

Why Do Central Banks Surprise the Public?: Online Appendix

Paul Bousquet*

February 18, 2026

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.

Table of Contents

B Replication of Table 1 Facts	2
B.1 Unstable Surprise and News Correlations	2
B.1.1 Correlation Drift	2
B.1.2 Out of Sample	2
B.2 Information Effect and News Correlations	2
B.3 Unstable Surprise and Revision Correlations	2
B.3.1 Magnitudes and Sensitivity	2
B.3.2 Higher Frequency Data	2
C Extensions of Section 2 Exercises	2
C.1 Table 2	2
C.2 Table 3	2
C.3 Checking for Revision Persistence	2
C.4 Figure 2	2
C.5 Figure 3	2
D Responses to Surprises in Caballero and Simsek (2022)	3

*University of Virginia, pbousquet@virginia.edu

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 interpretations

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

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*

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

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

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

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

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

$$\left\{ \begin{array}{ll} -\rho_i \geq \sqrt{1 - \frac{\sigma^2}{\sigma_b^2}} & \text{if } \sigma_b > \sigma \end{array} \right.$$

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

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

where $\tilde{\mu}^F \equiv \mu^F - \mathbb{E}[\mu^F | \mu^M] = \mu^F - \rho \mu^M$. 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.¹² 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 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.

A different special case of $\rho = 0$ is also illuminating. We can now recover the forecast interpretation, with a

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.

²We similarly cannot think about $\tilde{\mu}_t^F$ as a revision of a forecast for b after seeing new information.

caveat that the central bank does not believe it has to forecast b because it thinks $\mu^F = b$. So we can essentially think of μ^F as a forecast under a misspecified model. This framing underscores a particular point – the correlation of leads of aggregates with policy surprises in this model is proportional to the correlation between $b - \mu^F$ and μ^F . This recovers a common interpretation of thinking about structural policy shocks or monetary policy surprises as "mistakes". If μ^F was an optimal forecast of b , this correlation would be zero, but μ^F is not the optimal forecast. Instead, $\mathbb{E}[b | \mu^F] = \beta_F \mu^F$ with $\beta_F < 1$ because of a measurement error-esque attenuation from the signal noise.

Finding this measurement error analogy in the $\rho = 0$ special case further suggests that the specific results coming out of this model are generated by dogmatic beliefs leading to what we could describe as a very specific class of non-optimal forecast rules. Continuing with the measurement error analogy, non-classical measurement error (e.g., nonlinear measurement error) does not necessarily generate the usual attenuation bias relationship (Chen et al., 2011). Likewise, suppose the Fed followed a "conservative" forecast rule of $\alpha_F \mu^F$ with $\alpha_F < 1$. Then even with $\rho = 0$, $\beta_F \geq 1$ becomes possible. The concept of "dampening creating 'puzzles'" harkens back to the original price puzzle literature, where it was suggested an insufficiently aggressive initial response to inflation could create initial comovement with a contractionary shock and inflation (Sims, 1992; Balke and Emery, 1994). Relaxing $\rho = 0$, we can still similarly extend this theme – when $\tilde{\mu}^F$ varies less than b , we can have $\beta_F \geq 1$. A primary determinant of surprise volatility is the level of alignment between the Fed and the market. When the two interpretations are highly correlated (i.e., when ρ is large), surprises will be inherently be less volatile.

We can consider a broad class of parameterizations to formalize this intuition. 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 $S < 1$ ($\sigma_b < \sigma$). 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. If the Fed's interpretation is sufficiently precise ($S \approx 1$), then the feasible set expands to where large disagreement (small ρ) does not necessarily preclude $\beta_F \geq 1$. And though $\rho_M < 0$ is not a necessary condition, only a small fraction of the feasible set contains points where $\rho_M \geq 0$.

References

- Balke, Nathan S., and Kenneth M. Emery. 1994. "Understanding the price puzzle." *Economic and Financial Policy Review* 15–26.
- Caballero, Ricardo J., and Alp Simsek. 2022. "Monetary Policy with Opinionated Markets." *American Economic Review*, 112(7): 2353–2392.
- Chen, Xiaohong, Han Hong, and Denis Nekipelov. 2011. "Nonlinear Models of Measurement Errors." *Journal of Economic Literature*, 49(4): 901–937.
- Sims, Christopher A. 1992. "Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy." *European Economic Review*, 36(5): 975–1000.