Advanced Macroeconometrics Project

A replication and extension of:

Deconstructing Monetary Policy Surprises—The Role of Information Shocks

(Jarociński and Karadi, AER: Macroeconomics, 2020)

Paul Ritzinger

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1 Introduction and research question

This project replicates and extends the seminal work of Jarociński and Karadi (2020), titled *"Deconstructing Monetary Policy Surprises—The Role of Information Shocks"*. The paper addresses a central challenge in macroeconomics: the identification of monetary policy shocks and their transmission to the real economy.

1.1 Positive co-movements puzzle

The authors start by exposing a striking stylized fact regarding monetary policy announcements in the US and the Euro area. By inspecting high-frequency variations of stock markets and interest rate markets in a narrow time frame around FOMC and ECB announcements, they observe frequent positive co-movements between interest rates and stock prices.

This empirical evidence stands in sharp contrast to conventional economic theory. In a broad range of standard models, a monetary tightening (an increase in interest rates) should unequivocally lead to lower stock market valuations. This negative correlation is driven by two main channels:

- The Discount Cash Flow effect: Higher interest rates increase the discount factor applied to future dividends.
- The Economic Outlook effect: A tightening usually signals a contraction of the economy, lowering expected future dividends.

This theoretical relationship is summarized by the standard asset pricing equation:

$$P_t = \sum_{k=1}^{\infty} \frac{E_t[D_{t+k}]}{(1 + i_{t+k})^k} \tag{1}$$

However, the authors find that about one-third of the co-movements are positive in the US, and up to 40% in the Euro area (a difference potentially explained by the higher transparency of the ECB communication).

1.2 Monetary and information shocks

To resolve this anomaly, the authors argue that identifying the announcement as a sole monetary policy shock is flawed. They introduce the concept of an "Information Shock". The central intuition is that central bank announcements convey two distinct signals: the policy decision itself and private information regarding the economic outlook. For instance, if the central bank raises interest rates to prevent overheating, it implicitly signals that the economic outlook is strong. This positive "information shock" can drive stock prices up, overriding the negative effect of the rate hike.

Using a Bayesian VAR (BVAR) model identified with sign restrictions, the authors decompose the total variation into these two components. Their conclusion is twofold:

1. Identification Bias: Ignoring information shocks leads to an attenuation bias. Standard models misinterpret the restrictive policy shock with the expansionary information shock.

2. Policy Effectiveness: Once the "pure" monetary policy shock is disentangled from the information effect, the authors find that its impact on the real economy is significantly larger than previously expected.

1.3 Project replication and extension

The objective of this project is to test the robustness of these findings in a transformed economic landscape. Since the publication of the paper, the global economy has faced unprecedented events, including the COVID-19 pandemic and a return of high inflation. Our contribution is twofold:

- Data extension (2016-2025): We extend the original dataset to assess if unconventional monetary policy and the recent inflationary cycle have altered the transmission mechanisms.

- Sub-sample Analysis: To investigate the time-varying nature of these shocks, we split the dataset into three distinct macroeconomic regimes:

    1. The pre-crisis period (1994-2007): A period of relative stability ("Great Moderation").
    2. The ZLB (2008-2019): Characterized by the Zero Lower Bound and unconventional tools.
    3. The Post-COVID Era (2020-2025): Marked by pandemic-induced volatility and the aggressive tightening cycle to combat inflation.

2 Empirical Strategy

Our empirical approach relies on a structural Bayesian VAR (BVAR) identification using sign restrictions. The model dynamics are driven by two vectors of variables: a vector of high-frequency financial market surprises (m_t) and a vector of low-frequency macroeconomic aggregates (y_t).

To accommodate the extended timeframe (1994–2025) and ensure data availability up to the present day, we adapt the variable selection from the original paper. Table 1 summarizes the baseline specification of Jarociński and Karadi (2020) alongside our extended dataset.

Table 1: Replication data

Variable Role	**Original paper**	**Extension**
	High-Frequency Surprises (m_t)	
Monetary Policy	3-Month Fed Funds Futures	3-Month Fed Funds Futures
	(Gürkaynak et al. dataset)	*(Extended dataset)*
Information	S&P 500 change	S&P 500 change
	(30-min window)	*(30-min window)*
	Macroeconomic Variables (y_t)	
Policy Rate	1-Year Treasury Yield	1-Year Treasury Yield
	(FRED: GS1)	*(FRED: GS1)*
Stock Prices	S&P 500 (Monthly Avg)	S&P 500 (Monthly Avg)
	(Robert Shiller)	*(Robert Shiller)*
Real Activity	Real GDP	**Industrial Production Index**
	(Interpolated to monthly)	*(FRED: INDPRO)*
Price Level	GDP Deflator	**CPI (All Urban Consumers)**
	(Interpolated to monthly)	*(FRED: CPIAUCSL)*
Fin. Frictions	Excess Bond Premium (EBP)	**Corporate/Treasury Spread**
	(Gilchrist & Zakrajšek, 2012)	*(FRED: BAA10Y)*

Note: Bold items indicate a substitution from the original specification to ensure monthly data availability up to 2025.

2.1 Proxies and transformation

While we maintain the structural logic of the original paper, we introduce three necessary substitutions for the macroeconomic vector y_t:

- Real Activity: We substitute interpolated GDP with the Industrial Production Index (INDPRO). Unlike interpolated GDP, INDPRO is a native monthly indicator, allowing us to capture cyclical volatility without smoothing bias, which is crucial for identifying sharp shocks like the Covid-19 crisis.

- Price Level: We use the Consumer Price Index (CPI) instead of the interpolated GDP deflator. CPI is the standard high-frequency measure of inflation targeted by market participants.

- Financial Frictions: As the Excess Bond Premium (EBP) data is not readily available for the post-2020 period, we proxy financial frictions using the BAA-10Y Spread (difference between Moody's BAA corporate bond yield and the 10-Year Treasury constant maturity). This measure effectively captures the risk premium and credit conditions demanded by the market.

Consistent with the authors' methodology, Stock Prices, Industrial Production, and CPI are transformed by taking the natural logarithm and multiplying by 100 ($100 \times \log$). This transformation ensures that impulse response functions can be interpreted as percentage deviations.

2.2 BVAR Model Specification

Following the methodology of Jarociński and Karadi (2020), we estimate a Bayesian Vector Autoregression (BVAR) that jointly models the high-frequency surprises (m_t) and the low-frequency macroeconomic variables (y_t). The structural form of the model is given by:

$$\begin{pmatrix} m_t \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \begin{pmatrix} 0 & 0 \\ B^p_{YM} & B^p_{YY} \end{pmatrix} \begin{pmatrix} m_{t-p} \\ y_{t-p} \end{pmatrix} + \begin{pmatrix} 0 \\ c_y \end{pmatrix} + \begin{pmatrix} u^m_t \\ u^y_t \end{pmatrix} \tag{2}$$

where $u_t \sim \mathcal{N}(0, \Sigma)$.

A key feature of this specification is the restriction imposed on the first block of equations (the zero matrices in the upper row). This implies that the high-frequency financial surprises m_t are exogenous to the past values of both macroeconomic variables and their own lags. This restriction is consistent with the Efficient Market Hypothesis, which posits that financial surprises are unpredictable and i.i.d. disturbances.

Conversely, the macroeconomic variables y_t are allowed to respond dynamically to past financial surprises (B^p_{YM}) and their own lags (B^p_{YY}). To manage the large number of parameters and avoid overfitting, we employ standard Minnesota priors (Litterman, 1986), consistent with the original paper's hyperparameters.

3 Original Results

This section presents the quantitative results from the authors. We compare the biased results from the standard identification with the correct results obtained from the "purified" structural shocks.

3.1 Standard identification bias

When estimating the model using standard High-Frequency Identification (HFI), which ignores stock market reactions, we observe two major anomalies. First, the model shows a "Price Puzzle": after a monetary tightening, prices (GDP deflator) do not fall. They remain statistically close to zero or even rise slightly. Second, the model fails to capture the financial channel: the response of the Excess Bond Premium (EBP) is insignificant and stays near zero. These results indicate that the standard HFI suffers from an attenuation bias. This happens because it mixes up contractionary policy shocks with expansionary information signals, cancelling out the effects.

3.2 IRFS of the decomposed shocks

By isolating the "purified" monetary policy shock (identified by a drop in the S&P 500 of 23 to 52 basis points), we recover a logical economic transmission. Real GDP falls persistently, dropping by approximately 10 basis points after one year. Crucially, the GDP deflator falls immediately by about 5 basis points, which solves the price puzzle seen in the standard model. Also, this shock causes a sharp tightening of financial conditions: the EBP jumps significantly by 5 basis points.

On the other hand, the central bank information shock (identified by a rise in both interest rates and stock prices) creates the opposite effect. Even though interest rates go up, Real GDP grows by about 5 basis points, and prices rise by 3 basis points. This demand-side expansion is supported by a drop in the Excess Bond Premium of about 3 basis points. This confirms that when the central bank reveals positive news, it lowers risk premia, which offsets the cost of higher interest rates. The statistical foundations of our replication are summarized in Table 2, which reports the impact responses of the high-frequency surprises.

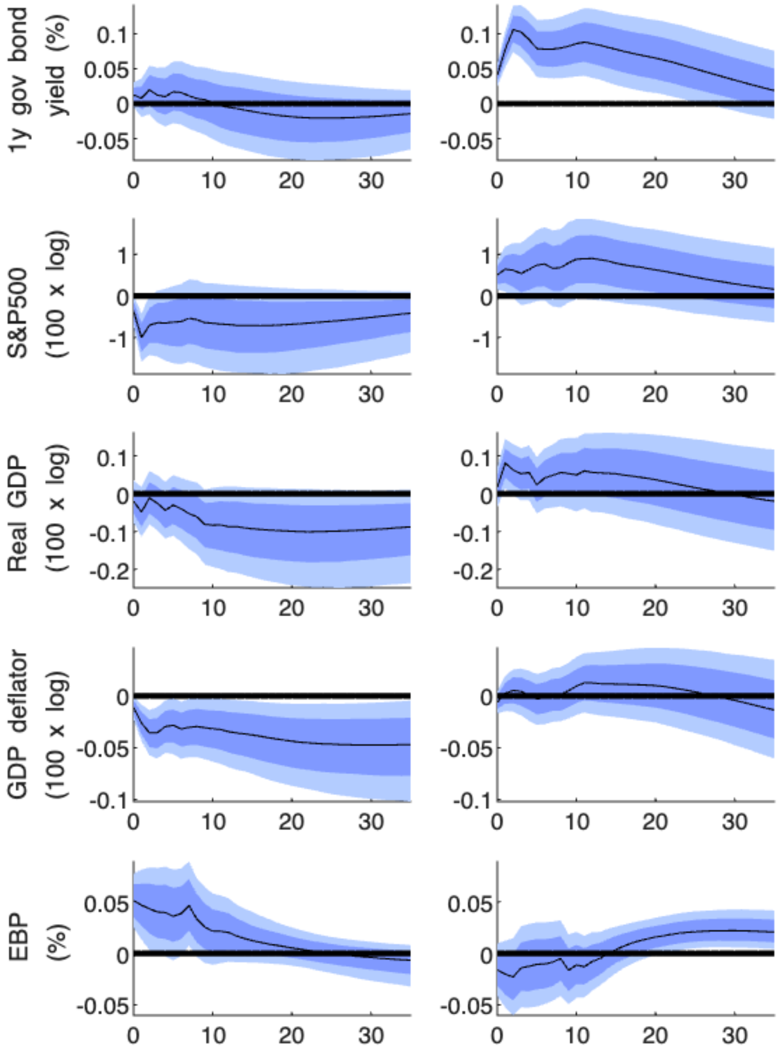
Under the sign restriction identification (Panel A), we successfully isolate the two shocks: a pure monetary policy shock is characterized by a 5 bp increase in the three-month Fed funds futures and a sharp -42 bp contraction in the S&P 500. In contrast, the information shock reveals a positive co-movement, with both interest rates (+3 bp) and stock prices (+28 bp) rising simultaneously.

Comparing these to the standard HFI (Panel B), we observe that the latter produces a much smaller stock market reaction (-21 bp). This confirms that the standard approach mixes the two structural shocks, leading to the attenuation bias discussed previously.

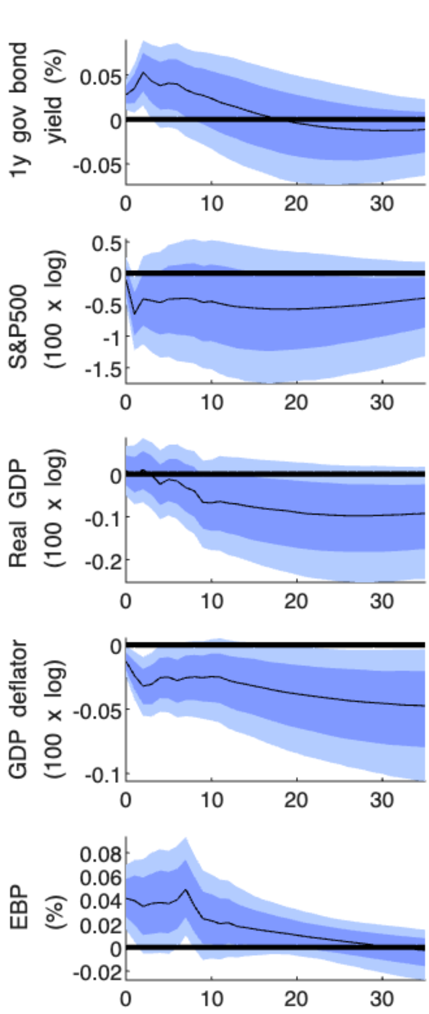
Table 2: Replication of Impact Responses of Announcement Surprises

	Panel A. Sign restrictions				**Panel B. Standard HFI**	
	Monetary policy		CB information		Monetary policy	
	Mean	(5^{pct}, 95^{pct})	Mean	(5^{pct}, 95^{pct})	Mean	(5^{pct}, 95^{pct})
Three-month fed funds futures	5	(3, 6)	3	(0, 5)	6	(5, 6)
S&P 500	-42	(-52, -23)	28	(3, 45)	-21	(-25, -16)

Notes: Posterior means and posterior percentiles (5 and 95) obtained from our replication on the original sample period. Units are in basis points.



(a) Panel A: Sign Restrictions (Purified)



(b) Panel B: Standard HFI (Biased)

Figure 1: Replication of Impulse Responses to One-Standard-Deviation Shocks (Figure 2 of the paper).

3.3 Structural implications

These empirical results force a re-estimation of the parameters in the authors' New Keynesian DSGE model. In the standard HFI model, to fit the data, the model assumes that prices are extremely rigid, with a Calvo probability of 0.94. However, with the "purified" shock, this parameter drops to 0.87, meaning prices are actually more flexible than previously thought. To explain why output falls so much (-10 bps) even though prices are flexible, the model relies on financial frictions. The portfolio adjustment cost parameter jumps from 0.0019 in the standard model to 0.0452 in the purified model. This huge increase confirms that the financial accelerator is the main driver of monetary policy transmission.

4 Extension Results

In this section, we apply the sign-restriction identification strategy to our extended dataset (1994-2025). The inclusion of the post-2019 period, characterized by the pandemic and the return of high inflation, allows us to test if the transmission of monetary policy has changed over time.

4.1 Descriptive analysis: a new regime of volatility

We begin by inspecting the raw distribution of surprises. Figure 2 plots the monetary policy surprise (horizontal axis) against the information surprise (vertical axis).

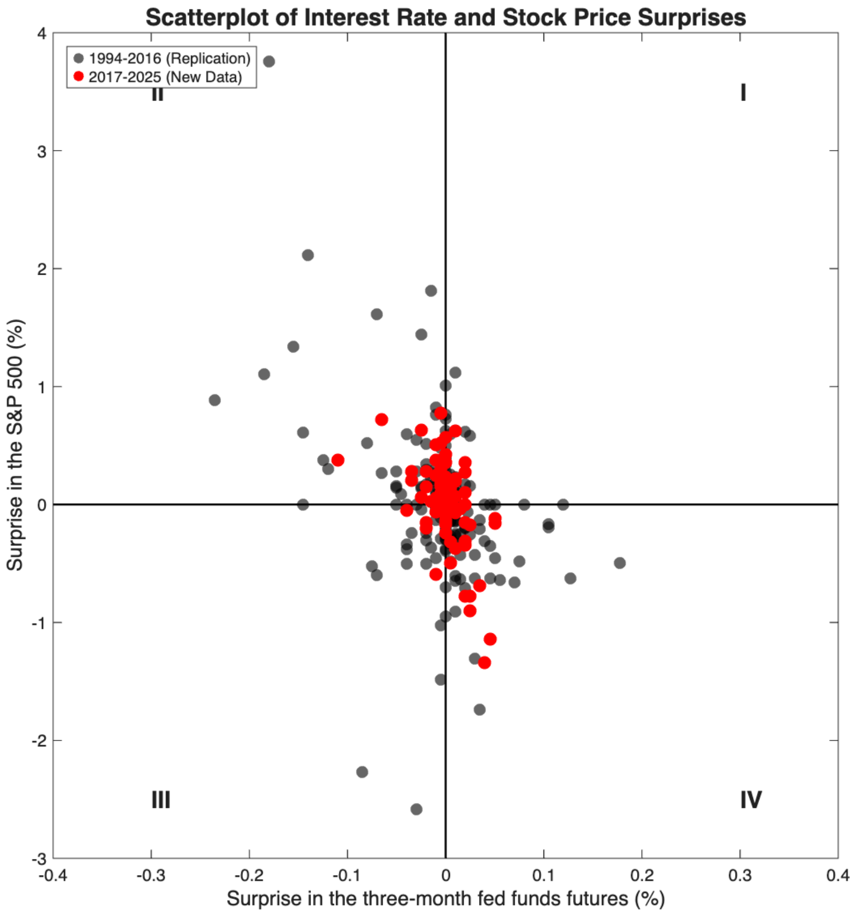


Figure 2: Scatterplot of Interest Rate and Stock Price Surprises. Grey dots represent the replication period (1994-2016), red dots represent the new data (2017-2025).

The scatterplot reveals an interesting contrast. Unlike the replication period (grey dots), which displays large outliers, the new data (red dots) are less spread out and more concentrated around the origin. This suggests that while the economic context was volatile, the surprises delivered by the Fed were smaller in magnitude. This is likely due to the use of "Forward Guidance": in recent years, the Fed has communicated its intentions well in advance. As a result, even aggressive policy actions (like the 2022 hiking cycle) were largely anticipated by markets, leading to smaller high-frequency surprises on the day of the announcement compared to the shocks of the 2000s.

4.2 Historical shock decomposition

To understand when these shocks happened, we decompose the historical fed funds futures surprises into their two components: the pure monetary policy shock and the central bank information shock (Figure 3).

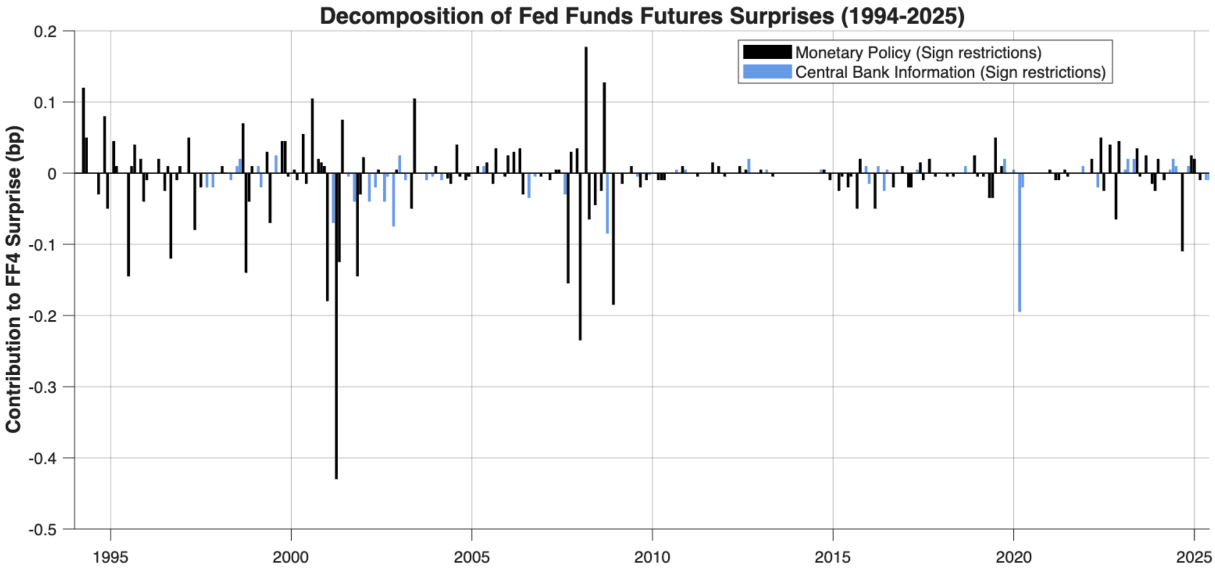


Figure 3: Decomposition of Fed Funds Futures Surprises (1994-2025). Black bars denote pure monetary policy shocks; blue bars denote central bank information shocks.

The decomposition tells a clear story:

- Monetary shocks (black bars): They are clustered around major tightening or easing cycles. We see large black bars in 2001, 2008, 2009, showing its importance during this period.
- Information shocks (blue bars): They dominate during periods of high uncertainty. Notably, at the start of the COVID-19 pandemic (early 2020), the bars are mostly blue. This means the market reacted more to the Fed's revealed information about the virus and the economy than to the interest rate changes themselves.

4.3 Time-varying importance of information shocks

Does the relative importance of these two shocks change over time? To answer this, we compute the Forecast Error Variance Decomposition (FEVD) of Industrial Production using a rolling window of 96 months (Figure 4).

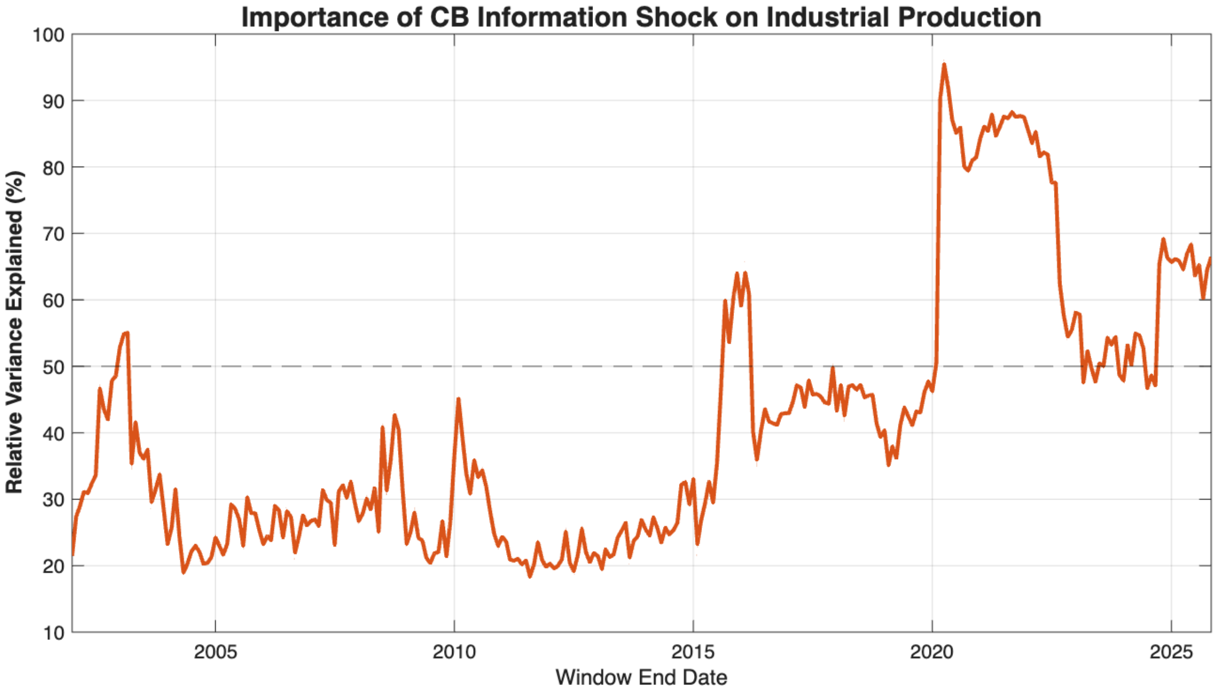


Figure 4: Importance of CB Information Shock on Industrial Production. Rolling window estimation showing the relative variance explained by the information shock.

The results show a massive structural break around 2020, where the share of variance explained by the information shock peaks near 95%. Economically, this peak is driven by the COVID-19 crash in March 2020. During this month, the Fed cut rates to zero while the stock market collapsed. Since our sign restrictions define any positive co-movement as an "Information Shock", the model mechanically classifies this crash as such. While the model interprets this as the Fed revealing negative news about the economy, it is likely an artifact of the identification strategy. The model is capturing the massive exogenous shock of the pandemic, which caused all asset classes to fall at once, rather than a true revelation of private information by the central bank. Nevertheless, this confirms that during crises and ZLB episodes, the traditional inverse relationship between rates and stocks breaks down, making standard monetary policy shocks less relevant.

Economically, when the policy rate is stuck at zero, the Fed cannot use traditional rate cuts. Instead, it relies on "Forward Guidance" (communication). Therefore, during the ZLB, the economy is driven almost entirely by the information conveyed by the central bank. However, as soon as the tightening cycle begins in 2022, this share drops. This signals a return to "normal" monetary mechanics, where rate changes regain their power.

4.4 Sub-sample impact responses

Before analyzing the full transmission, we quantify the immediate size of the shocks across our different regimes. Table 3 reports the immediate reaction ($t = 0$) of market variables.

This table confirms the "constraint" on monetary policy during the ZLB (Panel C). The impact of monetary shocks on Fed Funds Futures was minimal (1.0 bp), which is four times smaller than in the Pre-Crisis period (4.0 bp). However, the stock market reaction remained significant (-27.0 bp), suggesting that unconventional policy still moved asset prices even without large rate changes. In the Post-COVID period (Panel D), we see a

Table 3: Impact Responses of High-Frequency Variables

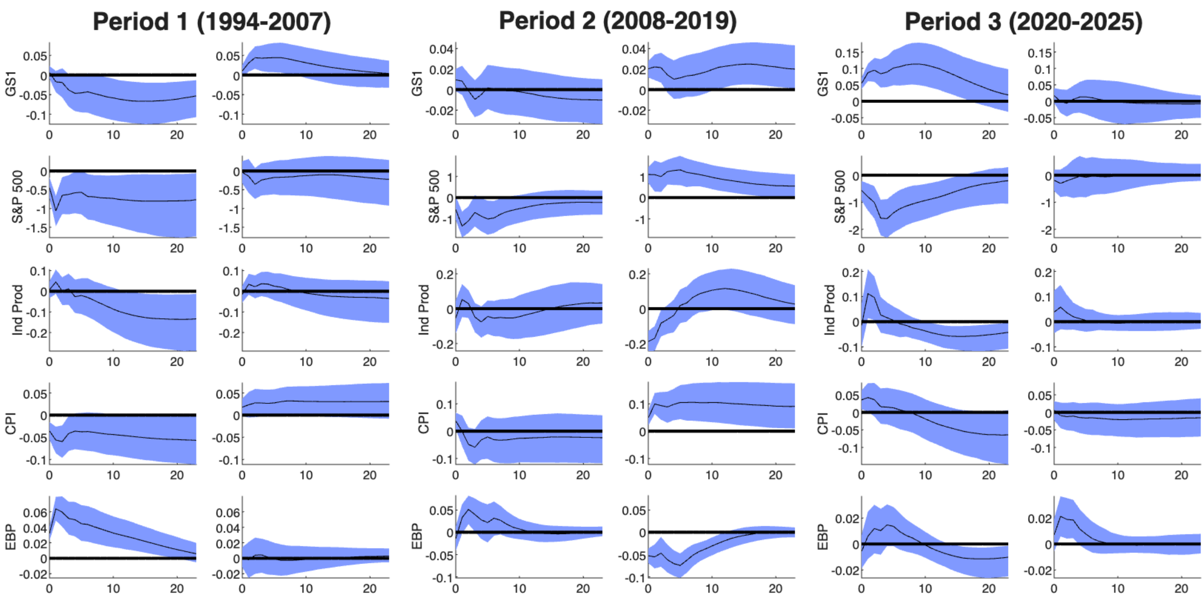
	Shock	
	Monetary Policy (Negative Co-movement)	CB Information (Positive Co-movement)
Panel A: Full Sample (1994–2025)		
Three-month fed funds futures	3.0 (1.0, 4.0)	3.0 (0.0, 4.0)
S&P 500	-47.0 (-66.0, -18.0)	38.0 (5.0, 63.0)
Panel B: Pre-Crisis (1994–2007)		
Three-month fed funds futures	4.0 (3.0, 6.0)	2.0 (0.0, 4.0)
S&P 500	-51.0 (-63.0, -35.0)	26.0 (3.0, 48.0)
Panel C: ZLB & Recovery (2008–2019)		
Three-month fed funds futures	1.0 (0.0, 1.0)	1.0 (0.0, 1.0)
S&P 500	-27.0 (-37.0, -14.0)	19.0 (2.0, 33.0)
Panel D: COVID & Inflation (2020–2025)		
Three-month fed funds futures	2.0 (1.0, 2.0)	1.0 (0.0, 2.0)
S&P 500	-32.0 (-41.0, -20.0)	17.0 (2.0, 30.0)

Notes: The table reports the posterior mean and the (5th, 95th) percentiles (in parentheses) of the impact responses ($t = 0$) of high-frequency variables to the identified shocks. Units are in basis points.

normalization: the volatility of interest rate surprises rises again (2.0 bp), although it has not yet fully returned to the high levels of the 1990s.

4.5 Regime-dependent impulse responses

Finally, to quantify how these structural shifts alter transmission over time, we estimate the BVAR separately for our three distinct sub-samples. Figure 5 compares the Impulse Response Functions (IRFs).



(a) Pre-Crisis (1994-2007) (b) ZLB (2008-2019) (c) Post-COVID (2020-2025)

Figure 5: Impulse Response Functions across Sub-samples. Comparison of the transmission of a monetary policy shock across three regimes.

The differences between the periods are very important:

Period 1: Pre-Crisis (1994-2007) This period displays the "textbook" transmission. A monetary tightening leads to a moderate decline in industrial production and prices. The transmission channel is functional and standard.

Period 2: ZLB (2008-2019) The transmission mechanism appears "broken". The response of industrial production is muted (the blue bands cross zero), and prices do not react significantly, because the policy rate was constrained near zero. As shown in Table 3, shocks to the fed funds futures were minimal (1.0 bp), making the "pure" monetary channel ineffective compared to the information channel.

Period 3: Post-COVID (2020-2025) We observe a violent resurgence of monetary power. The monetary policy shock triggers a sharp, statistically significant crash in industrial production and prices. With the return of aggressive rate hikes, the traditional monetary channel is back. The Fed's actions have a direct and powerful braking effect on the real economy, solving the "price puzzle" instantly.

5 Conclusion

This project replicated and extended the methodology of Jarociński and Karadi (2020) to identify pure monetary policy and central bank information shocks. Our results confirm that ignoring the information channel leads to a significant attenuation bias, underestimating the impact of policy on the real economy and creating "price puzzles". By using sign restrictions on high-frequency surprises, we show that monetary tightening remains powerful once purified from information noise, transmitted largely through a financial accelerator mechanism.

Our extension to the 2017–2025 period reveals a fundamental shift in the monetary landscape. While the information channel dominated the Zero Lower Bound sample, the recent inflationary cycle marks a return to a "traditional" regime where interest rate shocks have regained their contractionary force. However, the increased concentration of surprises around the origin suggests that Forward Guidance has successfully reduced market noise. Ultimately, this study underscores that the effectiveness of monetary policy is regime-dependent: low during periods of liquidity traps but really effective when the central bank aggressively tackles inflation.