How different is the transmission mechanism of monetary policy shocks when inflation is high?

XLI Encuentro de Economistas del BCRP

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Motivation

- After a long period of low and stable inflation, the outlook has suddenly changed in the aftermath of the COVID pandemic and most countries have seen inflation rates reaching unprecedented levels since the late 1970s.
- Initially, supply disruptions associated with the pandemic-induced reallocation of economic activity across sectors were thought to drive the rise in inflation. However, the massive expansionary fiscal stimulus national governments implemented in response to the COVID has made clear that demand factors are also important.
- The proper policy response may be dependent on the nature of the impulses driving the inflation surge. However, it may be the case that even if the nature of the impulses is identifiable, the transmission of policy action is impaired in situations of high inflation (credibility, expectations).

This paper I

- The task of this paper is to explore how the propagation of two types of monetary policy to the aggregate economy is altered in high vs. low inflation regimes.
- We use US data in the investigation and focus attention of conventional monetary policy shocks - shocks that alter aggregate conditions via changes in the nominal interest rate - and liquidity shocks - shocks that alter the quantity of money available in the economy by twisting the slope of the term structure of interest rates.
- Using a Bayesian Threshold Vector Autorregressive model with Stochastic Volatility (TBVAR-SV) and volatility feedback (Alessandri and Mumtaz, 2019).
- This model allows an endogenous selection of the threshold and, thus, of the two inflation regimes and volatility feedback that are important when the uncertainty directly affects the level of the endogenous variables of the model.
- We extend the existing structure by adding to the Gibbs sampler used to compute the posterior distribution of the parameters of interest a zero-sign restriction identification scheme following Canova and Pérez Forero (2015), that allows for over-identification of the shocks of system under analysis.

This paper II

- We find significant differences in the transmission of conventional monetary policy disturbances across the two regimes.
  - The peak response of output, unemployment and inflation is smaller but the effects lasts longer when inflation is high.
  - The differences seems to be due to the dynamics of the slope of the term structure which changes sign across regimes: long term rate reaction is larger than short term rate reaction at all horizons in the low inflation regime and the opposite is true in the high inflation regime.
  - This slope inversion is consistent with the idea that the increase in interest rates signal information private agents do not have about the future path of the economy.
  - As a consequence the response by adjusting their inflation expectations at all relevant horizons.
- Liquidity shocks are more expansionary in the short term when inflation is high:
  - That is output growth, the unemployment rate and inflation increase more within six months of the unexpected liquidity increase.

This paper III

- This is under the assumption that the central bank keeps the short term interest rate constant for at least 24 months.
- Financial market responses to the shock explain the differences across regimes.
- In fact, the stock market sees the liquidity increase as a good news when inflation is high but as a bad news when inflation is low.

Related Literature I

- How work contributes to different strands of literature. From a methodological viewpoint we extend the work of Alessandri and Mumtaz (2019) to allow a simpler and more direct sampling of the matrix of contemporaneous coefficients once zero and sign restrictions are employed for identification.
- Our work also is related to many studies which have employed nonlinear structural time series methodologies to investigate the transmission of US monetary policy, see the regime switching SVAR specification of Sims and Zha (2006); the continuous time varying parameters SVAR specification of Cogley and Sargent (2005), Primiceri (2005) , Canova and Gambetti (2009), Canova and Pérez Forero (2015). Relative to that literature we employ a model where the threshold is endogenously chosen and switches may repeatedly occur through the sample.
- Our work is also related to earlier papers employing sign restrictions Canova and De Nicoló (2002), Uhlig (2005), Rubio-Ramírez *et al.* (2010), Baumeister and Hamilton (2015), Baumeister and Hamilton (2021), to those employing mixed sign and zero restrictions, see Arias *et al.* (2018), and to those using non-recursive identification schemes, see Waggoner and Zha (2003), Sims and Zha (2006) and Canova and Pérez Forero (2015).

Related Literature II

- We integrate the use of sign and zero restrictions within the Gibbs sampler and efficiently employ a re-parametrization of the contemporaneous restrictions that allows for joint draws of all parameters without the need of additional steps.
- Finally, our work is related to earlier contributions by Ravn and Sola (1996), Weise (1999), Borio *et al.* (2017), Pellegrino (2021), Debortoli *et al.* (2020) who study whether nonlinearities affect the transmission of conventional monetary policy shocks.

Data

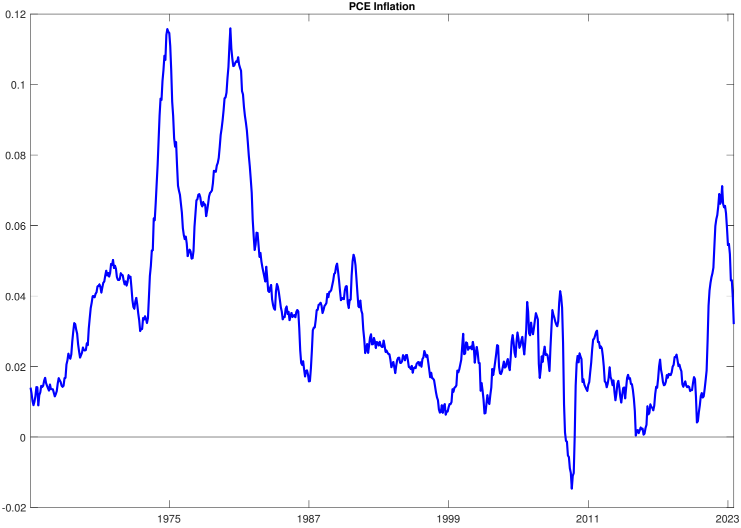
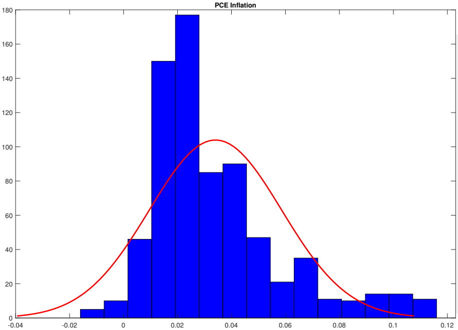


Figure: US Inflation Data (FRED Database): 1960-2023

US Inflation Data is far from Normal Distribution

Figure: PCE Inflation (FRED Database): 1960-2023



((a)) Histogram

```
Inflation Distribution
Mean and Median
    0.0341    0.0263

Skewness and Kurtosis
    1.3395    4.6256

Inter-Quartile Range
    0.0176    0.0438
```

((b)) Distribution

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Threshold-BVAR Model

- Consider the following setup (Alessandri and Mumtaz, 2019):

$$
\begin{aligned}
Z_t = &\left(c_1 + \sum_{j=1}^{P} \beta_1 Z_{t-j} + \sum_{j=0}^{J} \gamma_1 ln\lambda_{t-j} + \Omega_{1t}^{1/2} e_t\right) \tilde{S}_t + \\
&\left(c_2 + \sum_{j=1}^{P} \beta_2 Z_{t-j} + \sum_{j=0}^{J} \gamma_2 ln\lambda_{t-j} + \Omega_{2t}^{1/2} e_t\right) \left(1 - \tilde{S}_t\right)
\end{aligned} \tag{1}
$$

  where $Z_t = (Y_t, P_t, U_t, R_t, YCSlope_t, M_t, Pcom_t, SP500_t)'$.

- Y_t measures economic activity (Industrial Production), P_t is the YoY inflation rate, U_t is the Unemployment Rate, R_t is the Federal Funds Rate, $YCSlope_t$ is the proxy of Yield Curve Slope (10 years - 3 months), M_t is the M2 YoY growth rate, $Pcom_t$ is the commodity price index YoY growth rate, and $SP500_t$ is the SP500 Stock Market index YoY growth rate.
- The volatility component λ_t may also be interpreted as an Uncertainty measure.

Threshold-BVAR Model(2)

- The covariance matrix is as follows:

$$\Omega_{1t} = A_1^{-1} H_t A_1^{-1\prime} \tag{2}$$

$$\Omega_{2t} = A_2^{-1} H_t A_2^{-1\prime} \tag{3}$$

 where A_1 and A_2 are non-recursive matrices such that $vec\,(A_i) = S_A \alpha_i + s_A$ (Amisano and Giannini, 1997), with S_A and s_A being matrices governed by 0s and 1s. This is a useful transformation in order to sample the full parameter vector α_i (Canova and Pérez Forero, 2015).

- The regime indicator $\tilde{S}_t$ is defined by

$$\tilde{S}_t = 1 \iff P_{t-d} \leq Z^* \tag{4}$$

 where both the delay parameter d and the Threshold Z^* are unknown parameters.

Threshold-BVAR Model(3)

- The volatility process is defined by:

$$H_t = \lambda_t \Sigma \tag{5}$$

$$\Sigma = diag\left(\sigma_1^2, \ldots, \sigma_8^2\right) \tag{6}$$

$$ln\lambda_t = \mu + F\left(ln\lambda_{t-1} - \mu\right) + \eta_t \tag{7}$$

  where η_t is an i.i.d. process with variance Q.

- A single scalar process governs the time varying volatility (Carriero *et al.* (2016), Alessandri and Mumtaz (2019)).

Threshold-BVAR Model(4)

Variable - Shock	Monetary Policy (MP)	Uncon. Mon. Policy
Econ. Activity	0	0
PCE Inflation	≤ 0	0
Unemployment	0	0
Interest Rate	> 0	0
Yield Curve Slope	$?$	≤ 0
Money Growth	< 0	> 0
Commodity Prices	$?$	$?$
SP 500	$?$	$?$

Table: Identification Zero and sign restrictions

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Bayesian Estimation

Given the specified priors and the joint likelihood function, we combine efficiently these two pieces of information in order to get the estimated parameters included in Θ. Using the Bayes' theorem we have that:

$$p\left(\Theta \mid Y\right) \propto p\left(Y \mid \Theta\right) p\left(\Theta\right) \quad (8)$$

Gibbs Sampling

Recall that $\Theta = \left\{Z^*, d, \Phi_{1:2}, \alpha_{1:2}, s_{1:6}, \lambda^T, \mu, F, Q\right\}$. Then, use the notation Θ/χ whenever we denote the parameter vector Θ without the parameter.

Set $k = 1$ and denote K as the total number of draws. Then follow the steps below:

1. Draw $p\left(Z^* \mid \Theta/Z^*, Z^T\right)$: Adaptive Metropolis-Hastings step (Haario *et al.*, 2001)
2. Draw $p\left(d \mid \Theta/d, Z^T\right)$: Multinomial Distribution
3. Draw $p\left(\Phi_i \mid \Theta/\Phi_i, Z^T\right)$: Normal Distribution, $i = 1, 2$
4. Draw $p\left(\alpha_i \mid \Theta/\alpha_i, Z^T\right)$: Metropolis step (Canova and Pérez Forero, 2015), $i = 1, 2$
5. Draw $p\left(s_j \mid \Theta/s_j, Z^T\right)$: Inverse-Gamma Distribution, $j = 1, \ldots, M$
6. Draw $p\left(\lambda^T \mid \Theta/\lambda^T, Z^T\right)$: Single-Move Kalman Smoother (Kim *et al.*, 1998)
7. Draw $p\left(\mu \mid \Theta/\mu, Z^T\right)$: Normal Distribution
8. Draw $p\left(F \mid \Theta/F, Z^T\right)$: Truncated Normal Distribution
9. Draw $p\left(Q \mid \Theta/Q, Z^T\right)$: Inverse-Gamma Distribution
10. If $k < K$ set $k = k + 1$ and return to Step 1. Otherwise stop.

Estimation Setup

We run the Gibbs sampler for $K = 100,000$ and discard the first $50,000$ draws in order to minimize the effect of initial values. Moreover, in order to reduce the serial correlation across draws, we set a thinning factor of 10, i.e. given the remaining $100,000$ draws, we take 1 every 10 and discard the remaining ones. As a result, we have $10,000$ draws for conducting inference.

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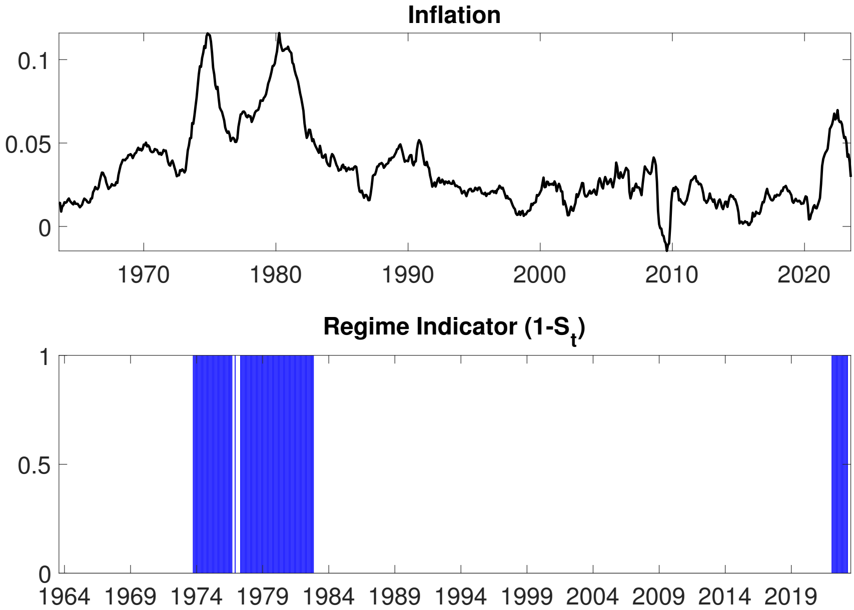

Figure: US Inflation Regimes 1960-2023

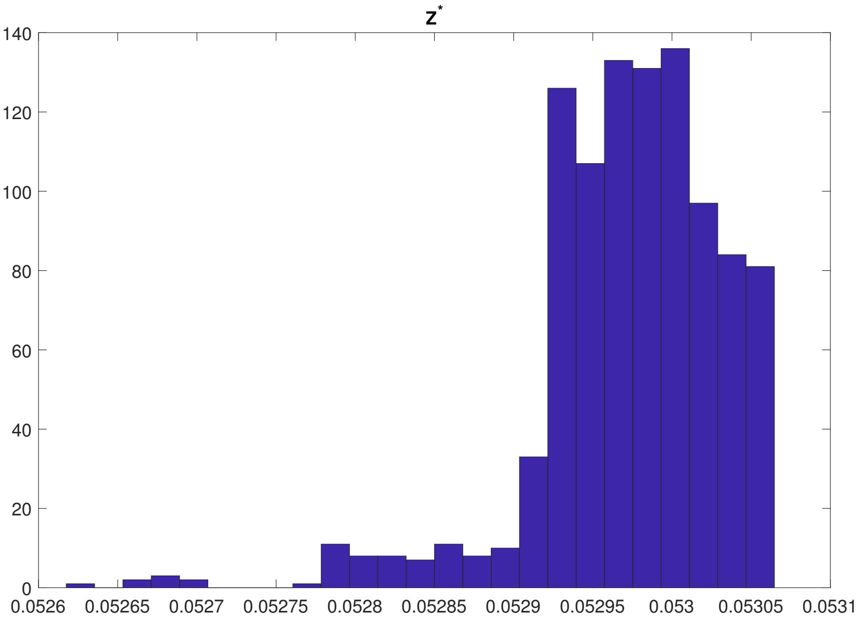

Figure: Estimated Threshold parameter Z^*

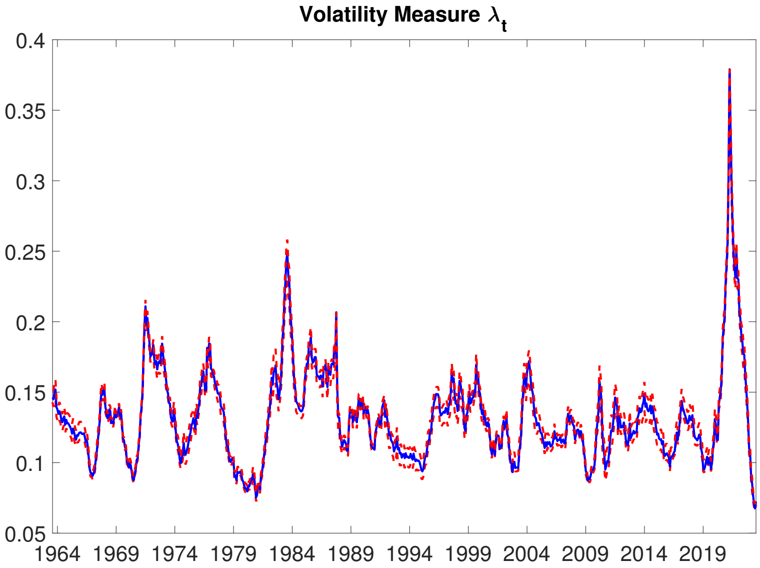

Figure: Volatility Measure (1960 - 2023)

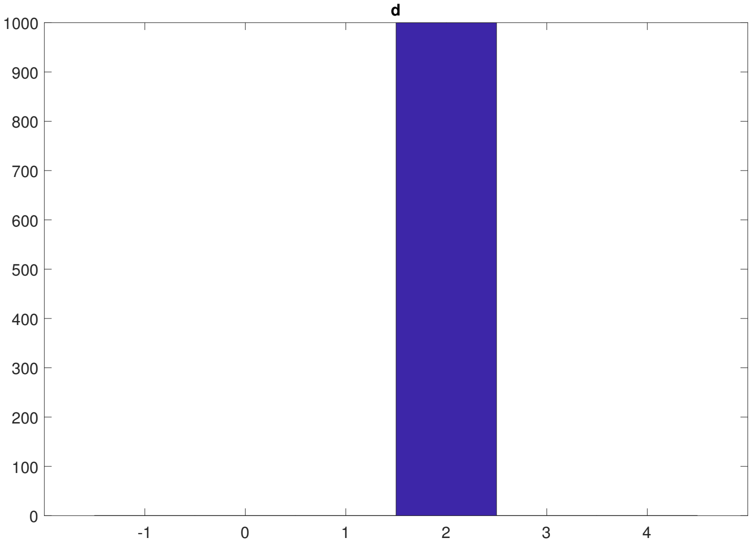

Figure: Estimated delay parameter d

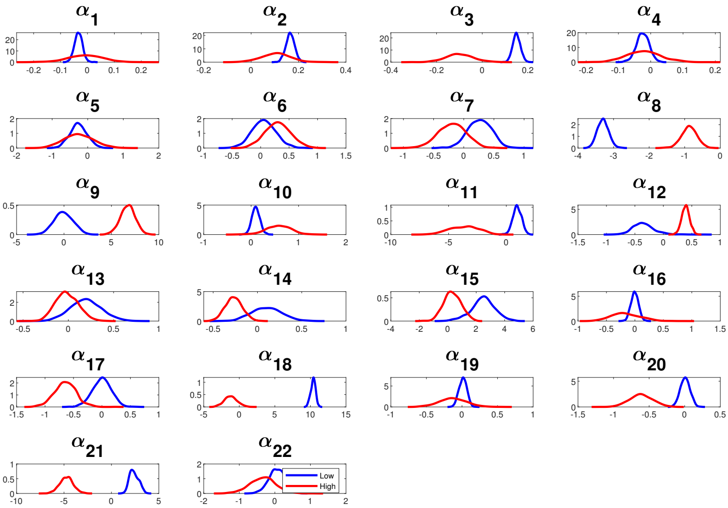

Figure: Estimated structural parameters α for Two Regimes

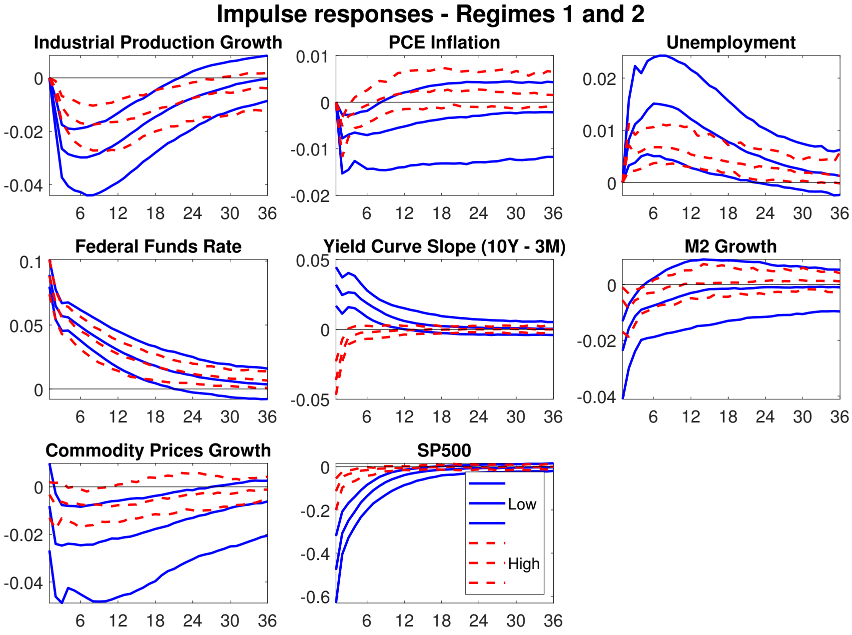

Figure: Monetary Policy Shocks for different inflation regimes (contractionary)

Impulse responses - Regimes 1 and 2

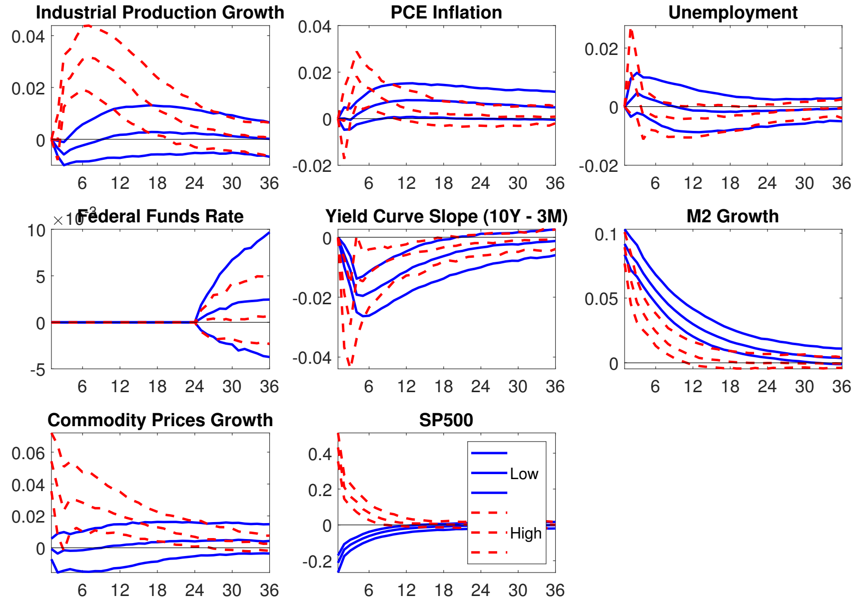

Figure: Unconventional Monetary Policy Shocks for different inflation regimes

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Impulse responses - Regime 1

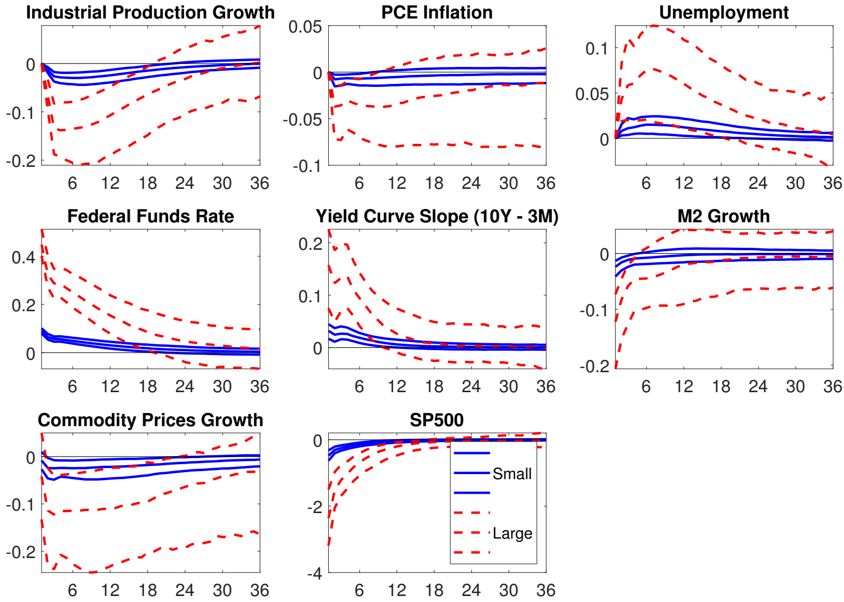

Figure: Monetary Policy Shocks for different shock size (low inflation regime)

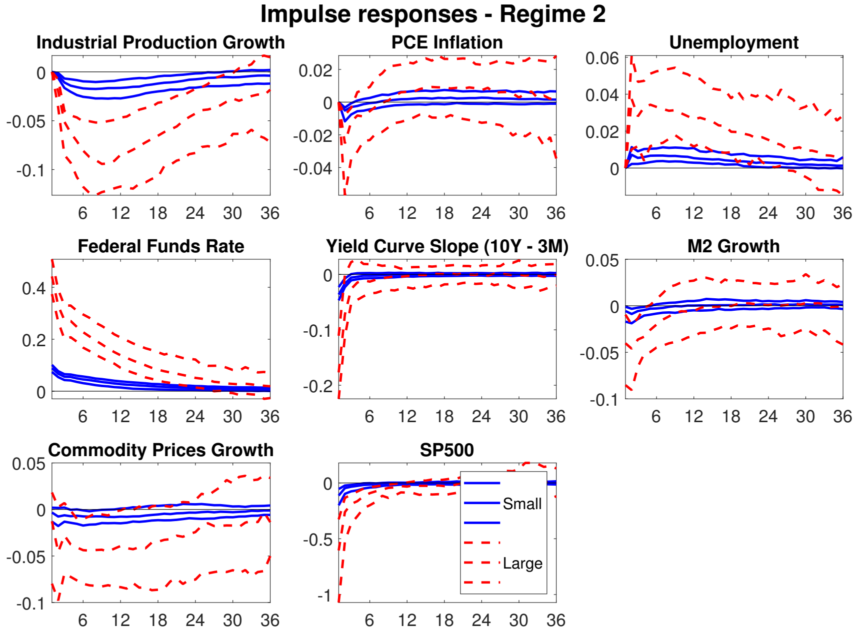

Figure: Monetary Policy Shocks for different shock size (high inflation regime)

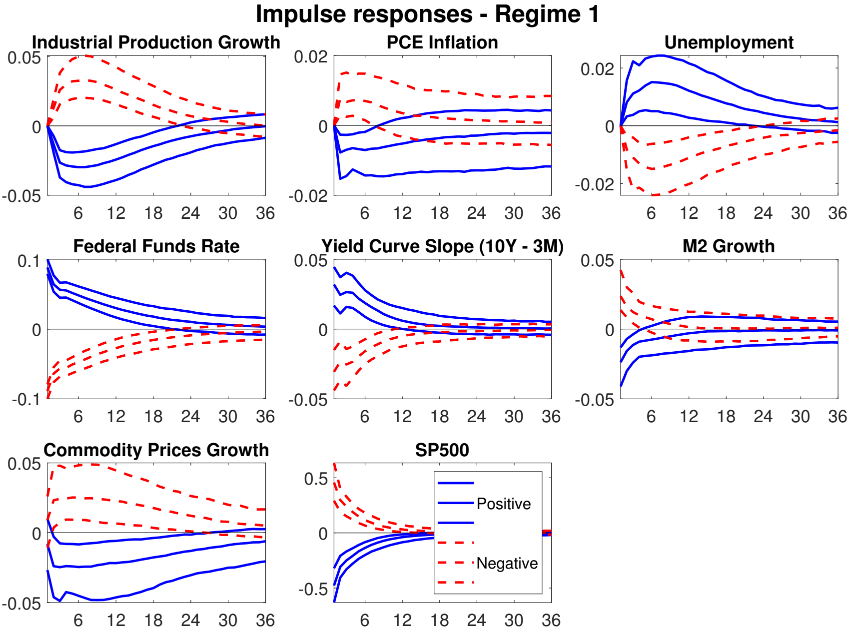

Figure: Monetary Policy Shocks for different shock sign (low inflation regime)

Impulse responses - Regime 2

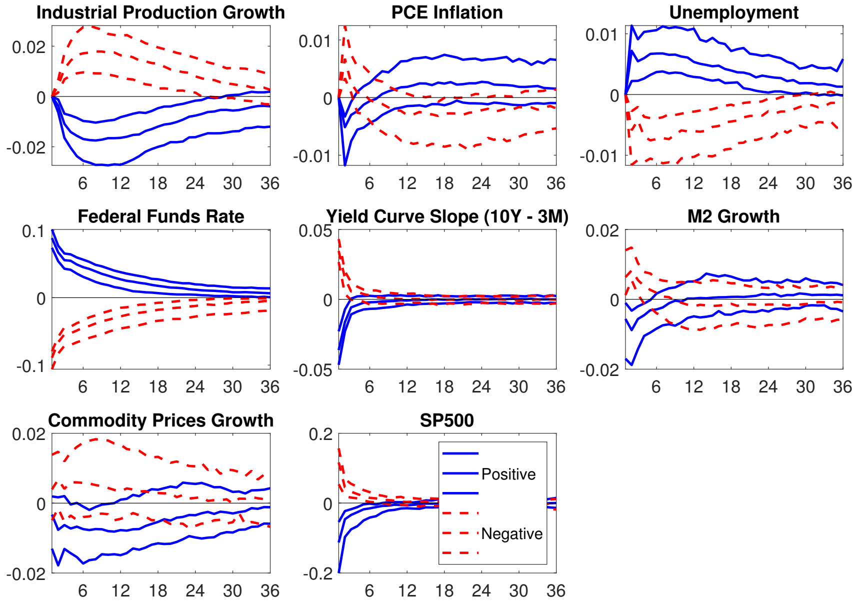

Figure: Monetary Policy Shocks for different shock sign (high inflation regime)

Concluding Remarks

- The task of this paper is to explore how the propagation of two types of monetary policy to the aggregate economy is altered in high vs. low inflation regimes.
- We use US data in the investigation and focus attention of conventional monetary policy shocks - shocks that alter aggregate conditions via changes in the nominal interest rate - and liquidity shocks - shocks that alter the quantity of money available in the economy by twisting the slope of the term structure of interest rates.
- Using a Bayesian Threshold Vector Autorregressive model with Stochastic Volatility (TBVAR-SV) and volatility feedback (Alessandri and Mumtaz, 2019).
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- We find significant differences in the transmission of conventional monetary policy disturbances across the two regimes.

Data

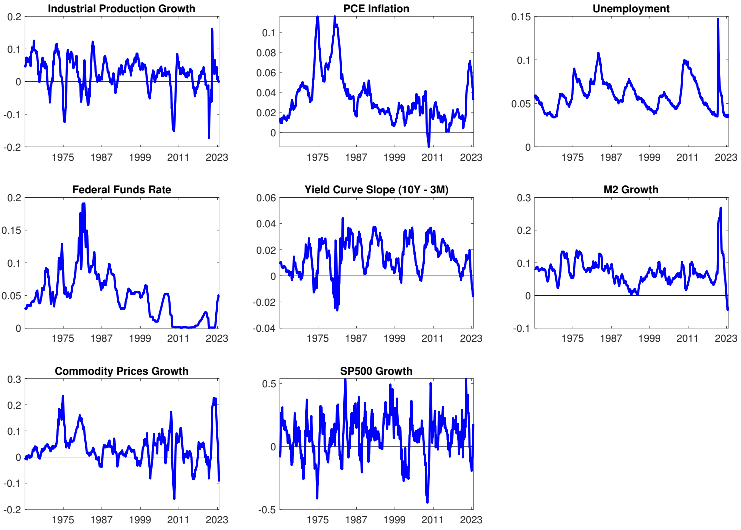

Figure: US Macroeconomic Data (FRED Database): 1960-2023

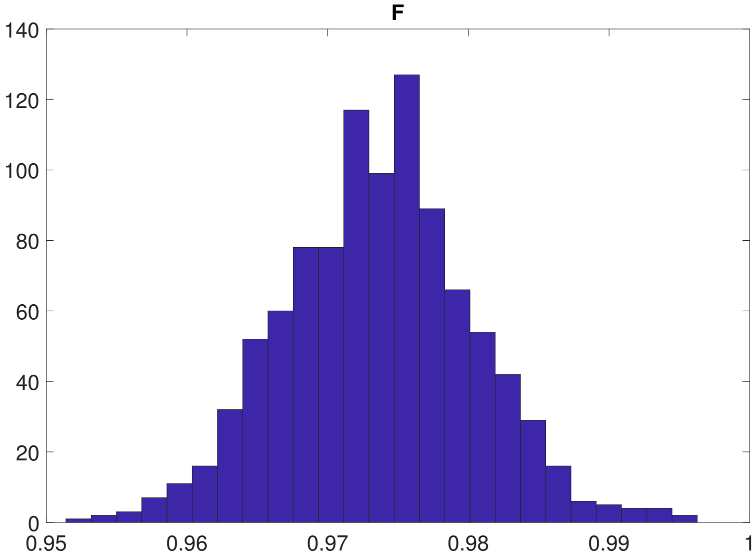

Figure: Estimated persistence parameter F

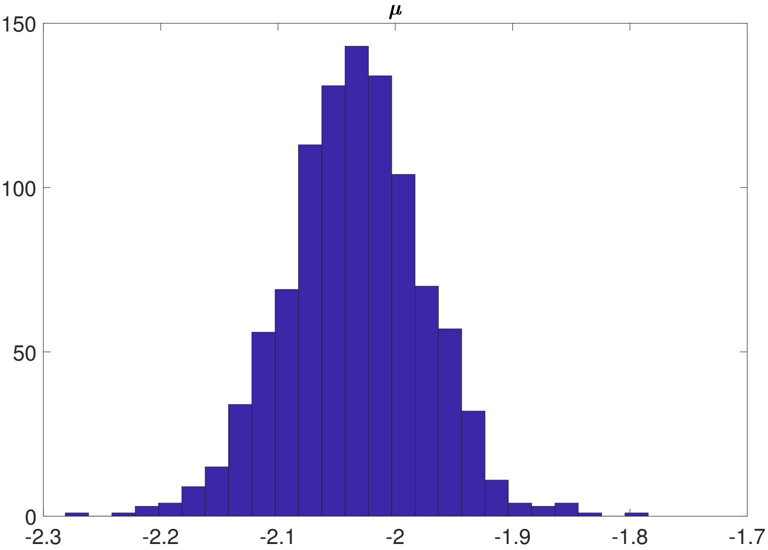

Figure: Estimated mean parameter μ

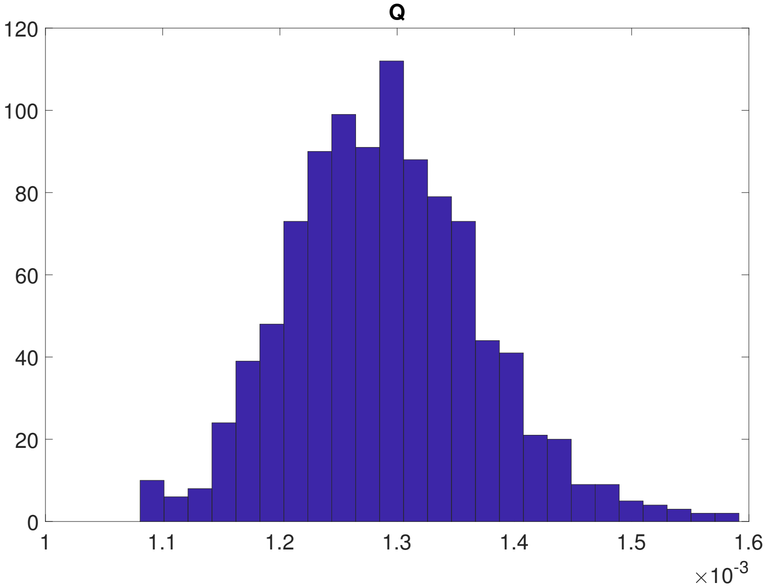

Figure: Estimated variance parameter Q

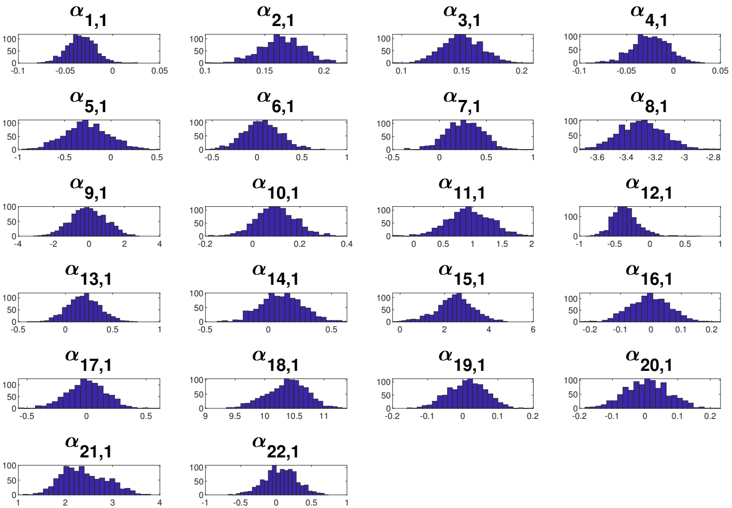

Figure: Estimated structural parameters α of Regime $S_t = 1$

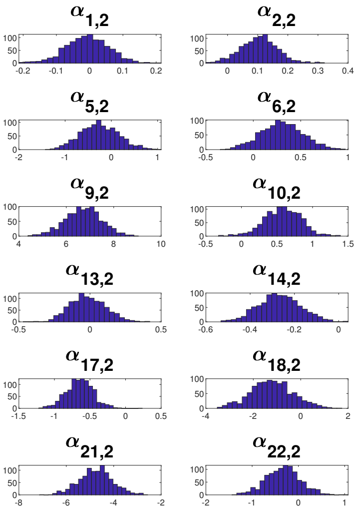

Figure: Estimated structural parameters α of Regime $S_t = 0$

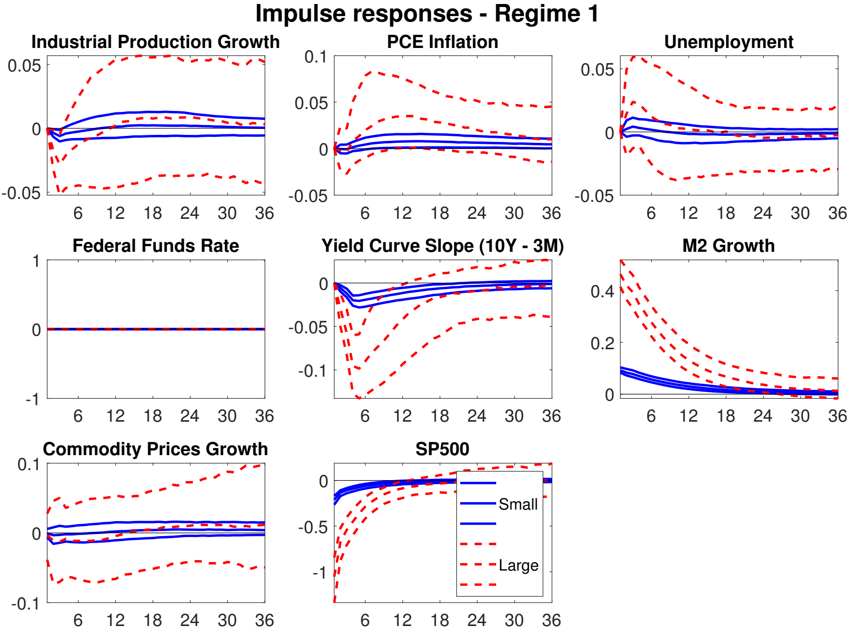

Figure: Unconventional Monetary Policy Shocks for different shock size (low inflation regime

Impulse responses - Regime 2

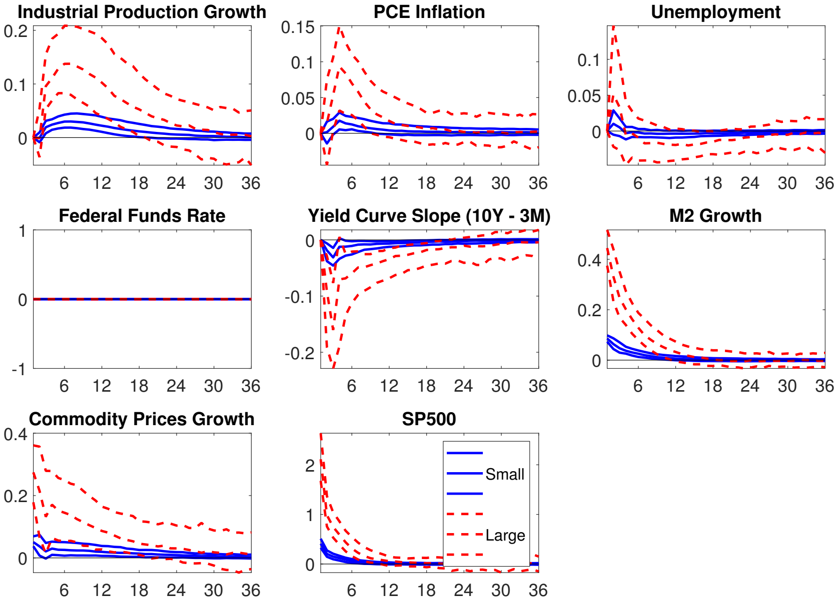

Figure: Unconventional Monetary Policy Shocks for different shock size (high inflation regime

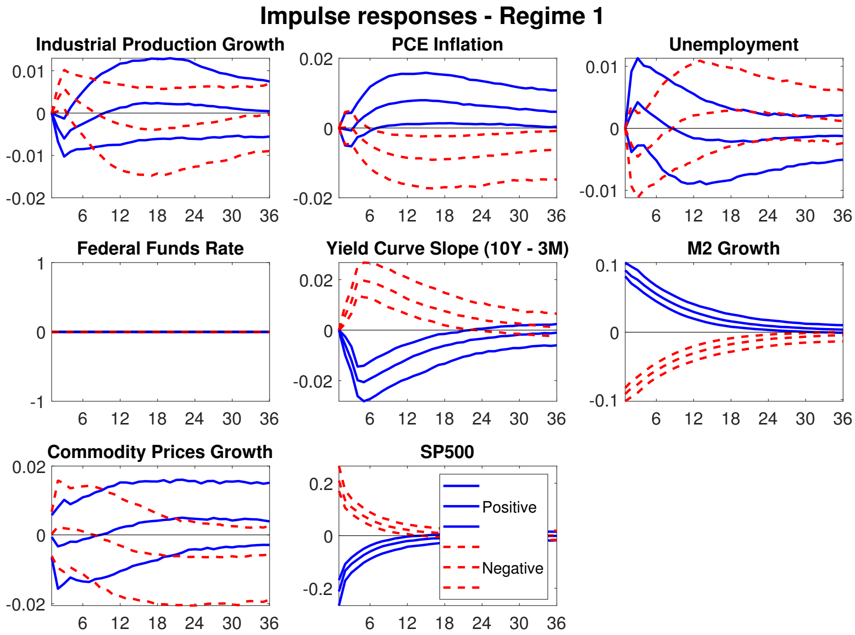

Figure: Unconventional Monetary Policy Shocks for different shock sign (low inflation regime

Impulse responses - Regime 2

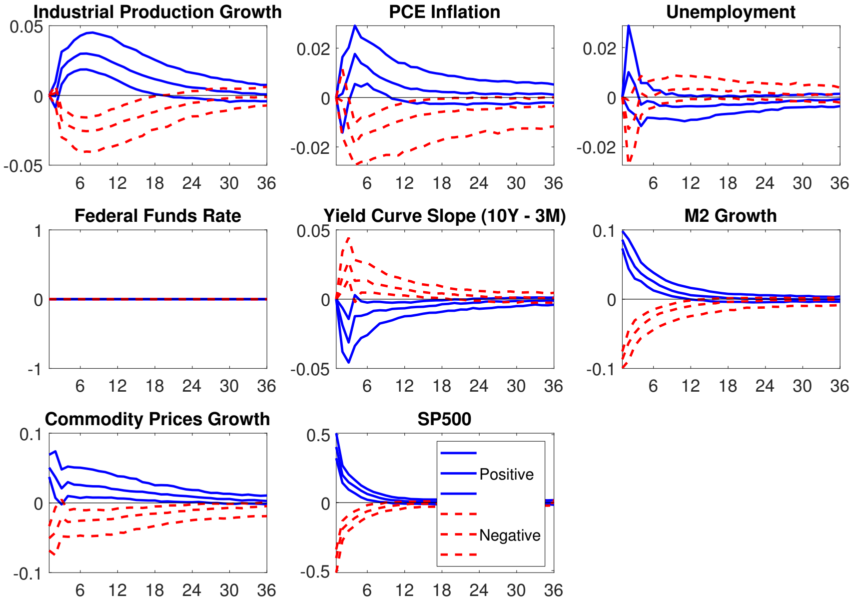

Figure: Unconventional Monetary Policy Shocks for different shock sign (high inflation regime

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