Learning from Fundamentals

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Introduction

In the forecast and expectation formation literature, Coibion and Gorodnichenko (2015) propose to use the forecast revisions to predict forecast errors to test the full information rational expectation (FIRE) assumption and find that information rigidity helps to explain the inflation expectation. Bordalo et al. (2020) find that individual forecasters typically overreact and consensus underreact to news with FIRE, and it can be reconciled by diagnostic expectations. de Silva and Thesmar (2024) decompose the forecast accuracy into information advantage, forecast bias, and forecast noise and find that a noise increasing with horizon generates a mechanical reversal of the forecast error-revision regression, which can be explained by a bounded rationality and noisy cognitive default. Wang (2021) finds that short-term rates underreact and long-term rates overreact to news and propose an autocorrelation averaging forecasting process. Bianchi et al. (2022) estimate a time-varying expectational error (belief distortion) on macro fundamental variables, which is evolving dynamically in response to cyclical shocks. Baley and Turen (2024) document that professional forecasters adjust inflation forecasts infrequently, and when adjusted, they are revised by a large amount. As the forecasting horizon shrinks, the frequency of revisions, the variance of revisions, and forecast errors decrease. However, the literature speaks relatively less about the relationship between the forecast of macro fundamentals and the forecast of the interest rates. This document is going to set a model framework to show how professional forecasters learn the interest rate from macro fundamentals and how the learning rule varies across the time cycle.

Framework

Assume a forecast observes signals of the next periods of the long-term bond price, which could be the foundation of the economy or other leading indicators, and help to form the subjective expectation of the asset price. Suppose the signal s_t at time t is in the form:

$$s_t = \underbrace{m_t}_{\text{Fundamental}} + \underbrace{\epsilon_t}_{\text{Noise}} \tag{1}$$

where f is some transform function of the price. It could incorporate some behavior bias patterns and suppose it is normal distributed. ϵ_t is the noise with the normal distribution and independent of other variables:

$$\epsilon_t \sim N(\mu_\epsilon, \sigma_\epsilon^2) \tag{2}$$

and m_t could reflect the economic conditions, such as GDP or CPI, which follows

$$m_t \sim N(\mu_m, \sigma_m^2). \tag{3}$$

Therefore the variance of the signal is $\sigma_s^2 = \sigma_m^2 + \sigma_\epsilon^2$.

If the agent is a Bayesian learner and assumes that the prior mean is set to be the previous price P_{t-1} and the prior variance is the previous posterior $\sigma_p^2 = \mathbb{V}_{t-1}[P_{t+1}|s_{t-1}]$, then

$$\mathbb{E}_t[P_{t+1}|s_t] = \frac{\frac{1}{\sigma_p^2}P_{t-1} + \frac{1}{\sigma_s^2}s_t}{\frac{1}{\sigma_p^2} + \frac{1}{\sigma_s^2}} = (1-\kappa)P_{t-1} + \kappa s_t \tag{4}$$

$$\mathbb{V}_t[P_{t+1}|s_t] = \frac{1}{\sigma_p^2} + \frac{1}{\sigma_s^2} \tag{5}$$

Therefore, the learning scheme is

$$\mathbb{E}_t[P_{t+1}|s_t] = \mathbb{E}_{t-1}[P_{t+1}|s_{t-1}] + \frac{\frac{1}{\sigma_s^2}}{\frac{1}{\sigma_p^2} + \frac{1}{\sigma_s^2}}\left(s_t - \mathbb{E}_{t-1}[P_{t+1}|s_{t-1}]\right) \tag{6}$$

$$\mathbb{V}_t[P_{t+1}|s_t] = \frac{1}{\mathbb{V}_{t-1}[P_{t+1}|s_{t-1}]} + \frac{1}{\sigma_s^2} \tag{7}$$

Here the signal s_t only includes fundamental information. I assume that they are some functions of real GDP growth and CPI.

$$s_t = m_t + \epsilon_t = h(g_t, \pi_t) + \epsilon_t \tag{8}$$

Although real GDP growth and CPI are public information, the interpretation could be idiosyncratic. The revelation of these different interpretations can be measured by the forecast of fundamentals. Therefore, $h(g_t, \pi_t)$ can be expressed as some functions of expectation of the real GDP growth and CPI:

$$s_t^i = h^i(g_t, \pi_t) + \epsilon_t \approx \alpha^i + \beta_1^i \mathbb{E}_t^i[g_{t+1}] + \beta_2^i \mathbb{E}_t^i[\pi_{t+1}] + \epsilon_t^i \tag{9}$$

Therefore, the learning equation (4) and (6) becomes

$$\mathbb{E}_t^i[P_{t+1}|s_t] \;=\; (1-\kappa)\mathbb{E}_{t-1}^i[P_{t+1}|s_{t-1}] + \kappa(\alpha^i + \beta_1^i \mathbb{E}_t^i[g_{t+1}] + \beta_2^i \mathbb{E}_t^i[\pi_{t+1}] + \epsilon_t^i) \tag{10}$$

I can run the empirical specification to test whether the financial sector analysts are following this learning rule with the blue chip data.

For each time t, I can estimate the following specification to explore how expectations of interest evolve with expectations of fundamentals:

$$\mathbb{E}_t^i[r_{t+1}] = \alpha + \beta_{0t}\mathbb{E}_{t-1}^i[r_{t+1}] + \beta_{1t}\mathbb{E}_t^i[g_{t+1}] + \beta_{2t}\mathbb{E}_t^i[\pi_{t+1}] + \epsilon_t^i$$

where the coefficients β_{1t} and β_{2t} response to growth and inflation expectations. The plot of coefficients is in figure 1. The pooled regression also can be explored with the following specifications with the time fixed effect α_t and horizon fixed effect α_{t+h}:

$$\mathbb{E}_t^i[r_{t+1}] = \alpha_t + \alpha_{t+h} + \beta_0\mathbb{E}_{t-1}^i[r_{t+1}] + \beta_1\mathbb{E}_t^i[g_{t+1}] + \beta_2\mathbb{E}_t^i[\pi_{t+1}] + \epsilon_t^i \tag{11}$$

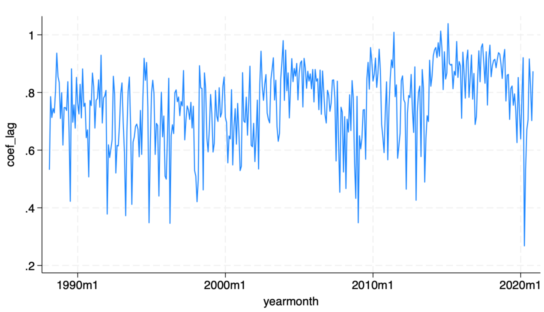
The assumption behind these specifications is that agents form the expectation of interest rates based on their expectation of fundamentals. I assume that any unanticipated economic shock, that changes agents' belief in macro fundamentals, will be reflected in their macro fundamental expectations. The residual terms only include the individual interpretation of the public signals that are not relative to GDP and CPI.

Table 1: Learning Gain and Response to Growth and Inflation Expectations

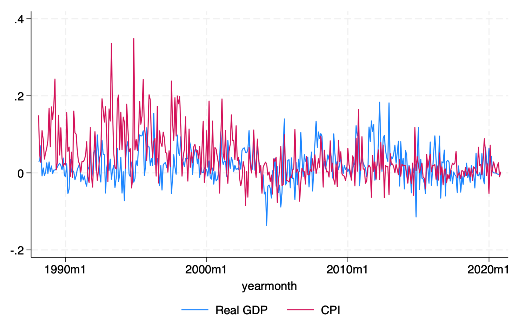
	(1) FFR	(2) 6 Mo	(3) 1 Yr	(4) 5 Yr	(5) 10 Yr
Lag	0.7948***	0.7801***	0.7744***	0.7518***	0.7574***
	(0.0016)	(0.0017)	(0.0018)	(0.0018)	(0.0018)
Real_GDP	-0.0026***	-0.0009*	0.0007	0.0017***	0.0021***
	(0.0004)	(0.0005)	(0.0006)	(0.0005)	(0.0005)
Cons_Price_Index	0.0162***	0.0218***	0.0216***	0.0269***	0.0269***
	(0.0010)	(0.0012)	(0.0012)	(0.0011)	(0.0010)
Constant	0.5974***	0.6582***	0.7140***	0.9625***	1.0611***
	(0.0053)	(0.0061)	(0.0066)	(0.0078)	(0.0084)
Observations	96614	87287	87753	94861	96099
r2	0.9929	0.9910	0.9902	0.9886	0.9880

Figure 1: Time varying learning gain

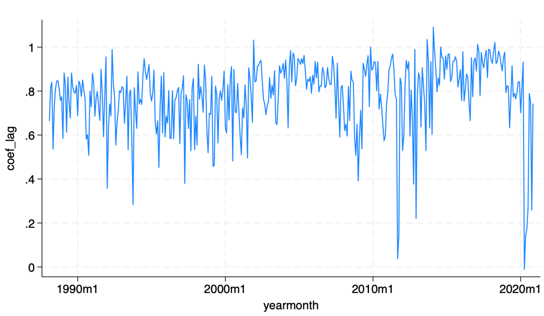
(A) Learning Gain: 10 Year



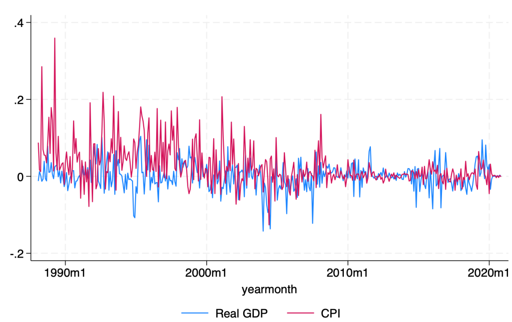
(B) Macro: 10 Year



(C) Learning Gain: Fed Funds



(D) Macro: Fed Funds



The table 1 shows the pooled regression specification. The coefficient of the lag term reflects the learning gain and it is slightly increasing over the term structure, around 0.2 to 0.25. The response of interest rate expectation to the real GDP growth expectation is increasing over the term structure: the shorter-end expectation (Fed funds rates or 6-month yield) negatively responds to real GDP growth expectation but the longer-end expectation positively responds to the real GDP growth expectation. This discrepancy between the shorter and longer ends reflects forecasters' belief about the hedging role of treasury securities.

References

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