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Draft version

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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 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 accounts for the differences. Implications for theoretical models are discussed.

JEL Classification: C3, E3, E5

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

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1 Introduction

After a prolonged period of low and stable inflation, the outlook has suddenly changed in the aftermath of the COVID pandemic, and most countries have experienced unprecedented inflation rates since the late 1970s. In the US, the GDP deflator started rising at the end of 2020 and peaked at 9.1 percent in second quarter of 2022. In the euro area, inflation was negative at the end of 2020, rose sharply in 2021 and peaked at around 10 percent on an annual basis in 2022. In some European countries (e.g., the Netherlands and Estonia) the annual inflation rate in 2022 exceeded 15 percent. Initially supply disruptions, associated with pandemic-induced reallocation of economic activity across sectors, were considered responsible for the inflation surge. Later, it became clear that the massive fiscal stimulus national governments implemented in response to the COVID pandemic was also important.

The proper policy response to the surge depends on the nature of the impulses driving the inflation. For example, mainstream New Keynesian theories suggest that a central bank should respond to demand driven inflation surges, but care should be exercised for supply driven inflation increases, because of the trade-off they generate Galí (2015). However, even if the nature of the impulses were identifiable and the appropriate policy decisions well understood, it may be the case that the mechanics of transmission of policy decisions depend on the level of inflation. This may occur because central bank credibility is affected, public expectations are dispersed or poorly anchored, or fiscal dominance prevails, Leeper *et al.* (2017). Hence, it is important to know to what extent and in what way a high inflation regime alters the transmission of monetary policy surprises and the reasons for why this occurs.

The dependence of monetary policy transmission on the level of inflation is of great interest also in academics. In most models nowadays used, 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 assumed stickiness. Such models have sharp 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. Consequently, the higher inflation is, the smaller the real effects of monetary policy disturbances should be. Models with rational inattentive consumers also have different implications for the conduct of monetary policy across inflation regimes, see e.g. Sims (2010) or, more recently, Pfauti (2023). When inflation is high, agents should be more attentive to news making inflation expectations more sensitive to the state of the economy. This internalization effect may lead to accelerating inflation, possibly ending in hyperinflation. In such models, monetary policy should aim at keeping inflation low so that agents do not pay attention to its movements when making economic decisions, see Powell (2022) for a recent statement of such a view. Furthermore, there is an inflation threshold that makes agents change the way they respond to economic disturbances. Non-linear (Slanted-L) models also predict that the transmission depends on the level of inflation, see Benigno and Eggertsson (2023), with the tightness of labor market conditions determining the regime the economy is in. In such models, economic news affects inflation differently because matching efficiency changes, see also Barnichon and Shapiro (2024).

Contribution. This paper explores how the propagation of two types of monetary policy shocks varies with the level of inflation. 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 rate - and liquidity shocks - disturbances that alter the quantity of money in circulation by twisting the long end of the term structure of interest rates. We study the responses of several macroeconomic variables and investigate the implications of our results for inflation expectations and net firm entries. We also analyze the dynamic response of the slope of the Phillips curve to bridge our results with existing theories.

We employ a Threshold Vector Auto-Regressive (VAR) model with Stochastic Volatility of the type used in Alessandri and Mumtaz (2019). This model fits into the class of switching models with sharp threshold and has at least two advantages over competing ones: it allows for an endogenous selection of the threshold of the inflation regimes; it permits uncertainty to directly affect the dynamics of the endogenous variables, a feature which is important when volatility is high. Estimation of the model is Bayesian in spirit. We numerically construct joint posterior distributions for the vector of structural parameters in each regime and for the parameters related to the threshold. We identify shocks using sign and zero restrictions and provide narrative evidence on the reasonableness of the posterior distributions we construct.

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 short-term nominal rate increase lasts longer when inflation is high. Differences across regimes are related to the dynamics of the slope of the term structure. Notably, the long-term rate reacts more than the short-term rate at all horizons in the low inflation regime, while the opposite occurs in the high inflation regime. The slope inversion present when inflation is low is consistent with the idea that surprise short-term interest rate increases provide private agents information about the future path of the economy. When inflation is low, an unexpected surge in the nominal rate signals to private agents that further increases are likely to come, perhaps because inflation will be higher for a while, and agents respond by adjusting their inflation expectations at all horizons. When inflation is instead high, the informational content of the nominal rate surprise is limited as agents expect systematic actions to be taken which will make the high inflation state temporary. Our state dependent signaling interpretation of the dynamics induced by conventional disturbances is supported by two independent pieces of evidence. First, a counterfactual exercise shows that, if the dynamics of the slope of term structure were forced to be the same in the two regimes, the responses of output growth, unemployment and inflation would also be similar. Second, CPI inflation expectations positively react to conventional 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 markets response to the shocks again accounts the differences across regimes. In particular, the stock market sees the liquidity increase as good news when inflation is high but not when inflation is low. Such dynamics are also consistent with the idea that monetary policy provides state dependent signals about the future of the economy. To verify such an interpretation, we run a counterfactual exercise keeping the reaction of the stock market constant across regimes and find that the response of output growth, unemployment and inflation are also unchanged across regimes. We also show that net entry, a variable which proxies for future profitability, positively responds to the liquidity shock in the high inflation regime but not in the low inflation regime.

The evidence we collect stands in stark contrast with the predictions of menu costs or slanted-L theories. There is a differential trade-off between unemployment (labor share, vacancies-to-unemployment ratio) and inflation across regimes but, contrary to what these theories suggest, the slope response is larger in the low inflation regime. There is more mixed evidence regarding the rational inattention paradigm. While the responses of production growth are in line with the predictions, see Mackowiak and Wiederholt (2009), inflation expectations only react to conventional shocks, but the reaction is larger in the low inflation regime.

The relationship with the literature. Our work contributes to and unifies different strands of literature. From a methodological viewpoint, we extend the work of Alessandri and Mumtaz (2019) by adding zero-sign identification restrictions and a reparameterization of the contemporaneous relationships, along the lines of Canova and Pérez Forero (2015), which allows for a simpler and more effective sampling from the posterior distribution. A recent contribution by Gargiulo *et al.* (2024) also employs a threshold model to investigate the transmission of policy shocks. We differ from their work in several respects. We employ a different estimation approach and a different identification strategy. Furthermore, we provide an interpretation of the evidence while they do not.

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 and are driven by an indicator, which may take time to inform agents 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, making posterior drawing easier and faster.

The conclusions we draw 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. They are also consistent with the inflation expectations evidence contained in Fisher *et al.* (2024). Our investigation qualifies the conclusions of these papers by showing that the informational effect is present only in particular inflation regimes.

Finally, our contribution is also related to work by Ravn and Sola (1996), Weise (1999), Tenreyro and Thwaites (2016), Pellegrino (2021), Ascari and Haber (2021), Debortoli *et al.* (2020), Degasperi *et al.* (2024), who study whether nonlinearities affect the transmission of conventional monetary policy shocks. Relative to this literature, we investigate whether the state dependency depends on an observable indicator and allow an uncertainty indicator among the predictors of the endogenous variables.

Outline. The rest of the paper is organized as follows: section 2 describes the data and provides US inflation statistics. Section 3 describes the empirical model. Section 4 briefly explains how estimation is conducted, and Section 5 presents a summary of the posterior results. Section 6 discusses the transmission of monetary policy shocks across regimes. Section 7 examines the evidence in light of existing theories. Finally, Section 8 concludes. The on-line Appendix contains technical details and the additional material mentioned in the paper.

2 Data

We use standard data. The endogenous variables 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 (calculated as 10-year rate minus 3-month rate), M_t is the year-on-year M2 growth, $Pcom_t$ is the year-on-year commodity price index growth, and $SP500_t$ is the year-on-year SP500 index growth. We take year-on-year growth rates to introduce smoothness in the series and facilitate estimation [1]. The sample is 1960m1-2023m6 and the source is the FRED database from the St. Louis Fed.

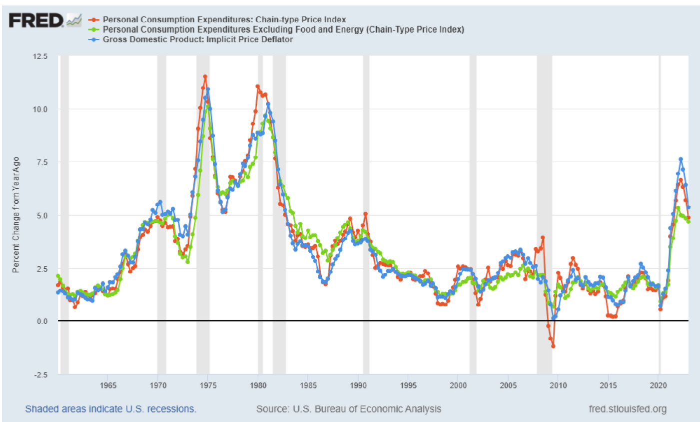


Figure 1: US Inflation, sample 1960-2023

The dynamics of US PCE inflation, of US PCE inflation excluding food and energy, and of US GDP implicit inflation are in Figure 1. Regardless of the measure employed, the dynamics are very similar. Thus, focusing on PCE inflation involves no loss of generality. It is also evident

[1]The presence of moving average terms may inflate the persistence of the responses. However, no excess persistence seems to be present in e.g. Figures 5 and 6 relative to the literature.

from Figure 1 that the recent surge of inflation is unprecedented since the late 1970s and that the sharpness of the increase is extraordinary, even by 1970s standards. As mentioned in the introduction, the dynamics of inflation in many developed countries are similar. Thus, the lessons one learns from analyzing how the transmission of policy shocks relates to the level of inflation in the US are useful to interpret the dynamics in other countries as well.

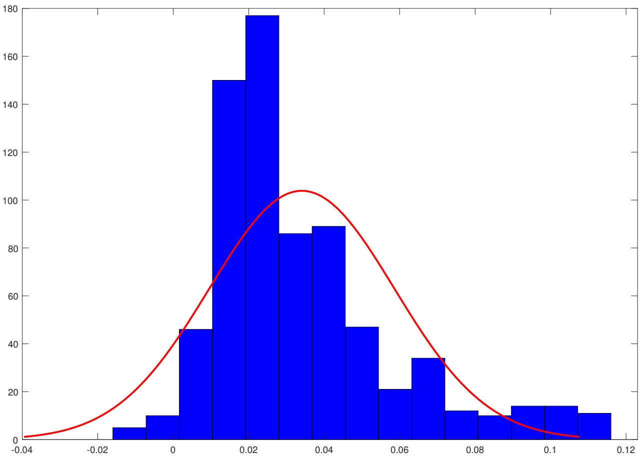


Figure 2: Distribution of PCE Inflation, sample 1960-2023

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. Consequently, the mean (0.0341) is larger than the median (0.0263) and the mode (0.0240); the skewness coefficient (1.33) is significantly different from zero and the kurtosis coefficient (4.62) statistically deviates from the one of a normal distribution. Note also that the inter-quartile range (0.0176, 0.0438) is smaller than the one of a normal distribution. Our empirical model endogenously separates the distribution of inflation in two sub-distributions using the information contained in the lags of Z_t. Our task is to measure the differences in the propagation in the two sub-distributions.

In standard models, the level of inflation depends on a measure of activity slack. In the literature, the latter is proxied by the unemployment rate, the output gap, the labor share or the labor market tightness, see e.g. Barnichon and Shapiro (2024). As Figure C-1 in the online appendix shows, the relationship between the level of inflation and basic real activity measures is blurred. For example, while during periods of high inflation the unemployment rate tends also to be high, the relationship between inflation and output growth is far from clear. Our investigation is also interested in examining the relationship between measures of real activity slack and inflation across regimes in light of existing theories.

3 The Empirical Model

The empirical specification we use is a two-regime Threshold Vector Bayesian Autoregressive model (Threshold-BVAR), see Alessandri and Mumtaz (2019). While alternative specifications, such as the time Varying parameter (TV)-BVAR (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:

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

where $e_t \sim i.i.d.N\left(0, I_{dim(Z)}\right)$. We set $p = 3, J = 2$ and use the sample 1963:01-2023:06 in the estimation. 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 parameter d (a-priori assumed to follow a discrete multivariate distribution with $d = 1, \ldots, 6$) and the threshold parameter P^* (a-priori assumed to follow a truncated normal distribution over the interval [1,10]) are unknown and jointly estimated with the parameters of (1). When inflation is low, the parameters are $(c_1, \beta_1, \gamma_1, \Omega_{1t})$; when it is high, they are $(c_2, \beta_2, \gamma_2, \Omega_{2t})$. Thus, the entire structure may shift with the regime. The constrain implicitly imposed by (1) - that the switch simultaneously occurs in all variables - is no more restrictive than the one employed in MS-BVAR or TV-BVAR models. Relative to Markov switching setups, where regimes are function of an *unobservable* variable, we assume that regimes are function of an observable variable making the evidence more transparent.

The matrix Ω_{it}, $i = 1, 2$, is time varying within each regime and evolves according to:

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

where H_t is defined by:

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

$\Sigma = diag[\sigma_1^2, \sigma_2^2, \ldots, \Sigma_{dim(Z)}^2]$ $\sigma_j^2 > 0$, while λ_t is a $AR(1)$ process with drift:

$$ln\lambda_t - \mu = F\left(ln\lambda_{t-1} - \mu\right) + \eta_t \tag{5}$$

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

The specification we employ uses a single scalar process to govern the time varying volatility of the system (Carriero *et al.*, 2016; Alessandri and Mumtaz, 2019). This allows a parsimonious representation of the fluctuations in the second moment fluctuations relative to e.g. Primiceri (2005), Canova and Pérez Forero (2015), among others. While λ_t is a scalar, the volatility of the endogenous objects, and in particular of financial and of non-financial variables, may be different because of the interactions that Ω_{it} involves. Note also that (5) allows, without imposing, a geometric random walk for the volatility term, centered around μ and that, even though Σ is constant, H_t is time-varying.

As it is clear in (1), the volatility indicator λ_t affects the level of the endogenous variables, much in the spirit of a GARCH-M specification (see Mumtaz and Zanetti (2013)). Following Alessandri and Mumtaz (2019) we interpret λ_t as the average uncertainty present in the innovations of the system. The presence of the volatility term among the regressors adds to the non-linearity associated with the regime switching. More on the role of λ_t for the estimation comes later.

The contemporaneous coefficient matrices A_i are, in general, non-triangular making sampling from their posterior distribution complicated. We impose a set of signs and zero identification restrictions to recover the 22 free parameters in each state. We collect the unrestricted entries of A_i into the vector α_i, so that each for $i = 1, 2$, $vec(A_i) = S_A \alpha_i + s_A$, where S_A is a 64×22 matrix and s_A is 64×1 vector of 0s and 1s. Such a transformation allows us to sample the full vector α_i jointly, rather than sequentially, see Canova and Pérez Forero (2015).

As it is standard, 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 contemporaneous effect on industrial production growth, inflation and the unemployment rate and that it decreases money growth within a month. We impose a negative contemporaneous correlation between the short-term nominal interest rate and the monetary aggregate following Uhlig (2005), and impose the restrictions only contemporaneously. After one period, all the variables are allowed to freely move in response to the shock.

We also identify a (expansionary) liquidity shock. Such a shock is effectively an increase in the amount of money in circulation, it is engineered through a decrease in the long-term rate and it is assumed to have no effect on the growth rate of real activity, on unemployment or inflation within a month. To make sure that the expansion is not sterilized by an increase in the short-term rate, which would automatically occur when, e.g. monetary policy is conducted with a Taylor rule, we require the short-term nominal interest rate to remain unchanged for a number of months. This way, monetary policy actions are consistent across maturities. The exact time span over which the short-term interest rate is kept constant does not matter. We report results obtained when we restrict the short-term rate for 24 months in the text and for 12 months in the on-line Appendix H. In response to both shocks, the growth rate of the stock market index may freely move, even within a month. Thus, as in Jarocinski and Karadi (2020), we let the data tell us how it reacts.

The liquidity disturbance we identify is a combination of several primitive policy shocks which may be active only in part of the sample. For example, it has the features of *Delphic Forward Guidance* (FG) shock in the terminology of Campbell *et al.*, 2012; Jarociński, 2021; Andrade and Ferroni, 2021 since communicating a path for interest rates for the future (open/end guidance or state/contingent guidance) implies a particular path for the long-term yields. It resembles certain large scale asset purchase (LSAP) shocks, see Tenreyro and Wazzi (2025) since the identification implies a swap in the portfolio of assets of agents (banks) and that liquidity is injected in the system when assets enter Central Bank balance sheet. Finally, it may also capture open market operation (OMO) shocks conducted in the 1980s and 1990s, see e.g. Strongin (1995), since as with LSAP there is a swap of assets. While in the case of LSAP the swap is in secondary markets, OMO works in primary, Government debt markets. We prefer to identify a generic liquidity shock rather than specific FG or LSAP shocks since disentangling these disturbances would require (i) a much larger number of VAR variables, (ii) concentrating attention on a short sample (starting in the early 2000s), and this would prevent us from effectively separating high vs. low inflation regimes and discuss differences.

We summarize the identification restrictions in table 1; an empty box indicates an unrestricted coefficient. Although all the shocks in our structural system are orthogonal, as this helps in better identify the shocks of interest, we do not give any structural interpretation to the other six disturbances. The exact structure of the A_i matrix is described in on-line Appendix A.

Variable - Shock	Conventional Monetary Policy	Liquidity
IP growth	0	0
PCE Inflation	0	0
Unemployment	0	0
Interest Rate	> 0	0 (for 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 liquidity when inflation is high. Since the sign of the shocks does not matter within a regime, what we present 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 of our model and its use as predictor in (1) requires some discussion. As in Alessandri and Mumtaz (2019) we use a measure of uncertainty that is linked to agents' inability to form predictions about the fundamentals. This avoids resorting to proxies that are at best weakly related to macroeconomic unpredictability, such as the VIX index. Relative to the factor model of Jurado *et al.* (2015), the specification uses less information to construct the indicator but has the advantage of modeling the variables' first and second moments jointly and in a consistent manner. According to our specification, agents form expectations treating uncertainty as an ordinary state variable: they estimate λ_t , project it forward, and take into account its influence 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 variables through a separate set of regressions. This advantage comes at the cost of a dimensionality increase and forced us to consider only the dynamics of a limited number of endogenous variables. We supplement the investigation by using identified shocks in local projection exercises. We conjecture that the costs of this sequential approach is quantitatively small given the arbitrage and theoretical relationships between VAR and local projection variables. The volatility-in-mean feature also takes our setup closer to the theoretical literature. In our model uncertainty stems from the volatility of the structural shocks, follows an AR(1) process, and is exogenous. Thus, it closely

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

resembles to the reduced-form of a Markov switching DSGE model with stochastic volatility with two exceptions: we use the average volatility of all shocks rather than the volatility of a specific structural disturbance; the threshold structure neglects interaction terms that would arise in high-order perturbed solutions.

Once the posterior distribution of the parameters are available, we compute impulse responses as differences between conditional expectations obtained by simulating the model under a shock scenario and under a no-shock scenario. For a given initial regime (S = 0 , 1) and a regime-specific history (Y_{t-1}^{S}), the responses are defined as $IRF_t^S = E(Y_{t+k}|\Psi_t, Y_{t-1}^S, \nu_t) - E(Y_{t+k}|\Psi_t, Y_{-1}^S)$, where Ψ_t are the parameters of the model, $k = 1, 2, \ldots$ is the response horizon and ν_t the structural shock of interest. Three key features of the IRFs we compute need to be stressed. First, the switch among regimes is treated as endogenous. Thus, the responses may freely transit from low to a high inflation regime and vice versa over the simulation horizon. This is different from the standard calculations performed in regime dependent models where responses are computed conditional on remaining in the same initial state for all horizons. The latter should be taken with caution as it overestimates differences across regimes, especially in the long run. Second, even within an initial regime S, the responses depend on the history prior to the shock (Y_{t-1}^S). Thus, the economy may respond differently when inflation is zero or when it is 0.5, even though both belong to the low inflation regime. For this reason, we report average responses. That is, the responses in the low inflation regime (high inflation regime) are calculated averaging the response to the shock of interest across all possible histories (Y_{t-1}^S) belonging to regime S = 1 (S = 0). Third, we compute impulse responses conditioning of the size of the shock (one standard deviation) and on its sign (negative for conventional shocks, positive for liquidity shocks). Thus, our responses are not ‘’generalized" in the sense of Koop *et al.* (1996), since it does not make sense to average of size and sign for the exercise we conduct. The numerical details regarding the computation of impulse responses are in the on-line Appendix B.

Unexpected changes in monetary policy are usually interpreted in the literature as reflecting an exogenous tightening or loosening of the monetary stance. The baseline assumption underlying this interpretation 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 news or processes public information more efficiently, monetary policy surprises may also reveal information about future economic outlook, see Miranda Agrippino and Ricco (2021). In this case, interest rate shocks could also have an information content, whereby markets upgrade their expectations and price-in an endogenous monetary policy change. Disentangling these channels is important because an information shock may have different effects on economic activity. To shed light on the issue, we leveraged the responses of financial variables, as in 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 rates. As we show below, such an effect is indeed present in certain states of the world.

3.1 Relationship with the literature

It is important to compare our setup to the one employed by Gargiulo *et al.* (2024) and Ascari and Haber (2021) and discuss similarities and differences.

There are a number of important differences with the first paper. Gargiulo *et al.* (2024) use a T-VAR with three regimes on a much shorter sample period (1970-2007) , while we consider only two regimes on the 1963-2023 sample. In addition, the specification is different. They use only three variables (interest rate, unemployment and inflation), the threshold delay parameter is fixed (d=1), they do not allow for stochastic volatility in the shocks, nor do they use the volatility indicator as VAR predictor. As we discuss later, the presence of a volatility indicator among the predictors has important implications for the conclusions one reaches.

The estimation procedure is also different. They use a two-step approach, where estimates of the threshold are obtained on a grid of values and the threshold that minimizes the residuals sum of squares is selected. In the second step they use the likelihood of the VAR, conditional on the (superconsistent) threshold estimate, to construct posterior mode estimates of the object of interest. We instead jointly estimate the parameters of the model and the threshold and construct full posterior distributions of both objects in one step.

On the more substantive side, they only identify conventional monetary policy shocks using a high-frequency IV procedure and, compute regime dependent impulse responses. More importantly, they do not offer any explanation for the differences they find across states. We identify two shocks using zero and sign restrictions, we compute impulse responses that allow for transition across states over the relevant horizon and we interpret the results in light of existing theories.

Ascari and Haber (2021) are not interested in measuring the differences in the monetary transmission across states. Rather, they care about testing two predictions of sticky price models, i.e. that the larger are monetary policy shocks, the larger (the smaller) should be the effects on inflation (real activity); and that the higher is the level of inflation, the larger (the smaller) should be the effect of monetary policy shocks on inflation (real activity) - a question we also investigate in section 7. To carry out their analysis they use non-linear local projections and smooth transition function methods where a 24-month moving average of PCE inflation (which they interpret as trend inflation) is employed to distinguish states. Furthermore, they use a shorter sample (1969-2007), three variables (output, inflation, and the nominal rate), and Romer and Romer monetary policy shocks in the exercise.

4 Estimation

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

$$p\left(\Theta \mid Z^T\right) \propto p\left(Z^T \mid \Theta\right) p\left(\Theta\right) \tag{6}$$

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 K be the total number of draws.

We compute the posteriors numerically 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 choose $K = 100,000$ and discard the first $50,000$ draws to insure convergence. To reduce the serial correlation across draws, we keep 1 every 10 draws, tossing the remaining ones. As a result, we have $5,000$ posterior draws for inference. Details on the steps of the Gibbs sampling algorithm are in the on-line Appendix A. In the same Appendix we present the baseline values for the parameters of the prior distribution we use.

5 Parameter estimates

We first present the posterior distribution of some relevant parameters. Figure 3 plots US PCE inflation and the estimated indicator for the high inflation regime. Consistent with the literature, we calculate the posterior mean of S_t (call it $\tilde{S}_t$) and a bar is plotted at t if $\tilde{S}_t \geq 0.5$.

The high inflation regime includes the two bursts of inflation of the 1970s (1973-1975 and 1977-1983) and the post Covid19 period. Interestingly, neither the end of the 1960s nor the early 1990s, when inflation was higher than average, are classified as the high inflation regime. In addition, the high inflation regime is similar to the high expected inflation disagreement regime identified by Barbera *et al.* (2023) using the survey of professional forecasts; and it matches reasonably well with the conventional wisdom that the inflation coefficient in a Taylor rule rose from the 1980 on.

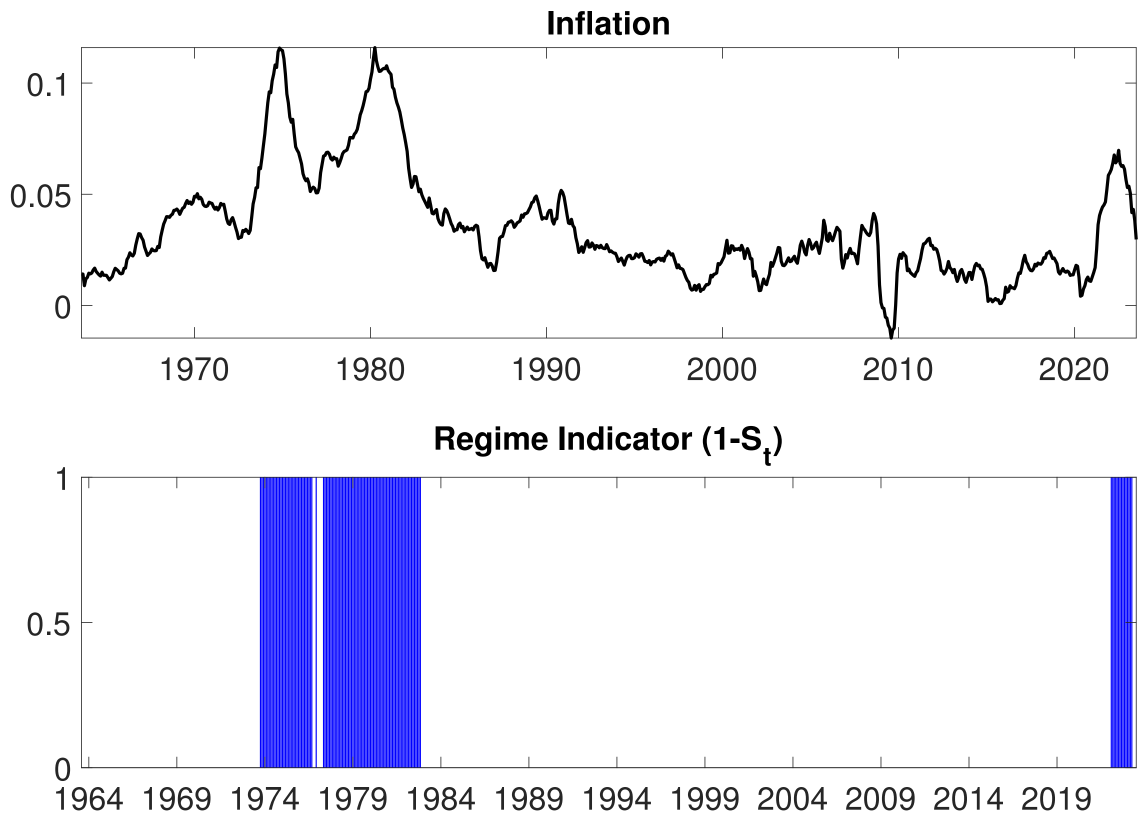
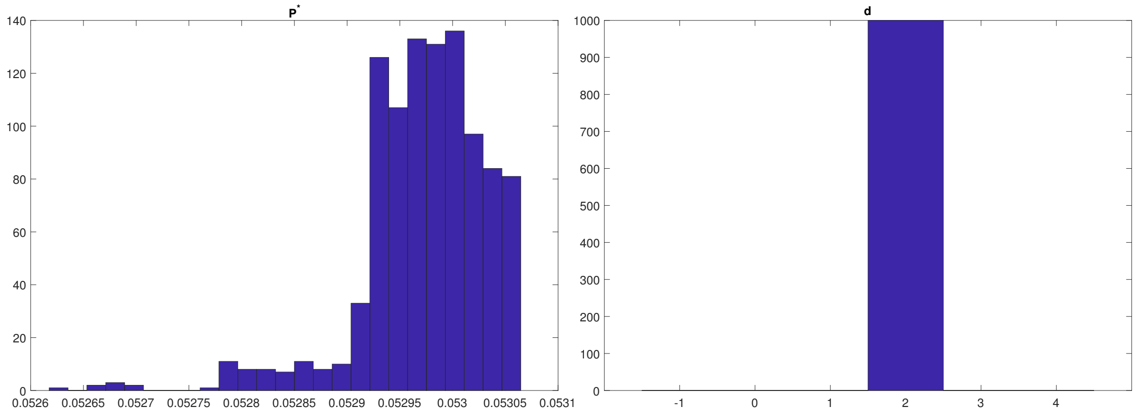


Figure 3: US inflation and estimated regime indicator,sample 1960-2023.

Figure 4 plots the posterior distribution of the threshold parameter P^*. The distribution is concentrated around a 5.3 percent annual inflation rate and the posterior minimum and maximum values are less than 0.1 of the mean value. This high precision is obtained even though



(a) P* (b) d*

Figure 4: Posterior distributions of the threshold $P*$ and the delay $d*$.

the prior is uninformative, and the results are unchanged, for example, if the prior distribution of the variance parameters is increased by a factor of 10.

Note that the estimated level of the threshold is twice as large as the mean value for the sample, is quite similar to the lowest of the two thresholds estimated by Gargiulo *et al.* (2024) (5.49) and also close to the value estimated by Pfauti (2023) using survey data (5.5). Thus, the high inflation regime has a smaller number of observations and it is rare, in the sense that the observations belonging to this regime belong to the upper tail of the distribution of inflation, roughly from the 80th percentile up.

The data seems also informative about the delay parameter d. Notably, the model structure shifts from one regime to the other two months after the inflation rate has crossed the 5.3 percent level. Posterior uncertainty is negligible. Once again, this is remarkable since the prior is quite uninformative over the selected range and the concentration of the posterior is unchanged, if the prior distribution of the variance parameters is increased by a factor of 10.

Figure C-10 in the on-line Appendix C plots the posterior distribution of the free parameters $\alpha_{ij},\ i = 1, 2; j = 1, \ldots, 22$ entering the contemporaneous matrix A_i in the two regimes. The posterior of key parameters differs. In particular, both the location and the spread of some parameters reflecting how variables instantaneously react to the two identified monetary policy shocks $(a_{12}, a_{14}, a_{16}, a_{20}, a_{21})$ change across regimes.

5.1 The role of the uncertainty indicator

Although it is not the focus of the paper, 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 innovations. Thus, it is conditional measure rather than an unconditional one; it is constructed using a small-scale information set rather than a large one; it is related to the volatility of the innovations rather than the volatility of the variables; it is an average rather than a principal component, as it is common in the literature, and it is exogenous to the first moment of US 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, because the VAR includes M2, not typically considered in earlier analyses, our measure has independent interest.

Figure C-5 in on-line Appendix C presents the median and a robust 68% posterior credible intervals of the distribution of λ_t at each t. Robust intervals are computed following Giacomini and Kitigawa (2021). The uncertainty indicator captures the massive volatility present during the COVID period. Thus, it helps to filter out excess variability due to the COVID outlier from the dynamics induced by the two structural shocks. Apart from this period, the indicator captures two other episodes of generalized uncertainty: the early 1970s, when the first oil crisis hit the US economy, and the mid 1980s, when important tax cuts were legislated to stimulate the supply side of the economy. For all other periods the indicator is randomly fluctuating around the mean with small absolute variations. Interestingly, it does not display any momentum around the 2008 financial crisis or the 2001 dotcom bubble. Thus, λ_t serves a different purpose than standard uncertainty measures employed in the literature [3].

To confirm the impression figure C-6 in the on-line Appendix C plots the component of inflation at each t predictable solely on the basis of λ_t. Remarkably, even though the indicator is constructed using the innovations of eight different variables, it is active as an inflation predictor only in the three above mentioned episodes and quiescent in the others. Furthermore, in these episodes it accounts for about two percent of the level of inflation. Thus, it is important to include λ_t in the specification both to absorb excess inflation volatility and to account for the ''excess" inflation dynamics present in the high inflation state.

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

5.2 The time path of estimated monetary policy shocks

Our estimation procedure produces as a side product the posterior distribution of the two estimated monetary policy shocks at each t. These distributions can be used as sanity checks to evaluate the reasonableness of our identification procedure. Figures C-11 and C-12 plot the time series of the median shocks and of the robust 68 percent sets over time. The conventional monetary policy shock was volatile in the 1970s, in the early 1980s and again at the end of the sample. In agreement with the conventional wisdom, our estimates imply that monetary policy was expansionary in 1975 and in 1979 and contractionary in 1973, 1976 and 1982. Furthermore, it became somewhat expansionary in 2020-2021 and quite restrictive in 2022.

The liquidity shock also displays high volatility around the same dates. However, its fluctuations are generally smaller in magnitude than those of the conventional shocks. Except for the 2020-2021 period, when the posterior distribution was primarily on the positive side, the series fluctuates randomly with the robust 68 percent intervals including the zero line. Note that the median times series of the liquidity shock is related to the forward guidance factors of Swanson (2021) (regression coefficient is 1.43 and the t-statistics 1.69, which significant at the 10 percent level) and, as shown in Figure C-4 in the online Appendix C, the shock has the intended effects on the balance sheet of the Federal Reserve.

6 The propagation of monetary policy shocks

6.1 Transmission in the linear model

As a benchmark, we first present in Figures 5 and 6 the dynamics in response to the two identified monetary policy shocks in a linear SVAR model. The variances of the shocks are allowed to be time varying, but the volatility indicator is excluded from the predictors. In each box, we report the pointwise median and the robust 68% credible posterior interval.

The transmission of conventional policy shocks is standard. A surprise increase in the short-term nominal rate temporarily decreases production growth, persistently increases unemployment, and depresses stock market growth up to two years. The shock slowly affects inflation and commodity prices growth, which fall with a delay. M2 growth temporarily decreases, and the long-term interest rate increases but, consistent with the expectation hypothesis, less than the short-term rate.

An unexpected liquidity injection makes output growth increase and unemployment fall with a 5-6 month delay; inflation and commodity prices growth persistently increase, while the long-term rate falls and the stock growth temporarily increases. The qualitative features of the

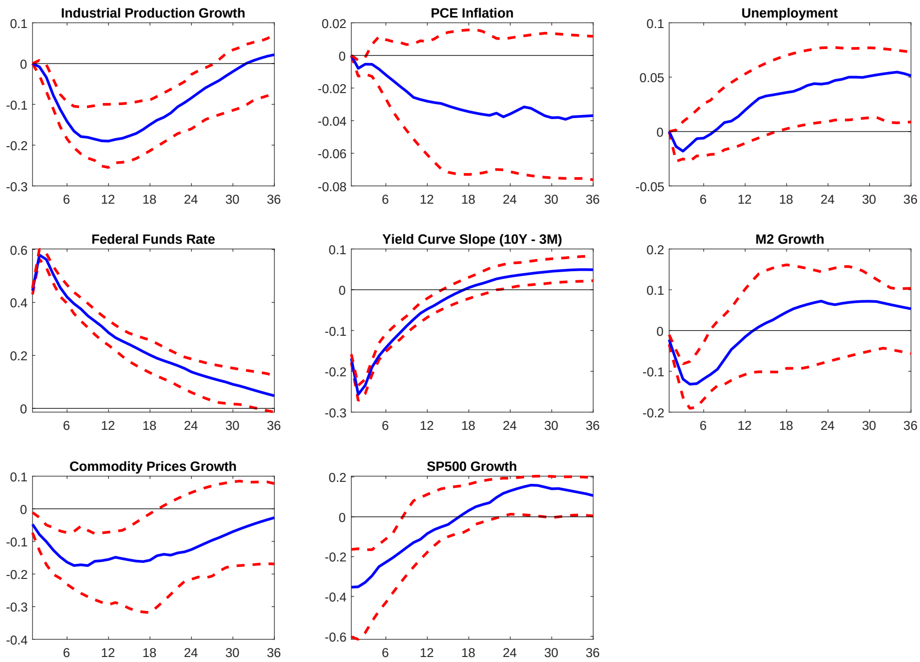


Figure 5: Responses to contractionary conventional policy shocks, linear model.

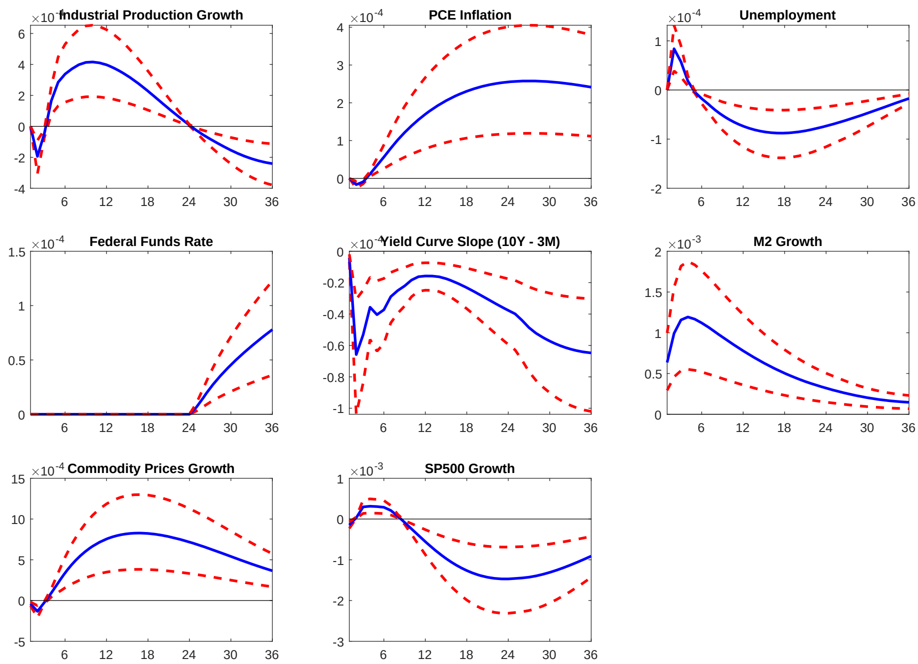


Figure 6: Responses to expansionary liquidity shocks, linear model.

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 initial counter-intuitive response of output growth, unemployment and inflation would be absent, see figure C-2 in the on-line Appendix C. Thus, the transmission of liquidity shocks is also standard and qualitatively similar to the transmission of conventional policy shocks. This is unsurprising, given that both types of policy actions, although working through different channels, are designed to achieve the same goal.

6.2 Transmission in 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 7. In each box the lines represent the pointwise median and the robust 68% credible interval at each horizon. Qualitatively, the propagation of shocks in the two regimes is similar and in line with what the linear model suggests. The disturbance in fact generates a fall in industrial production growth, an increase in the unemployment rate and a temporary fall in inflation. Stock prices and commodity prices growth fall in both regimes.

Quantitatively, the median effects differ. In the low inflation regime, the effect on industrial production growth and unemployment is larger than in the high inflation regime (and the maximum effect is twice as large) but the persistence of the real responses is stronger in the latter regime. Similarly, stock prices growth falls more in the low inflation regime. Hence, a surprise increase in the short-term rate in the high inflation regime has somewhat muted but longer lasting effects on economic activity.

These quantitative differences are consistent with dynamics of the term structure of interest rates. 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 regime but not by as much. The inversion of the yield curve in the low inflation regime is unexpected but consistent with the idea that the central bank possesses more information about the future of the economy in this state. The signal the shock provides is valuable for private agents and the fact that long-term rates react more agrees with the idea that they adjust their inflation expectations correspondingly. To put the idea differently, a short-term interest rate surprise in the low inflation regime is not interpreted as shift in the policy stance. Instead, it is perceived as indicating that inflation is going to be higher than the market expected over the relevant policy horizons, perhaps because of fiscal considerations, as in Melosi (2017).

One possibility for why the signaling effect is stronger in the low inflation regime is that, when

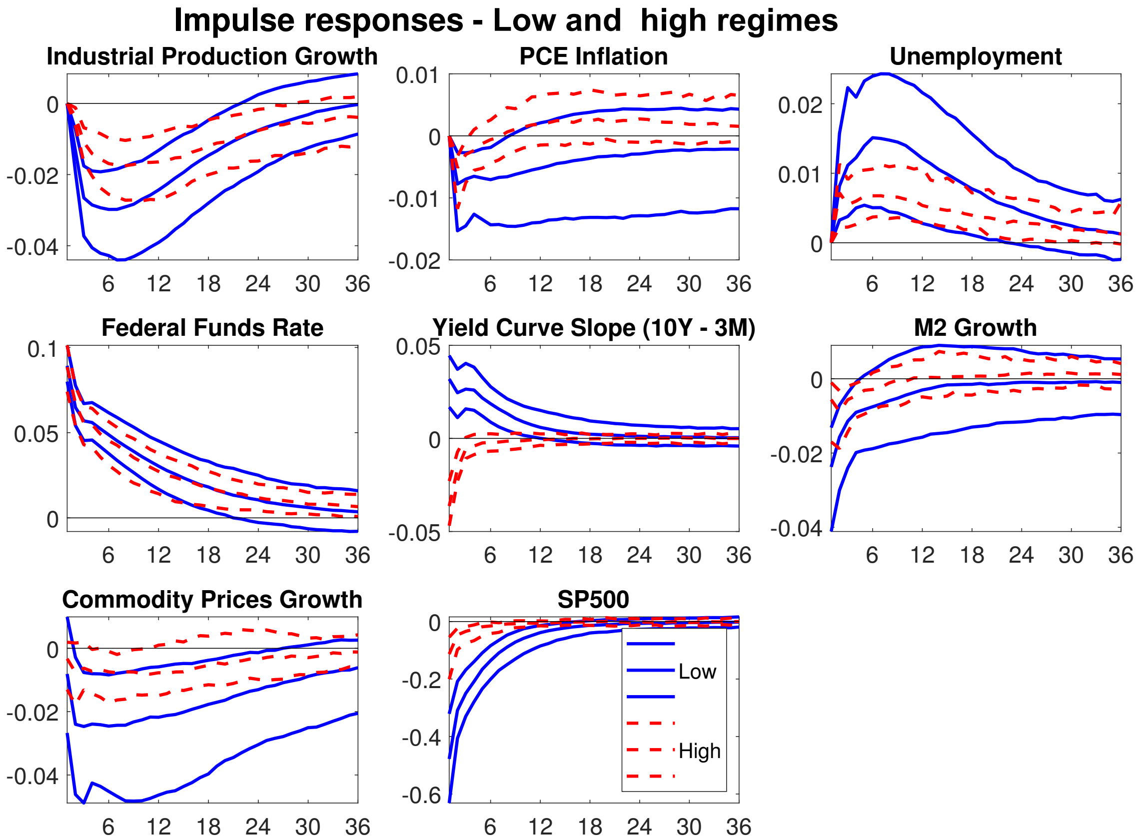


Figure 7: Contractionary conventional monetary policy shocks, different regimes.

inflation is high, agents already factor in increases in the short-term rate. That is, markets believe that the central bank will fight the inflation surge by what is dictated by the existing monetary policy rule. Note that an alternative possibility, highlighted by Bauer and Swanson (2023), that the Fed responded to news in a stronger way than market expected is inconsistent with the way the figure is constructed - the only news causing the variables to respond is the monetary policy shock. To put the result differently, while Bauer and Swanson (2023) examine unconditional correlations between output and interest rates, we condition the analysis on monetary policy shocks and focus on the reaction of the bond markets.

The dynamics across regimes could also be consistent with the idea that the level of inflation affects the credibility of central bank actions. Such an explanation, while potentially valid for developing countries, is at odds with current perceptions about how US monetary policy has been conducted over the last forty years.

The signaling effect we detect is similar to the one empirically documented in Miranda Agrippino and Ricco (2021) and Jarocinski and Karadi (2020). Melosi (2017) provides a theoretical model with this feature. Relative to this literature, the main finding here is that the mechanism appears to be regime dependent.

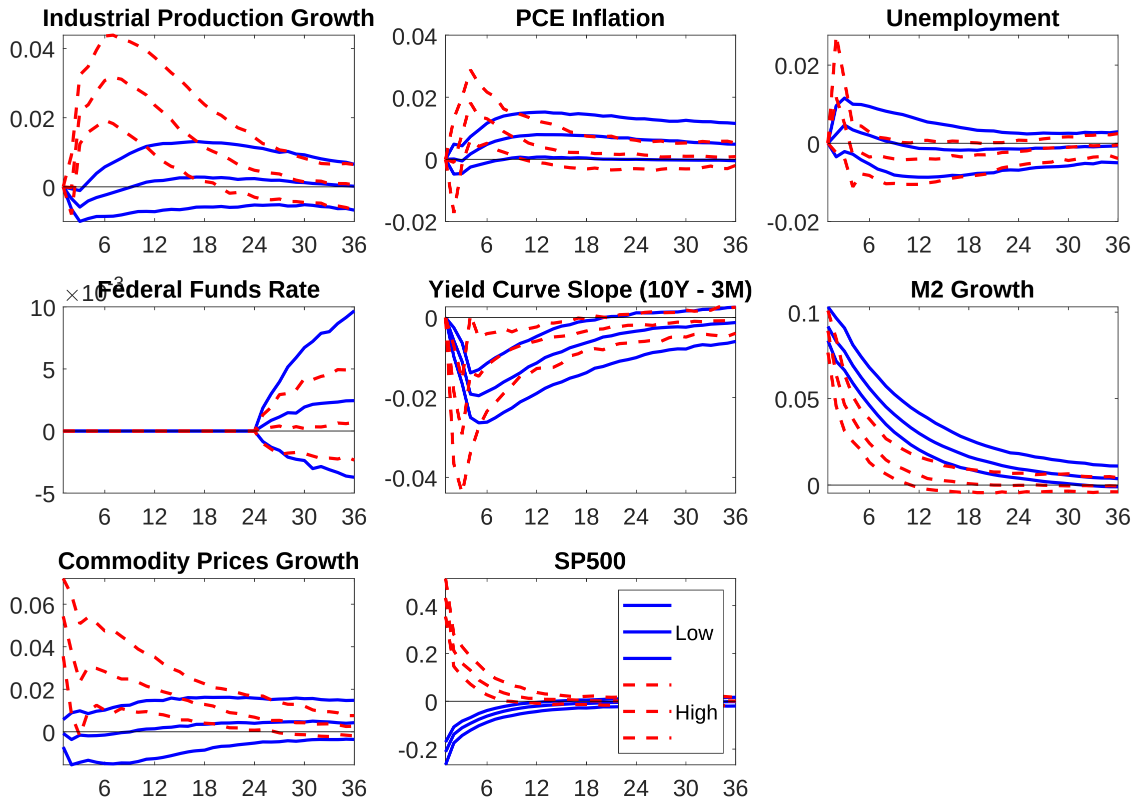


Figure 8: Expansionary liquidity shocks, different regimes.

Figure 8 presents the responses to a liquidity disturbance. The magnitude and the sign of the dynamic responses now differ across regimes. In the low inflation regime a liquidity shock, 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, a surprise increase in the amount of money in circulation, engineered through purchases of long-term assets, has negligible real effects in the low inflation regime; do not significantly affect inflation; and produce negative repercussions in the stock market.

Liquidity expansions in the high inflation regime instead boost industrial production growth, increase inflation, while leaving the unemployment rate roughly unchanged. The different median dynamics of production growth are reflected in the responses of commodity prices growth and of SP500 growth, which are now significantly positive at all horizons. Thus, when inflation is high, a surprise increase in M2 is interpreted as good news by the stock market. While inflation temporarily inches up, the asset purchase is seen by agents as boosting the profitability of firms and thus stock valuation. This interpretation is supported, in part, 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. If one associates the high inflation regime to a situation where disagreement and thus uncertainty is high as inBarbera *et al.* (2023), then the evidence is consistent with the idea that asset purchases are less effective in normal than abnormal times, see Tenreyro and Wazzi (2025)

It is worth mentioning that, quantitatively, the responses in the non-linear model are smaller than in the linear one. While many reasons may contribute to the difference, one should remember that what we find is exactly what one should predict to happen when the DGP is nonlinear, but a linear model is used, since the state aggregation bias is likely to be positive, see also Gargiulo *et al.* (2024) The differences in the persistence of the responses across regimes to conventional shocks we find agree with their work. However, in their model the response of the unemployment rate is hardly significant in both states.

6.3 The role of λ_t in the transmission across regimes

One question of interest is whether the regime differences we obtain are in some way related to the presence of the uncertainty indicator among the right-hand side variables. As mentioned, the use of the λ_t as a predictor is one of the key differences between our work and Gargiulo *et al.* (2024). Thus, we have re-estimated the model dropping λ_t from the list of regressors. Figures D-1 and D-2 in the on-line Appendix D indicate that both the timing of the two states and posterior distribution of P^* are unaffected.

The regime dependent impulse responses in a model that excludes λ_t from the predictors are in Figures D-3 and D-4 in the on-line Appendix D. Having λ_t in the specification is important. If it is omitted, credible sets become large making and the responses in the two states insignificantly different. In addition, the informational effect previously detected disappears for liquidity shocks and, for conventional monetary policy shocks, no slope inversion is obtained.

6.4 Counterfactuals

To evaluate the credibility of the signaling role of monetary policy shocks we conduct a simple counterfactual exercise. We ask what would happen to the endogenous variables of the model if either the median response to the slope of the term structure to conventional policy shocks or the median response of stock prices growth in response to liquidity shocks would be forced to be identical in the two states. If the mechanism driving the differences is indeed the asymmetric signal that shocks have on financial markets, then forcing the slope and stock price growth to display the same reaction across regimes should make differences in the other endogenous variables insignificant.

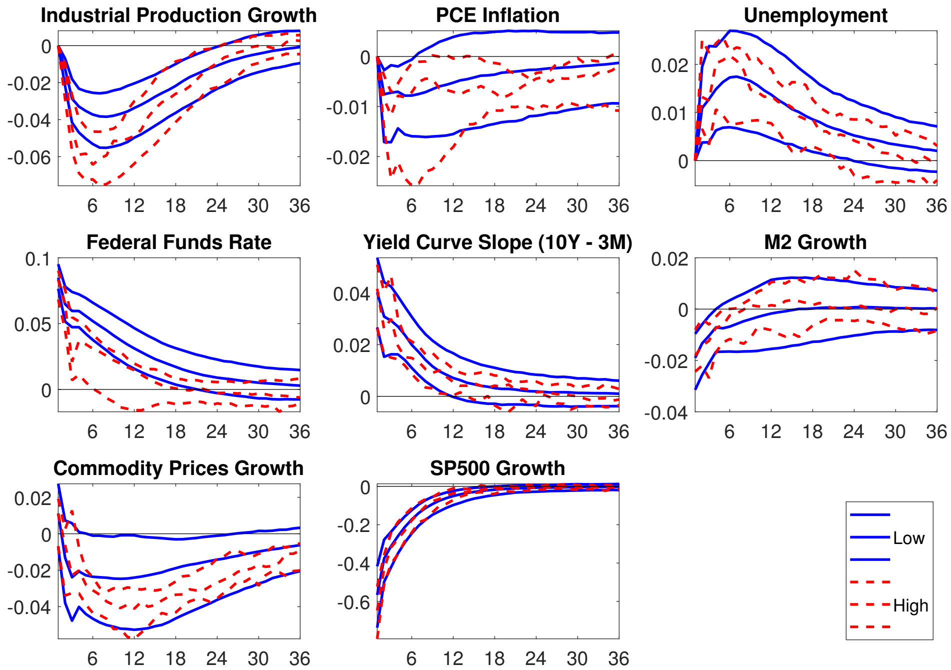


Figure 9: Counterfactual contractionary conventional monetary policy shocks.

The counterfactual responses are in Figures 9 and 10. They both report the pointwise median and the 68% credible sets. For conventional monetary policy disturbances, the dynamics of industrial production growth, unemployment and inflation are indeed insignificantly different across states. For liquidity shocks, differences across states are quantitatively and qualitatively insignificant. Hence, the information effect we emphasize seems important: without it the transmission of policy shocks would be state independent and the dynamics in response to both types of shocks roughly linear.

6.5 The reaction of inflation expectations

Crucial to the narrative we have associated with Figure 7 is the reaction of inflation expectations. In particular, if the signaling story has a solid foundation, inflation expectations should significantly react in the low inflation regime but not in the high inflation regime. To verify whether this is the case, we use Survey of professional forecast (SPF) data from the Philadelphia Fed and ran local projections to compute the dynamics of the median inflation expectation using the posterior distribution of conventional policy shocks. The responses are in Figure 11.

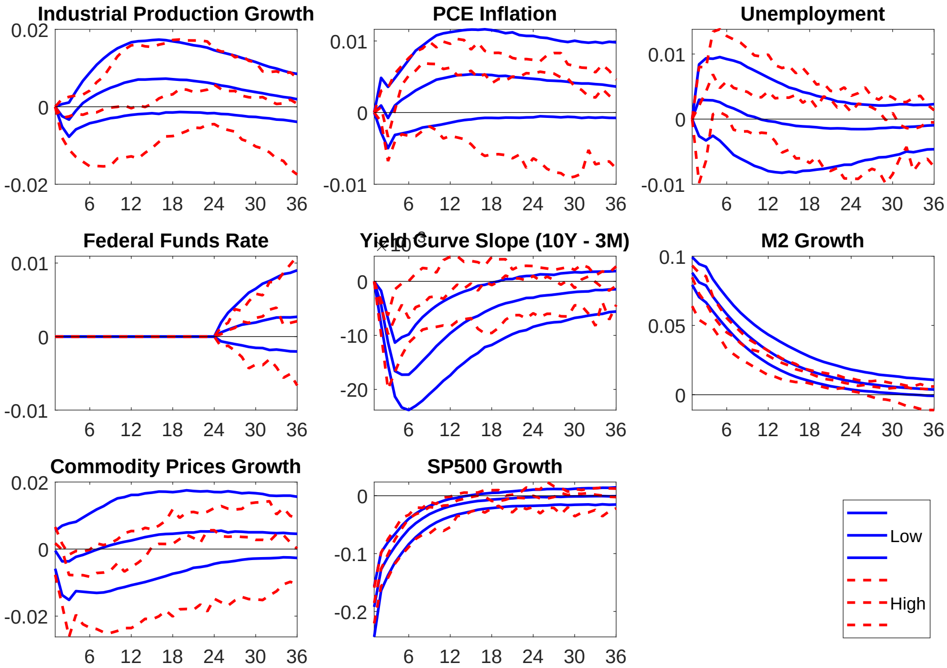


Figure 10: Counterfactual expansionary liquidity shocks.

Consistent with the signaling hypothesis, Figure 11 shows that an unexpected increase in the short-term rate produces a significant reaction of CPI inflation expectations in the low inflation regime. The effect is positive for two months and turns negative afterwards. On the contrary, the responses in the high inflation regime are generally insignificant. These outcomes are robust to the measure of expectations employed: substituting one-year ahead GDP deflator expectations or shorter-term inflation expectations lead to the same qualitative conclusions. Interestingly, the response of CPI inflation expectations to liquidity shocks is insignificantly different in both regimes (see Figure E-1 in the on-line Appendix E). This lines up well with the fact that the responses of the slope of term structure to liquidity shocks in the two regimes are similar.

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

6.6 The reaction of net entry

Crucial to the narrative we have associated with Figure 8 is the reaction of some measure of future economic activity. If stock prices are the discounted sum of future dividends, higher

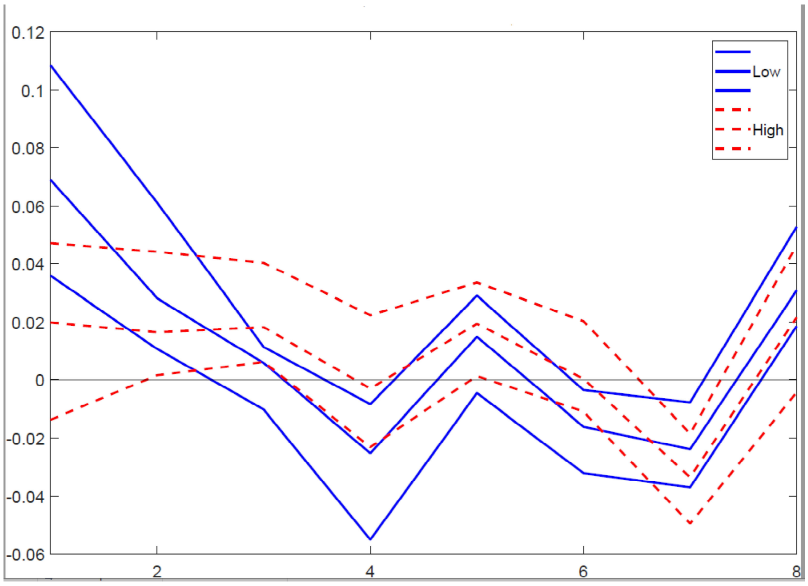


Figure 11: Responses of CPI inflation expectations, conventional policy shocks

stocks price growth in the high inflation regime should be associated with higher future output growth and higher expected business profitability. IP growth is indeed increasing 6-12 months after the shock. To check whether future profitability rises we use a net entry series. We construct it, as it is standard, splicing the net business formation series from BEA Survey of Current Business up to 1993 and the business employment dynamics BLS series after 1993. As the series is quarterly, we aggregate the monthly disturbances prior the computation of the responses.

Figure 12 presents the results. Consistent with our interpretation, the response of net entry is significant four quarters after the shock in the high inflation regime but not in the low inflation regime. The evidence is however weak, and the large credible intervals prevent us from making strong statements in this case.

6.7 Robustness

We have estimated several versions of the baseline model to verify the robustness of the main conclusions we reach. Here we briefly discuss the outcomes of four exercises. The first consists in estimating the model over the 1984-2019 sample. We wish to examine two separate questions: a) whether the identified low inflation regime is actually a mixture of two separate states: an average inflation state and a low inflation state, possibly associated with the zero lower bound on the short-term rate; and b) whether the 1970s are important to separate the high vs. the low

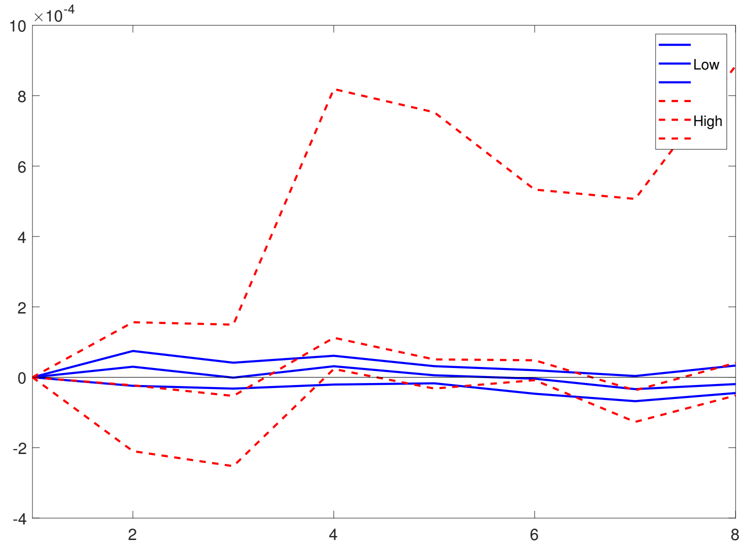


Figure 12: Responses of net entry, liquidity shocks

inflation regime. In this sample, our algorithm picks 3.3 percent as the inflation threshold and the normal state occurs in 1986, 1989-1992, 2004, 2006, two quarters in 2008 and two quarters in 2009. Thus, the likelihood function does not consider the zero lower bound period as separate period since the dynamics of the variables other than the short-term rate determine P^* and the timing of the threshold. Furthermore, dynamic responses are not statistically different across states in response to both shocks. Thus, there seems no need to further split the low inflation state into two independent regimes and what happens in the 1970s is crucial to separate the dynamic responses in the two states. The results obtained with this specification are in on-line Appendix F.

The second variation we consider uses the shadow rate of Wu and Xia (2016). We wish to examine whether the zero lower bound on short term interest rate affects the nature of the results we obtain. As shown in the on-line Appendix G, none of our conclusions regarding the transmission of monetary shocks is affected by this change.

The third modification involves dropping food and energy items from the PCE inflation series. Using core inflation attenuates a bit the inflation spikes in the 1970s and in 2021-2022 but does not alter either the persistence of inflation or the correlation structure among variables. Hence, estimates of the state indicator coincide with those in Figure 3 and the role of λ_t is unchanged. Similarly, the pattern of responses to conventional shocks is maintained. In particular, the response of the slope of the term structure switches signs across regimes although now the differences in other variables are only marginally significant. In response to liquidity shocks the response of stock market growth changes sign but, because credible intervals are large no significance differences are detected.

The final change concerns 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 of interest here is whether the non-linear effects we find could be due 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 high states the years 1974-1983, 1989 and 2021-2022. The role of λ_t in predicting inflation is reduced but the indicator still has spikes in 1974-1979-1980 and 2021-2022. The qualitative differences in production growth, inflation and unemployment across regimes remain but now they are insignificant. Overall, commodity prices seem a better indicator of future inflation then WTI oil prices when it comes to examine the monetary transmission mechanism [4].

7 The inflation-real activity slack trade-off

The standard framework to explain inflation dynamics, the so-called Phillips curve (PC), links inflation to unused capacity. Intuitively, if the economy heats up, demand tends to exceed capacity, causing an upward pressure on prices and thus higher inflation. Since the original paper linking the unemployment rate to (wage) inflation, Phillips (1958), a number of theoretical works focused on deriving the foundations for the Phillips curve. Friedman (1968) emphasized the notion of the unemployment gap; that is, the deviation of unemployment from its natural level, a concept later microfounded by the New-Keynesian literature Galí (2015). However, unemployment is not the only available capacity slack measure. Popular candidates include also the average real marginal cost (the output gap or the labor share), see e.g. Galí (2015), and the vacancy–unemployment (VU) ratio, see e.g. Barnichon and Shapiro (2024)

As mentioned, menu costs and slanted-L theories have sharp implications for the magnitude of the slope of the Phillips curve. In particular, conditional on any demand shock, both types of models predict a steeper PC when inflation is high, regardless of the way the inflation-slack trade-off is measured. This is because when inflation is high, firms should readjust prices more rapidly, making the response of output smaller and the response of inflation larger as menu costs or hiring costs increase. Empirical evidence is mixed. While Ascari and Haber (2021) shows that the PC is steeper, Beaudry *et al.* (2025) questions results suggesting that they are due to improper accounting of inflation expectations.

[4] Figures for the third and fourth case discussed in this subsection are available on request from the authors.

We examine what our analysis has to say about popular theories of inflation dynamics, conditional on the identified monetary policy shocks. We measure real activity slack by the unemployment rate, the labor share, or the VU ratio. We construct estimates of the PC slope by taking the responses of inflation and dividing them by the responses of the real activity measure, horizon by horizon, draw by draw, for each of the two shocks. Our approach is similar, in spirit, to Barnichon and Mesters (2019).

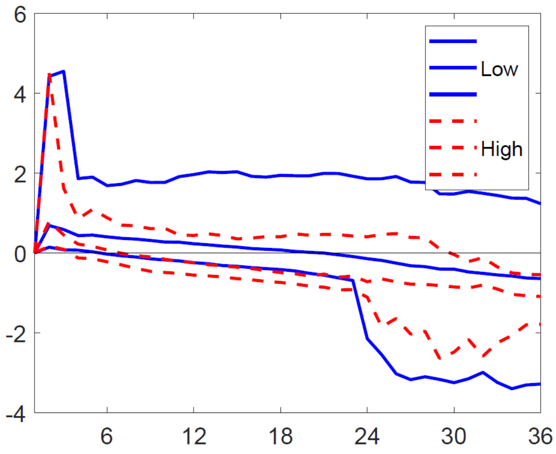
The first row of Figure 13 suggests that, when the unemployment rate is used as a measure of real activity slack, the PC relationship hardly changes across regimes. One potential confounding factor, often discussed in the literature, which may blur the relationship is the presence of supply disturbances. If these are not properly accounted for, 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 the dynamics represent responses to identified monetary policy shocks, rather than regression coefficients where the dependent variable is potentially endogenous. Furthermore, the disturbances we use are orthogonal to all other system shocks, including various potential supply shocks.

The second row of Figure 13 provides evidence using the labor share as a measure of real economic slack [5]. While there are significant differences across regimes at the 5 months horizon in response to conventional disturbances, no statistically significant differences are obtained in response to liquidity shocks. However, PC slope responses are larger in the low inflation regime - the opposite of what menu costs would imply.

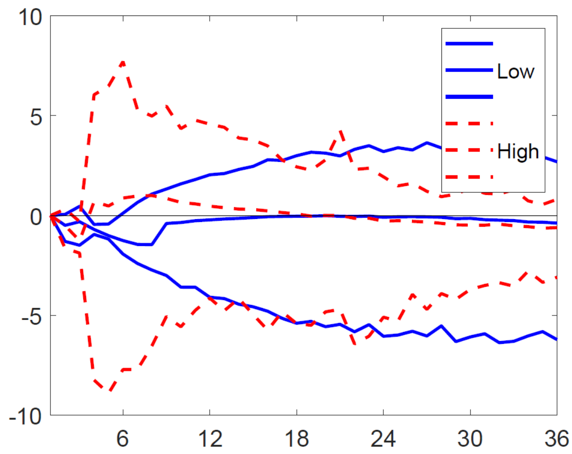
Finally, the third row of Figure 13 presents the responses of the slope of PC curve to the two identified shocks when the VU rate is used as measure of real activity slack. While quantitative differences are present, the qualitative effects are similar to those obtained with the labor share. Specifically, there are significant differences across regimes at the 10 months horizon in response to conventional policy disturbances, but the responses are larger in the low inflation regime. This piece of evidence is consistent with Inoue *et al.* (2022), who use a continuously varying approach to measure the evolution of the Phillips curve over time. Furthermore, no statistically significant differences across regimes are obtained for liquidity shocks.

Turning to rational inattention models, the evidence we have collected is mixed. While the industrial production growth dynamics in Figure 7 are consistent with the evidence of Mackowiak and Wiederholt (2009), the dynamics of inflation expectations in Figures 11 and E-1

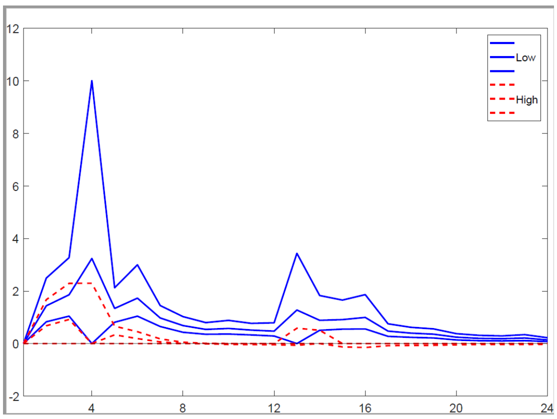
[5] Data on the labor share is obtained from the FRED database.



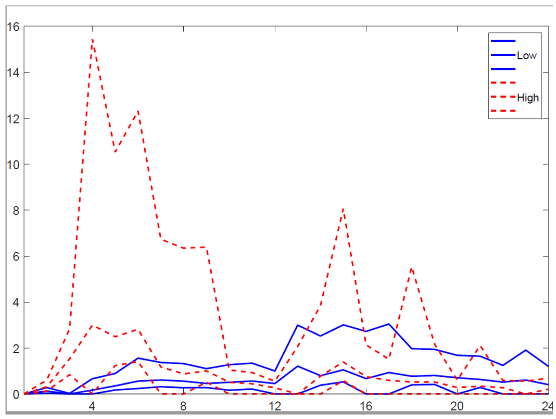
(a) Unemployment-Conventional



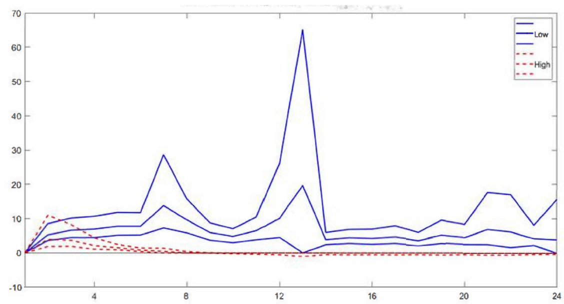
(b) Unemployment-Liquidity



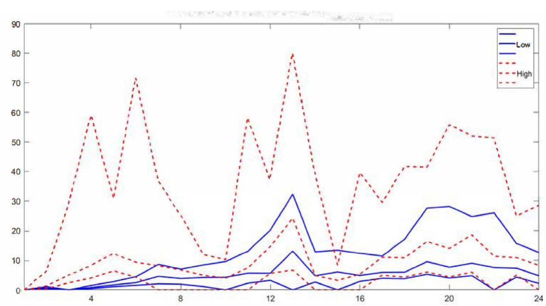
(c) Labor Share-Conventional



(d) Labor Share-Liquidity



(e) VU Ratio - Conventional



(f) VU Ratio - Liquidity

Figure 13: Responses of the slope of the Phillips curve

do not line up well with the implications of the theory. Such models in fact predict that inflation expectations should be more responsive when inflation is high. The evidence suggests the opposite, at least in response to conventional policy shocks.

8 Conclusions

This paper explored the propagation of two types of monetary policy shocks in high and low inflation regimes. We use monthly US data 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 which allows for an endogenous selection of the switching threshold and, thus, of the two states, and direct effects of shock uncertainty on the endogenous variables. We refine the available technology by adding to the Gibbs sampler a zero-sign restriction identification scheme and a reparameterization step of contemporaneous relationships, which allows for a more efficient sampling from the posteriors of the parameters.

We find 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 dynamic effects last longer when inflation is high. The differences are due to the dynamics of the slope of the term structure, which changes sign across regimes: the long-term rate increases more than short-term rate at all horizons in the low inflation regime; the opposite is true in the high inflation regime. The slope inversion is consistent with the idea that a monetary policy shock provides informational content about the future, but that happens only in the low 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. Stock market responses to the shock explain the differences across regimes. In fact, the stock market sees the rise in liquidity as good news when inflation is high but not when inflation is low. We show via counterfactuals that the informational content of monetary policy shocks for financial markets is non-negligible and that the reaction of inflation expectations and net entry is consistent with the interpretation we provide.

The evidence has implication for theories of inflation dynamics. In particular, we find little evidence in favor of menu costs or slanted-L theories, while the support for rational inattention models is at best mixed. Overall, the dynamics we uncover are consistent with the idea that monetary policy disturbances provide information about the future state of the economy. The twist of our paper is to show that the informational content is nonlinear and state dependent.

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Does the transmission of monetary policy changes when inflation is high?

Fabio Canova and Fernando Perez-Forero

On-line 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[6]:

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

   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:

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

[6] The matrix A_i takes the restrictions imposed by Sims and Zha (2006) as a starting point. The 4th and 6th columns are those identifying conventional and liquidity 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 $\alpha_i \sim N\left(\overline{\alpha}_i, \bar{c}\overline{V}_{\alpha_i}\right)$ where $\bar{c}$ 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 $u_{j,t} = A_1\tilde{e}_{1t}S_t + A_2\tilde{e}_{2t}\left(1 - S_t\right)$ 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.

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

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

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

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

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

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

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

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

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

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 $p(\Theta \mid Y)$.

Parameter	Distribution	Hyper-parameters
$P^{\dagger}$	Truncated Normal	$N\left(c_P\overline{P}, \sigma_P^2\right)$
d	Uniform	$\frac{1}{d_{max}}$
$\phi_{i=1,2}$	Truncated Normal	$N\left(\underline{\phi}_i, \underline{V}_i\right)$
$\alpha_{i=1,2}$	Normal	$N\left(\mu_\alpha, \Omega_\alpha\right)$
$\sigma^2_{j=1,\ldots,N}$	Inverse-Gamma	$IG\left(d_\sigma \times \underline{\sigma}, d_\sigma\right)$
λ_0	Normal	$N\left(\mu, \frac{Q}{1-F^2}\right)$
μ	Normal	$N\left(0,1\right)$
F	Truncated Normal	$N\left(0.8, 0.01\right)$
Q	Inverse-Gamma	$IG\left(d_\sigma \times \underline{\sigma}, d_\sigma\right)$

Table 2: Priors for the parameters

where $\overline{P}$ is the sample mean for inflation and $c_P = 1.5$ is a scalar factor. $\sigma_P^2 = \left(P^{\dagger}_{max} - P^{\dagger}_{min}\right)/6$, with $P^{\dagger}_{max} = 1.05 * c_P\overline{P}$ and $P^{\dagger}_{min} = 0.95 * c_P\overline{P}$. $d_{max} = 6$. $\underline{\phi}_i = 0$ and $\underline{V}_i$ is a diagonal matrix with Minnesota structure. $\mu_\alpha = 0$ and $\Omega_\alpha = I_{dim_\alpha}$. Finally, $d_\sigma = 10$ and $\underline{\sigma} = 0.01$.

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 $t^* \sim U\left(1, T\right)$.

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 (5). 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

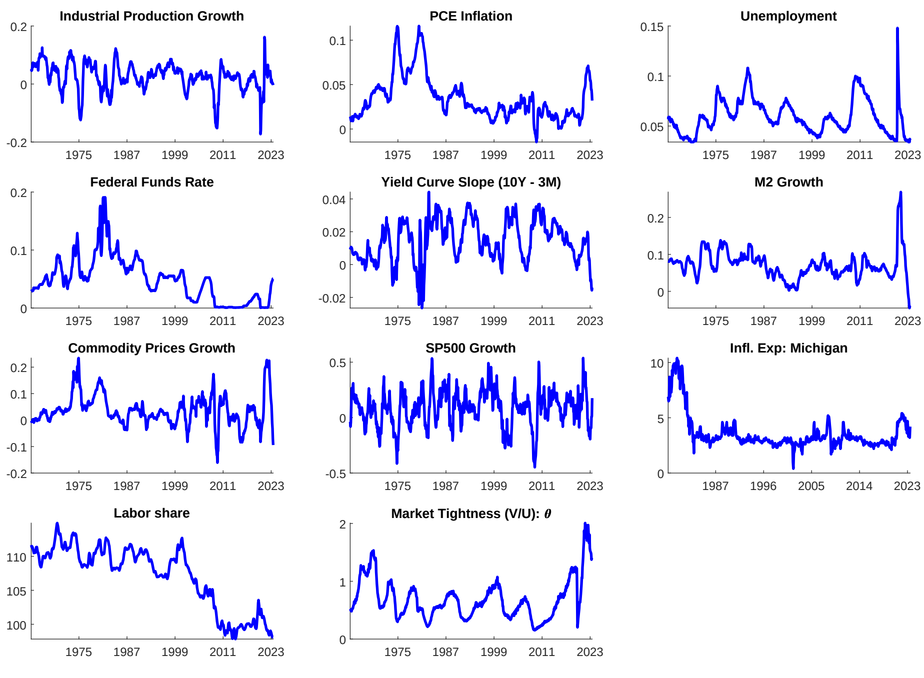

Figure C-1: Time series of the data, sample 1960-2023.

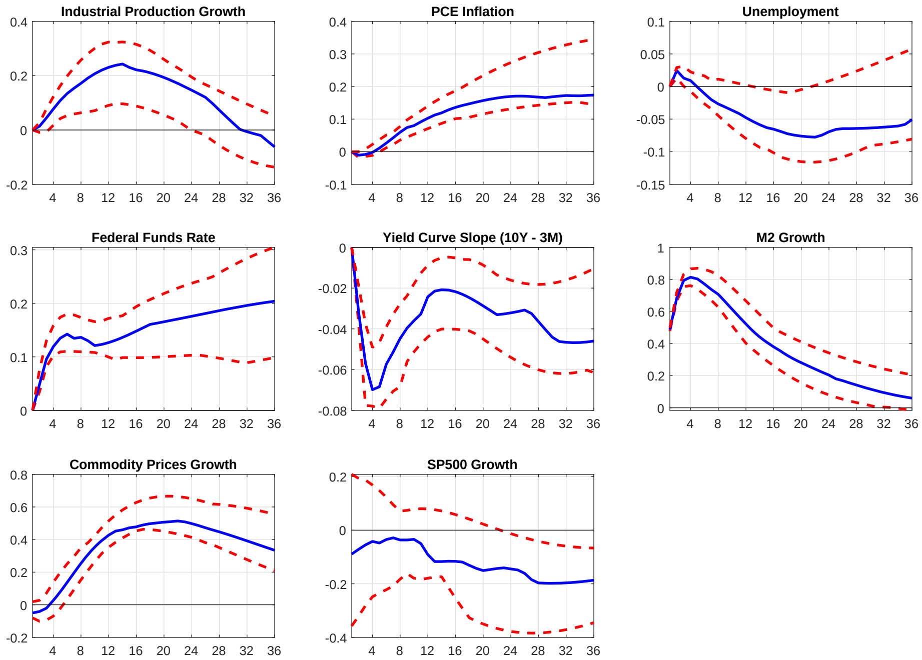

Figure C-2: Responses to liquidity shocks, no constraint on the short-term rate.

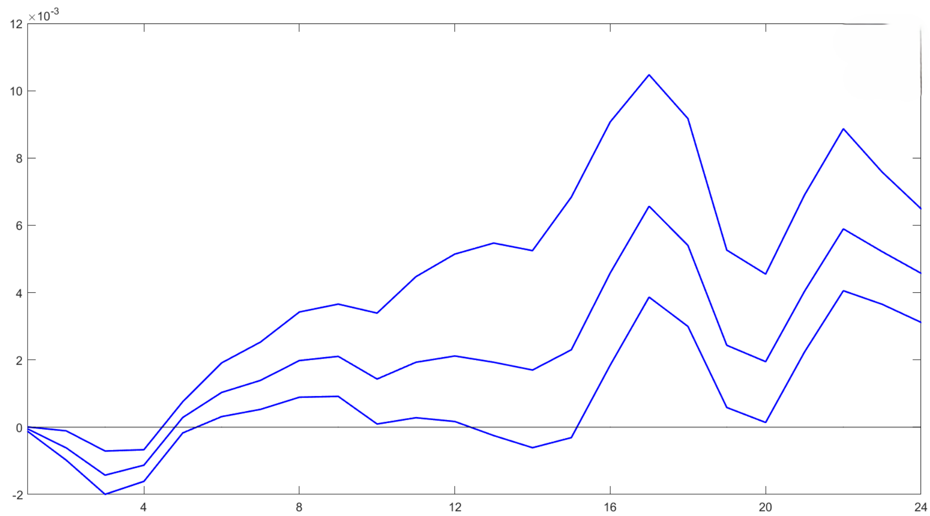

Figure C-3: Responses of M0 to liquidity shocks.

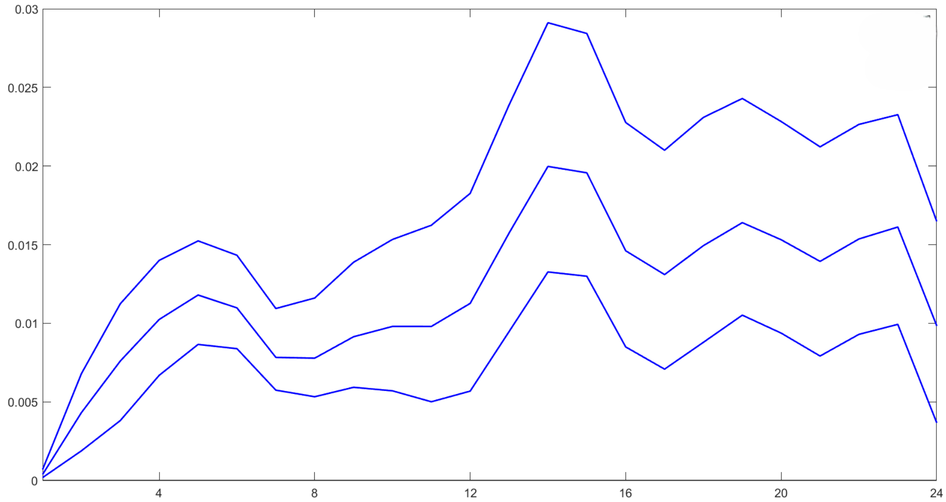

Figure C-4: Responses of Fed balance sheet to liquidity shocks.

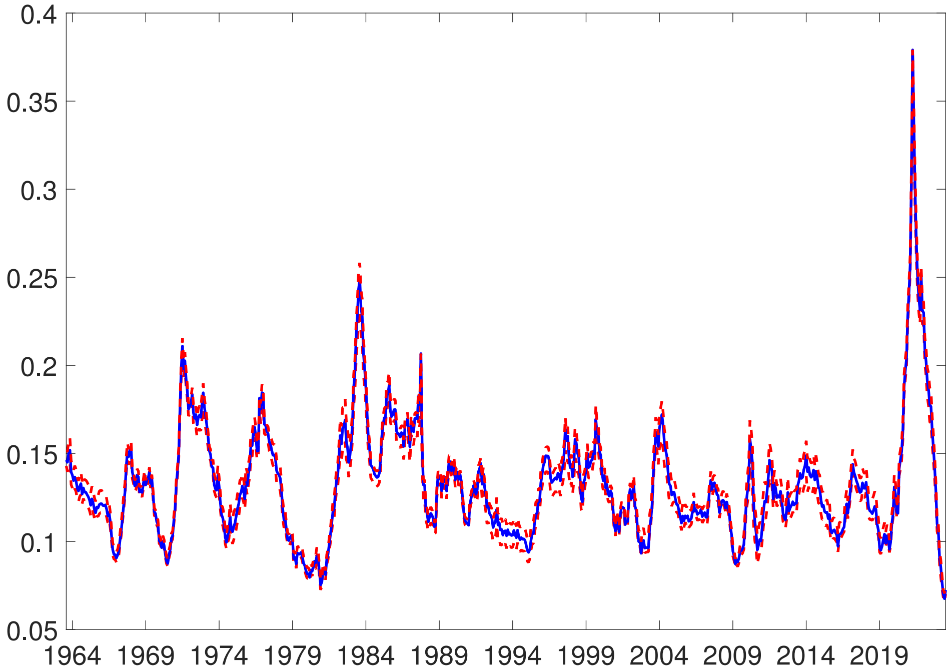

Figure C-5: Posterior 68% credible sets for the λ_t process.

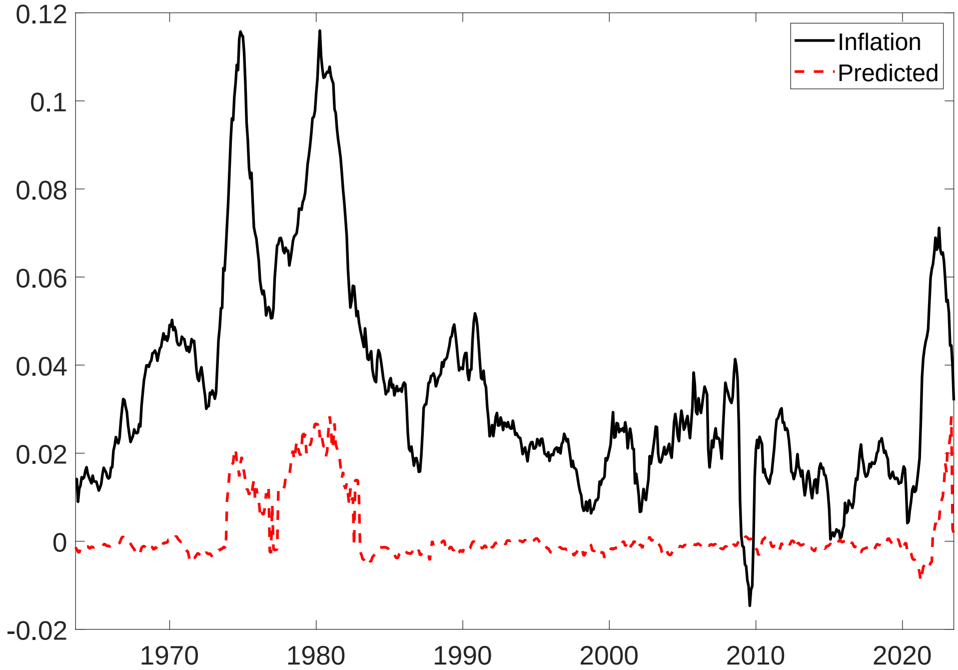

Figure C-6: Predicted inflation based only on λ_t.

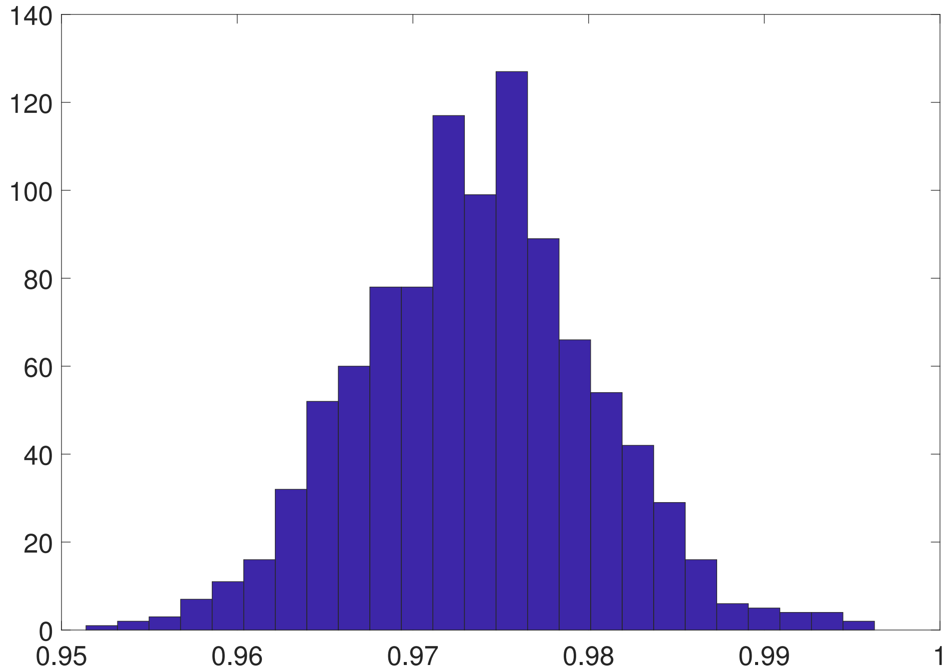

Figure C-7: Posterior distribution of the volatility persistence parameter F.

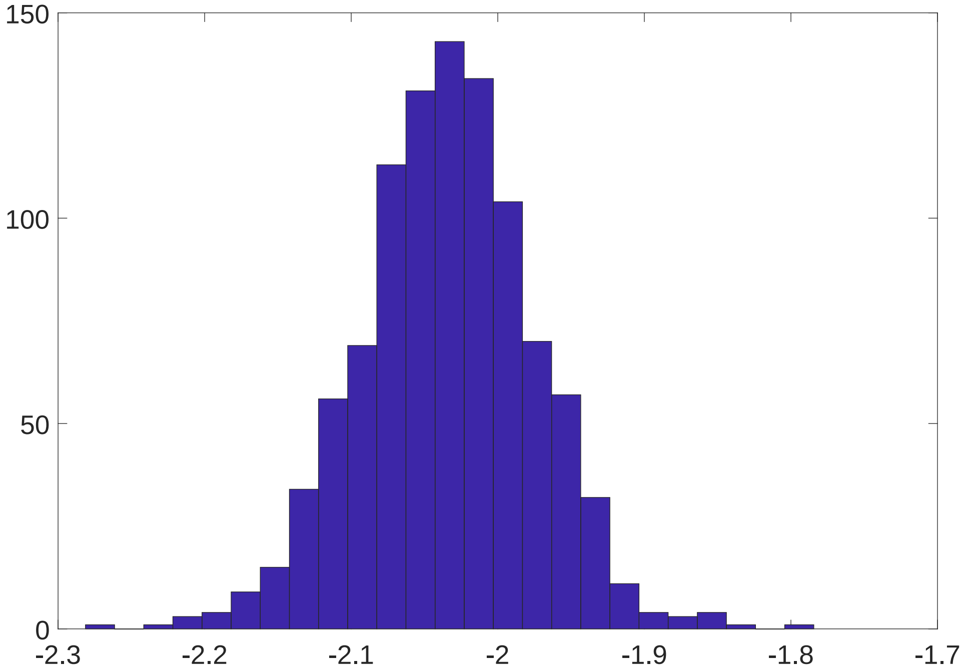

Figure C-8: Posterior distribution of the volatility mean parameter μ.

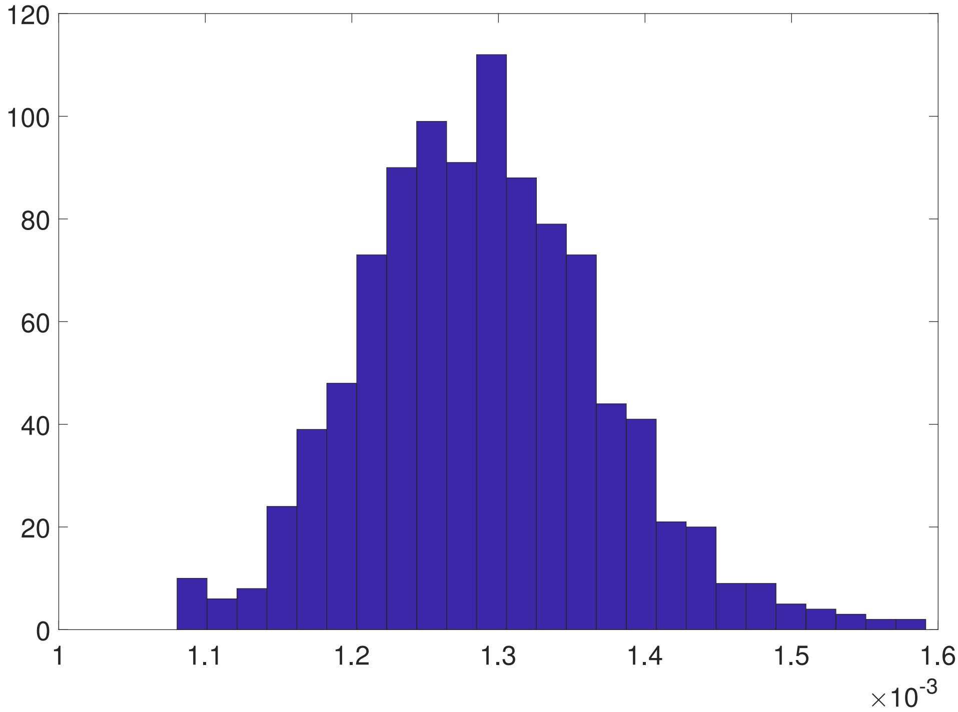

Figure C-9: Posterior distribution of the volatility variance parameter Q.

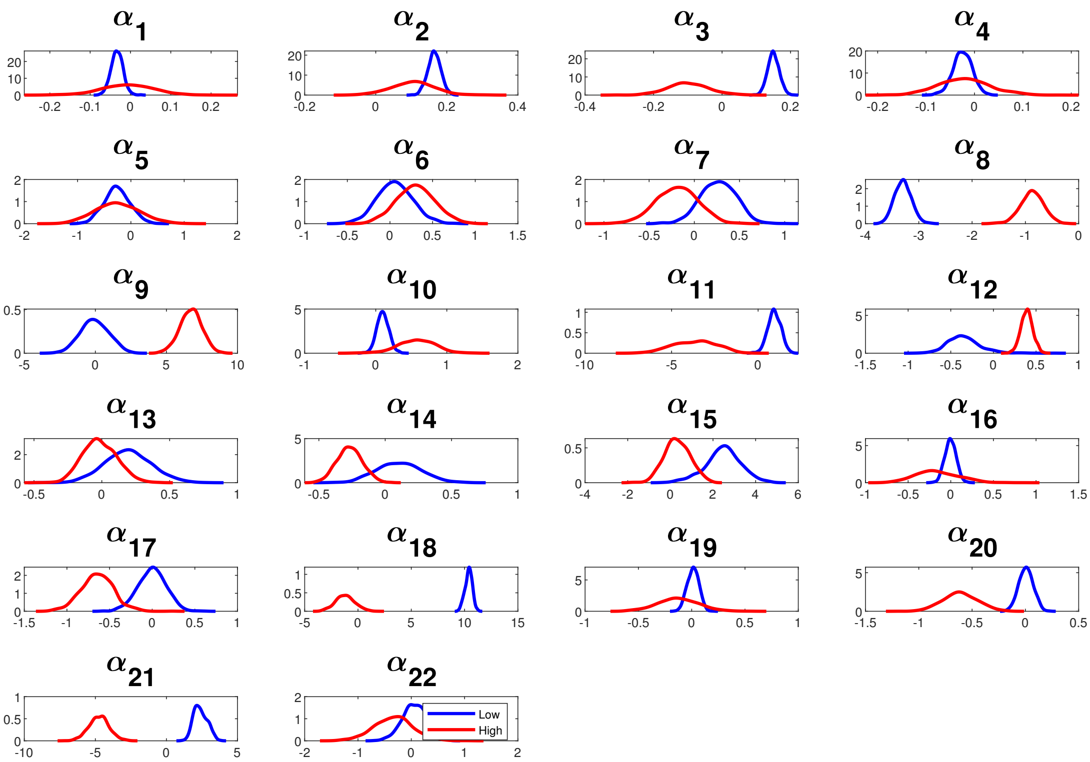

Figure C-10: Posterior distributions of α_i vector parameters in the two regimes.

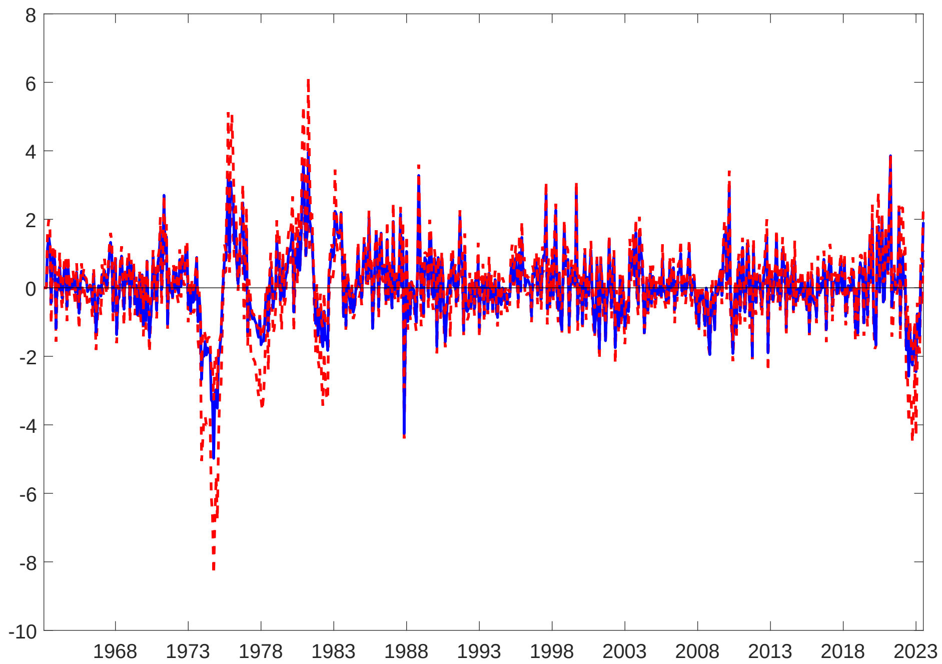

Figure C-11: Posterior distribution of the conventional monetary policy shocks.

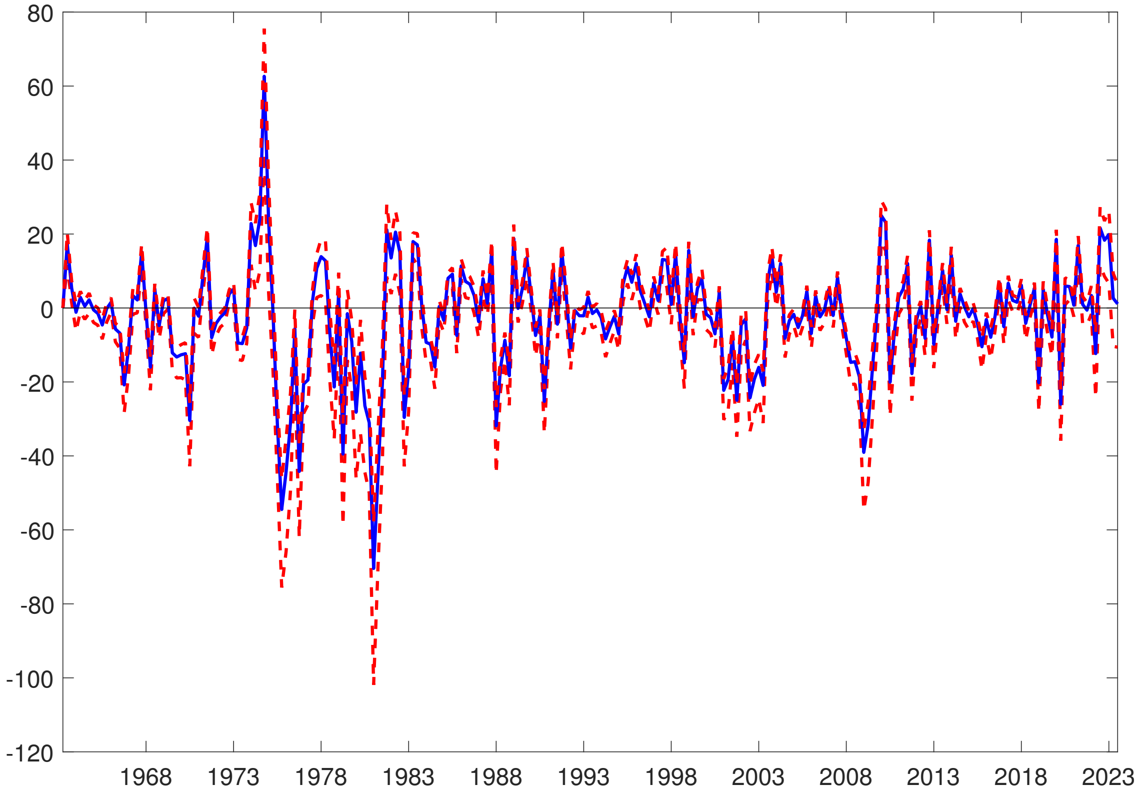

Figure C-12: Posterior distribution of the liquidity shocks.

D Results obtained excluding λ_t from the regressors

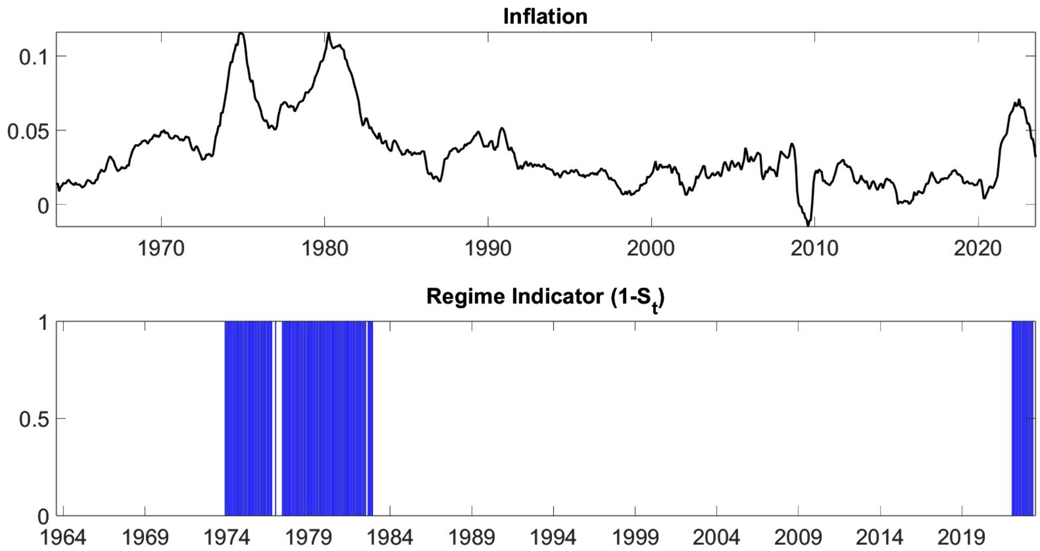

Figure D-1: US Inflation and estimated regime indicator, no λ_t.

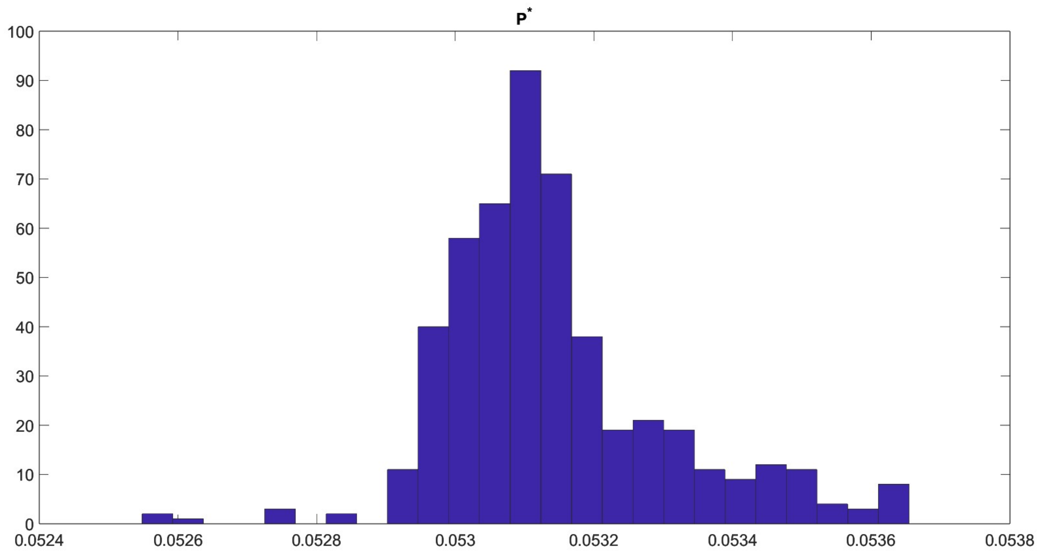

Figure D-2: Posterior distribution of P^*, no λ_t.

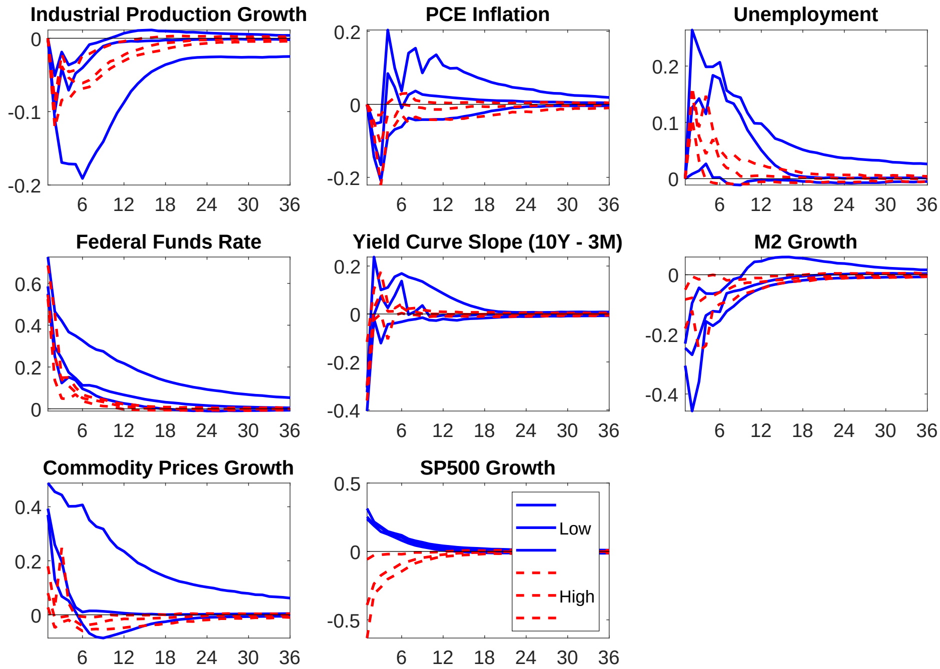

Figure D-3: Contractionary conventional monetary policy shocks, no λ_t.

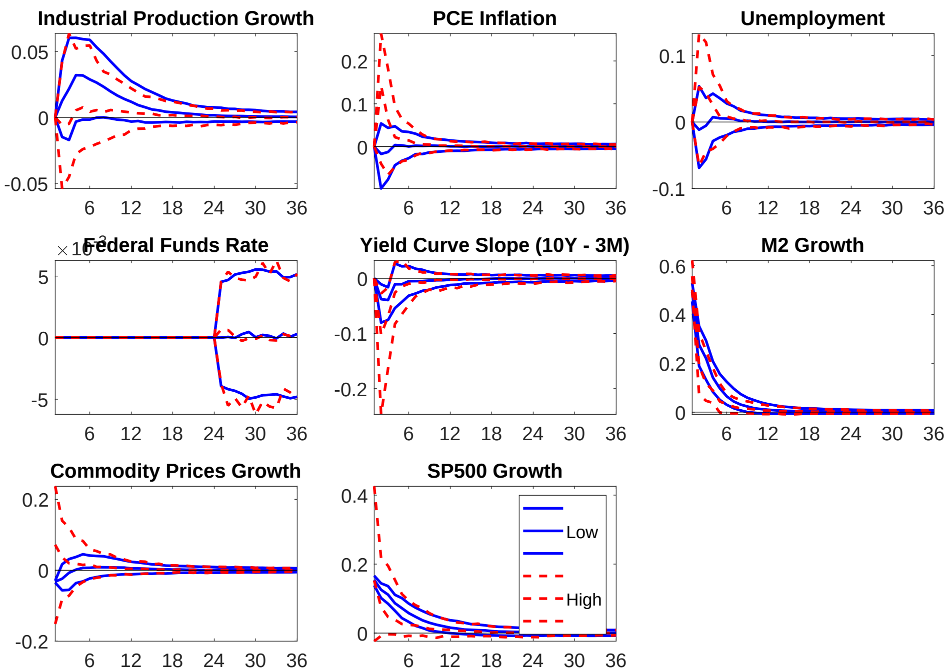

Figure D-4: Expansionary liquidity shocks, no λ_t.

E The reaction of SPF expectations

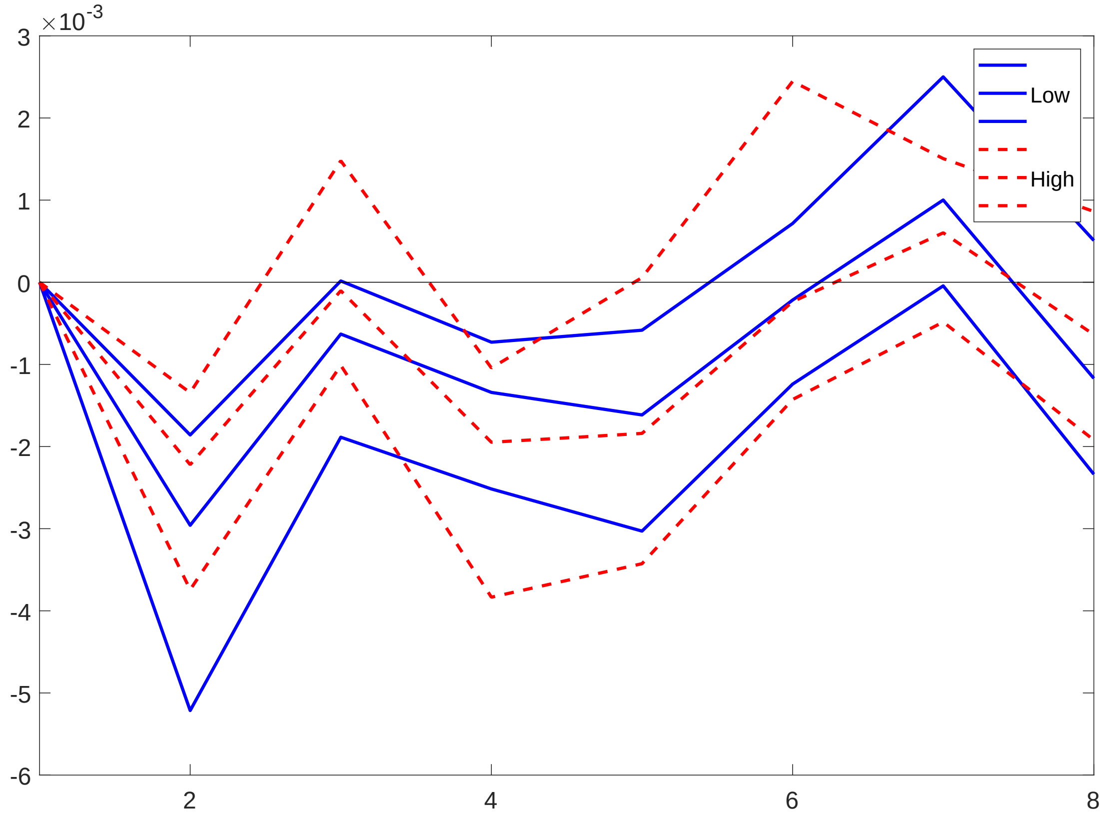

Figure E-1: Responses of CPI inflation expectations, liquidity shocks.

F Results obtained using the 1984-2019 sample

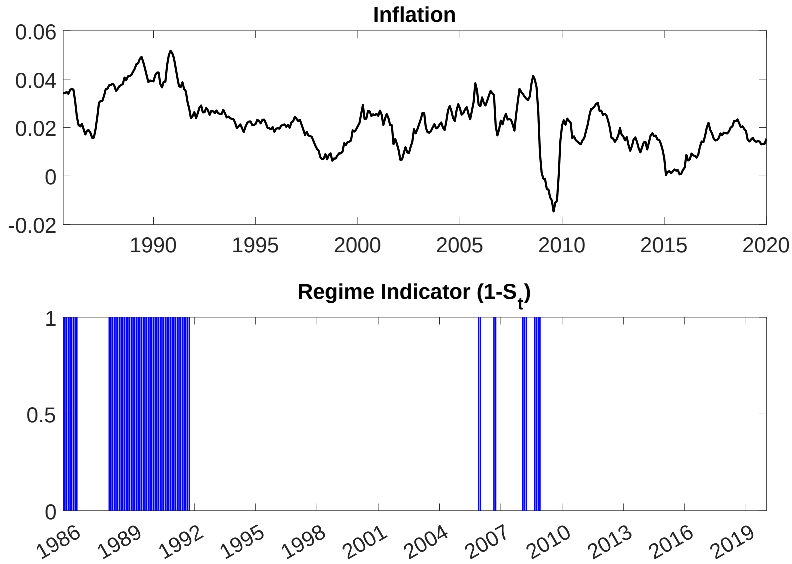

Figure F-1: US Inflation and estimated regime indicator, 1984-2019.

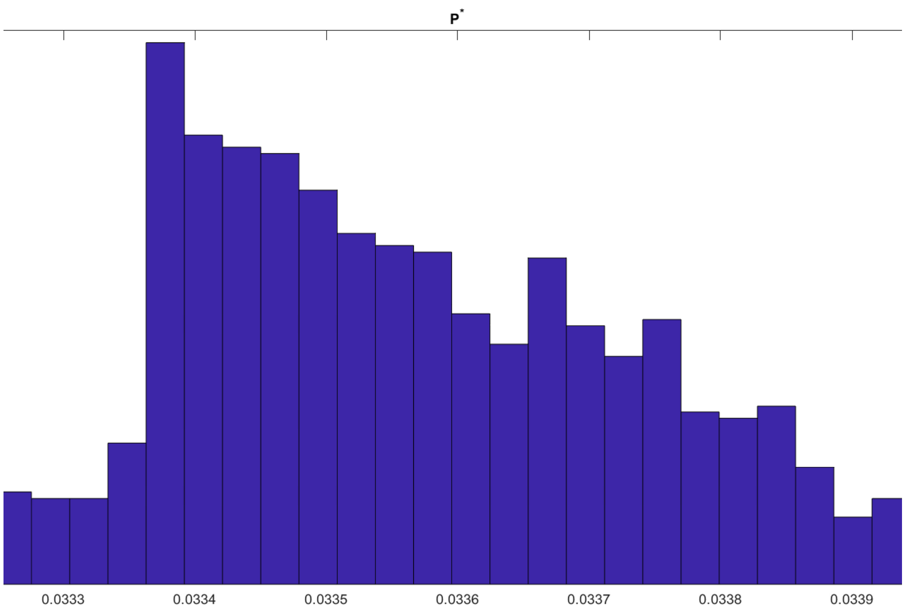

Figure F-2: Distribution of the threshold P^*, 1984-2019.

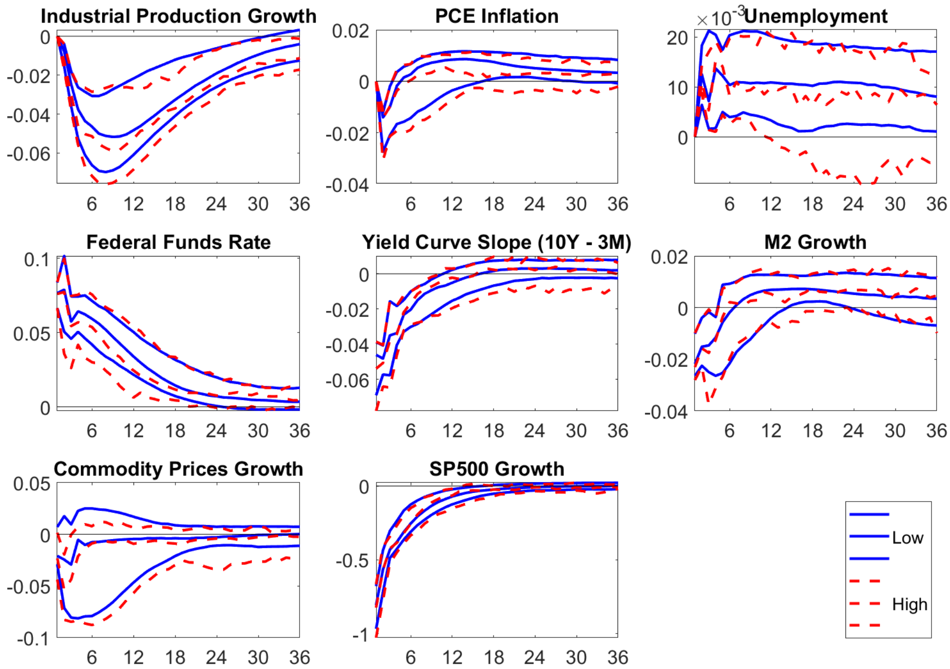

Figure F-3: Contractionary conventional monetary policy shocks, 1984-2019.

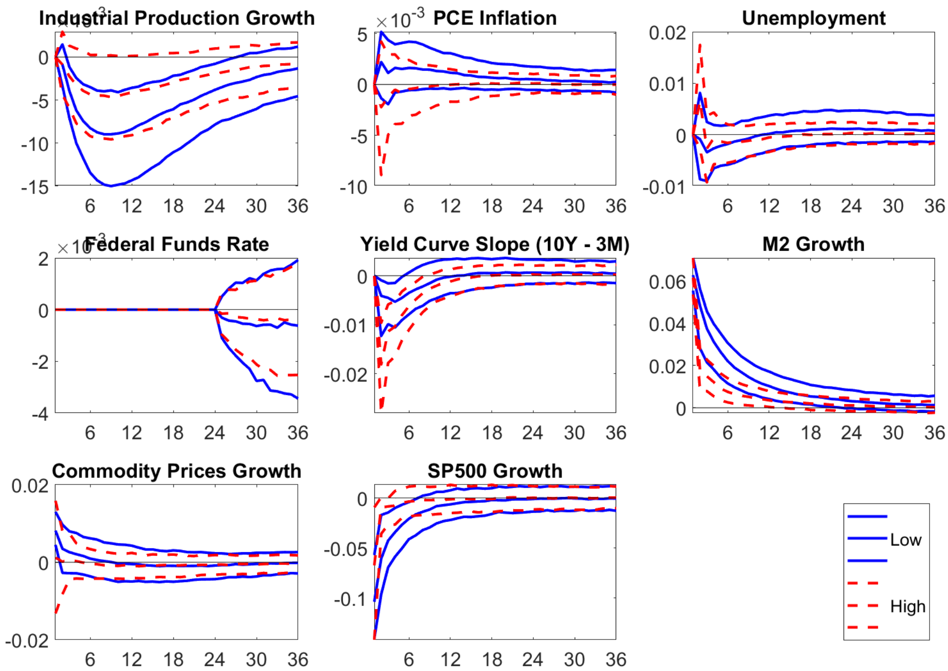

Figure F-4: Expansionary liquidity shocks, 1984-2019.

G Results obtained using the shadow short term rate

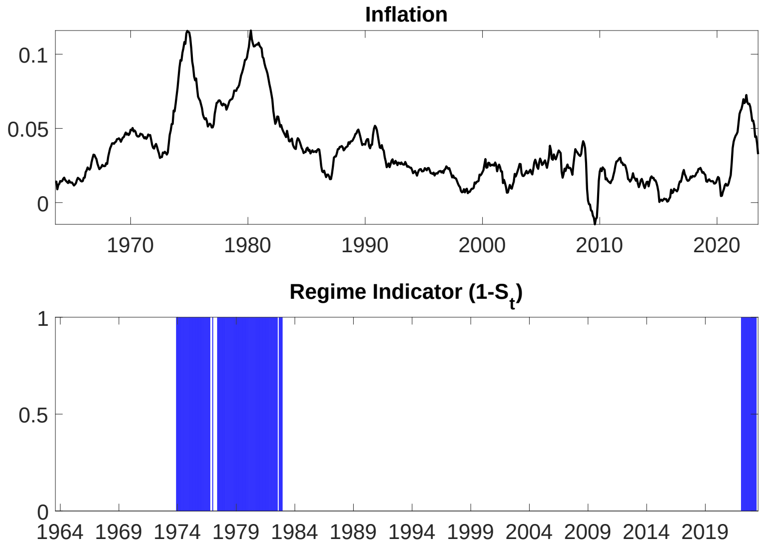

Figure G-1: US Inflation and estimated regime indicator, shadow rate.

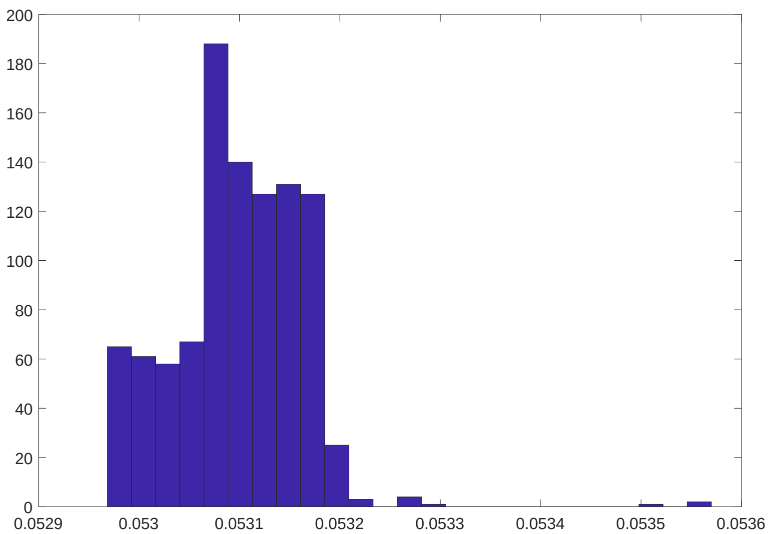

Figure G-2: Distribution of the threshold P^*, shadow rate.

H Transmission of liquidity shocks, 12 months constraints on FFR

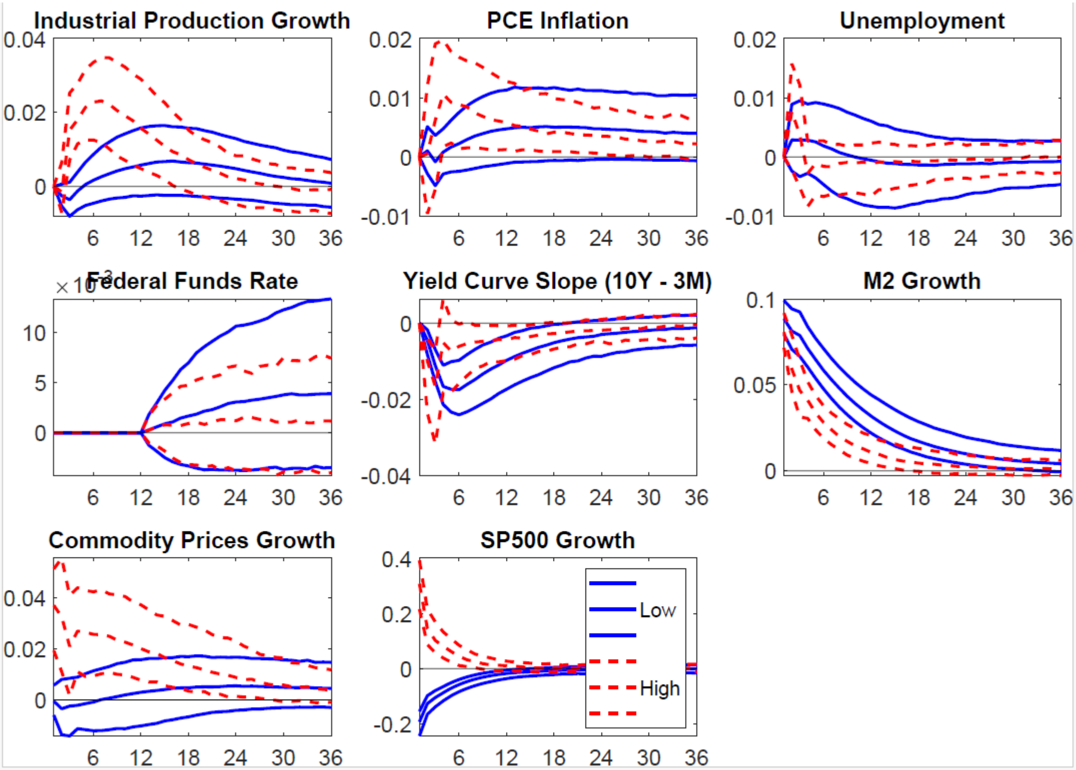

Figure H-1: Expansionary liquidity shocks, 12 months constraints on FFR.