

Why Do Central Banks Surprise the Public?: Online Appendix

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Disclaimer: Everything except Appendix D is to be written; at the moment this is otherwise strictly an outline. Please email me with any comments or questions.

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B Replication of Table 1 Facts

B.1 Unstable Surprise and News Correlations

B.1.1 Correlation Drift

B.1.2 Out of Sample

B.2 Information Effect and News Correlations

B.3 Unstable Surprise and Revision Correlations

B.3.1 Magnitudes and Sensitivity

B.3.2 Higher Frequency Data

C Extensions of Section 2 Exercises

C.1 Table 2

C.2 Table 3

C.3 Checking for Revision Persistence

C.4 Figure 2

C.5 Figure 3

D Responses to Surprises in Caballero and Simsek (2022)

In Caballero and Simsek (2022), the central bank and the market disagree because they form a different "interpretation" of the public signal. To formalize their results for the correlation of policy surprises with the expected future path of aggregates, it's useful to clarify exactly what interpretation means in this context and what restrictions their assumptions place on responses. To begin, the interpretation of agent i is μ^i . Both agents know the *true* joint distribution of responses.

$$\mu^M, \mu^F \sim \mathcal{N} \left(0, \begin{pmatrix} \sigma^2 & \rho\sigma^2 \\ \rho\sigma^2 & \sigma^2 \end{pmatrix} \right).$$

Where does this interpretation come from? For much of the theoretical results, this point is not relevant. Caballero and Simsek (2022) add an additional element, called μ^{TRUE} , to their discussion in order to characterize correlations with policy surprises and leads of aggregates. μ^{TRUE} offers a rationalization of why the two agents form interpretations of the signal to begin with, and here I flesh out the implications from introducing this new object. Redefine μ^{TRUE} as $b \sim \mathcal{N}(0, \sigma_b^2)$, the *true* bias in the signal both agents observe. Agent i *dogmatically believes*

$$\begin{aligned} \mu^i &= b \\ \mu^j &= b + e^j, \end{aligned}$$

meaning they also believe $\sigma_b = \sigma$. However, they also know μ^j has standard deviation σ , which places a restriction on their belief for e^j

$$b, e^j \sim \mathcal{N} \left(0, \begin{pmatrix} \sigma^2 & (\rho - 1)\sigma^2 \\ (\rho - 1)\sigma^2 & 2(1 - \rho)\sigma^2 \end{pmatrix} \right)$$

In reality, this need not be true. We have

$$\mu^i = b + u^i$$

but we still must have μ^i, μ^j have common variance and known correlation. We introduce parameters $(\rho_M, \rho_F, \rho_e, \sigma_M, \sigma_F)$ relating to innovation correlations and variance, leading to joint distribution

$$b, u^M, u^F \sim \mathcal{N} \left(0, \begin{pmatrix} \sigma_b^2 & \rho_M \sigma_b \sigma_M & \rho_F \sigma_b \sigma_F \\ \rho_M \sigma_b \sigma_M & \sigma_M^2 & \rho_u \sigma_M \sigma_F \\ \rho_F \sigma_b \sigma_F & \rho_u \sigma_M \sigma_F & \sigma_F^2 \end{pmatrix} \right).$$

For this distribution to be well-defined and consistent with the initial assumptions, restrictions need to be placed on the new parameters. Given (σ, σ_b, ρ) , moment restrictions pin down the standard deviations and residual

correlation

$$\sigma_i(\rho_i) = \pm \sqrt{\sigma^2 - \sigma_b^2 + (\rho_i \sigma_b)^2} - \rho_i \sigma_b$$

$$\rho_u(\rho_M, \rho_F) = \frac{\rho \sigma^2 - \sigma_b^2 - \sum_i \rho_i \sigma_i \sigma_b}{\sigma_M \sigma_F}$$

and a final feasible set

$$|\rho_u - \rho_M \rho_F| \leq \sqrt{(1 - \rho_M^2)(1 - \rho_F^2)}$$

$$\begin{cases} -\rho_i \geq \sqrt{1 - \frac{\sigma^2}{\sigma_b^2}} & \text{if } \sigma > \sigma_b \end{cases}$$

Consider a regression of b on μ^M and μ^F and define the corresponding projection coefficients as β_M and β_F . Using the above definitions and $S = \left(\frac{\sigma_b}{\sigma}\right)^2$

$$\beta_F = S \left(\frac{1}{1 + \rho} + \frac{\rho_F \sigma_F - \rho \rho_M \sigma_M}{\sigma_b(1 - \rho^2)} \right).$$

[Caballero and Simsek \(2022\)](#) show the correlation of leads of aggregates with monetary policy surprises will be proportional to $\beta_F - 1$. That is, the correlation will have the same sign as the correlation with a structural monetary policy shock in a textbook New Keynesian model if and only if $\beta_F < 1$. [Caballero and Simsek \(2022\)](#) interpret this result as meaning if the "residual interpretation" of the central bank "overestimates" the bias b , then the policy surprise correlation will have the conventional sign. They ascribe this interpretation because

$$\mathbb{E}[b \mid \tilde{\mu}^F] = \beta_F \tilde{\mu}^F,$$

where $\tilde{\mu}^F \equiv \mu^F - \mathbb{E}[\mu^F \mid \mu^M] = \mu^F - \rho \mu^M$. This form structurally corresponds to canonical notions of over and underestimating (i.e., $\beta_F = 1$ implies an "unbiased" estimation). However, this characterization is not well-posed in this context because $\tilde{\mu}^F$ is not actually a forecast of b ; the conditional mean of b just happens to be linear in $\tilde{\mu}^F$ because of the assumptions made about the data generating process.¹ To see this point more formally, consider a special cases where both agents observe the bias exactly. Then a regression of b on μ^M and μ^F is not defined because the design matrix will be singular. But what about parameterizations that exist in a "neighborhood" of this special case? β_F now exists, but it should be unsurprising that it's an arbitrary object. Consider again the special case – the singularity can be represented by noting that any $(\alpha_M, \alpha_F) \in \mathbb{R}^2$ such that $\alpha_M + \alpha_F = 1$ will satisfy $b = \alpha_M \mu^M + \alpha_F \mu^F$. Similarly, there are several functionally equivalent parameterizations where β^F can be wildly different. Put differently, if we jointly send $\rho \rightarrow 1$, $\mu^M \rightarrow b$, $\mu^F \rightarrow b$, the limit of β^F will depend on the relative convergence rates.

This discussion shows there are no clear implications of the result that the correlation of leads of aggregates

¹Though the linearity of the conditional mean function implies $\beta_F \tilde{\mu}^F$ is the "best predictor of b given $\tilde{\mu}^F$ ", there is no sense in which $\tilde{\mu}^F$ can be thought of as a biased or unbiased forecast.

with monetary policy surprises is proportional to $\beta_F - 1$. We can explore this further by considering more explicit parameterizations based on the form of β_F . Recall ρ_M, ρ_F are correlations of the "interpretation error" with the actual signal bias. Each agent dogmatically believes that for the other agent j has a negative ρ_j . In a classical setup, we would not impose that noise and the unobserved fundamental are correlated. In that case, we would typically have $\beta_M < 1$, given that most parameterizations will have $\sigma_b < \sigma$. In more general settings where ρ_M, ρ_F are unrestricted, by Cauchy-Schwarz we can have $\beta_F \in \pm \sqrt{S(1 - \rho)^{-1}}$. So a necessary condition for $\beta_F \geq 1$ if $\sigma_b < \sigma$ is for ρ to be sufficiently large. Given 4 free parameters $(S, \rho, \rho_M, \rho_F)$, it's difficult to further characterize the feasible set beyond the form of β_F , and the form itself does not lend itself to economic interpretation.

References

Caballero, Ricardo J., and Alp Simsek. 2022. "Monetary Policy with Opinionated Markets." *American Economic Review*, 112(7): 2353–2392.