\beta) + 4\alpha\beta(\sigma_\pi^2)^2(1-\rho^{2h}) + 1][\alpha\rho^h - 4\alpha\beta\sigma_\pi^2\rho^{2h}]\big),\end{aligned}$$

which is negative if and only if

$$\begin{aligned}&\big([2\sigma_\pi^2(\alpha+\beta) + 4\alpha\beta(\sigma_\pi^2)^2(1-3\rho^{2h}) + 1][\alpha\rho^h + \beta + 2\alpha\beta\sigma_\pi^2(1-\rho^{2h})] \\ &-[2\sigma_\pi^2(\alpha+\beta) + 4\alpha\beta(\sigma_\pi^2)^2(1-\rho^{2h}) + 1][\alpha\rho^h - 4\alpha\beta\sigma_\pi^2\rho^{2h}]\big) > 0\end{aligned}$$

or, after straightforward algebra,

$$\beta + 2\beta^2\sigma_\pi^2 + 2\alpha\beta\sigma_\pi^2[2 + 4\beta\sigma_\pi^2(1-\rho^{2h}) + \rho^{2h}] + 4\alpha^2\beta(\sigma_\pi^2)^2[2\beta\sigma_\pi^2(1-\rho^{4h})^2 + 1 + \rho^{2h} - 2\rho^{3h}] > 0.$$

The first square bracket is clearly positive. The second square bracket is also positive since $\rho^{2h} > \rho^{3h}$ for $0 < \rho < 1$ and $h \geq 1$. As a result, δ_h is decreasing in h. Finally, from equation (16), it is immediate to verify that $\delta_h \to -1$.

Part (ii). From (16) with $h = 1$,

$$\begin{aligned}\delta_1 &= \frac{\alpha\rho + \beta\rho + 2\alpha\beta\rho\sigma_\pi^2(1-\rho^2) + \rho/2\sigma_\pi^2}{\alpha\rho + \beta + 2\alpha\beta\sigma_\pi^2(1-\rho^2)} - 1 \\ &= \frac{-2\beta(1-\rho) - 4\alpha\beta(1-\rho)\sigma^2 + (1-\rho^2)\rho/\sigma^2}{2\alpha\rho + 2\beta + 4\alpha\beta\sigma^2} \\ &= (1-\rho)\frac{\rho/\sigma^2 + \rho^2/\sigma^2 - 2\beta - 4\alpha\beta\sigma^2}{2\alpha\rho + 2\beta + 4\alpha\beta\sigma^2}.\end{aligned}$$

The latter is negative if and only if

$$\rho + \rho^2 - 2\beta\sigma^2(1 + 2\alpha\sigma^2) < 0,$$

which is condition (15). ■

Proof of Proposition 5. We derive an expression for the coefficient θ_h^r of the OLS regression

(6). From the definition of real rate (5), we have

$$\widetilde{r}_t^{(h)} = r^{(h)} - \frac{1}{h}\sum_{j=1}^{h}\pi_{t+j} + \frac{1}{h}\sum_{j=1}^{h}\mathbb{E}_t^m(\pi_{t+j})$$

or, using the process for inflation (13),

$$\widetilde{r}_t^{(h)} = r^{(h)} - \frac{1}{h}\sum_{j=1}^{h}(\rho^j\pi_t - \mathbb{E}_t^m(\pi_{t+j})) + \sigma\frac{1}{h}\sum_{j=1}^{h}\epsilon_{t+j}.$$

From (14), we let $e_h \equiv \mathbb{E}_t^m(\pi_{t+h})/\pi_t$, which is independent of π_t. As a result,

$$\widetilde{r}_t^{(h)} = r^{(h)} - \pi_t\frac{1}{h}\sum_{j=1}^{h}(\rho^j - e_j) + \sigma\frac{1}{h}\sum_{j=1}^{h}\epsilon_{t+j}.$$

Similarly,

$$\mathbb{E}_t^m\left(\overline{\pi_{t+1,h}}\right) = \frac{1}{h}\sum_{j=1}^{h}\mathbb{E}_t^m\pi_{t+j} = \pi_t\frac{1}{h}\sum_{j=1}^{h}e_j.$$

The OLS coefficient θ_h^r satisfies

$$\begin{aligned}\theta_h^r &= \frac{Cov\left(\widetilde{r}_t^{(h)}, \mathbb{E}_t^m\left(\overline{\pi_{t+1,h}}\right)\right)}{Var\left(\mathbb{E}_t^m\left(\overline{\pi_{t+1,h}}\right)\right)} \\ &= -\frac{\left(\frac{1}{h}\sum_{j=1}^{h}(\rho^j - e_j)\right)\left(\frac{1}{h}\sum_{j=1}^{h}e_j\right)}{\left(\frac{1}{h}\sum_{j=1}^{h}e_j\right)^2} \\ &= -\frac{\sum_{j=1}^{h}e_j\delta_j}{\sum_{j=1}^{h}e_j},\end{aligned}$$

where the last line uses the fact that $\delta_h = \rho^j/e_j - 1$ from Proposition 4. Equation (17) follows from letting

$$w_j \equiv \frac{e_j}{\sum_{j=1}^{h}e_j}. \tag{38}$$

Next, we derive an expression for the coefficient θ_h^{rx} of the OLS regression (8). Above we showed that $\mathbb{E}_t^m\left(\overline{\pi_{t+1,h}}\right) = \left(\pi_t\sum_{j=1}^{h}e_j\right)/h$. By the same logic,

$$\mathbb{E}_{t+1}^m\left(\overline{\pi_{t+2,h}}\right) = \pi_{t+1}\frac{1}{h-1}\sum_{j=1}^{h-1}e_j$$

and

$$\mathbb{E}_t^m\left(\overline{\pi_{t+2,h}}\right) = \pi_t \frac{1}{h-1}\sum_{j=2}^{h} e_j.$$

Substituting the latter into (7) gives

$$\begin{aligned} rx_{t,t+1}^{(h)} &= -(h-1)r^{(h-1)} + hr^{(h)} - r^{(1)} - \pi_{t+1}\sum_{j=1}^{h-1} e_j + \pi_t \sum_{j=2}^{h} e_j \\ &= -(h-1)r^{(h-1)} + hr^{(h)} - r^{(1)} - \pi_t \sum_{j=1}^{h-1} \rho e_j + \pi_t \sum_{j=2}^{h} e_j - \sigma\epsilon_{t+1}\sum_{j=1}^{h-1} e_j. \end{aligned}$$

Therefore,

$$\begin{aligned} \theta_h^{rx} &= \frac{Cov\left(rx_{t,t+1}^{(h)}, \mathbb{E}_t^m\left(\overline{\pi_{t+1,h}}\right)\right)}{Var\left(\mathbb{E}_t^m\left(\overline{\pi_{t+1,h}}\right)\right)} \\ &= -\frac{\left(\sum_{j=1}^{h-1}\rho e_j - \sum_{j=2}^{h} e_j\right)\left(\frac{1}{h}\sum_{j=1}^{h} e_j\right)}{\left(\frac{1}{h}\sum_{j=1}^{h} e_j\right)^2} \\ &= -\frac{\sum_{j=1}^{h-1}\rho e_j - \sum_{j=2}^{h} e_j}{\frac{1}{h}\sum_{j=1}^{h} e_j}. \end{aligned} \tag{39}$$

Using the fact that $\delta_j = \rho^j/e_j - 1$ yields

$$\begin{aligned} \sum_{j=1}^{h-1}\rho e_j - \sum_{j=2}^{h} e_j &= \sum_{j=1}^{h-1}(\rho^{j+1} - \rho e_j\delta_j) - \sum_{j=2}^{h}(\rho^j - e_j\delta_j) \\ &= \sum_{j=2}^{h} e_j\delta_j - \rho\sum_{j=2}^{h} e_{j-1}\delta_{j-1}. \end{aligned}$$

Substituting the latter into (39) and rearranging gives

$$\theta_h^{rx} = h\Big(-\frac{\sum_{j=2}^{h} e_j\delta_j}{\sum_{j=1}^{h} e_j} + \rho\frac{\sum_{j=2}^{h} e_{j-1}\delta_{j-1}}{\sum_{j=1}^{h} e_j}\Big).$$

From (17) and (38), the first term in the bracket equals $\theta_h^{rx} + \delta_1 w_1$, while the second term equals

$-\rho(\theta_h^{rx} + \delta_h w_h)$. Therefore,

$$\begin{aligned}\theta_h^{rx} &= h\Big(- \frac{\sum_{j=2}^{h} e_j \delta_j}{\sum_{j=1}^{h} e_j} + \rho \frac{\sum_{j=2}^{h} e_{j-1}\delta_{j-1}}{\sum_{j=1}^{h} e_j}\Big) \\ &= h\Big((1-\rho)\theta_h^{rx} + \delta_1 w_1 - \rho\delta_h w_h)\Big),\end{aligned}$$

which is (18).

Evaluating (14) at $\beta = 0$ yields

$$e_h = \frac{\alpha\rho^h}{\alpha + 1/2\sigma_\pi^2},$$

hence, $\rho e_h = e_{h+1}$, which implies $\theta_h^{rx} = 0$ from (39).

Evaluating (14) at $\alpha = 0$ yields

$$e_h = \frac{\beta}{\beta + 1/2\sigma_\pi^2},$$

hence, $e_h = e_{h+1}$, which implies $\theta_h^{rx} = (1-\rho)(h-1)$ from (39). ■

B.3 Simulation Algorithm: CE Estimation

1. **Parameters' Initialization:**
   - Define forecast horizons $h = 1, 2, \ldots, 10$ years.
   - Construct a grid of parameter values for $(\alpha, \beta) \in [0, 1]^2$ with a step size of 0.01, yielding over 10,000 possible parameter pairs.
2. **Data Loading:**
   - For each country c, load annual realized inflation data, $\pi_{c,t}$, covering the period from t_0 to T as specified in Appendix Table 6, which details the starting and ending dates for each country based on the available data sources.
3. **Forecasts' Simulations:** For each parameter combination (α, β), for each country c, for each horizon h (from 1 to 10), and for each period t:
   - Calculate the model-implied expectation $\mathbb{E}_t^m(\pi_{c,t+h} \mid \alpha, \beta)$ as the weighted forecast:

$$\mathbb{E}_t^m(\pi_{c,t+h} \mid \alpha, \beta) \;= \frac{\sum_{k=t_0+h}^{t-1} \pi_{c,k} e^{-\alpha(\pi_{c,k-h} - \pi_{c,t})^2 - \beta(\pi_{c,k} - \pi_{c,t})^2}}{\sum_{k=t_0+h}^{t-1} e^{-\alpha(\pi_{c,k-h} - \pi_{c,t})^2 - \beta(\pi_{c,k} - \pi_{c,t})^2}}$$

- For the 6-10 year horizon, calculate the average model-implied expectation:

$$\mathbb{E}_t^m(\pi_{c,t+6,\ldots,t+10} \mid \alpha, \beta) = \frac{1}{5} \sum_{h=6}^{10} \mathbb{E}_t^m(\pi_{c,t+h} \mid \alpha, \beta)$$

4. **Parameters' Estimation:**

   - For each (α, β), compute the average absolute distance between observed and model-implied forecasts, where $\mathbb{F}_t(\pi_{c,t+h})$ represents the observed forecast from the CE dataset averaged annually. Select the optimal parameter pair $(\hat{\alpha}, \hat{\beta})$ that minimizes this distance accordingly:

$$\min_{\alpha,\beta} \sum_{t,c,h} |\mathbb{F}_t(\pi_{c,t+h}) - \mathbb{E}_t^m(\pi_{c,t+h} \mid \alpha, \beta)|$$

B.4 Bootstrapping Procedure – Simulation Algorithm: CE Estimation

Let

$$X = \{\, t \,:\, t = 1989, 1990, \ldots, 2022\}, \quad L = |X| = 34,$$

and denote by

$$\left\{\hat{p}_{c,t}^{(\alpha_i,\beta_j)} : (i,j) \in \{1,\ldots,101\}^2,\ t \in X\right\}$$

the $M = 10201$ series of model-produced inflation expectations for country c, one per (α_i, β_j) pair. Our bootstrap procedure consists of $N = 1000$ iterations. In each iteration n, we perform the following steps:

1. **Drawing the sample indices:**

   - Generate with replacement a multiset:

$$X^{(n)} = \{\, t_1^{(n)}, \ldots, t_L^{(n)}\} \subseteq X$$

     of size L.

   - In what follows, the *position* $k = 1, \ldots, L$ in $X^{(n)}$ matters; the actual calendar year $t_k^{(n)}$ is used only to pick the model value.

2. **Reconstructing bootstrapped model series:**

   - For each parameter pair (α_i, β_j), consider

$$\hat{p}_{c,k}^{(n,i,j)} = \hat{p}_{c,\, t_k^{(n)}}^{(\alpha_i,\beta_j)}, \quad k = 1, \ldots, L.$$

3. **Adjusting for country-specific start dates:**
   If country c' has actual CE CPI data beginning at $t^0_{c'} > \min X$:

   (a) Let $L_{c'} = 2022 - t^0_{c'} + 1$.

   (b) Discard the first $L - L_{c'}$ positions in $X^{(n)}$, reindexing $k \leftarrow k - (L - L_{c'})$ for $k = L - L_{c'} + 1, \ldots, L$.

   (c) Whenever $t^{(n)}_k < t^0_{c'}$, replace $t^{(n)}_k \leftarrow t^0_{c'}$.

   This means that country-specific histories shorter than 1989–2022 are handled by truncation and year-replacement as explained above.

4. **Distance minimization problem:**

   - Compute distance to observed CPI from CE. Let $\{t^{\text{obs}}_k\}_{k=1}^{L_{c'}}$ be the chronological CPI (from CE) positions for country c'. Then for each (α_i, β_j) define

$$D^{(n)}_{c'}(\alpha_i, \beta_j) = \sum_{k=1}^{L_{c'}} \left| p^{\text{obs}}_{c', t^{\text{obs}}_k} - \hat{p}^{(n,i,j)}_{c',k} \right|.$$

   - Select optimal parameters:

$$(\alpha^*, \beta^*)^{(n)} = \arg\min_{i,j} \; D^{(n)}_{c'}(\alpha_i, \beta_j).$$

Once all N bootstrap replications have been performed, we exploit the empirical distribution of the N draws $\{(\alpha^*, \beta^*)^{(n)}\}_{n=1}^{N}$ to construct the confidence intervals through the relevant percentiles (Kolesár, 2025). For standard-error estimation, we conservatively set the sample size to $S = 535$, which equals the number of annual CPI-forecast observations available in the Consensus Economics dataset.

B.5 Simulation Algorithm: Constant-Gain Learning

1. **Parameters' Initialization:**

   - Define forecast horizons $h = 1, 2, \ldots, 10$ years.
   - Construct a grid of parameter values for $\gamma \in [0, 1)$ with a step size of 0.01.

2. **Data Loading:** For each country c, load annual realized inflation data, $\pi_{c,t}$, covering the period from t_0 to T as specified in Appendix Table 6, which details the starting and ending dates for each country based on the available data sources.

3. **Forecasts' Simulations:** Following Nagel (2024), we assume the true inflation process for country c follows the AR(1) $\pi_{c,t} = a_c + \rho_c \pi_{c,t-1} + \varepsilon_{c,t}$. Agents estimate the true parameters $\mathbf{b_c} := (a_c, \rho_c)'$ using:

$$\mathbf{b}_{c,t} = \mathbf{b}_{c,t-1} + \gamma \mathbf{R}_{c,t}^{-1} \mathbf{x}_{c,t-1} (\pi_{c,t} - \mathbf{b'}_{c,t-1} \mathbf{x}_{t-1,c})$$
$$\mathbf{R}_{c,t} = \mathbf{R}_{c,t-1} + \gamma (\mathbf{x}_{c,t-1} \mathbf{x'}_{c,t-1} - \mathbf{R}_{c,t-1}),$$

where $\mathbf{x}_{c,t} = (1, \pi_{c,t})'$ and with initial conditions $\mathbf{b}_{c,0} = (0, 0)$ and $\mathbf{R}_{c,0} = diag(1, 1)$.

We consider a global constant-gain learning parameter γ.

- We calculate the model-implied expectation $\mathbb{E}_t^m(\pi_{c,t+h} \mid \gamma)$ as the weighted forecast:

$$\mathbb{E}_t^m(\pi_{c,t+h} \mid \gamma) = a_{c,t} + \rho_{c,t}^h \pi_{c,t}$$

- For the 6-10 year horizon, calculate the average model-implied expectation:

$$\mathbb{E}_t^m(\pi_{c,t+6,\ldots,t+10} \mid \gamma) = \frac{1}{5} \sum_{h=6}^{10} \mathbb{E}_t^m(\pi_{c,t+h} \mid \gamma)$$

4. **Parameters' Estimation:**

- For each γ, compute the average absolute distance between observed and model-implied forecasts, where $\mathbb{F}_t(\pi_{c,t+h})$ represents the observed forecast from the CE dataset averaged annually. Select the optimal parameter ($\hat{\gamma}$) that minimizes this distance accordingly:

$$\min_{\gamma} \sum_{t,c,h} |\mathbb{F}_t(\pi_{c,t+h}) - \mathbb{E}_t^m(\pi_{c,t+h} \mid \gamma)|$$

- The estimated global constant-gain learning parameter is $\hat{\gamma} = 0.02$.

B.6 Simulation Algorithm: Costly-Recall Learning

We implement Afrouzi et al. (2023) model of expectation formation, where agents form h-step-ahead inflation forecasts $E_t[\pi_{c,t+h}]$ using a gain parameter $K_{c,h}$. The true inflation process is modeled as $\pi_{c,t+1} = \mu_c + \rho_c(\pi_{c,t} - \mu_c) + \varepsilon_{c,t+1}$.
The model computes:

$$E_t[\pi_{c,t+h}] = \mu_c + [\rho_c^h + (1 - \rho_c^h)K_{c,h}](\pi_{c,t} - \mu_c)$$

with

$$K_{c,h} = \min \left\{ 1, \left[\frac{\omega \, \tau_c}{(1 - \rho_c^h)^2} \right]^{\frac{1}{1+\gamma_c}} \right\} \qquad \tau_c = \frac{\sigma_c^2}{1 - \rho_c^2}$$

Here μ_c denotes the mean of realized inflation, ρ_c and σ_c are estimated from country-level AR(1) regressions of inflation for all countries in the sample. Following Halperin and Mazlish (2025), we set $\gamma = 2$ and $\omega = 0.42$. In addition, we internally calibrate ω, by running a grid search over [0,0.2] with step size 0.001 and we minimize the absolute value distance between model implied and measured expectations from CE. We find $\hat{\omega} = 0.004$.