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Does the transmission of monetary policy shocks change when inflation is high?

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Abstract

We investigate the transmission of US monetary policy shocks in high and low inflation regimes using a Bayesian threshold vector autoregressive model. The propagation of conventional disturbances differs: the peak response of output growth and of inflation is smaller but the effects lasts longer when inflation is high. Liquidity shocks are more expansionary when inflation is high. The reaction of financial markets to the shocks account for the differences. Implications for theoretical models of monetary policy transmission are discussed.

JEL Classification: C3, E3, E5

Keywords: Threshold vector autoregressions, Monetary policy shocks, Inflation regimes, Bayesian methods, Menu costs models, rational inattention models.

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1 Introduction

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. In the US, the GDP deflator started rising at the end of 2020 and peaked at 9.1 percent in 2022:Q2. In the euro area, inflation was negative at the end of 2020 and rose sharply in 2021 and peaking around 10 percent on an annual basis in 2022. In some European countries (e.g., the Netherlands, Estonia) the annual inflation rate in 2022 exceeded 15 percent. Initially supply disruptions, associated with pandemic-induced reallocation of economic activity across sectors, were thought to drive the inflation surge. Later, it became clear that the massive expansionary fiscal stimulus national governments implemented in response to the COVID pandemic was also important.

The proper policy response to the event may depend on the nature of the impulses driving the inflation surge. For example, mainstream New Keynesian theories suggest that a central bank should respond to demand driven but not to supply driven inflation increases. However, even if the nature of the impulses driving inflation is identifiable and the appropriate policy decisions to be taken well understood, it may be the case that the transmission mechanism of policy decisions are altered depending on the level of inflation, because central bank credibility may be affected, public expectations may be dispersed or poorly anchored, or fiscal dominance may prevail. Hence, to allow central banks to consider alternative measures in the case traditional ones become ineffective, it is important to know to what extent and in what way a high inflation regime alters the transmission of monetary policy surprises.

The dependence of monetary policy transmission on the level of inflation is an issue of great interest also from an academic point of view. In most models nowadays used in the literature, monetary policy has real effects because prices are sticky. Menu costs models of the type proposed by, e.g. Alvarez and Lippi (2020), provide a state dependent micro-foundation for the price stickiness generally assumed. Such models typically have clear cut predictions regarding the effects of monetary policy disturbances in high and low inflation regimes, see Ascari and Haber (2021). In particular, the frequency of price changes should be an increasing function of the level of inflation making prices more flexible when inflation is high. As a consequence, the higher inflation is, the smaller the real effects of monetary policy shocks should be. Models with rational inattentive consumers also have different implications for the effects of monetary policy across inflation regimes, see e.g. Sims (2010) or, more recently, Pfauti (2023). When inflation is high, in fact, agents should be more attentive making inflation expectations more sensitive to news. This internalization effect may lead to accelerating inflation, possibly ending in hyperinflation. In such models, monetary policy should aim to keep inflation low so that agents do not pay attention to it when they are making their economic decisions, see Powell (2022) for a recent statement of such a view. Furthermore, there is a threshold that makes agents change the way they respond to shocks. Non-linear (Slanted-L) models of the Phillips curve also predict a different transmission between periods of high or low inflation, see Benigno and Eggertsson (2023), with the tightness of labor market conditions determining the regime the economy it is in. In such models, economic news produce larger effects on inflation when the labor market is tight.

Contribution. This paper explores how the propagation of two types of monetary policy shocks varies with the inflation regime. We employ US data and focus attention on conventional policy shocks - disturbances that alter aggregate demand conditions by changing the nominal (and the real) short term interest rate - and liquidity shocks - disturbances that alter the quantity of money by twisting the long end of the term structure of interest rates. We study the dynamics of several variables and investigate the implications for inflation expectations and for the slope of the Phillips curve to interpret our results in light of existing theories.

We conduct the investigation using a Bayesian Threshold Vector Auto-Regressive (VAR) model with Stochastic Volatility of the type employed in Alessandri and Mumtaz (2019). This model has at least two advantages over competing ones: it allows for an endogenous selection of the threshold and, thus, of the inflation regimes; and it permits uncertainty to directly affect the endogenous variables, which could be important when economic uncertainty is high.

Results. The transmission of conventional monetary policy disturbances differs across inflation regimes. In particular, the peak response of output growth, unemployment and inflation is smaller but the effect of a surprise increase in the short-term nominal rate lasts longer when inflation is high. Differences across regime are related to the dynamics of the slope of the term structure. Notably, the long-term rate reaction is larger than short term rate reaction at all horizons in the low inflation regime; while the opposite is true in the high inflation regime. The slope inversion occurring when inflation is low is consistent with the idea that surprise increases in short-term interest rates provide private agents information about the future path of the economy. When inflation is low, an unexpected surge in the nominal interest rate signals that inflation will be higher for a while and markets respond by adjusting their inflation expectations at all horizons. When inflation is instead high, the informational content of the nominal interest rate surprise is absent as agents expect systematic actions to be taken which will make the high inflation state temporary. This interpretation of the dynamics is supported by two independent pieces of evidence. First, a counterfactual exercise shows that, if the dynamic of the slope of term structure is forced to be the same across regimes, the responses of output growth, unemployment and inflation would also be similar across regimes. Second, short term CPI inflation expectations positively react to conventional policy shocks in the low regime but not in the high inflation regime.

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. The financial market responses to the shocks explain the differences across regimes. In particular, the stock market sees the liquidity increase as good news when inflation is high but as a bad news when inflation is low. Such a behavior is also consistent with monetary policy actions providing signals about the future state of the economy that private agents do not know. To verify the informational content these shocks contain, we run a counterfactual exercise keeping the reaction of the stock market constant across regimes. With this restriction in place, the response of output growth, unemployment and inflation are unchanged across regimes.

The evidence we present is not necessarily in line with the predictions of menu costs or slanted-L Phillips curve theories. We find do evidence of a differential trade-off between output (unemployment, labor share, vacancies-to-unemployment ratio) and inflation in different regimes but, contrary to what these theories would suggest, the slope response is larger in low inflation regime. There is more mixed evidence regarding rational inattention theories. While the response of production growth is in line with the predictions of the theory, see Mackowiak and Wiederholt (2009), inflation expectations react only to conventional but not to liquidity shocks. Furthermore, the reaction in the low inflation regime is larger than in the high inflation regime for the former types of disturbances. Overall, the evidence is more in line with signaling theories provided the non-linear effects discussed above are taken into consideration.

Relationship with the literature. Our work contributes to different strands of literature. From a methodological viewpoint, we extend the work of Alessandri and Mumtaz (2019) by adding zero-sign identification restrictions and reparameterization of the contemporaneous relationships, that allows for a simpler and more efficient sampling from the posterior distribution of the parameters, see Canova and Pérez Forero (2015). A recent contribution by Gargiulo *et al.* (2024) also employs a threshold model to investigate a similar question. We differ from their work in two respects: we include the volatility indicator among the predictors of the endogenous variables, which we show is important to properly filter out uncertainty bursts in certain historical episodes; and we use a different identification strategy to disentangle two types of monetary policy shocks.

Many studies have employed a structural time series methodology to investigate the transmission of US monetary policy disturbances over time; for example, Sims and Zha (2006) use a regime switching SVAR specification; Cogley and Sargent (2005), Primiceri (2005) , Canova and Gambetti (2009), Canova and Pérez Forero (2015) a continuous time varying parameters SVAR specification, and Ascari and Haber (2021) a smooth transition SVAR specification. Relative to this literature we use a model where the threshold is endogenously selected, switches may repeatedly occur over time and are driven by an indicator, which may take time to inform about the nature of the changes.

Our contribution is also related to earlier papers employing sign restrictions, see Canova and De Nicoló (2002), Uhlig (2005), Rubio-Ramírez *et al.* (2010), Baumeister and Hamilton (2015), Baumeister and Hamilton (2021), mixed sign and zero restrictions, see Arias *et al.* (2018), and non-recursive identification schemes, see Waggoner and Zha (2003), Sims and Zha (2006) and Canova and Pérez Forero (2015). Relative to these works, we integrate the use of sign and of zero restrictions within a posterior sampler and reparametrize the contemporaneous restrictions making posterior drawing easier and faster.

The results of the paper are in line with a strand of literature emphasizing the informational content of monetary policy disturbances see e.g. Jarocinski and Karadi (2020), Miranda Agrippino and Ricco (2021); see also Melosi (2017) for a model which rationalizes such a mechanism. It is also consistent with the inflation expectations evidence contained in Fisher *et al.* (2024). Our investigation qualifies their conclusions by showing that the informational content of monetary policy disturbances is present only in particular inflation regimes.

Finally, our contribution is related to work by Ravn and Sola (1996), Weise (1999), Tenreyro and Thwaites (2016), Pellegrino (2021), Ascari and Haber (2021), Debortoli *et al.* (2020), who study whether nonlinearities affect the transmission of conventional monetary policy shocks. Relative to this literature, we study whether the state dependency is endogenously driven by observable indicators and allow uncertainty to predict the endogenous variables of the model.

Outline. The rest of the paper is organized as follows: section 2 describes the data and provides a few statistics of the US inflation rate Section 3 describes the Threshold VAR model we use for the empirical analysis, section 4 explains how Bayesian estimation is conducted, and section 5 presents a summary of the results. Section 6 discusses the differences in the transmission of monetary policy shocks across regimes. Section 7 examines the results in light of existing theories. Finally, section 8 concludes.

2 Data

The data used in the exercise is standard. The endogenous variables included in the VAR are $Z_t = (Y_t, P_t, U_t, R_t, Slope_t, M_t, Pcom_t, SP500_t)'$, where Y_t is the year-on-year industrial production growth, P_t is the year-on-year Personal consumption expenditure (PCE) inflation rate, U_t is the unemployment rate, R_t is the federal funds rate, $Slope_t$ is the slope of the yield curve (10 years rate - 3 months rate), M_t is the year-on-year growth rate of M2, $Pcom_t$ is the year-on-year commodity price index growth rate, and $SP500_t$ is the year-on-year growth rate of the SP500 index. The sample covers the period 1960m1-2023m6 and the source of the data is the FRED database from the St. Louis Fed.

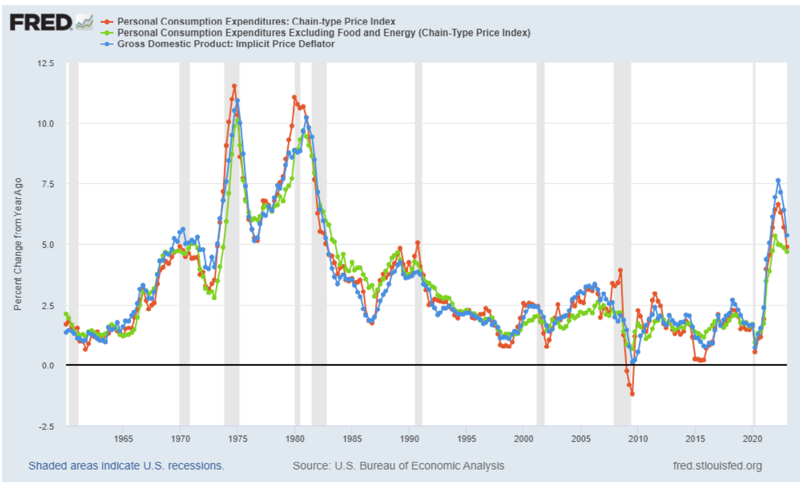
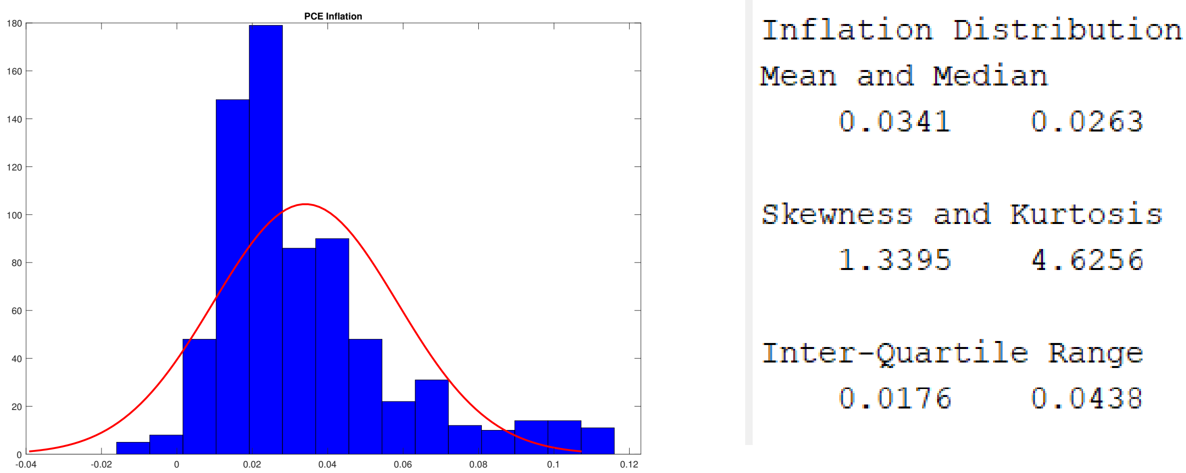


Figure 1: US Inflation, sample 1960-2023. Source: FRED Database

The dynamics of three measures of US inflation (PCE inflation, PCE inflation excluding food and energy, GDP implicit price inflation) are presented in Figure 1. Regardless of the measure employed, the qualitative dynamics of the series are very similar. Thus, focusing on PCE inflation involves no loss of generality. Also, it is clear from Figure 1 that the recent surge of inflation is unprecedented since the late 1970s. Finally, the sharpness of the recent increase is uncommon, even by 1970s standards.



(a) Histogram (b) Distribution

Figure 2: Distribution of PCE Inflation, sample 1960-2023

US inflation data does not seem to come from a normal distribution. As Figure 2 shows, the distribution of inflation rates is left skewed and has a long right tail, which is much thicker than the one of a normal distribution. As a consequence, the mean (0.0341) is larger than the median (0.263) and the mode (0.0240); the skewness coefficient (1.33) is significantly different from zero and the kurtosis coefficient statistically deviates from the one of a normal distribution. Note also that the inter-quartile range is considerably smaller than the one of a normal distribution. Our empirical model tries to endogenously separate the distribution of inflation in two parts, using the information contained in the lags of Z_t.

In standard models, the level of inflation depends on a measure of economic activity. In the literature, the latter is proxied by the output gap, the labor share or a measure of labor market tightness. As shown in Figure C.14 in the online appendix, the link between the level of inflation and real activity measures is somewhat blurred. For example, while during periods of high inflation the unemployment rate tends also to be high, the link between inflation and the vacancy-to-unemployment ratio or the labor share is not visually clear.

3 The Empirical Model

The econometric specification we use to analyze the data is a two-regime Threshold Vector Auto-Regressive model (Threshold-BVAR), see Alessandri and Mumtaz (2019). While alternative specifications, such as the time Varying parameter-VAR (Cogley and Sargent, 2005), with

Stochastic Volatility (Primiceri, 2005; Canova and Gambetti, 2009) or the Markov Switching (MS)-BVAR (Sims and Zha, 2006), could be used, our model has the advantage of fitting a mixture of normal distributions to the data and of endogenously selecting the threshold.

The model is:

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

where the shocks $e_t \sim i.i.d.N\left(0, I_{dim(Z)}\right)$. The binary regime indicator $\tilde{S}_t$ is defined by

$$\tilde{S}_t = 1 \iff \Pi_{t-d} \leq P^* \tag{2}$$

where both the delay d (which is assumed to follow a discrete multivariate distribution with $d = 1, \ldots, d^*$ values) and the threshold P^* (which is assumed to follow a continuous truncated distribution) are unknown parameters and will be estimated together with those in (1). In words, the entire model structure may shift with the regime as the constant, the autoregressive parameters, and the volatility parameters may be affected. The restriction implicitly imposed (that the switch occurs simultaneously in all variables) is no more restrictive than the one employed in MS-BVAR or TV-BVAR models.

The covariance matrix of the reduced form disturbances $\Omega_{it}^{1/2}$, $i = 0, 1$, is time varying and evolves according to:

$$\Omega_{it} = A_i^{-1} H_t (A_i^{-1})' \tag{3}$$

where the H_t process is defined by:

$$H_t = \lambda_t \Sigma \tag{4}$$

with Σ being a diagonal matrix with constant elements:

$$\Sigma = \begin{bmatrix} \sigma_1^2 & 0 & \ldots & 0 \\ 0 & \sigma_2^2 & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & \ldots & \sigma_{dim(Z)}^2 \end{bmatrix} \tag{5}$$

and $\sigma_j^2 > 0$ for $j = 1, \ldots, dim\,(Z)$, while λ_t is a stationary $AR(1)$ process with drift:

$$ln\lambda_t - \mu = F\,(ln\lambda_{t-1} - \mu) + \eta_t \tag{6}$$

with $0 < F < 1$ and $\eta_t \sim i.i.d.N\,(0, Q)$.

Notice that there is a single scalar process governing the time varying volatility of the system (Carriero *et al.*, 2016; Alessandri and Mumtaz, 2019). We do so to achieve a more parsimonious representation of the volatility present in the data relative to the one used by others in the literature (see e.g. Primiceri (2005), Canova and Pérez Forero (2015), among others). Notice also that the time varying volatility directly affects the level of the variables (see Mumtaz and Zanetti (2013)), much in the spirit of a GARCH-M specification. Following Alessandri and Mumtaz (2019) we interpret λ_t as the average level of uncertainty present in the economy. The fact that shocks have time-varying volatility is desirable as we include in the VAR a number of financial variables, and their direct effect on the endogenous variables adds to the non-linearity associated with the regime switching.

The contemporaneous relationships coefficient matrices A_1 and A_2 are, in general, non-triangular which make sampling from their posterior distribution generally complicated. In our case, they are characterized by a set of sign and zero identification restrictions. We collect the free parameters present in A_i into the vector α_i, so that for $i = 1, 2$ $vec(A_i) = S_A \alpha_i + s_A$, where S_A and s_A are matrices of 0s and 1s. Such a transformation is useful to sample the full parameter vector α_i jointly, see Canova and Pérez Forero (2015).

As it is standard in the literature, we assume that a (contractionary) conventional monetary policy shock is engineered through a surprise increase in the short term nominal interest rate. We also assume that the shock has no effect within the month on industrial production growth and the unemployment rate and that it produces a decrease in money growth and in inflation. The instantaneous responses of the other variables are unrestricted. We impose a negative contemporaneous correlation between the short term nominal interest rate and the monetary aggregate following Uhlig (2005), among others, and impose restrictions on the response of real activity only contemporaneously. After one period, all responses are unrestricted.

We also identify an (expansionary) unconventional monetary policy shock. Such a shock is effectively an increase in the amount of money in circulation and it is engineered through a decrease in the long term rates. To make sure that the expansionary shock is not sterilized by an increase in the short term rate, which would be automatically produced when, e.g. monetary policy is conducted with a Taylor rule, we require the short term nominal interest rate not react for 24 months after the shock. This way, monetary policy actions are consistent across maturities. The exact time span over which the short term interest rate is keep constant is irrelevant for the results, as long as a minimum of 12 months is assumed. The liquidity disturbance we identify is a *Delphic Forward Guidance* shock in the terminology of Campbell *et al.*, 2012; Jarociński, 2021; Andrade and Ferroni, 2021. Such a shock has also no effect on real activity or inflation within a month, while the response of commodity prices growth and stock prices growth are unrestricted.

We summarize the identification restrictions in table 1; a ? indicates an unrestricted coefficient. The remaining six shocks of the system are not given a structural interpretation [1].

Variable - Shock	Conventional Monetary Policy	Liquidity
IP growth	0	0
PCE Inflation	≤ 0	0
Unemployment	0	0
Interest Rate	> 0	0 (24 months)
Slope Yield Curve	?	≤ 0
Money growth	< 0	> 0
Commodity price growth	?	?
SP500 growth	?	?

Table 1: Identification restrictions.

Because we normalize liquidity shocks to be expansionary in both regimes, one may wonder why a central bank would surprisingly expand the money supply when inflation is high. Since the sign of the shocks does not matter within a regime, what we present below is the mirror image of what would happen comparing an expansionary liquidity shock in the low inflation regime and the negative of a contractionary liquidity shock in the high inflation regime [2].

Discussion The uncertainty indicator is an important building block in our empirical model and its use as regressor in (1) requires some discussion. As in Alessandri and Mumtaz (2019) we use a model-based measure of uncertainty directly linked to the agents' inability to form predictions about the fundamentals. This allows us to avoid resorting to proxies that are at best weakly related to macroeconomic predictability, such as the VIX index. Relative to the factor model employed by Jurado *et al.* (2015), the volatility- in-mean specification has the advantage of modeling the economy's first and second moments in a unified and consistent manner. According to our specification, agents form expectations treating uncertainty as an ordinary state variable: they estimate λ_t , project it forward using its persistence, and take into account its influence on the economy (when $\gamma_{ij} \neq 0$). Clearly, this would not be possible in a two-step procedure where uncertainty is first estimated using a forecasting model and then linked to macroeconomic fundamentals through a separate set of regressions. This advantage

[1] The A_i matrices with the full set of identification restrictions are presented in Appendix A.

[2] Although not entirely relevant here, one should also remember that the level of liquidity may be decreasing when the inflation is high, because of an endogenous feedback rule, even when its innovations are expansionary.

comes at the cost of a dimensionality increase, and we are forced to jointly model the dynamics of only a limited number of variables. We supplement our analysis when needed by using the identified shocks in local projection exercises. We conjecture that the costs of this sequential approach is quantitatively relatively small given the arbitrage and theoretical relationships between first round and second round variables. The volatility-in-mean feature also takes our set up closer to the theoretical literature. In our model uncertainty (i) stems from the volatility of the structural shocks, (ii) follows an AR(1) process, and (iii) is exogenous. Thus, it closely resembles the reduced-form of a DSGE model with stochastic volatility even though our setup considers the average volatility of all shocks rather than the volatility of a specific structural shock; and the threshold structure neglects interaction terms that would arise in high-order (unpruned) perturbed solutions of a nonlinear DSGE model.

Once the posterior distribution of the parameters is available, we compute responses as differences between conditional expectations obtained by simulating the model under a shock scenario and under a no-shocks scenario. For a given initial regime (S = 0 , 1) and a regime-specific history (Y^S_{t-1}), the responses are defined as $IRF^S_t = E(Y_{t+k}|\Psi_t, Y^S_{t-1}, \nu_t) – E(Y_{t+k}|\Psi_t, Y^S_{-1})$, where Ψ_t represents all the parameters of the model, $k = 1, 2, \ldots$ is the horizon and ν_t denotes the structural shock of interest. Notice two important features of the IRFs we calculate. First, the switch among regimes is treated as endogenous. Thus, the economy may freely transit from low to a high inflation regime and vice versa over the simulation horizon, depending on the sign and size of the shocks. This is different from the standard calculations performed in regime dependent models where responses are computed conditional on remaining in the same initial state over all horizons. The latter should be taken with caution as it tends to overestimate the difference across regimes , especially in the long run. Second, even within a given initial regime S, the responses depend on the specific history prior to the shock (Y^S_{t-1}). Thus, the economy may respond differently when inflation is zero and when it is just above that value, even though both belong to the "low inflation" regime. The numbers we report measure the average responses in each regime. That is, the responses in the low inflation regime (high inflation regime) are calculated averaging the response to the shock of interest across all histories (Y^S_{t-1}) belonging to regime S = 1 (S = 0). The numerical details regarding the computation of impulse responses are in the appendix B.

Unexpected changes in monetary policy are generally interpreted in the literature as reflecting an exogenous tightening or loosening of the monetary stance. The underlying assumption is that private markets and the central bank share the same information so that any market reaction must reflect shifts in the central bank's policy stance. However, if the central bank has access to private information or processes public information more efficiently, monetary policy surprises may also reveal information about the economic outlook, see Miranda Agrippino and Ricco (2021). In this case, interest rate shocks could reflect an information shock, whereby markets upgrade their expectations about the outlook and price-in an endogenous monetary policy tightening. Disentangling these channels is important because a positive interest rate surprise produced by an information shock may have different effects on economic activity. To shed light on this issue, we leveraged the response of financial variables at the time innovations take place, see also Jarocinski and Karadi (2020). In particular, an innovation carrying positive information about future economic outlook should persistently boost equity valuation and/or twist the slope of the term structure of interest rate as inflation expectations may be affected. As the next section shows, such an effect is indeed present in certain states of the world.

4 Bayesian Estimation

Estimation of the model is performed with Bayesian methods. Given a prior for the parameters and the likelihood function, and conditional on the data, we combine the two pieces of information to construct the posterior distribution of Θ using Bayes' theorem:

$$p\left(\Theta \mid Z^T\right) \propto p\left(Z^T \mid \Theta\right) p\left(\Theta\right) \tag{7}$$

where $\Theta = \left\{P^*, d, \Phi_{1:2}, \alpha_{1:2}, \sigma^2_{1:dim(Z)}, \lambda^T, \mu, F, Q\right\}$. Let Θ/χ denote the vector of parameters, excluding the parameter χ. Let $k = 1$ and denote with K the total number of draws.

We compute a numerical approximation to the posterior distribution using a Gibbs sampler. The steps are as follows:

1. Draw $p\left(P^* \mid \Theta/P^*, Z^T\right)$ with a Metropolis-Hastings step.
2. Draw $p\left(d \mid \Theta/d, Z^T\right)$ from a multinomial distribution.
3. Draw $p\left(\Phi_i \mid \Theta/\Phi_i, Z^T\right)$ from a (truncated) normal distribution, $i = 1, 2$
4. Draw $p\left(\alpha_i \mid \Theta/\alpha_i, Z^T\right)$ using a Metropolis-Hastings step, $i = 1, 2$
5. Draw $p\left(\sigma^2_j \mid \Theta/\sigma^2_j, Z^T\right)$ from an inverse-gamma distribution, $j = 1, \ldots, dim(Z)$
6. Draw $p\left(\lambda^T \mid \Theta/\lambda^T, Z^T\right)$ using a Single-Move Kalman Smoother
7. Draw $p\left(\mu \mid \Theta/\mu, Z^T\right)$ from a normal distribution
8. Draw $p\left(F \mid \Theta/F, Z^T\right)$ from a truncated normal distribution
9. Draw $p\left(Q \mid \Theta/Q, Z^T\right)$ from an inverse-gamma distribution

10. Set $k = k + 1$ and return to Step 1. If k=K stop.

We set $K = 100,000$ and discard the first $50,000$ draws to insure convergence. To reduce the serial correlation across draws, we keep 1 every 10 draws and discard the remaining ones. As a result, we have $5,000$ posterior draws for conducting inference. Details on the steps of the Gibbs sampling algorithm are contained in the on-line appendix A.

5 Estimation results

We start by presenting the posterior estimates of some relevant parameters. Figure 3 plots US PCE inflation and the estimated indicator for the high inflation regime. As it is standard, we compute the posterior mean of S_t (call it $\tilde{S}_t$) and a bar is plotted at that t if $\tilde{S}_t \leq 0.5$.

The model selects as high inflation regime the two bursts of inflation in the earlier part of the sample (1973-1975 and 1977-1983) and the post Covid19 period. Interestingly, neither the end of the 1960s nor the early 1990s, two periods in which inflation was higher than average, are considered high inflation periods by the model.

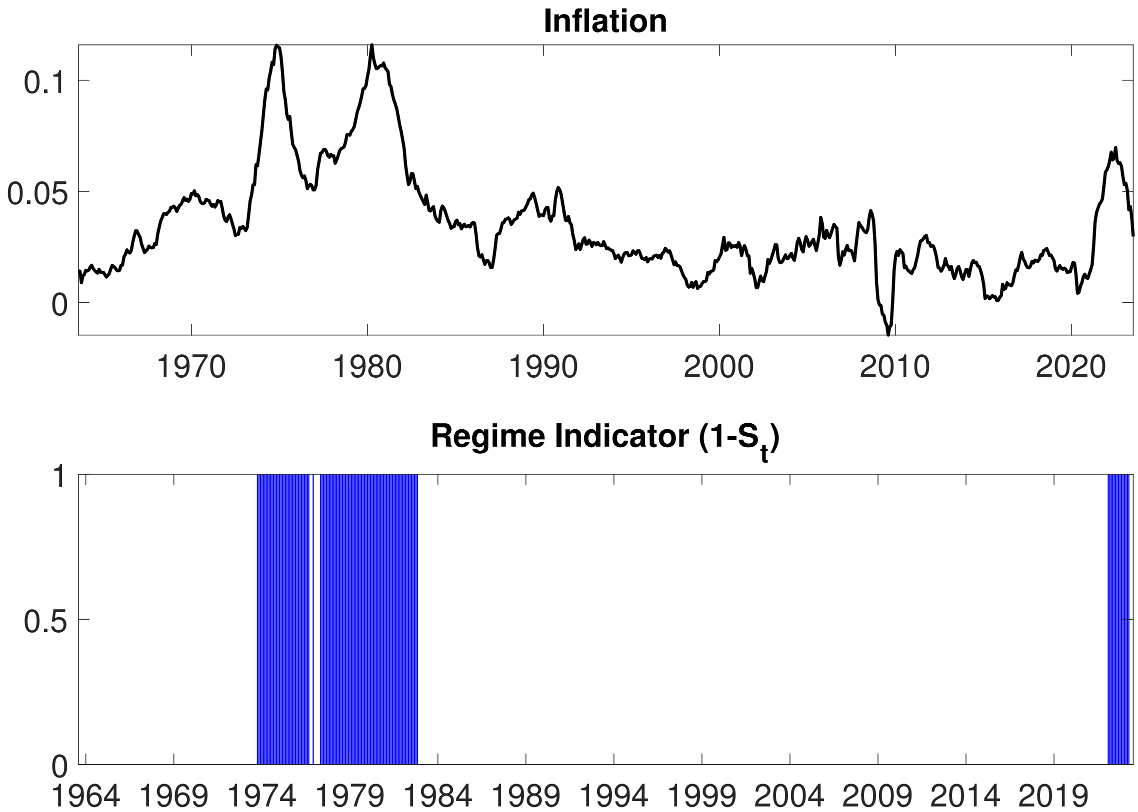


Figure 3: US Inflation and estimated regime indicator, sample 1960-2023.

Figure 4 plots the posterior distribution of the threshold parameter P^*. The distribution is highly concentrated around a 5.3 percent annual inflation rate and the posterior minimum and maximum values are less than 0.1 of this central value. Thus, the data seem to be very informative about the level of this threshold which, incidentally, is twice as large as the mean value for the sample and close to the value estimated by Pfauti (2023) using survey data. As a consequence the high inflation regime has a much smaller number of observations than the low inflation regime; and it is rare, in the sense that the observations belonging to this regime are in the very upper tail of the distribution of inflation.

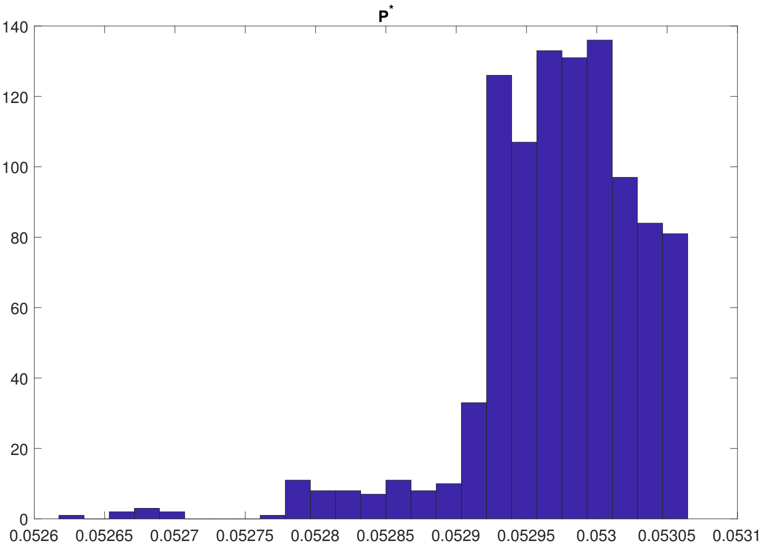


Figure 4: Posterior distribution of threshold parameter P^*.

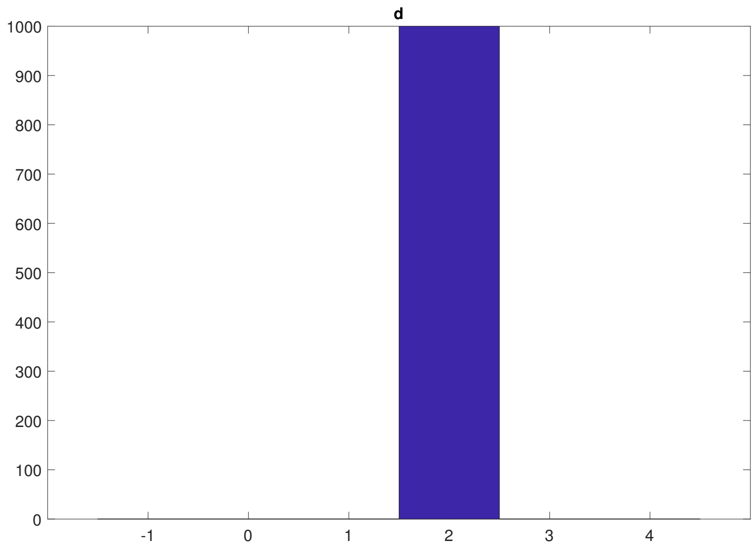


Figure 5: Posterior distribution of the delay parameter d.

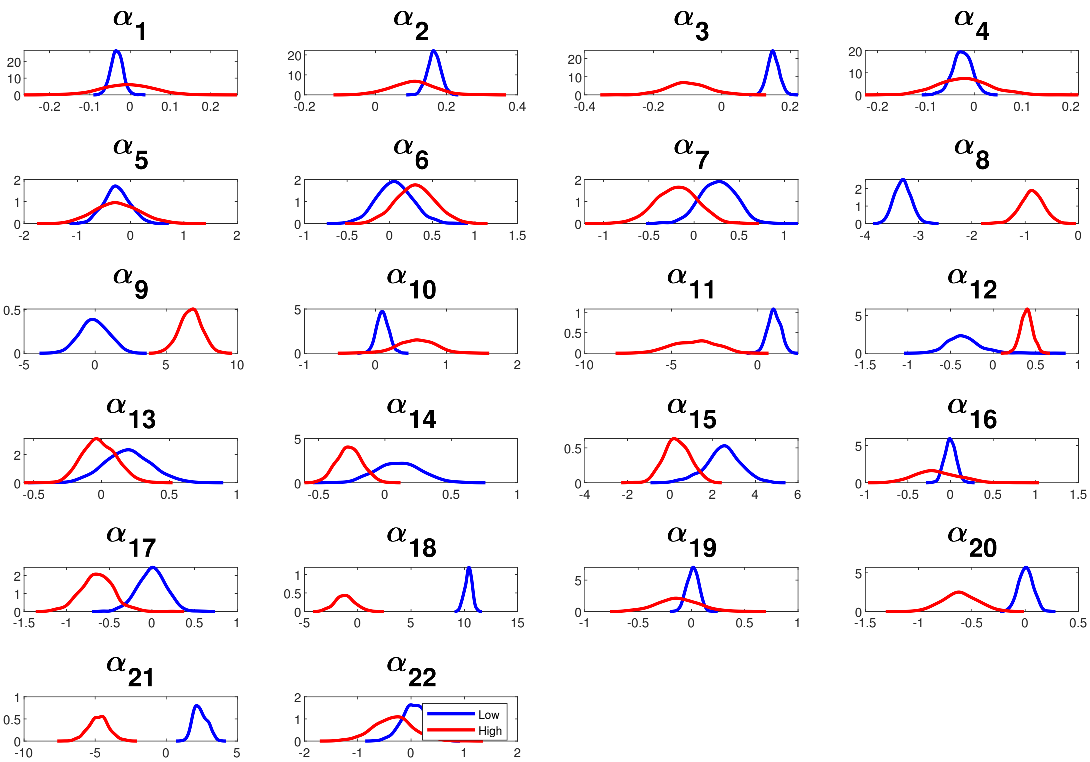


Figure 6: Posterior distributions of α in the two regimes.

The data seems also very informative about the delay parameter d. Notably, the model structure shifts from one regime to the other two periods after the inflation rate has crossed the 5.3 percent level. Once again, posterior uncertainty is negligible, see figure 5. Thus the data is very informative about both the location and the timing of the two inflation regimes.

Figure 6 plots the posterior distribution of the contemporaneous parameters α_i, $i = 0, 1$. Recall that these parameters govern the impact effect of the shocks (they are the free entries of the matrices A_i). Hence, sign difference in the location or magnitude discrepancies in the spread of the posterior distribution of some parameter provide preliminary evidence that changes in the instantaneous transmission of monetary policy shocks have occurred across regimes.

Indeed, the posterior distributions of some key parameters differs in the two states. For example, the posteriors of α_1 to α_4 are relatively flatter in the high inflation regime; while for α_8 and α_{18} the location of the posterior changes. Since patterns of this type are also present in the estimated distribution of some of the autoregressive parameters, we expect important and economically significant changes in the transmission mechanism of identified shocks across regimes.

5.1 The uncertainty indicator

Although it is not the focus of our interest, it is worth briefly discussing how the posterior distribution of the uncertainty indicator evolves over time. As mentioned, the indicator measures the average uncertainty in the system and it is assumed to be exogenous to the first moments of US economic variables. Thus, it can not be directly compared with proxy measures such as the VIX of Bloom (2009), the excess bond premium of Gilchrist and Zakrajšek (2012) or the government debt to GDP ratio of Mumtaz and Surico (2018). Furthermore, since the vector of VAR variables include series not typically considered (such as M2), our measures has independent interest.

Figure C.16 in Appendix C presents the median and the robust 68% credible posterior intervals of the distribution of λ_t at each t [3]. The volatility measure captures the massive uncertainty present in the COVID period. Thus, it filters out the excess volatility due to this huge outlier from the dynamics induced by the two structural shocks. It also captures two other episodes of marked and generalized uncertainty: the early 1970s, when the first oil crisis hit the US economy, and the mid 1980s, when the growing budget deficits following tax cuts to stimulate supply side expansions were implemented. For all other periods the index is randomly fluctuating around the mean value with small absolute variations and does not display any momentum, e.g., around 2008 or the 2001 dotcom bubble. Thus, in our system, λ_t serves a different purpose than the uncertainty measures employed in the literature [4].

To confirm this impression figure C.17 in the on-line Appendix C plots the component of inflation at each t predictable solely on the basis of λ_t. The indicator is active as inflation predictor only in the three above mentioned periods and quiescent in all the others. Furthermore, in all three episodes it accounts for about two percent of the inflation surge. Thus, it is important to include it in the specification both to absorb excess inflation volatility and to account for inflation dynamics in the high inflation state.

5.2 The time path of estimated monetary policy shocks

Our estimation procedure produces as output the posterior distribution of the estimated monetary policy shocks at each t. These distributions can be used as a sanity checks to evaluate the reasonableness of our identification procedure. Figures C.21 and C.22 plot the time series of the median and of the robust 68 percent bounds over time. The conventional monetary policy

[3]We use the approach of Giacomini and Kitigawa (2021) to construct such bounds

[4]The on-line Appendix C also reports the posterior distributions of the autoregressive parameter F, of the mean parameter μ, and for the variance parameter Q of the λ_t process.

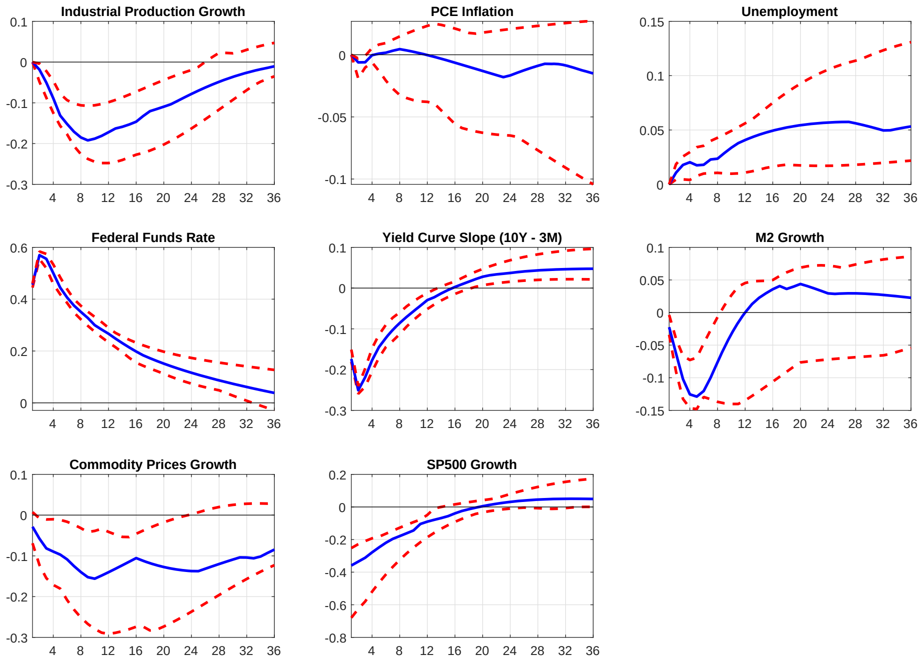


Figure 7: Responses to contractionary conventional policy shocks, linear model.

shock was volatile in the 1970s and in the first part of 1980s and again at the end of the sample. Interestingly, in agreement with the conventional wisdom, the time series indicates that monetary policy was expansionary in 1975 and 1979 and contractionary in 1973, 1976 and 1982. For the latest period, conventional monetary policy was somewhat expansionary in 2020-2021 and it became quite restrictive in 2022.

The liquidity shock also displays high volatility around the same dates. However, its fluctuations are in general smaller than those of the conventional shocks and, except for the 2020-2021 period, when the posterior distribution was primarily on the positive side, it generally fluctuates randomly with the 68% credible bounds including the zero line.

6 The propagation of monetary policy shocks

6.1 The linear model

As a benchmark, we first present the dynamics in response to the two identified monetary policy shocks in a standard linear SVAR model, see Figures 7 and 8.

The transmission of conventional policy shocks is standard. A surprise increase in the short-term nominal interest rate temporarily decreases production growth, persistently increases unemployment, depresses the stock market growth up to two years and slowly transmits to inflation and

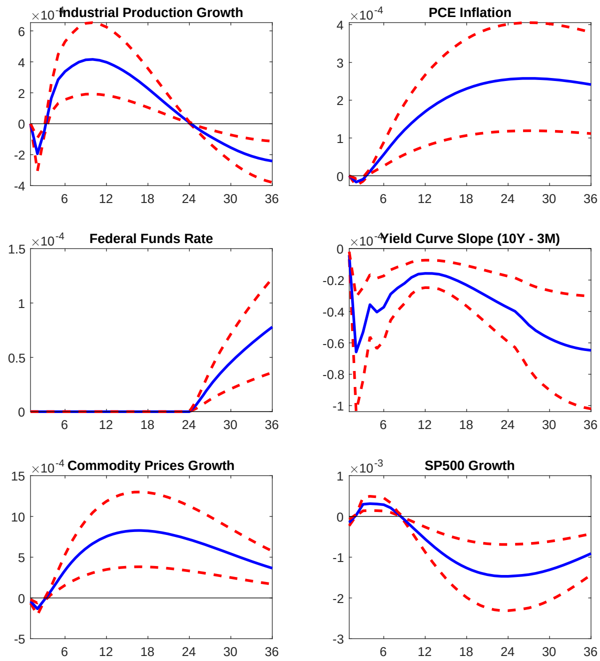


Figure 8: Responses to expansionary liquidity shocks, linear model.

to commodity prices, which fall only after a delay. Notice that M2 growth temporarily decreases and that the long-term interest rate increases but less than the short-term rate.

The transmission of liquidity shocks, not neutralized by short-term interest rate increases, is also standard. Output growth increases and unemployment falls, although with a delay of about 5-6 months; inflation and commodity prices persistently increase, while the long-term rate falls and the shock growth temporarily increases. Notice that, the qualitative features of the dynamics would not have changed, had the short-term rate be allowed to move, except that the stock growth response would have been insignificant and the effect on production growth and unemployment would materialize earlier, see figure C.15 in the on-line appendix C.

6.2 The state dependent model

We present the effect of a one standard deviation surprise increase in the short -term rate in the two regimes in figure 9. The lines represent the median and the robust 68% credible interval of the posterior distribution at each horizon. The propagation of shocks across regimes is qualitatively similar to those of the linear model. The disturbance generates a fall in industrial production growth, an increase in the unemployment rate and a temporary fall in inflation. Stock prices growth fall and commodity prices also fall.

Quantitatively, the effects across regimes however differ. The largest impact on industrial

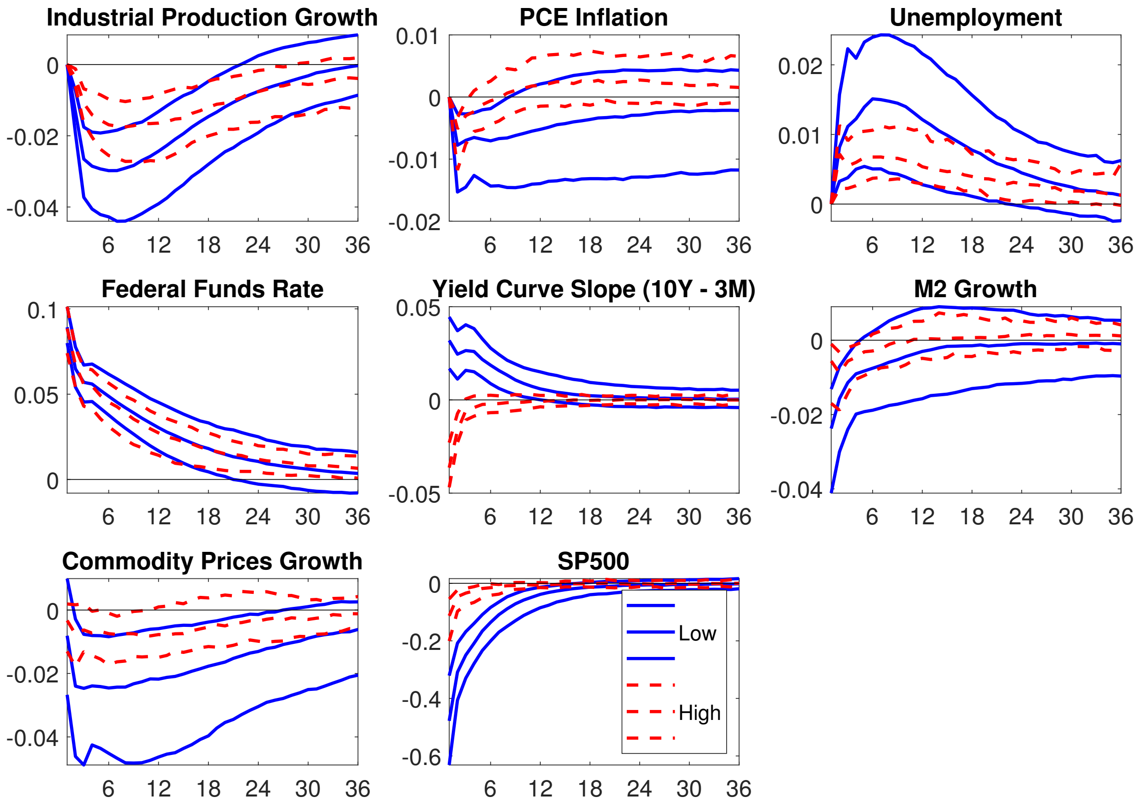


Figure 9: Contractionary conventional monetary policy shocks, different regimes.

production growth and unemployment in the low inflation regime exceeds the one in the high inflation regime but the persistence of the real responses is stronger in the latter state. Similarly, stock prices fall more in the low inflation regime. Overall, a surprise increase in the short-term rates has somewhat muted but longer lasting effects on economic prospects in the high inflation regime.

These quantitative differences in the transmission are in line with dynamics of the term structure of interest rates. In fact, while in the low inflation regime the increase in the short-term interest rate is accompanied by a larger increase in the long-term interest rate at all horizons, this is not the case in the high inflation regime. Long-term interest rates increase also in this case but not by as much as in the low inflation regime. The inversion of the yield curve in the low inflation regime is consistent with the idea that the central bank possesses more information about the future path of inflation. The signal the shock provides is thus valuable to private agents which adjust their inflation expectations correspondingly. To put this idea differently, a surprise increase in the short-term nominal interest rate in a low inflation regime is not interpreted by financial markets as shift in the policy stance. Instead, it is perceived as providing information

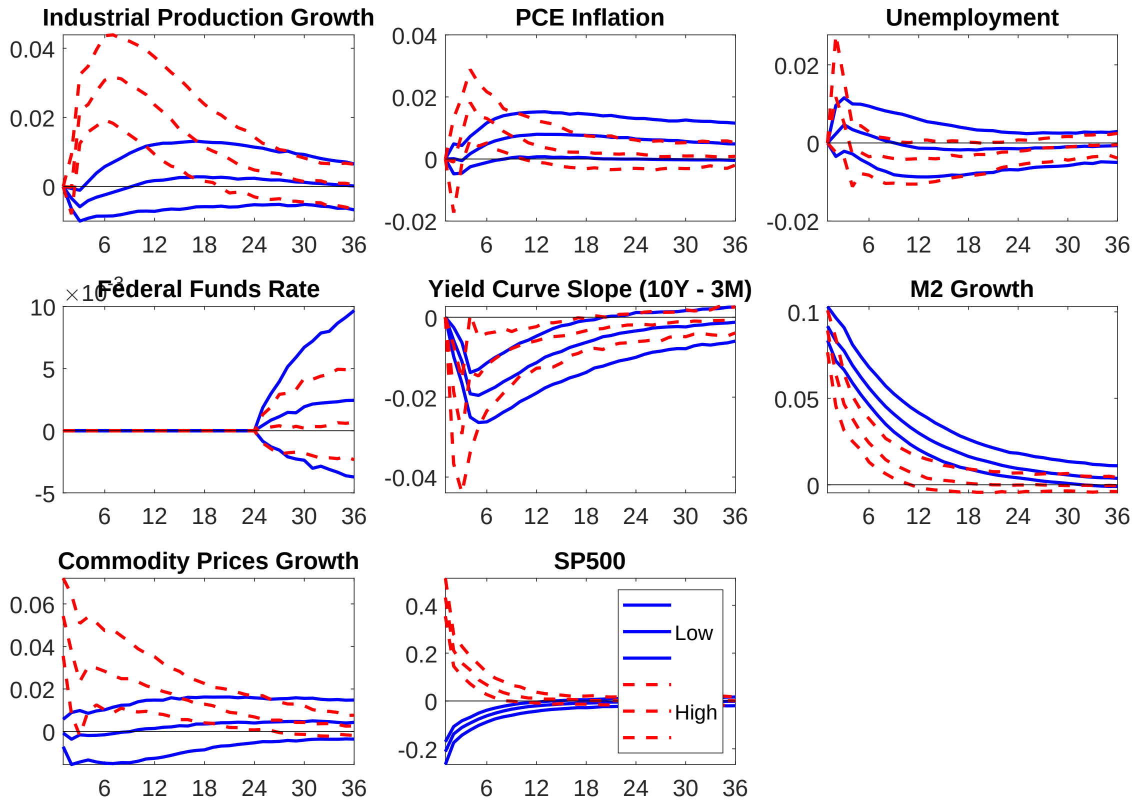


Figure 10: Expansionary liquidity shocks, different regimes.

that the inflation in the future is going to be higher than expected over the relevant policy horizon. The signaling effect of a conventional monetary policy shock is stronger when inflation is low probably because, when inflation is high, increases in short term rates are already factored in by private agents. That is, private agents believe that the central bank will fight the inflation increase over and above what is dictated by the monetary policy rule. This signaling effect we detect is similar to the one empirically documented in Miranda Agrippino and Ricco (2021) and Jarocinski and Karadi (2020), see also Melosi (2017) for a model with this feature. The main finding here is that the mechanism appears to be regime dependent. Notice also that while the dynamics across regimes could also be consistent with the idea that the credibility of central bank actions changes with the level of inflation, such an explanation is at odds with current perceptions about how US monetary policy has been conducted over the last forty years.

Figure 10 presents the responses to a pure liquidity disturbance. The magnitude and the sign of the dynamic responses now differ across regimes. In the low inflation regime a liquidity shock, which is not sterilized by an automatic increase in the short-term interest rate, does not have any significant effect on inflation and the unemployment rate. Industrial production growth temporarily falls, and the long-term interest rate and stock prices growth fall as well. Thus, in the low inflation regime, surprise increases in the balance sheet of the central bank, engineered through purchases of long term assets, have close to negligible real effects; do not significantly affect inflation; and produce a somewhat negative repercussions in financial markets.

Liquidity expansions in the high inflation regime instead boost industrial production growth, increase inflation, while leaving the unemployment rate roughly unchanged. The different dynamics of production growth is reflected in the response of SP500 growth, which are now significantly positive at all horizons. Thus, when inflation is high, a surprise increase in the balance sheet of the central bank is interpret as good news by the stock market. While inflation temporarily inches up, the asset purchase is seen by private agents as potentially boosting the profitability of firms and thus stock valuation. This interpretation is supported by the dynamics of unemployment rate. While the responses of unemployment are insignificant in both regimes, the median fall in the high inflation regime is larger at all horizons.

6.3 The role of λ_t

One question of interest is whether the differences across regimes we obtain depend on the presence of the uncertainty indicator among the VAR predictors. As mentioned, the use of the λ_t as a regressor is one of the key differences between our work and Gargiulo *et al.* (2024).

To analyze the issue, we have estimated the model dropping λ_t from the list of the independent variables of the model. Figures D.23 and D.24 in on-line Appendix D indicate that both the timing of the two states and posterior distribution of the threshold P^* are unaffected if a more traditional model, which excludes λ_t from the list of VAR regressors, is estimated.

With the specification that abstracts from the direct effect of λ_t on the endogenous variables we have also computed regime dependent impulse responses to the two structural shocks. The results are in figures D.25 and D.26 in on-line Appendix D. Having λ_t directly entering the specification is important. If it is omitted, the error bands become large making the responses in the two states insignificantly different. Furthermore, the informational effects previously described disappears for liquidity shocks and, for conventional monetary policy shocks, there is no slope inversion. Thus, it is important to control for the general level of uncertainty to find significant differences in the responses across regimes.

6.4 Counterfactuals

To evaluate the role of signaling in the transmission of monetary policy shocks we conduct a simple counterfactual exercise. We ask what would happen to the endogenous variables if: i) the

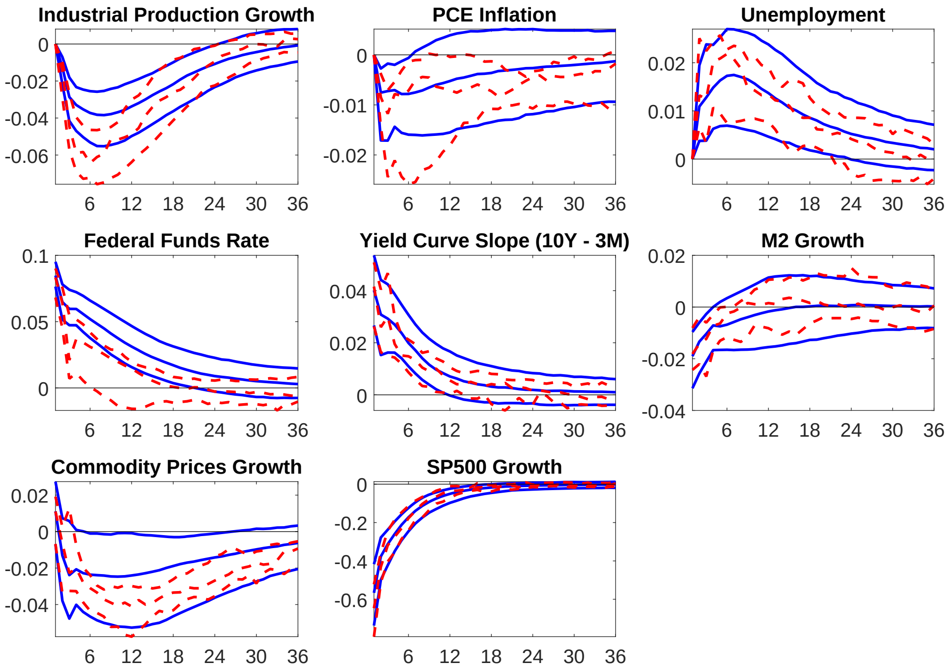


Figure 11: Counterfactual contractionary conventional monetary policy shocks, different regimes.

dynamics of the slope of the term structure in response to conventional policy shocks, and ii) the dynamics of stock prices growth in response to liquidity shocks, would be forced to be the same in the two inflation states. If the mechanism driving the differences is indeed the asymmetric signal effect that shocks have on financial markets, then forcing financial variables to display the same reaction across regimes should make differences in the remaining endogenous variables insignificant.

The counterfactual responses are in Figures 11 and 12. In the case of conventional monetary policy disturbances the dynamics of industrial production growth, unemployment and inflation are insignificantly different across inflation states, although now the median response of industrial production growth is more negative in the high inflation regime. For liquidity shocks, differences across inflation states are quantitatively and qualitatively insignificant. Hence, the information effect we emphasize seems crucial: without it the transmission of policy shocks would be state independent and the dynamics in response to both types of policy shocks roughly linear.

6.5 The reaction of inflation expectations

Crucial to the narrative that Figure 9 suggests is the reaction of inflation expectations to conventional monetary policy shocks. In particular, if the signaling story has some appeal

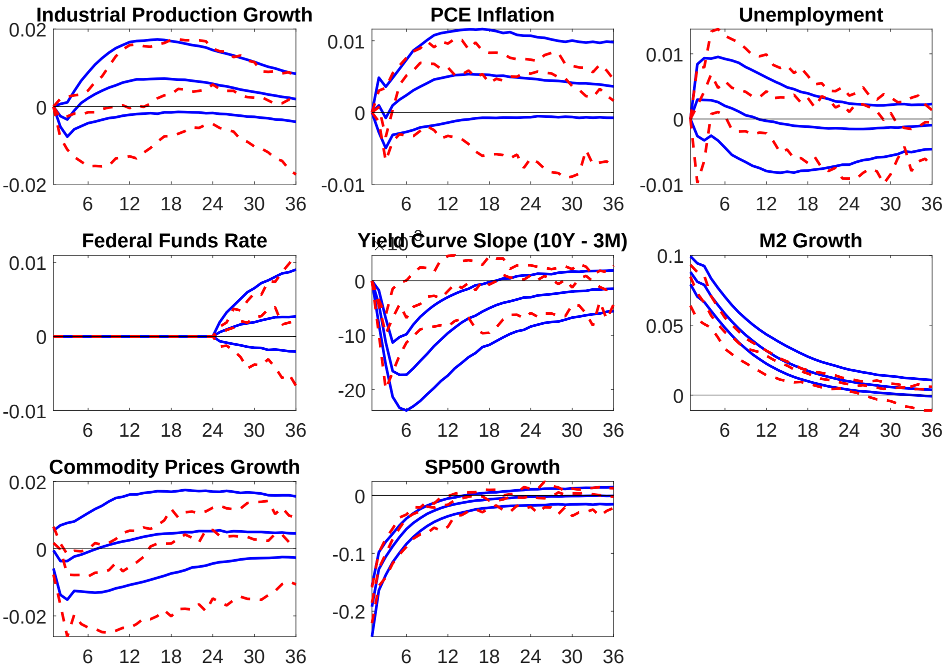


Figure 12: Counterfactual expansionary unconventional monetary policy shocks, different regimes.

inflation expectations should significantly react in the low inflation regime but not in the high inflation regime. To verify this implication we obtained Survey of professional forecast (SPF) data from the Philadelphia Fed and we have ran local projections to compute the dynamics of the median inflation expectation using the posterior distribution of the conventional policy shocks we have recovered. The resulting responses are in Figure 13.

Consistent with the signaling hypothesis, Figure 13 shows that an unexpected increase in the short-term rate produces a significant reaction of one-year ahead CPI inflation expectations in the low inflation regime. The effect is positive for two months and turns negative after that. On the contrary, the response of CPI inflation expectations in the high inflation regime is insignificant at all horizons. These outcomes are robust to the measure of expectations employed: substituting one year ahead GDP deflator expectations or longer term inflation expectations lead to the same qualitative conclusion. Interestingly, the response of CPI inflation expectations to liquidity shocks is insignificantly different from zero in both regimes (see Figure E.27 in the on-line appendix E) and this lines up well with the similar response of the slope of term structure in the two regimes.

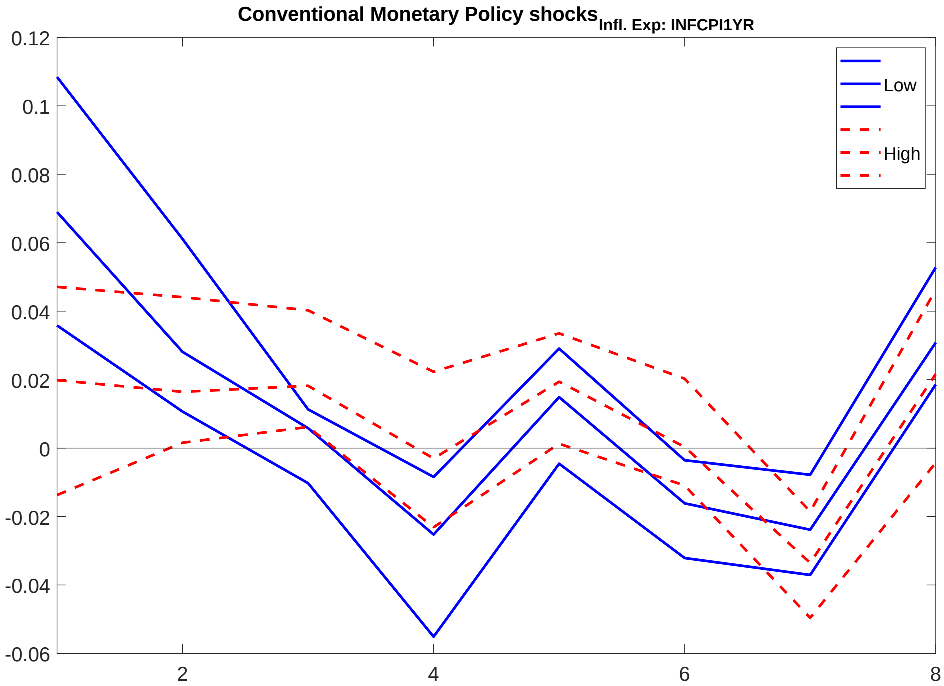


Figure 13: Responses of CPI inflation expectations, conventional policy shocks, different regimes

This evidence is consistent with the findings in Fisher *et al.* (2024). However, we qualify their conclusions by showing that i) short-term inflation expectations are responsive to conventional policy shocks, and ii) that their dynamics is regime dependent. Our results also suggests that deviations from rationality are smaller than those they estimate, perhaps because we condition on identified monetary policy shocks, while theirs analysis is unconditional.

6.6 Robustness

We have estimated versions of the baseline model to examine the robustness of the conclusions we have reached. Here we briefly discuss the outcomes obtained in three relevant cases [5].

The first variation consists in estimating the model using only the 1984-2019 sample. We want to check whether what we have identified as the low inflation state is actually a mix of two separate states: an average inflation state and a low inflation state, possibly associated with the zero lower bound on interest rates. The regime indicator now picks a 3.3 percent as the threshold for inflation and the normal inflation state occurs in 1986, 1989-1992, 2004, 2006, two quarters in 2008 and two quarters in 2009. Thus, the likelihood function does not focus attention on the zero nominal interest rate period as independent state since the dynamics of

[5]Plots corresponding to the cases discussed in this subsection are available on request from the authors.

the other variables of the system are important to determine P^* and the timing of the states. Furthermore, the dynamics are not statistical different across states in response to conventional and liquidity shocks. We interpret this evidence as suggesting that there is no need to further split the low inflation state in two independent regimes.

The second modification we consider involves dropping food and energy items from the PCE inflation series. Using core inflation attenuates a bit the spikes in inflation observed in the 1970s and in 2021-2022 but does not alter the persistence or the correlation structure of the inflation series. Hence, the estimates of the state indicator coincide with those presented in figure 3 and the role of λ_t in adjusting for the excess volatility in the inflation series is unchanged. The qualitative pattern in response to conventional shocks is maintained. In particular, the response of the slope of the term structure switches sign across inflation regimes although now differences in other variables are only marginally significant. In response to liquidity shocks the response of stock market growth changes sign but bands are quite large and no significance differences are detected. Overall, it seems that the state dependent effects of monetary policy become weaker when food and energy prices are factored out from the PCE inflation indicator.

The final change concerns the role of commodity prices. Since Sims (1992) commodity prices are included in a VAR to proxy for future changes in inflation and to attenuate the so-called price puzzle. The question we are concerned with here is whether the non-linear effects could be due entirely to energy price inflation and the fact that the US is an oil producer. We thus re-estimate the model using WTI oil prices in place of commodity prices. The state indicator now identifies as belonging to the high state 1974-1983, 1989 and 2021-2022. The role of λ_t in predicting inflation is reduced but the uncertainty indicator still has spikes in 1974-1979-1980 and 2021-2022. The responses of oil price inflation to the two identified shocks are positive for contractionary conventional shocks and negative for expansionary liquidity shocks, independent of the state. The qualitative differences for production growth, inflation and unemployment across regimes remain but now they are insignificant. Overall, this evidence suggests that commodity prices are a better indicator for future inflation if one hope to find differences across states in the transmission of monetary policy disturbances.

7 Empirical evidence and theories of inflation

As the evidence of the previous section makes it clear, our results are not very supportive of popular theories of inflation. As mentioned, menu costs and slanted-L theories have sharp implications for the magnitude of the slope of the Phillips curve (PC). Both types of models in fact predict a steeper PC when inflation is high, conditional on any demand shock. This is because when inflation is high, firm should readjust prices more rapidly, making the response of output smaller and the response of inflation larger as menu costs or hiring costs become larger.

Figures 9 and 10 suggest that, if the unemployment rate is used as a measure of real activity, the PC relationship hardly changes across regimes. One potential confounding factor, often discussed in the literature, is the presence of supply disturbances. If these are not properly accounted for, in fact, the relationship between measures of unemployment and inflation do not reflect the slope of the Phillips curve, see Benigno and Eggertsson (2023). This criticism does not apply to our setup since we explicitly examine the dynamics in response to identified monetary policy shocks, rather than regression coefficients where the dependent variable is potentially endogenous. Furthermore, the disturbances we construct are orthogonal by construction to all other shocks of the system, including various potential supply disturbances.

Figures F.28 and F.29 in the on-line appendix F provide complementary evidence using the labor share as measure of real activity [6]. While there are significant differences across regimes about 5 months after the shock in response to conventional disturbances, no statistically significant differences are obtained for liquidity shocks. However, the responses of the slope of the Phillips curve are larger in the low inflation regime, the opposite of what a menu costs theory would imply.

To gain further evidence on the dynamics of the slope of the Phillips curve across regimes, Figures F.30 and F.31 in the on-line appendix F present the responses to the two identified shocks when the vacancy to unemployment rate is used as measure of real activity [7]. While quantitative difference are present, qualitatively, the effects produced with the labor share are unchanged. In particular, there are significant differences across regimes about 5 months after the shock in response to conventional policy disturbances, but the responses are larger in the low inflation regime. Furthermore, no statistically significant differences across regimes are obtained for liquidity shocks.

Turning to rational inattention models, the evidence we collected is somewhat mixed. While the industrial production growth dynamics in Figure 9 are consistent with the evidence in Mackowiak and Wiederholt (2009), the dynamics of inflation expectations in Figures 13 and E.27 do not line up well with the implications of the theory. In fact, while such models predict that inflation expectations should be more responsive when inflation is high, the evidence seems to suggest the opposite, at least in response to conventional policy shocks. For liquidity

[6] Data on the labor share is obtained from the FRED database.

[7] We thank Pierpaolo Benigno for kindly supplying the time series for this variable.

shocks, instead, there is no statistical difference in the response of inflation expectations across regimes.

All in all, the evidence seems broadly consistent with theories emphasizing the signaling role of monetary policy. Our results, however, suggest that the effect occurs only in certain regimes.

8 Conclusions

The paper explored how two types of monetary policy shocks propagate to the economy in high vs. low inflation regimes. We use US data in the investigation and focus attention on conventional policy disturbances - shocks that alter aggregate conditions by changing the short term nominal interest rate - and liquidity disturbances - shocks that alter the quantity of money in circulation by twisting the long end of the slope of the term structure of interest rates.

We conduct the investigation using a Bayesian Threshold Vector Auto-Regressive model with Stochastic Volatility which allows for an endogenous selection of the switching threshold and, thus, of the two states and direct volatility effects on the endogenous variables.

We find significant differences in the transmission of conventional monetary policy disturbances across the two regimes. The peak response of output growth, unemployment and inflation is smaller but the effects lasts longer when inflation is high. The differences seem to be due to the dynamics of the slope of the term structure, which changes sign across regimes: the long term rate increase is larger than short term rate increase at all horizons in the low inflation regime and the opposite is true in the high inflation regime. The slope inversion in the low inflation regime is consistent with the idea that a monetary policy shock has larger informational content about future inflation when inflation is low, which seems reasonable given the long period of low inflation following the great recession.

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 result obtained under the assumption that the central bank keeps the short term interest rate constant for at least 12 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.

We show via counterfactuals that the informational content of monetary policy shocks in certain regimes is non-negligible and that the reaction of inflation expectations is consistent with the theoretical predictions.

The evidence has implication for theories of inflation. In particular, while we find little support for menu costs or slanted-L theories, the dynamics of the financial variables we consider are consistent with the idea that monetary policy disturbances provide information about the future state of the economy to private agents. The twist our paper provides is that the informational content of policy shocks is nonlinear and state dependent. In particular, the signaling effect is stronger when inflation is low for conventional shocks and when inflation is high for liquidity shocks.

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Appendix

A The Gibbs Sampler

The algorithm used to compute the posterior distributions in section 4 uses a set of conditional distributions for each parameter block. Here we provide details about the form these distributions take and how they are constructed.

1. **Block 1**: Draw $p\left(P^{\dagger} \mid \Theta/P^{\dagger}, Z^{T}\right)$: Metropolis-Hastings step (Chen and Lee, 1995)

   We first draw a candidate P^{can} using a random-walk proposal distribution:

   $$P^{can} = P^{\dagger} + \varepsilon^{Z} \tag{A.1}$$

   where $P^{\dagger}$ is the current draw and $\varepsilon^{Z} \sim N\left(0, c_{P}\right)$ where $c_{P} > 0$ is a constant calibrated to yield an acceptance rate between 0.2 and 0.4. To improve the mixing properties of the MCMC algorithm, we use the modified adaptive proposal distribution suggested by Haario *et al.* (2001), taking equation ($A.1$) as a starting point. Then, the acceptance probability is given by the transition kernel:

   $$\alpha\left(P^{can}, P^{\dagger}\right) = min\left\{1, \frac{p\left(P^{can} \mid P^{\dagger}, \Theta_{-P^{\dagger}}\right)}{p\left(P^{\dagger} \mid P^{can}, \Theta_{-P^{can}}\right)}\right\} \tag{A.2}$$

   where the posterior $p\left(P^{\dagger} \mid \Theta_{-P^{\dagger}}\right)$ is:

   $$p\left(P^{\dagger} \mid \Theta_{-P^{\dagger}}\right) = L\left(P^{\dagger}, \Theta/P^{\dagger} \mid Z^{T}\right) \times p\left(P^{\dagger}\right) \tag{A.3}$$

   and $L\left(P^{\dagger}, \Theta/P^{\dagger} \mid Z^{T}\right)$ is the likelihood function of the model as described in equation (1) and $p\left(P^{\dagger}\right)$ is the prior distribution for the parameter vector.

2. **Block 2**: Draw $p\left(d \mid \Theta/d, Z^{T}\right)$ from a discrete multinomial distribution (Chen and Lee, 1995)

   The conditional posterior distribution for d is a discrete multinomial with conditional probability

   $$p\left(d \mid \Theta/d, Z^{T}\right) = \frac{L\left(d, \Theta/d \mid Z^{T}\right)}{\sum_{d=1}^{d_{max}} L\left(d, \Theta/d \mid Z^{T}\right)} \tag{A.4}$$

   where we set $d_{max} = 6$ and $L\left(d, \Theta/d \mid Z^{T}\right)$ is the likelihood function, as described in equation (1).

3. **Block 3**: Draw $p\left(\Phi_i \mid \Theta/\Phi_i, Z^T\right)$ from a normal distribution, $i = 0, 1$

   Given the model in (1), we take the SUR transformation as in Koop and Korobilis (2010). In particular, let $\phi_i = vec\left(\Phi_i\right)$. Given the prior $p\left(\phi_i\right) = N\left(\underline{\phi}_i, \underline{V}_i\right)$, then the conditional posterior distribution of ϕ_i is:

$$p\left(\phi_i \mid \Theta/\phi_i, Z^T\right) = N\left(\overline{\phi}_i, \overline{V}_i\right) I\left(\phi_i\right) \tag{A.5}$$

   where $I\left(.\right)$ is the prior truncation for stationary draws, and

$$\overline{V}_i = \left(\underline{V}_i^{-1} + \sum_{t=p+1}^{T} X_t' \Omega_{it}^{-1} X_t\right)^{-1} \tag{A.6}$$

$$\overline{\phi} = \overline{V}_i \left(\underline{V}_i^{-1} \underline{\phi}_i + \sum_{t=p+1}^{T} X_t' \Omega_{it}^{-1} Z_t\right) \tag{A.7}$$

   where $X_t = x_t' \otimes I_{dim(Z)}$ and $x_t = \left[Z_{t-1}', \ldots, Z_{t-p}'\right]'$. In addition, $\Omega_{it} = A_i^{-1} H_t A_i^{-1\prime}$ as in equation (3) and $H_t = \lambda_t \times S$ as in equation (4).

4. **Block 4**: Draw $p\left(\alpha_i \mid \Theta/\alpha_i, Z^T\right)$ from a normal distribution, $i = 0, 1$

   Consider the reduced-form residual $\varepsilon_{it} \sim i.i.d.N\left(0, \Omega_{it}\right)$ of the BVAR in equation (1), where $\Omega_{it} = A_i^{-1} H_t A_i^{-1\prime}$ and A_i takes the form[8]:

$$A_i = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \alpha_{1,i} & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \alpha_{2,i} & \alpha_{6,i} & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \alpha_{12,i} & 1 & \alpha_{16,i} & 0 & 0 \\ \alpha_{3,i} & \alpha_{7,i} & 0 & \alpha_{13,i} & \alpha_{17,i} & 1 & 0 & 0 \\ \alpha_{4,i} & \alpha_{8,i} & \alpha_{10,i} & \alpha_{14,i} & \alpha_{18,i} & \alpha_{20,i} & 1 & 0 \\ \alpha_{5,i} & \alpha_{9,i} & \alpha_{11,i} & \alpha_{15,i} & \alpha_{19,i} & \alpha_{21,i} & \alpha_{22,i} & 1 \end{bmatrix} \tag{A.8}$$

   The standardized innovations are $A_i \varepsilon_{it} = \tilde{\varepsilon}_{it}$. Recall that $vec\left(A_i\right) = S_A \alpha_i + s_A$, so that (Canova and Pérez Forero, 2015):

$$vec\left(A_i \varepsilon_{it}\right) = \left(\varepsilon_{it}' \otimes I\right)\left(S_A \alpha_i + s_A\right) \tag{A.9}$$

   As a consequence, define $\tilde{e}_{it} = \left(\varepsilon_{it}' \otimes I\right) s_A$ and $\tilde{x}_{it} = -\left(\varepsilon_{it}' \otimes I\right) S_A$. We then have the following linear-normal regression model:

$$\tilde{e}_{it} = \tilde{x}_{it} \alpha_i + \tilde{\varepsilon}_{it} \tag{A.10}$$

[8] The form of matrix A_i takes the restrictions imposed by Sims and Zha (2006) as a starting point. The 4th and 6th columns are related with conventional and unconventional monetary policy shocks, respectively. The variable order is the same as in Table 1.

Given the prior $\alpha \sim N(\mu_\alpha, \Omega_\alpha)$ we sample the conditional posterior $p\left(\alpha_i \mid \Theta/\alpha_i, Z^T\right)$ using a Metropolis-Hastings step as follows:

- Draw a candidate α_i^{can} from $\alpha_i \sim N\left(\overline{\alpha}_i, \overline{c}\overline{V}_{\alpha_i}\right)$ where $\overline{c}$ is a constant value for targeting the acceptance rate and with

$$\overline{V}_{\alpha_i} = \left(\Omega_\alpha^{-1} + \sum_{t=p+1}^{T} \tilde{x}_{it}' H_t^{-1} \tilde{x}_{it}\right)^{-1} \tag{A.11}$$

$$\overline{\alpha}_i = \overline{V}_{\alpha_i}\left(\Omega_\alpha^{-1}\mu_\alpha + \sum_{t=p+1}^{T} \tilde{x}_{it}' H_t^{-1} \tilde{e}_{it}\right) \tag{A.12}$$

- Accept α_i^{can} with probability τ given by the evaluation of the transition Kernel:

$$\tau\left(\alpha_i^{can}, \alpha_i\right) = min\left\{1, \frac{p\left(\alpha_i^{can} \mid \alpha_i, \Theta_{-\alpha_i}, Z^T\right)}{p\left(\alpha_i \mid \alpha_i^{can}, \Theta_{-\alpha_i^{can}}, Z^T\right)}\right\} \tag{A.13}$$

  see details in Canova and Pérez Forero (2015).

5. **Block 5**: Draw $p\left(\sigma_j^2 \mid \Theta/\sigma_j^2, Z^T\right)$ from a inverse-gamma distribution, $j = 1, \ldots, dim(Z)$

   Variance parameters $\sigma_j^2 > 0$ are simulated using an inverse-gamma distribution. Given the prior $\sigma_j^2 \sim IG\left(d_\sigma \times \underline{\sigma}, d_\sigma\right)$, the conditional posterior distribution is:

$$p\left(\sigma_j^2 \mid \Theta/\sigma_j^2, Z^T\right) = IG\left(d_\sigma \times \underline{s} + \sum_{t=p+2}^{T} u_{j,t}^2, d_\sigma + T - p - 1\right) \tag{A.14}$$

   where residuals are defined as $u_{j,t} = A_1\tilde{e}_{1t}S_t + A_2\tilde{e}_{2t}(1 - S_t)$ for $t = p+1, \ldots, T$.

6. **Block 6**: Draw $p\left(\lambda^T \mid \Theta/\lambda^T, Z^T\right)$ using a single-move Kalman smoother

   Sampling latent variable λ^T is non-trivial, since it also enters in the model as an exogenous variable with contemporaneous and lagged effects. This implies that the state space in non-linear, and the popular multi-move method of Kim *et al.* (1998) cannot be used. Given the complexity of the system, we employ the single-move techniques described in Jacquier *et al.* (1994), among others.

$$f\left(\lambda_t \mid \lambda_{-t}, \Theta_{-\lambda^T}, Z^T\right) \propto f\left(\lambda_t \mid \lambda_{-t}, \Theta_{-\lambda_t}\right) f\left(Z_t \mid \lambda_t, \Theta_{-\lambda_t}\right) \tag{A.15}$$

$$\begin{aligned} f\left(\lambda_t \mid \lambda_{-t}, \sigma_\eta, \phi, \mu\right) = &\quad f\left(\lambda_t \mid \lambda_{t-1}, \lambda_{t+1}, \sigma_\eta, \phi, \mu\right) \\ \Rightarrow &\quad \lambda_t \sim N\left(\lambda_t^* \upsilon^2\right) \end{aligned} \tag{A.16}$$

$$\lambda_t^* = \mu + \frac{F\{(\lambda_{t-1} - \mu) + (\lambda_{t+1} - \mu)\}}{1 + F^2} \tag{A.17}$$

$$\upsilon^2 = \frac{Q}{1 + F^2} \tag{A.18}$$

Given that $\exp(-\lambda_t)$ is a convex function, it is bounded by any linear function in λ_t, so that:

$$\ln f(Z_t, \lambda_t, \sigma_\eta, \phi, \mu) = const + \ln f^*(Z_t, \lambda_t, \sigma_\eta, \phi, \mu) \tag{A.19}$$

$$\begin{aligned} \ln f^*(Z_t, \lambda_t, \sigma_\eta, \phi, \mu) &= -\frac{1}{2}\lambda_t - \frac{Z_t^2}{2}\{\exp(-\lambda_t)\} \\ &\leqslant -\frac{1}{2}h_t - \frac{y_t^2}{2}\left\{ \begin{array}{c} \exp(-h_t^*)(1 + h_t^*) \\ -h_t \exp(-h_t^*) \end{array} \right\} \\ &= \ln g^*(y_t, h_t, \sigma_\eta, \phi, \mu, h_t^*) \end{aligned} \tag{A.20}$$

$$\begin{aligned} f(h_t \mid h_{-t}, \sigma_\eta, \phi, \mu) \times f^*(y_t, h_t, \sigma_\eta, \phi, \mu) \leqslant \; & f_N\left(h_t \mid h_t^*, \upsilon^2\right) \times \\ & g^*(y_t, h_t, \sigma_\eta, \phi, \mu, h_t^*) \end{aligned} \tag{A.21}$$

$$f_N\left(h_t \mid h_t^*, \upsilon^2\right) g^*(y_t, h_t, \sigma_\eta, \phi, \mu, h_t^*) \propto f_N\left(h_t \mid \mu_t, \upsilon^2\right) \tag{A.22}$$

where

$$\mu_t = \lambda_t^* + \frac{\upsilon^2}{2}\left[y_t^2 \exp(-\lambda_t^*) - 1\right] \tag{A.23}$$

We draw a candidate $h_t^c \sim N\left(\mu_t, \upsilon^2\right)$ and accept it with probability α_λ

$$\alpha_\lambda = \min\left\{1, \frac{f_t^*}{g_t^*}\right\} \tag{A.24}$$

7. **Block 7**: Draw $p\left(\mu \mid \Theta/\mu, Z^T\right)$ from a normal distribution. This is standard.
8. **Block 8**: Draw $p\left(F \mid \Theta/F, Z^T\right)$ from a truncated normal distribution. This is standard.
9. **Block 9**: Draw $p\left(Q \mid \Theta/Q, Z^T\right)$ from an inverse-gamma distribution.

The variance parameter $Q > 0$ is also simulated using an inverse-gamma distribution. Given the prior $Q \sim IG\left(d_Q \times \underline{Q}, d_Q\right)$, the conditional posterior distribution is:

$$p\left(Q \mid \Theta/Q, Z^T\right) = IG\left(d_Q \times \underline{Q} + \sum_{t=2}^{T} \eta_t^2, d_Q + T - 1\right) \tag{A.25}$$

where residuals are defined as $\eta_t = (\lambda_t - \mu) - F(\lambda_{t-1} - \mu)$ for $t = 2, \ldots, T$.

A complete cycle around these nine blocks produces a draw of Θ from $p(\Theta \mid Y)$.

B The computation of impulse responses

We calculate impulse response functions taking into account that during the horizon of interest the S_t indicator can change. Thus, we fully integrate over the path of S_t rather than condition on the initial value S_0.

After performing the MCMC simulations, we collect the posterior draws for all parameter blocks. Using the draws from each block, to get the impulse responses we perform the following steps $\overline{S}$ times:

1. **Step 1**: Set the number of periods $\overline{H}$ and select a draw for $\Theta = \left\{P^*, d, \Phi_{1:2}, \alpha_{1:2}, s_{1:N}, \lambda^T, \mu, \rho, Q\right\}$ from the estimated posterior distribution.
2. **Step 2**: Pick a random initial point t^* from $t^* \sim U(1, T)$.
3. **Step 3**: Given t^*, P^*, d and the data vector Z_{t^*}, determine the initial regime S_0 according to equation (2).
4. **Step 4**: Use the same initial value for the two regimes, $Z_0^\delta = Z_{t^*}$ and $Z_0^0 = Z_{t^*}$. Set the initial value $\lambda_0^0 = \lambda_{t^*}$.
5. **Step 5**: Repeat $\overline{L}$ times the following steps:
   (a) For each $t = 1, \ldots, \overline{H}$ forecast λ_t according to equation (6). When $t = 1$, set $e_1^\delta = \delta$ and $e_1^0 = 0$.
   (b) Given the values of e_t^δ, e_t^0, and λ_t, for each $t = 1, \ldots, \overline{H}$ forecast Z_t^δ and Z_t^0 according to equation (1). Notice that in each case it is necessary to determine the current regime, i.e. S_t^δ and S_t^0, according to equation (2).
   (c) If we have zero restrictions for a given horizon $\tilde{H}$ (see Table 1), then when forecasting Z_t^δ and Z_t^0 impose shock values e_t for each $t \leq \tilde{H}$ such that the variable $y_t \in Z_t$ remains constant (in this case the interest rate for the UPM shocks).
   (d) Compute impulse responses $IRF_{1:\overline{H}} = Z_{1:\overline{H}}^\delta - Z_{1:\overline{H}}^0$.
6. **Step 6**: Take averages over $IRF_{1:\overline{H}}$.

We set $\overline{S} = 1000$, $\overline{L} = 200$. In addition, we set $\overline{H} = 36$ (three years) and $\delta = 1$. Given the number of draws $\overline{S}$, we split the complete set of impulse responses to draws in two groups, the low regime group ($S_{t^*} = 1$) and the high regime group ($S_{t^*} = 1$). To to that, we consider the initial regime determined in Step 3. Then, for each group of impulse responses we report the median value and the robust 16th and 84th percentiles.

C Additional Figures

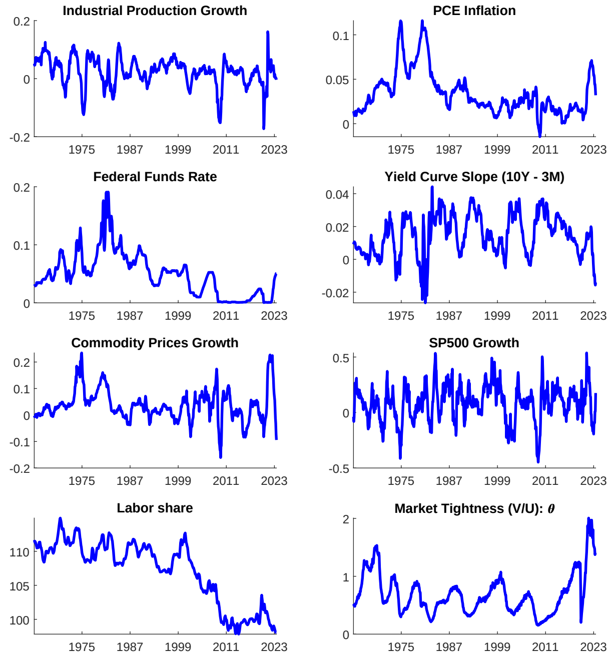

Figure C.14: Time series of the data, sample 1960-2023.

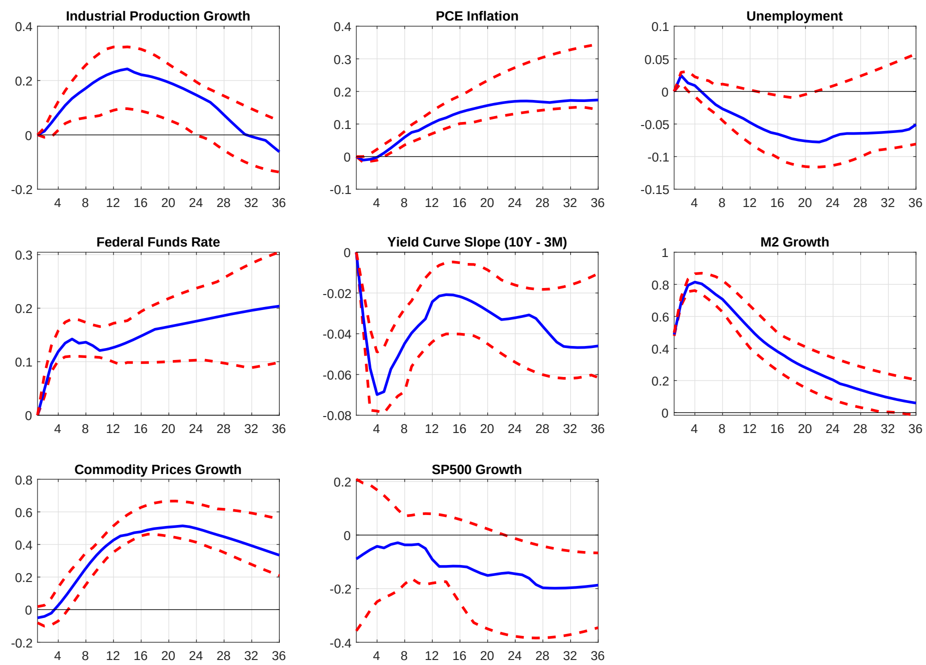

Figure C.15: Responses to liquidity shocks, no constraint on the short-term rate.

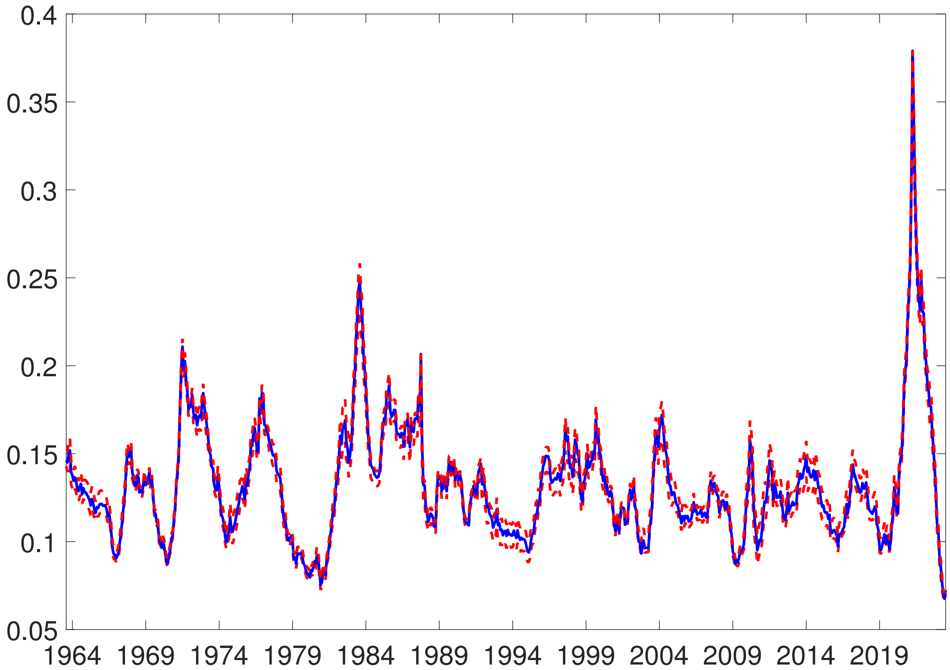

Figure C.16: Posterior 68% credible sets for the λ_t process.

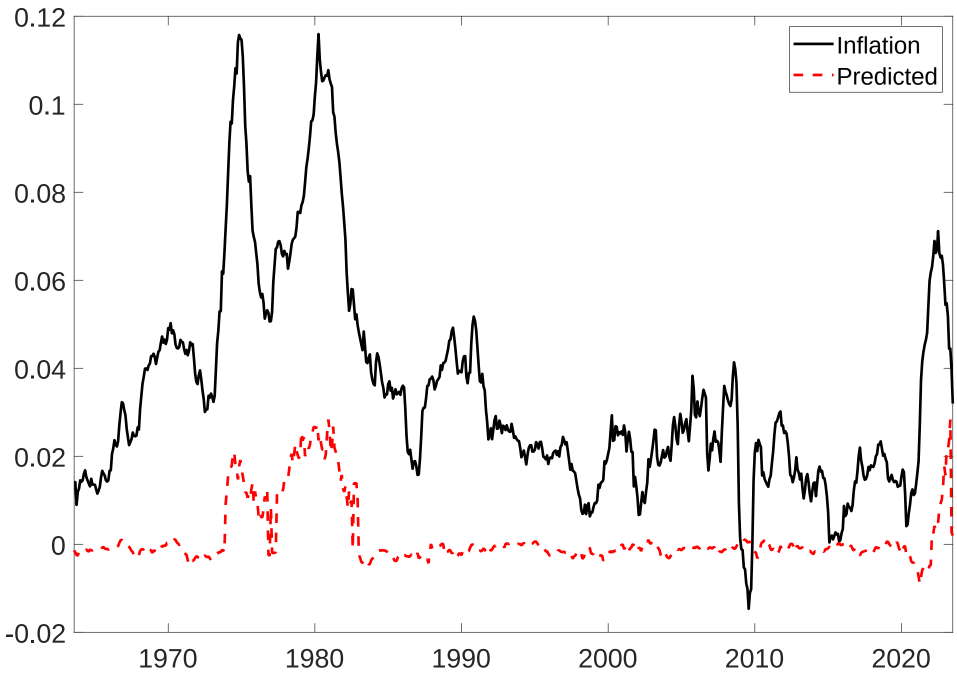

Figure C.17: Predicted inflation based only on λ_t.

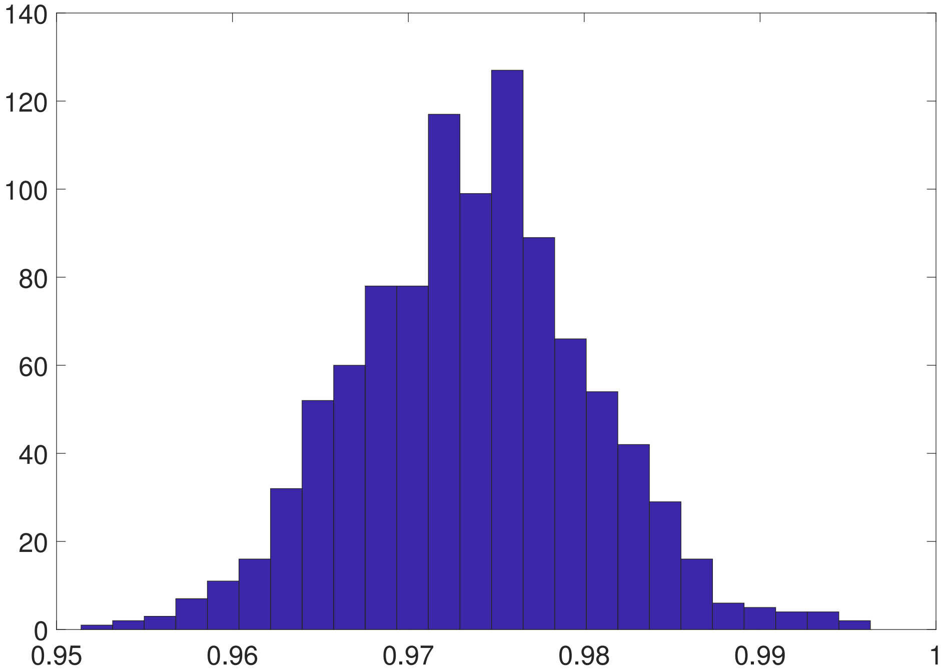

Figure C.18: Posterior distribution of the volatility persistence parameter F.

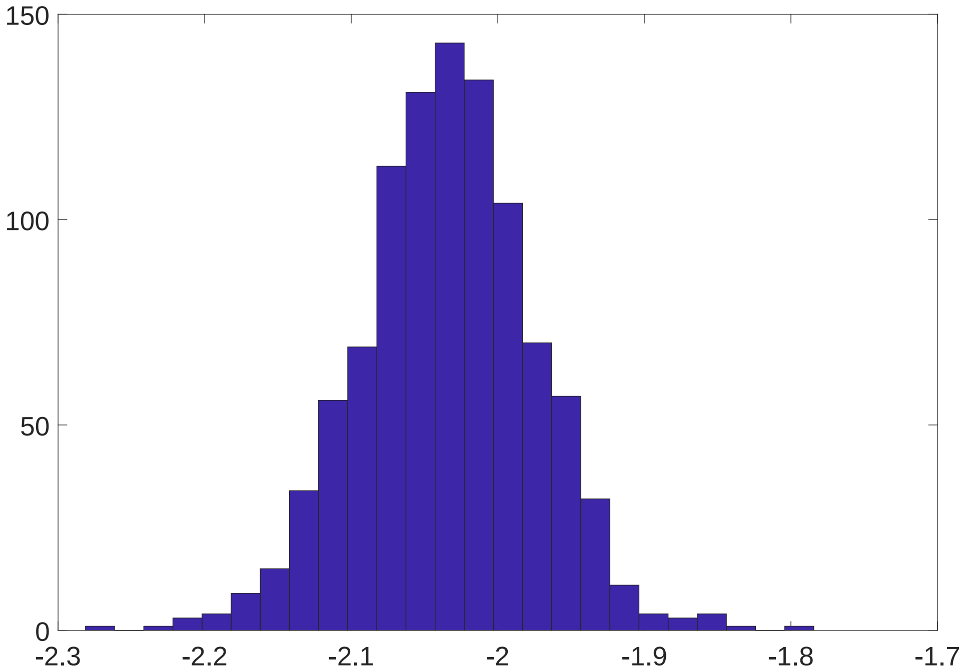

Figure C.19: Posterior distribution of the volatility mean parameter μ.

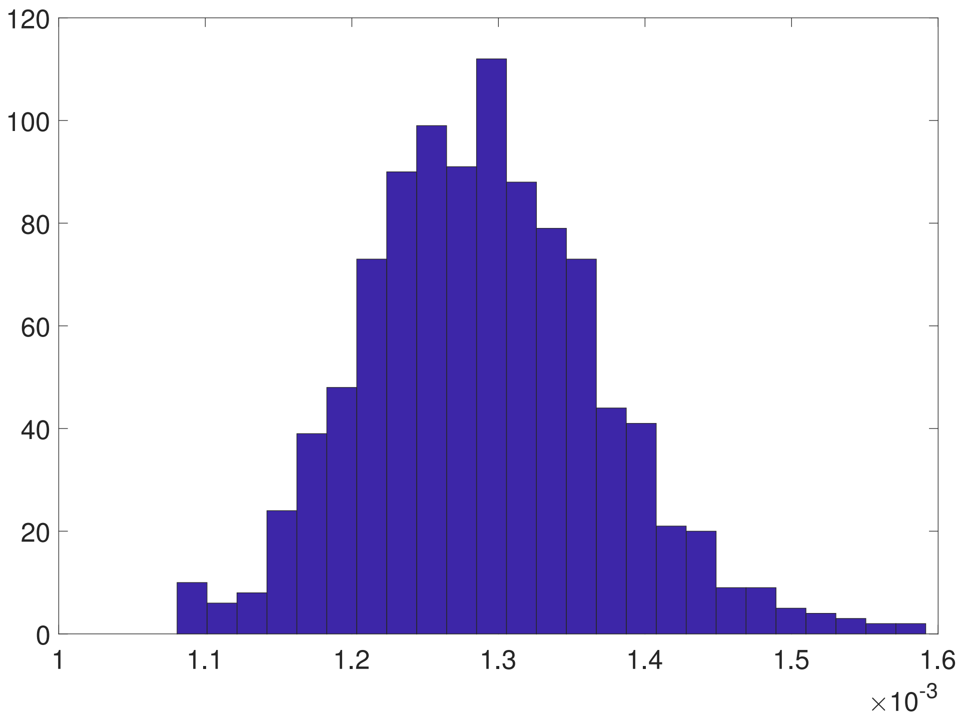

Figure C.20: Posterior distribution of the volatility variance parameter Q.

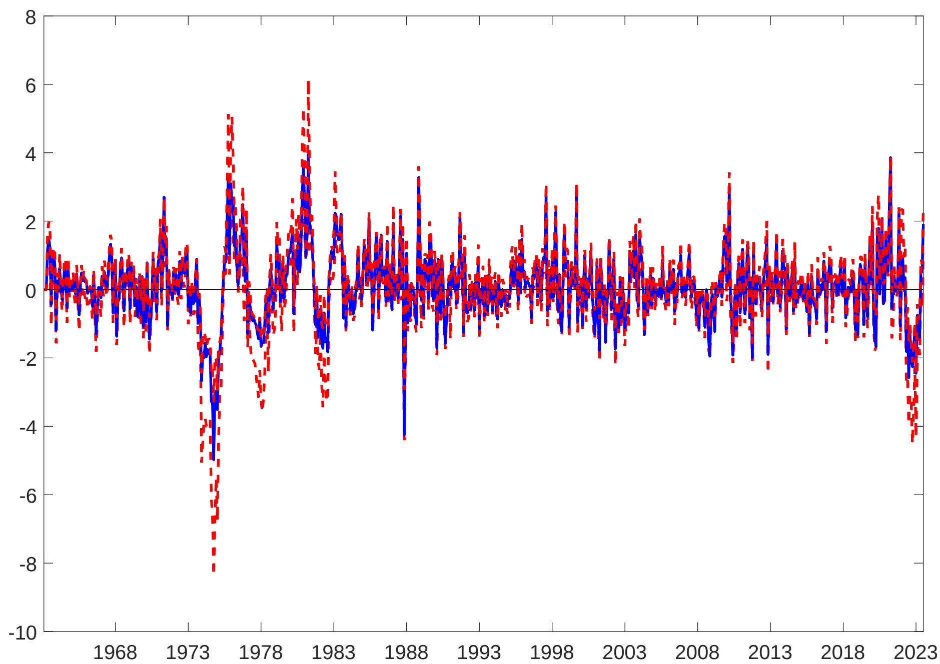

Figure C.21: Posterior distribution of the conventional monetary policy shocks.

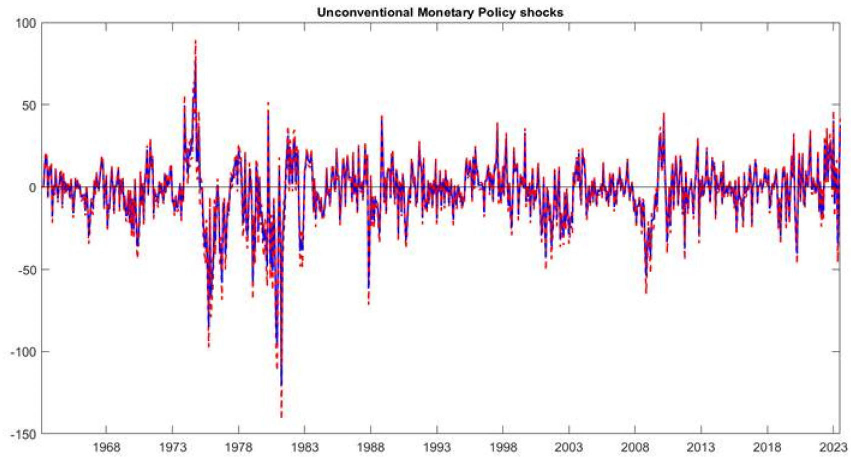

Figure C.22: Posterior distribution of the liquidity shocks.

D Results obtained excluding λ_t from the regressors

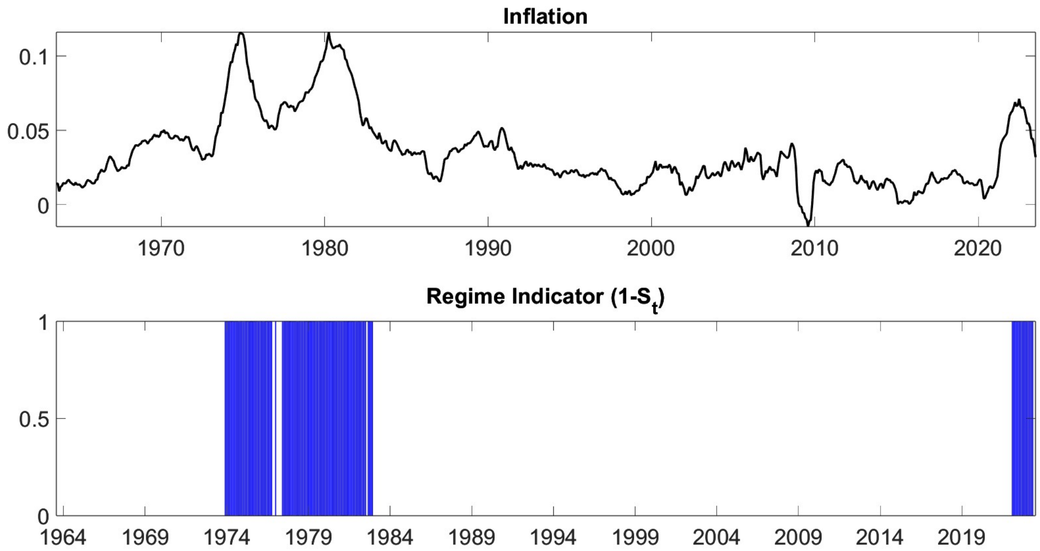

Figure D.23: US Inflation and estimated regime indicator, no λ_t.

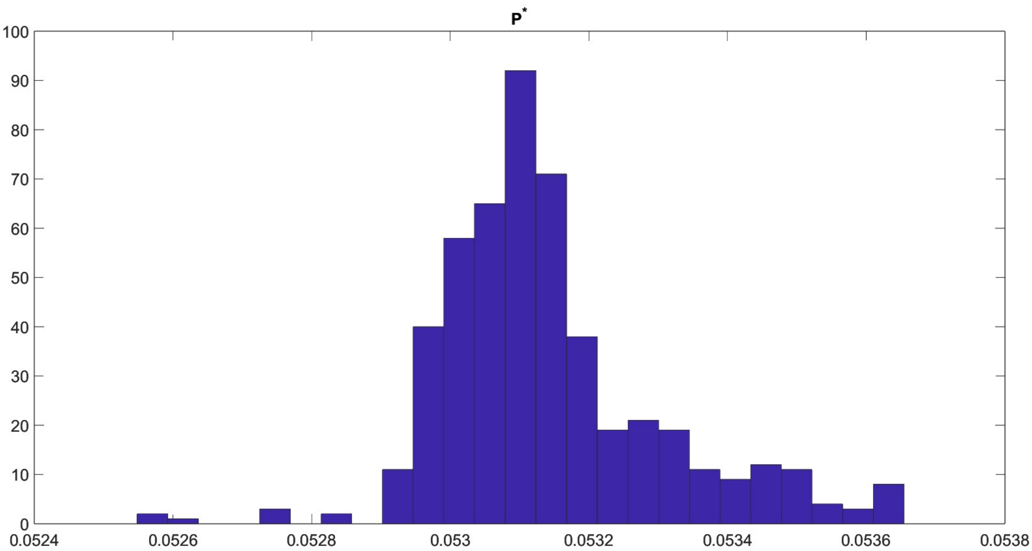

Figure D.24: Posterior distribution of P^*, no λ_t.

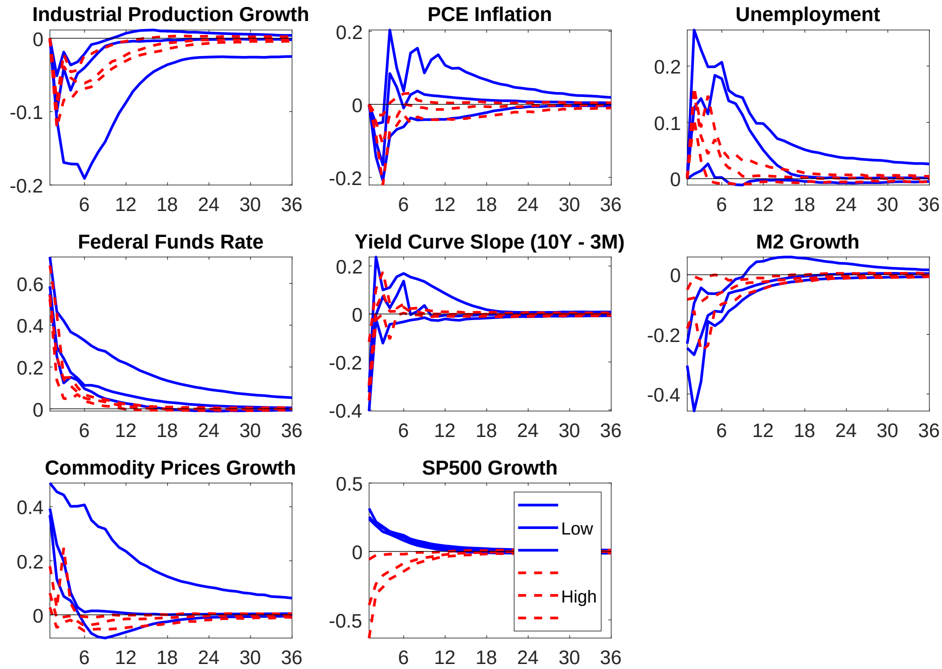

Figure D.25: Contractionary conventional monetary policy shocks, different regimes, no λ_t.

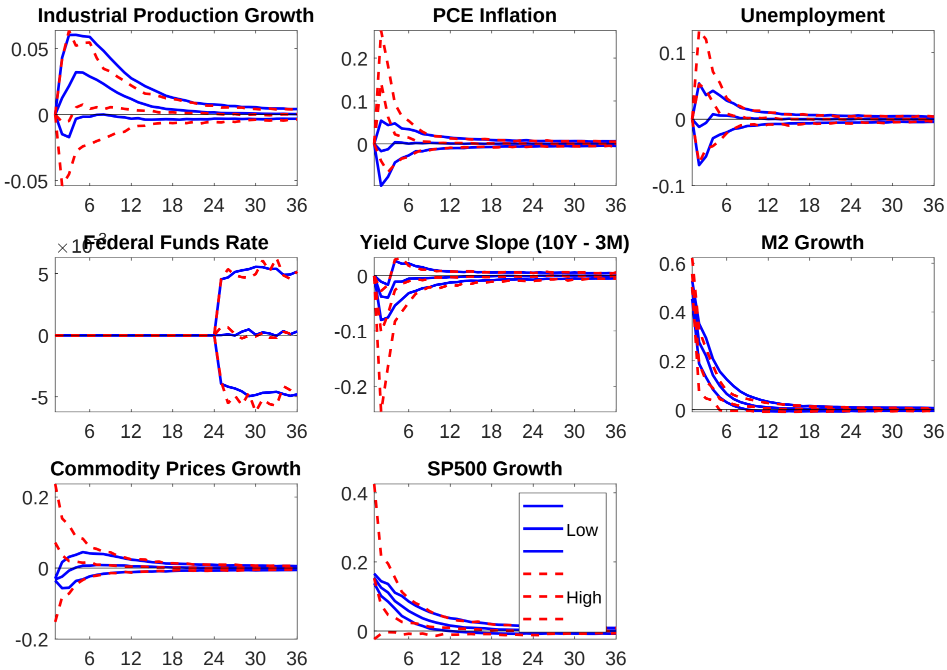

Figure D.26: Expansionary liquidity shocks, different regimes, no λ_t.

E The reaction of SPF expectations

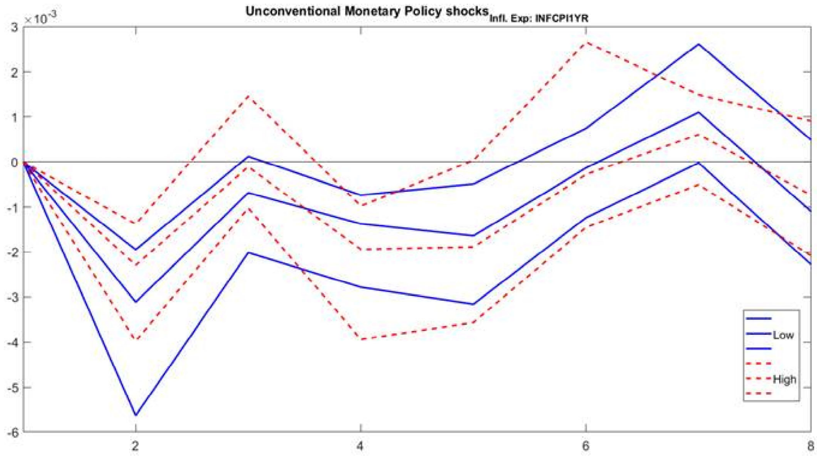

Figure E.27: Responses of CPI inflation expectations, different regimes, liquidity shocks.

F The dynamics of the slope of the Phillips curve

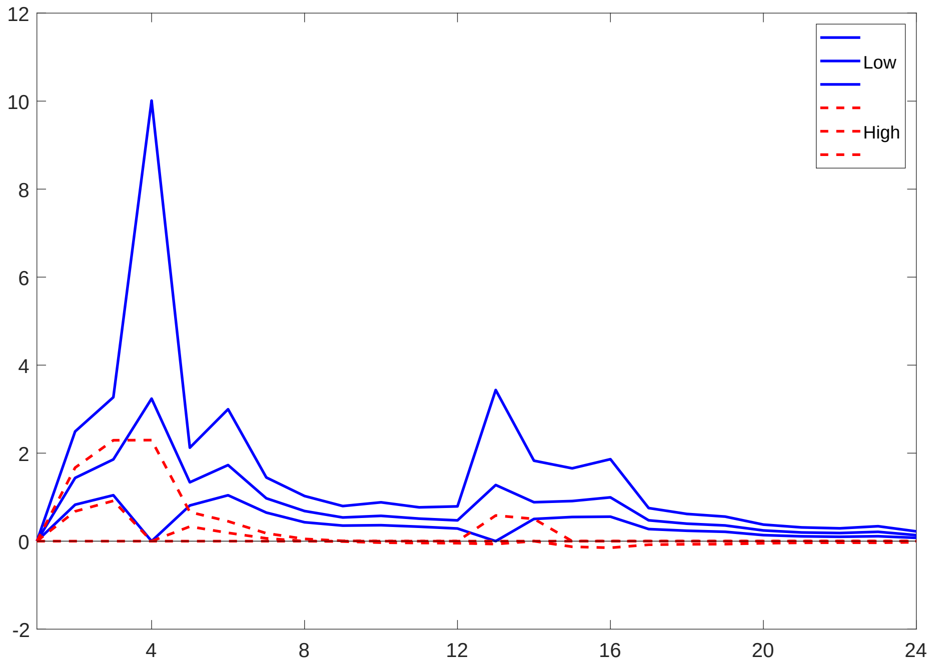

Figure F.28: Slope of the Phillips curve, labor share, conventional monetary policy shocks.

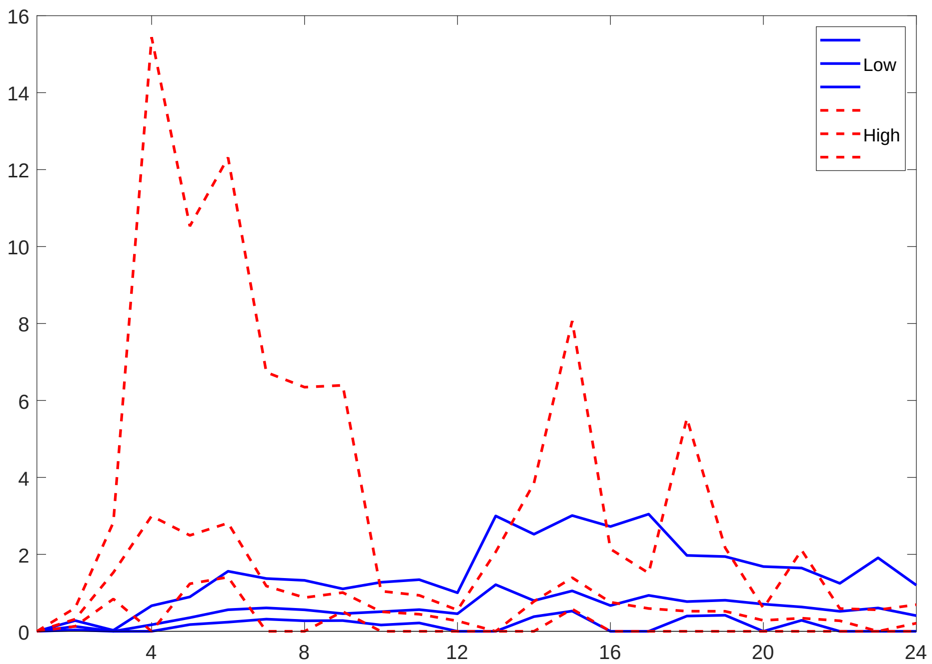

Figure F.29: Slope of the Phillips curve, labor share, liquidity shocks.

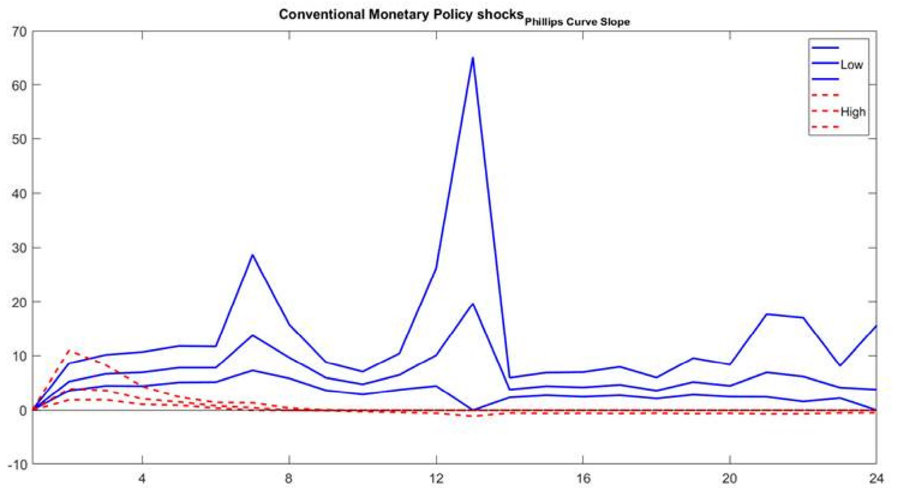

Figure F.30: Slope of the Phillips curve, VU ratio,conventional monetary policy shocks.

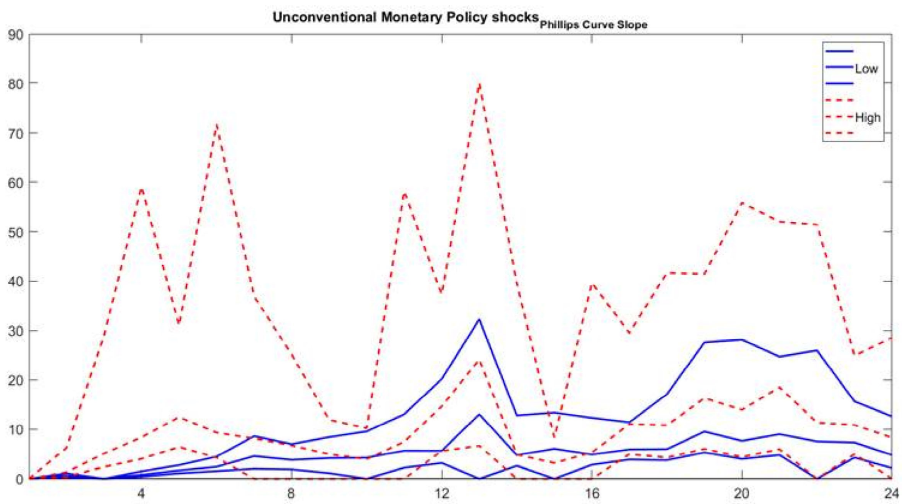

Figure F.31: Slope of the Phillips curve, VU ratio, liquidity shocks.