# Nonlinear Impact of Monetary Policy Shocks: The Role of Monetary Policy Uncertainty

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**Abstract:** This study investigates the impact of monetary policy shocks on asset prices and the Consumer Price Index (CPI) in the United States across low and high monetary policy uncertainty (MPU) regimes. We employ a Markov switching model to identify uncertainty regimes and a time-varying parameter vector autoregression model to analyze the state-dependent effects of monetary policy disruptions, which are measured using high-frequency surprises derived from financial markets and incorporated into the model as an exogenous variable. Using monthly data spanning from 2005 to 2023, our empirical findings reveal asymmetry in the impacts of monetary policy shocks across uncertainty regimes. Specifically, contractionary monetary policy shocks cause more pronounced declines in asset prices and the CPI in periods of relatively low MPU. Under high MPU, the monetary policies' effectiveness is diminished, and the economy incurs a higher sacrifice ratio, which refers to the output cost of reducing inflation or stabilizing asset prices. These results underscore the critical role of policy credibility, transparency, and forward guidance in enhancing monetary policy effectiveness. A stable and predictable

policy environment can amplify the intended effects of policy interventions and minimize the economic costs associated with disinflationary efforts.

**Keywords:** Monetary policy uncertainty; Monetary policy surprises; External instrument; Time-varying parameter vector autoregression model

## 1. Introduction

Since the United States (US) Federal Open Market Committee (FOMC) began releasing policy statements in 1994, the nation's Federal Reserve (Fed) has steadily enhanced its communication and transparency. Nevertheless, the unpredictable nature of the economy and inherent policy uncertainty mean that monetary policy always entails some degree of uncertainty. Monetary policy uncertainty (MPU) rose sharply during the 2008 financial crisis and again surged to exceptionally high levels during the COVID-19 pandemic. In both periods, the Fed injected liquidity to cushion the downturn. The coexistence of high uncertainty and active policy intervention naturally raises the question of how heightened MPU impacts monetary policy effects. This issue has become increasingly salient over the past decade with the rise of unconventional monetary policy (UMP) and the blurring boundaries between policy and market dynamics.

Regarding MPU, scholars have increasingly focused on how it affects the economy in recent years. Doehr & Martínez-García (2021) constructed a model for interest rate uncertainty, employing a time-varying parameter vector autoregression (TVP-VAR) model, determining that increased MPU raises unemployment and suppresses core inflation. Istrefi

& Mouabbi (2018) constructed a subjective interest rate uncertainty model using survey forecasts with a cross-country panel structural VAR (SVAR) model, finding that rising short-term MPU has a stronger and more persistent negative impact on output and investment. Quelhas (2022) used text analysis to construct a Euro-area MPU index and estimated a nonlinear interacted VAR, revealing that higher MPU leads to contractions in economic activity. Lastauskas & Nguyen (2023) extend a global VAR model with stochastic volatility to quantify the effects of US MPU shocks, demonstrating that they raise global macroeconomic volatility and reduce output, inflation, and interest rates across countries. With deepening research on MPU, scholars have developed various indicators to quantify its different dimensions. Among them, a widely used measure is the MPU index constructed by Baker et al. (2016), which uses the frequency with which terms related to the economy, uncertainty, and monetary policy jointly appear in major US newspapers. In a related study, Husted et al. (2020) developed a text-based MPU indicator by analyzing the language in FOMC statements, minutes, and news reports to capture uncertainty arising from the communication and interpretation of monetary policy communications. While MPU has been shown to have sizable macro financial effects, its implications for the strength of monetary policy transmission remain underexplored.

Notably, limited research has examined whether monetary policy effectiveness is state-dependent with respect to MPU. Most existing studies focus on broad economic uncertainty rather than MPU specifically. Within this broader strand, some studies have

provided microdata and structural evidence on policy effectiveness. For example, using firm level microdata, Bloom (2007) showed that stimulus measures such as interest rate cuts or tax reductions have limited impact when uncertainty about future business conditions rises. Bloom et al. (2018) find that heightened time-varying uncertainty of idiosyncratic productivity shocks dampens the transmission efficiency of expansionary policies in a dynamic stochastic general equilibrium model integrating nonconvex adjustment costs. Vavra (2014) constructed a model with fixed price adjustment costs, demonstrating that policy effects significantly diminish when firm level uncertainty is high. Bachmann et al. (2013) demonstrated that economic uncertainty dampens policy shocks through mechanisms such as price adjustment costs and firm learning. Consistent with these micro-founded mechanisms, macro-level empirical studies have documented similar dampening effects. Andrade et al. (2019) extended a New Keynesian monetary policy model, determining that forward guidance is less effective when policy signals are unclear. Aastveit et al. (2017) used an interactive SVAR model to compare monetary policy effects across high and low economic uncertainty states, found that policy impacts on output and investment are much weaker when uncertainty is high. Pellegrino (2021) and Castelnuovo & Pellegrino (2018) demonstrated that elevated uncertainty environments significantly weaken monetary policy effectiveness. Turning to the specific role of MPU, three recent studies provide relevant insights. De Pooter et al. (2021) used a high-frequency event study with derivatives-based MPU, revealing that long-term nominal and real yields exhibit

stronger responses to policy shocks when uncertainty is low. Using an event study approach, Bauer et al. (2022) demonstrated that stock returns exhibit stronger reactions to monetary policy shocks in periods of low pre-FOMC uncertainty. Sekandary (2023) employed a panel smoothed transition regression model and showed that sensitivity to monetary policy shocks is greater under high MPU during 1994–2008, but shifts toward stronger responses under low MPU when the sample is expanded to include a zero lower bound (ZLB) phase (1994–2015).

In these circumstances, this study sheds new light on how monetary policy shocks' effectiveness is contingent on the state of MPU. Previous studies have generally confirmed that monetary policy shocks have significant macroeconomic and financial effects. However, subsequent research has revealed significant nonlinearity. Policy effects tend to strengthen during booms and weaken in recessions (Barnichon and Matthes, 2018; Tenreyro and Thwaites, 2016). This indicates that linear models may obscure policies' underlying state dependence. To extend this research, we focus on MPU as another key source of nonlinearity in monetary policy effects. When evaluating the nonlinear monetary policy effects, price stability is the fundamental objective of central banks that logically deserves close attention. However, rapid asset price increases are often accompanied by financial fragility (Jordà et al., 2015). Therefore, we examine the effects of monetary policy on consumer prices as well as asset prices, enabling a more comprehensive assessment of price and financial stability.

Given this, this paper examines whether the impact of monetary policy shocks on asset prices and inflation differs across MPU regimes in the United States. Specifically, we identify these regimes using a Markov-switching (MS) model. To capture the nonlinear impact of policy shocks, we employ the time-varying parameter vector autoregression model with exogenous variable (TVP-VARX) proposed by Paul (2020). In this framework, we use the pure monetary policy surprises derived by Karadi and Jarociński (2020), which exclude central bank information effects, as a proxy for structural monetary policy shocks. These surprises are incorporated into the TVP-VARX model as an exogenous variable, enabling us to capture the simultaneous effects of monetary policy shocks on asset prices and inflation. This framework overcomes the limitations of traditional time series or sign constraint approaches. First, asset prices respond almost immediately to monetary policy news, therefore identification must rely on exogenous high-frequency policy surprises. Second, timing-based identification approaches do not accommodate contemporaneous two-way reactions between policy and financial variables, and this assumption is often violated in financial markets. High-frequency surprises avoid this simultaneity problem and provide cleaner identification. Using this approach, we analyze monthly data from January 2005 to June 2023 to identify conventional and unconventional policy shocks and examine their nonlinear effects across MPU states.

The primary finding of this study is that while tightening monetary policy shocks induce negative responses in US asset and consumer prices under low and high MPU, the

effects are nonlinear and state-dependent. The magnitude of these effects is larger under low-MPU environments, with asset and consumer prices exhibiting deeper and more persistent declines. This finding aligns with classical uncertainty theory. According to real options theory, when investments are irreversible, higher uncertainty creates a "wait-and-see" option. Firms and households that face uncertain prospects, raise their decision thresholds, postpone investment and hiring, and exhibit reduced sensitivity to interest rate movements (Bernanke, 1983; Dixit & Pindyck, 1994; Bloom, 2009). Furthermore, Bloom (2014) noted that risk-averse agents tend to increase precautionary savings in uncertain periods, further diminishing the interest rate sensitivity of aggregate demand. In addition, drawing on Ball's (1994) concept of the sacrifice ratio and extending it to the domain of asset prices, we compute state-dependent sacrifice ratios based on impulse response (IR) functions to assess the economic costs of stabilizing consumer and asset prices under high and low MPU. Further quantification reveals that sacrifice ratio is consistently higher under high MPU than under low MPU across all three indicators (stock, housing, and consumer prices). These results indicate that the real economic costs of suppressing inflation and deflating asset bubbles are higher in periods of high MPU. These findings remain robust under alternative sampling periods and alternative MPU measures. Overall, the results demonstrate that elevated MPU dampens monetary policy effects and raises policy implementation costs.

This study contributes to the literature in three ways. First, it expands empirical research on monetary policy effects from an MPU perspective, revealing its role as a key source of nonlinearity that modulates the marginal effects of policy shocks, offering new insights into the dynamics of policy effectiveness. Second, we adopt a MS model to endogenously identify high and low MPU states, using the latest robust framework (TVP-VARX model) to analyze the time-varying effects of conventional and unconventional monetary policy surprises conditional on the state of MPU, overcoming the limitations of linear models and predefined thresholds. Previous studies have not explored this area in depth. Third, this study broadens the perspective on sacrifice ratio, demonstrating that price or financial market stability demands higher economic costs under high MPU. This finding emphasizes the significance of enhancing policy transparency and strengthening forward-looking communication to mitigate the costs of macroeconomic regulation.

The remainder of this paper is structured as follows. Section 2 presents a theoretical construct, Section 3 introduces the dataset, Section 4 details the methods employed, Section 5 presents the benchmark findings, Section 6 conducts robustness tests, and Section 7 concludes.

## 2. Theoretical motivation

To lay a foundation for our empirical analysis, we present a simple theoretical framework that illustrates how MPU generates a “cautionary effect” within a partial equilibrium setting. This stylized model follows the real options intuition that

irreversibility and uncertainty establish value in waiting (see Bernanke, 1983; Dixit & Pindyck, 1994; particularly simple two/three period examples and investment thresholds). For richer general equilibrium treatments of uncertainty and monetary policy transmission, see Bloom (2009), Vavra (2014), and Bloom et al. (2018).

We formalize the assumption that MPU raises the option value of waiting, reducing initial investment and weakening interest rate sensitivity of investment (the cautionary effect). Time is $t = 0,1,2$. A representative entrepreneur faces an irreversible investment cost ($\gamma > 0$), which is uniformly distributed over the interval $[\bar{\gamma} - \alpha / 2, \bar{\gamma} + \alpha / 2]$ with density $1/\alpha$, where $\bar{\gamma}$ denotes the mean of the cost distribution. If the entrepreneur invests at $t = 0$, the project yields per period payoff $y$ in $t = 1,2$. At $t = 1$, the aggregate state is revealed, $y \in \{y^H, y^L\}$ with $\Pr(H) = p \in (0,1), \Pr(L) = 1 - p$. High $(H)$ denotes the high-payoff state and low $(L)$ denotes the low-payoff state of the project. Let the gross interest factor be $R > 1$ (i.e., the discount factor is $1/R$). Define the mean payoff as $\mu \equiv \mathrm{E}[y] = py^H + (1-p)y^L$ and an uncertainty (dispersion) index as $\Delta \equiv y^H - y^L > 0$. Without loss of generality, we adopt a symmetric parameterization of the two payoff realizations, $y^H = \mu + (1-p)\Delta$ and $y^L = \mu - p\Delta$.

If the entrepreneur invests at $t = 0$, the time $t = 0$ net present value (NPV) is:

$$V_{now} = \frac{\mu}{R} + \frac{\mu}{R^2} - \gamma. \tag{1}$$

The entrepreneur that waits until $t = 1$ observes the state and invests only in $H$. If $H$ occurs, the entrepreneur pays $\gamma$ at $t = 1$ and receives $y^H$ at $t = 2$; if $L$, the entrepreneur does not invest. Therefore, the following holds:

$$V_{wait} = p\left(-\frac{\gamma}{R} + \frac{\mu+(1-p)\Delta}{R^2}\right). \quad (2)$$

The entrepreneur invests at $t = 0$ if $V_{now} \geq V_{wait}$, yielding a threshold on the sunk cost $\gamma$ as follows:

$$\gamma \leq \gamma^* \equiv \frac{\frac{\mu}{R}+\frac{(1-p)(\mu-p\Delta)}{R^2}}{1-\frac{p}{R}}. \quad (3)$$

To ensure an interior investment margin and rule out extreme cases in which all entrepreneurs invest immediately or all postpone, we assume $\bar{\gamma} - \alpha / 2 < \gamma^* < \bar{\gamma} + \alpha / 2$. Equation (3) is the discrete-time analogue of a hurdle rule, which implies investing now only if the sunk cost is sufficiently low.

We can now examine how uncertainty affects investment. As is standard in real options models (see Bertola and Caballero, 1994; Aastveit et al, 2017), we normalize the mass of entrepreneurs to one and assume that each entrepreneur invests one unit when investing. Therefore, aggregate investment at $t = 0$, denoted by $I_0$, corresponds to the share of entrepreneurs whose individual cost ($\gamma_i$) lies below the investment threshold ($\gamma^*$). Given the uniform distribution of investment costs introduced above, $I_0 = 1/2 + (\gamma^* - \bar{\gamma}) / \alpha$, and we obtain the following:

$$\frac{\partial I_0}{\partial \Delta} = -\frac{p(1-p)}{\alpha R(R-p)} < 0. \quad (4)$$

The economic reading is with irreversibility, waiting helps the firm avoid investing in the bad state. Increased uncertainty raises the option value of waiting, making firms more reluctant to invest immediately.

Next, we analyze how the magnitude of interest rate changes affects investment incentives under high uncertainty. For interest rate sensitivity, we calculate cross partial derivatives as follows:

$$\frac{\partial^2 I_0}{\partial R \partial \Delta} = \frac{p(1-p)(2R-p)}{\alpha(R^2-pR)^2} > 0. \quad (5)$$

Since $R > 1$ and $0 < p < 1$, this equation always holds. Since $\partial I_0 / \partial R < 0$, and the above equation is positive, indicating that when uncertainty $\Delta$ increases, the $|\partial I_0 / \partial R|$ becomes smaller, that is, uncertainty reduces monetary policy effectiveness. Because higher uncertainty elevates the risk associated with investment decisions, it diminishes the marginal effect of changes in R on investment incentives. This means that uncertainty raises the hurdle for irreversible investment and monetary easing stimulates less investment when uncertainty is high because it also boosts the value of waiting.

Notably, the previously discussed uncertainty refers to economic uncertainty, whereas we analyze the nonlinear effects of monetary policy shocks under MPU. Building on this distinction, we next examine how MPU cultivates a cautionary effect.

NPV investment projects depend on the expected future path of short-term interest rates. We determine the uncertainty of the policy rate path using the standard deviation (SD) of the expected short-term rate trajectory, denoted by $\sigma_R$, defining MPU using this

SD.[1] Therefore, a higher MPU implies wider dispersion in short-term interest rates' expected trajectory. We define the dispersion of project investment payoffs, which we use to determine the level of uncertainty as follows:

$$\Delta = F(\sigma_R; \zeta), \text{ with } \quad F_\sigma(\sigma_R; \zeta) > 0, \tag{6}$$

where ζ denotes policy independent structural parameters such as baseline dispersion ($\Delta_0$), the strength of interest rate pass-through to project cash flow, and technological heterogeneity. Intuitively, when the policy rate path is more uncertain, the chain of discount factors becomes more volatile and the valuation of future returns is more dispersed. This assumption aligns with Newell and Pizer (2003), who demonstrated that uncertainty in discount rate paths raises project valuation dispersion through the convexity of discounting. Therefore, $F_\sigma > 0$. As shown above, $\partial I_0 / \partial \Delta < 0$ and $\partial^2 I_0 / \partial R \partial \Delta > 0$, and the chain rule implies the following:

$$\frac{\partial I_0}{\partial MPU} = \frac{\partial I_0}{\partial \Delta} F_\sigma < 0 \tag{7}$$

$$\frac{\partial^2 I_0}{\partial R \partial MPU} = \frac{\partial^2 I_0}{\partial R \partial \Delta} F_\sigma > 0 \tag{8}$$

We summarize the theoretical implications in the following proposition.

**Proposition 1** Cautionary effect of monetary policy uncertainty.

(i) Higher MPU reduces aggregate investment at time 0. Formally, $\frac{\partial I_0}{\partial MPU} < 0$.

[1] In the NPV expression, future payoffs are discounted by the product of short rates ($\prod_{j=1}^{H} R_{t+j}$) with a logarithm of $\sum_{j=1}^{H} logR_{t+j}$. Therefore, the SD ($\sigma_R = SD_t\left(logR_{t+1:t+H}\right)$ ) quantifies the volatility of the discount-factor chain.

(ii) Higher MPU weakens the interest rate sensitivity of investment. Formally, $\frac{\partial^2 I_0}{\partial R \partial MPU} > 0$.

Part (i) indicates that higher MPU lowers aggregate investment ($I_0$). Part (ii), combined with $\partial I_0 / \partial R < 0$, implies that MPU weakens investment sensitivity to interest rate changes. Therefore, in periods of high MPU, the influence of monetary policy weakens. This represents the cautionary effect of MPU, which we subsequently evaluate empirically.

## 3. Data

Our dataset includes monthly US observations from January 1990 to June 2023. The variables include the S&P 500 stock price index (SP), the S&P/Case-Shiller National Home Price Index (HP), the Consumer Price Index (CPI), Industrial Production (IP), monetary policy surprises constructed by Jarociński and Karadi (2020), and the MPU index developed by Baker et al. (2016). Monetary policy stance is represented using Wu and Xia's (2016) shadow Federal Funds Rate (FFR),[2] which determines the length of the sample due to data availability. Seasonally adjusted IP, HP, and CPI series are obtained from the Federal Reserve Bank of St. Louis FRED database. End-of-month S&P 500 prices are obtained from Bloomberg. In the monetary policy literature, the conventional Federal Funds Rate is commonly employed as the policy instrument. However, because our sample

[2] Historically, the FFR has served as the Fed's principal monetary policy instrument; however, since December 2008, the FFR has remained close to zero. Consequently, the Fed has increasingly relied on UMP tools to stimulate the economy. Wu and Xia's (2016) constructed the shadow FFR measure to quantify the stance of monetary policy in the zero lower bound environment, determining that the shadow FFR can be used to summarize the macroeconomic effects of UMPs.

spans the US zero lower bound period, using the standard rate would mask policy accommodation under unconventional measures. To address this concern, we adopt Wu and Xia's (2016) shadow rate, which was derived from a multifactor term structure model and can take negative values during the ZLB. This property enables the model to reflect the stance of monetary policy more accurately than the conventional rate. The shadow FFR data are obtained from Wu's homepage.[3]

In addition to the shadow short rate that captures the monetary policy stance, we require an exogenous measure of monetary policy shocks. For this purpose, we use the monetary policy surprises constructed by Jarociński and Karadi (2020), which are based on high-frequency financial market data around FOMC announcements. The key assumption is that asset price movements within a narrow window around these announcements primarily reflect the unanticipated component of policy decisions. Specifically, we rely on the policy component developed by Jarociński and Karadi (2020), which is calculated using the joint response of short-term interest rate futures and equity prices in a 30-minute window around policy announcements. By exploiting the covariance between interest rates and stock returns, this method decomposes overall market surprises into pure monetary policy shock and central bank information effect components. We use the pure policy shock series, which filters out the information component and is commonly regarded as a clean measure of unexpected monetary policy changes (Breitenlechner et al.,

[3] The data are available for download from Wu's website at https://sites.google.com/view/jingcynthiawu/shadow-rates.

2022; Hoek et al., 2022). This series is our key proxy for monetary policy shocks because it isolates the exogenous policy surprise that is most informative for tracing monetary policy transmission.

As a proxy for the MPU, this study uses the Baker–Bloom–Davis (BBD) US MPU index (Baker et al., 2016) as a proxy for the MPU.[4] This index is a composite measure calculated using scaled frequencies of newspaper articles referencing MPU and constructed using coverage from hundreds of US newspapers archived in Access World News.[5] Figure 1 plots the MPU indicator (in blue lines) together with National Bureau of Economic Research (NBER) recessionary periods (gray vertical bars). First, MPU has fluctuated markedly over time. In modern US history, elevated MPU predominantly emerged during the recent recession period and more generally. The most uncertain episodes since the 1990s correspond to the Gulf War, the September 11 terrorist attacks, the Internet bubble burst, the subprime mortgage crisis, and the onset of the COVID-19 pandemic. Second, since the Fed implemented UMP in 2008, major events and policy shifts in US monetary policy have contributed to MPU fluctuations. For example, quantitative easing (QE) implementation and subsequent exit, the US debt-ceiling standoff, and sovereign credit downgrades in 2011, the 2016 Brexit referendum, and the Silicon Valley Bank collapse in

[4] The MPU index constructed by Baker et al. (2016) is regularly updated and available at https://www.policyuncertainty.com/monetary.html.

[5] Access World News is a comprehensive news database operated by NewsBank, providing access to hundreds of US national and local newspapers (https://www.newsbank.com).

2023 all coincide with notable jumps in MPU. Combined, this indicates that in addition to macroeconomic recessions, major policy adjustments and emergencies are also significant sources of MPU.

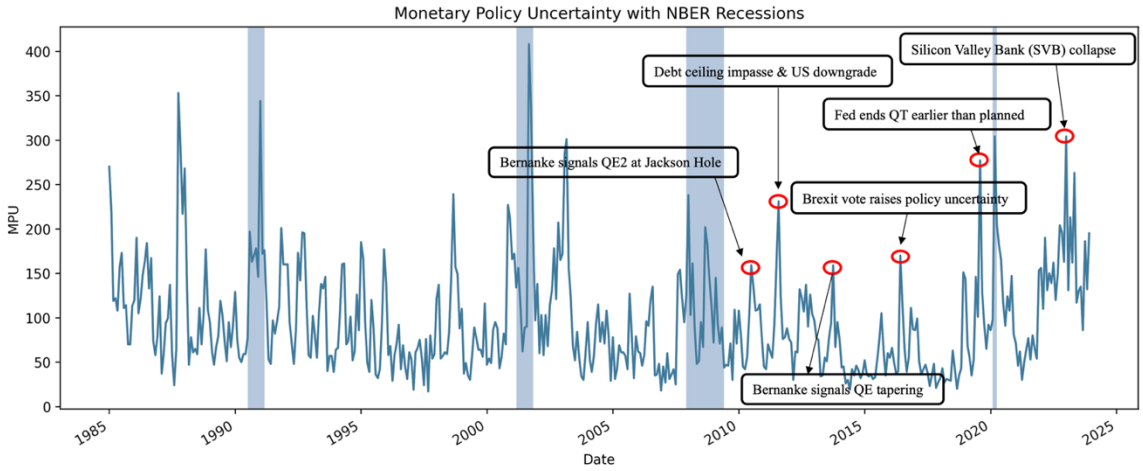



**Fig. 1.** MPU measures over time.

Notes: This figure plots the US MPU index, sourced from Baker et al. (2016). Shaded areas denote NBER-dated recession periods. Key policy events and economic shocks are marked at their occurrence dates.

## 4. Methodologies

To empirically examine the nonlinear impacts of monetary policy, we employ a two-stage empirical approach combining a MS model and a TVP-VARX framework. The MS model first endogenously identifies high and low MPU regimes, and the resulting regime-specific indices are subsequently integrated into the TVP-VARX to trace how the dynamic impacts of monetary policy shocks differ across uncertainty states, referencing Paul (2020) and Cepni and Gupta (2021).

### *4.1 Markov switching model for monetary policy uncertainty*

As noted, this study employs a MS model to examine the nonlinear and state-dependent nature of MPU. Originally introduced by Hamilton (1989), the MS framework allows key parameters of a time series process to shift between discrete regimes according to a Markov chain with fixed transition probabilities. This feature makes the MS model particularly suitable for analyzing macro financial variables that exhibit recurrent but unobserved shifts between high and low volatility states. We adopt an MS specification in alignment with applications of MS models in monetary economics (Cepni and Gupta, 2021; Ching and Chen, 2007; Kurov, 2010), which have been used to identify stock market and investor sentiment regimes, to classify the US economy into states of high and low uncertainty based on the BBD MPU index as follows:

$$m_t = u_{R_t} + \beta_{R_t} m_{t-1} + \epsilon_t, \qquad \varepsilon_t \sim i.i.d.N(0, \sigma^2_{R_t}), \tag{9}$$

where $m_t$ denotes the MPU index, and $u_{R_t}$ and $\sigma^2_{R_t}$ are the corresponding state-specific mean and variance. The MS model is estimated using maximum likelihood methods, typically implemented through the Expectation-Maximization algorithm or Hamilton filter (Hamilton, 1990). The resulting filtered and smoothed probabilities are then used to date periods of elevated and subdued MPU. These probabilities enable endogenous classification of MPU regimes, avoiding reliance on arbitrary threshold rules. $R_t$ is an unobserved dummy state indicator that distinguishes between high and low MPU periods. $R_t$ is set equal to one if the smoothed probability of being in the high uncertainty state exceeds 0.5, and zero otherwise. We obtain regime-specific MPU indices ($m_t^j$) by

multiplying this state indicator with the MPU index, where $j$ refers to high or low MPU regimes. By combining the regime classification from the MS model with the TVP-VARX methodology of Paul (2020), we are able to systematically compare the nonlinear impact of monetary policy shocks across high and low MPU states.

*4.2 TVP-VARX model*

We employ the TVP-VAR model from Cogley and Sargent (2001), which introduced drifting coefficients to capture evolving macroeconomic dynamics, and build on the structural identification and stochastic volatility framework of Primiceri (2005). We also adopt the exogenous variable framework from Paul (2020), who augmented the TVP-VAR with externally identified monetary policy surprises, demonstrating that the exogenous variable approach enables consistent estimation of contemporaneous relative responses. Moreover, as long as policy shocks are orthogonal to the remaining regressors, this approach yields reliable estimates of the ensuing relative responses. The reduced-form TVP-VARX framework is specified as follows:

$$y_t = B_{0,t} + B_{1,t}y_{t-1} + \cdots + B_{p,t}y_{t-p} + A_t Z_t + u_t, \qquad u_t \sim N(0, \Sigma_t), \tag{10}$$

$$y_t \equiv [ffr_t, \Delta sp_t, m_t^j, \Delta hp_t, \Delta cpi_t, \Delta ip_t]', \tag{11}$$

where $y_t$ denote the $n \times 1$vector of endogenous variables, which includes shadow FFR ($ffr_t$), the S&P 500 log real end of the month stock price index ($sp_t$), the log real S&P/Case–Shiller national home price index ($hp_t$), the log of CPI ($cpi_t$), the log of real IP ($ip_t$), and MPU indices ($m_t^j$). The exogenous regressor ($Z_t$) represents the monetary policy

shock series ($MP_{pm}$) derived from Jarociński and Karadi (2020), which is linked to the structural disturbance of interest but orthogonal to all other structural shocks. The n $\times$ 1 vector of time-varying coefficients ($A_t$) captures the contemporaneous response to monetary policy shocks, and $\Sigma_t$ denotes the time-varying covariance matrix of reduced-form innovations. $B_{0,t}$ is an n $\times$ 1 vector of time-varying intercepts and $B_{j,t}$ for j = 1, 2, ..., k are n $\times$ n time-varying coefficient matrices associated with the lagged endogenous variables.[6] The evolution of parameters over time is calculated using the following random walk state equations:

$$\theta_t = \theta_{t-1} + v_t, v_t \sim N(0, Q), \tag{12}$$

where $\theta_t =$ vec $(B_{0,t}, B_{1,t}, \ldots, B_{p,t}, A_t)$ collects all time-varying coefficients, and $Q$ is the covariance matrix of state innovations. Similarly, the log-volatility of structural shocks evolves according to a stochastic volatility process, enabling time-varying uncertainty.

Estimation is conducted within a Bayesian framework using Markov Chain Monte Carlo (MCMC) methods. Posterior inference relies on Gibbs sampling, where the state–space representation of the model enables efficient updating of time-varying coefficients and volatilities. Referencing Paul (2020), the prior distributions are obtained using ordinary least squares estimates of a constant VAR applied to the training sample spanning January 1990–December 2004. We then compute the time-varying IRs for January 2005–June 2023 using MCMC methods with 5,000 iterations, discarding the first 2,000 draws as burn-in to

[6] A lag length of k = 3 is chosen based on the Akaike Information Criterion (AIC).

achieve convergence (Primiceri, 2005). We obtain time-varying IRs that evolve over time by tracing the dynamic effects of a one-unit exogenous monetary policy shock on the endogenous variables across different periods. A crucial step is normalizing these responses to ensure comparability over time by scaling the shock so that it corresponds to a 20-basis points reduction in the policy rate in the first month of the sample (January 2005).

# 5. Empirical results

*5.1 Results of uncertainty regimes identification*

Figure 2 illustrates the smoothed regime probabilities estimated using the monthly MPU measure. The red line depicts the probability of being in the high MPU state (State = 1), the blue line represents the low MPU state (State = 0), and the shaded grey regions indicate NBER-dated recession periods. The estimated probabilities reveal a distinct switching pattern between high and low MPU states across the sample period. High MPU states (red) primarily appear during episodes of heightened financial and macroeconomic stress, including the 1990 Gulf conflict, the 1998 hedge fund failure linked to Long-Term Capital Management, the 2000 dot com collapse, the 2008 Global Financial Crisis, the 2011 European sovereign debt turmoil, the 2020 COVID-19 pandemic shock, and the recent 2023 banking turmoil. In contrast, extended periods of stability such as the mid-1990s and much of the 2010s, are characterized by a dominance of a low MPU regime (blue). The MS model effectively captures the switching between regimes. Furthermore, the comovement between shaded NBER recessions and high MPU states supports the view

that macroeconomic downturns often coincide with elevated MPU. However, this relationship is not exclusive, as several nonrecessionary, policy-relevant events (e.g., the taper tantrum, Brexit vote, or the US debt ceiling crisis) also triggered temporary high-MPU spikes. Overall, these regimes lay the foundation for our subsequent empirical analysis of monetary policy shocks.

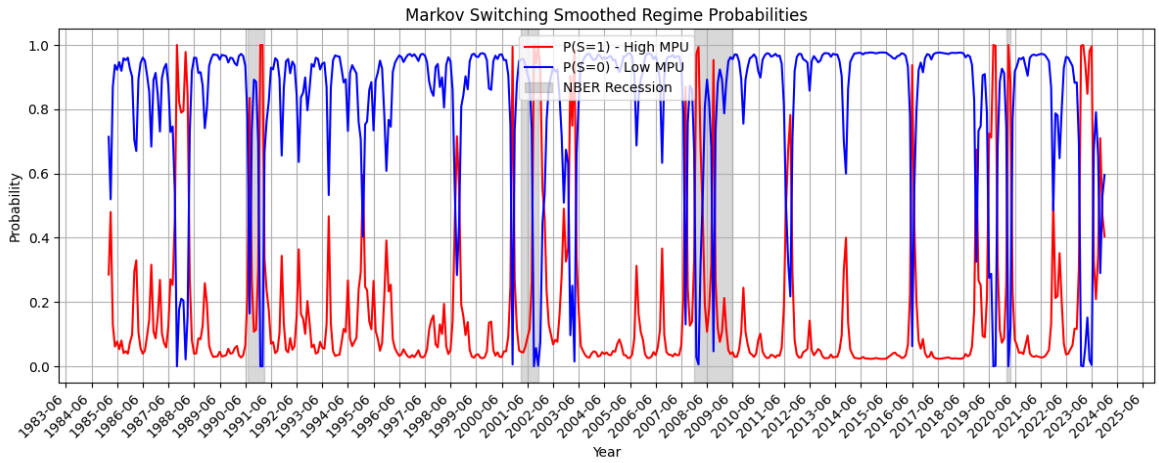



**Fig. 2.** Smoothed regime probabilities from the Markov switching model.

Notes: This figure displays the smoothed probabilities from a two-state MS model estimated using the monthly MPU measure. Shaded regions denote NBER recession periods.

*5.2 Impulse response analysis*

Figures 3 and 4 plot the respective IRs estimated using the TVP-VARX model conditional on high and low MPU. The sample covers the period from January 2005 to June 2023. The key advantage of the TVP-VARX framework is its capacity to trace responses that evolve over time. To ensure comparability across dates, we scale shocks following Paul (2020). Using January 2005 as the reference month, we normalize monetary

policy shocks to generate a contemporaneous 20-basis point decline in the shadow FFR.[7] After normalization, we obtain the remaining variables' contemporaneous IRs for January 2005 and each subsequent period. Figures 3 and 4 reveal four noteworthy observations.

First, as a comprehensive proxy for the monetary policy stance, the shadow rate generally rises following monetary policy shocks of equal magnitude, signaling monetary tightening. Moreover, unlike the nominal FFR, the shadow rate maps the effects of UMP tools (such as large-scale asset purchases, targeted lending facilities, and forward guidance) at the effective lower bound into equivalent shifts in the path of short-term interest rates (Wu and Xia, 2016). Therefore, even during ZLB periods, the IR exhibits economically meaningful temporal variations, rather than the near-flat response observed during ZLB periods based on the FFR, as noted by Cepni and Gupta (2021).

Second, stock prices under both regimes consistently exhibit negative estimated responses to monetary tightening. This occurs because stock prices represent the expected present value of future cash flow; therefore, tightening policies reduce stock returns by raising discount rates or lowering projected future cash flow (Thorbecke, 1997). Notably, this effect is slightly more pronounced under low-MPU regimes. As shown in Figures 3 and 4, in periods of heightened MPU, the maximum negative response in stock prices was approximately 2.5%, whereas during low-MPU periods, the maximum decline in stock

[7] To calculate the IRs, we assign a specific $z^-$ value to the instrument. The variation in $z_t$ is represented by $z^- = 0.2/\overline{A}_{2005M1,1}$, where $\overline{A}_{2005M1,1}$ denotes the estimated posterior mean for the shadow FFR at time of January 2005.

prices was 2.8%. The weaker decline in stock returns under high MPU is consistent with real options theory. This theory indicates that when fixed costs or irreversible investment components exist, heightened MPU prompts decision makers to delay choices while awaiting more precise information or more urgent demand. This cautious stance makes them less responsive to changes in the economic environment, including interest rates, subsequently reducing the economy's sensitivity to any policy stimulus (Bernanke, 1983; Dixit & Pindyck, 1994; Bloom, 2009). Furthermore, this finding aligns with behavioral channels, where lower consumer and investor confidence levels are associated with stock market behavior that exhibits muted reactions to news and diminished downside risk sensitivity (Deaves et al., 2010; Greenwood and Shleifer, 2014; Cepni and Gupta, 2021). Consistent with this behavioral mechanism, real options theory indicates that investment demand declines under MPU, and this decline fosters pessimistic investor sentiment. When financial markets face high uncertainty, pessimistic behavior among utility-maximizing investors tends to prevail (Schröder, 2011). Consequently, policy changes are less likely to be promptly and fully reflected in prices, resulting in attenuated stock price reactions under high MPU.

Third, regardless of high or low MPU conditions, HP exhibits immediate negative reactions to contractionary monetary policy shocks, with greater magnitude under low uncertainty, which aligns with the risk-taking channel. When markets have greater confidence about the policy path, interest rates and mortgage-backed securities markets

tend to accumulate greater duration exposure and leverage. Once a hawkish shock occurs, the rapid rise in rates and ensuing deleveraging are transmitted to the housing market through mortgage pricing, amplifying downward pressure on HP (Borio and Zhu, 2012). In contrast, during high-MPU periods, more cautious prior positioning with lower leverage and shorter duration results in a more muted shock transmissions of the same magnitude.

Fourth, inflation and IP generally exhibit negative responses to contractionary monetary policy shocks. Regarding CPI, under high-MPU regimes, the disinflationary effect of monetary tightening is weaker and shorter-lived. The response curve exhibits shallower troughs in the initial quarters and returns to zero more rapidly, indicating that when uncertainty rises, the policy transmission to prices is weakened and becomes more unstable. Conversely, the negative response of CPI is larger and longer-lasting under low-MPU regimes, remaining significantly negative over extended forecasting horizons and sample periods. This implies smoother policy transmission to aggregate demand and prices, with more effective channels for inflation suppression. Turning to IP, a similar state dependent pattern emerges, under high uncertainty conditions, the magnitude of output contraction is smaller. The underlying rationale for these findings aligns with the notion that high uncertainty weakens policy transmission to the real economy. Specifically, firms raise their investment thresholds and delay adjustments out of caution, reducing the marginal sensitivity of output and inflation to interest rate hikes (Bernanke, 1983; Bloom, 2009; Dixit & Pindyck, 1994). Moreover, under the precautionary savings channel,

households' increased precautionary savings in response to high MPU reduce the sensitivity of demand to policy changes. This mechanism flattens the IS curve (Bansal and Yaron, 2004; Bloom, 2014). Therefore, under a given contractionary shock, the marginal decline in aggregate demand is smaller, manifesting through the Phillips curve as a more moderate and less persistent disinflationary effect. Additionally, the impulse response function (IRF) diagram for CPI yields an extremely small positive short-term response in inflation. This pattern aligns with Gertler and Karadi (2015), who demonstrated that monetary policy shocks have limited short-term effects on inflation due to nominal rigidities that constrain price adjustment.

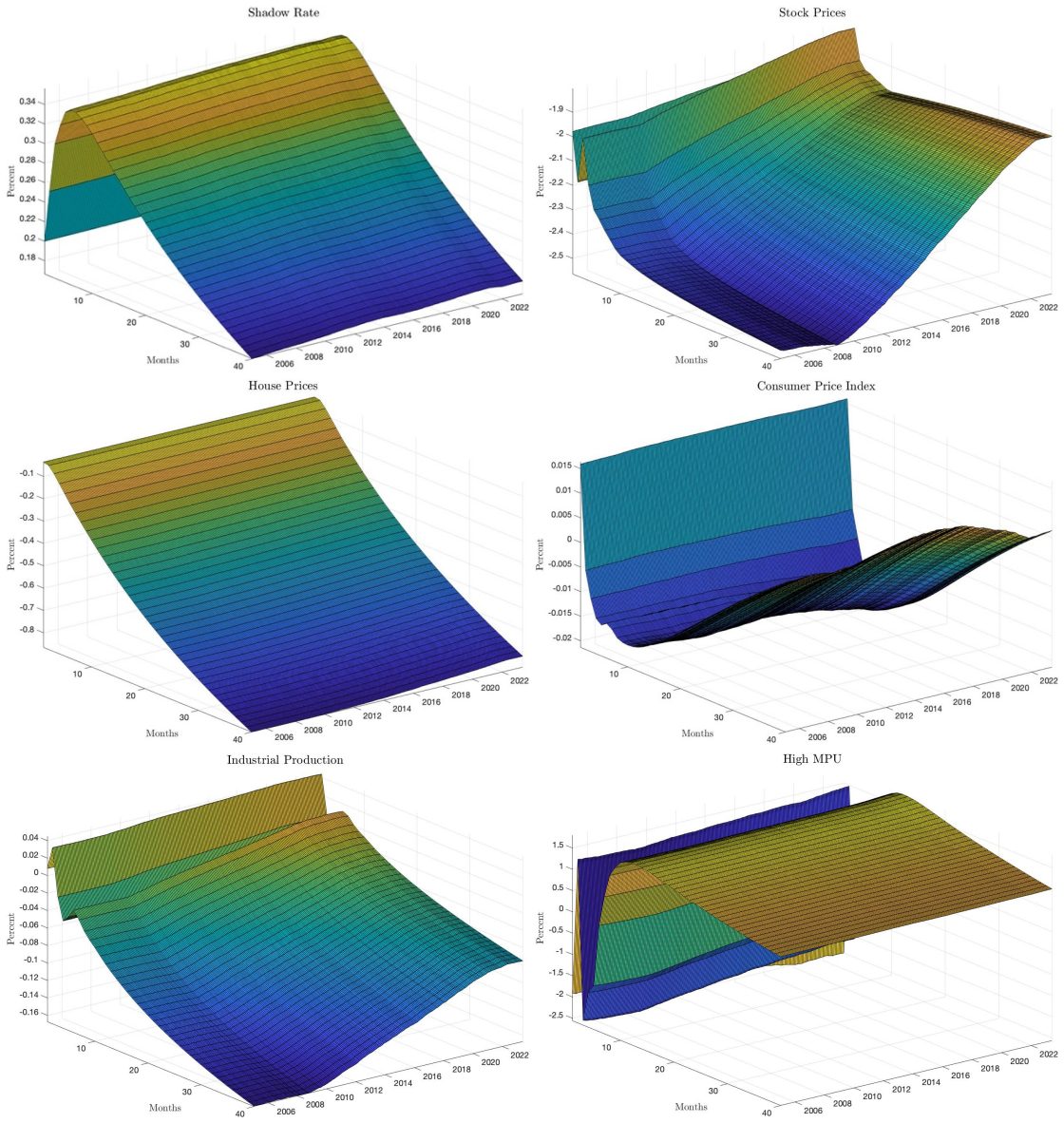



**Fig. 3.** Time-varying impulse responses: High MPU regime.

Notes: This figure shows the time-varying cumulative impulses responses to a monetary tightening obtained from the time-varying parameter vector autoregression model for the sample January 2005 to June 2023. Vertical axis: Percentage change. Front axis left: monthly response horizon. Front axis left: Years.

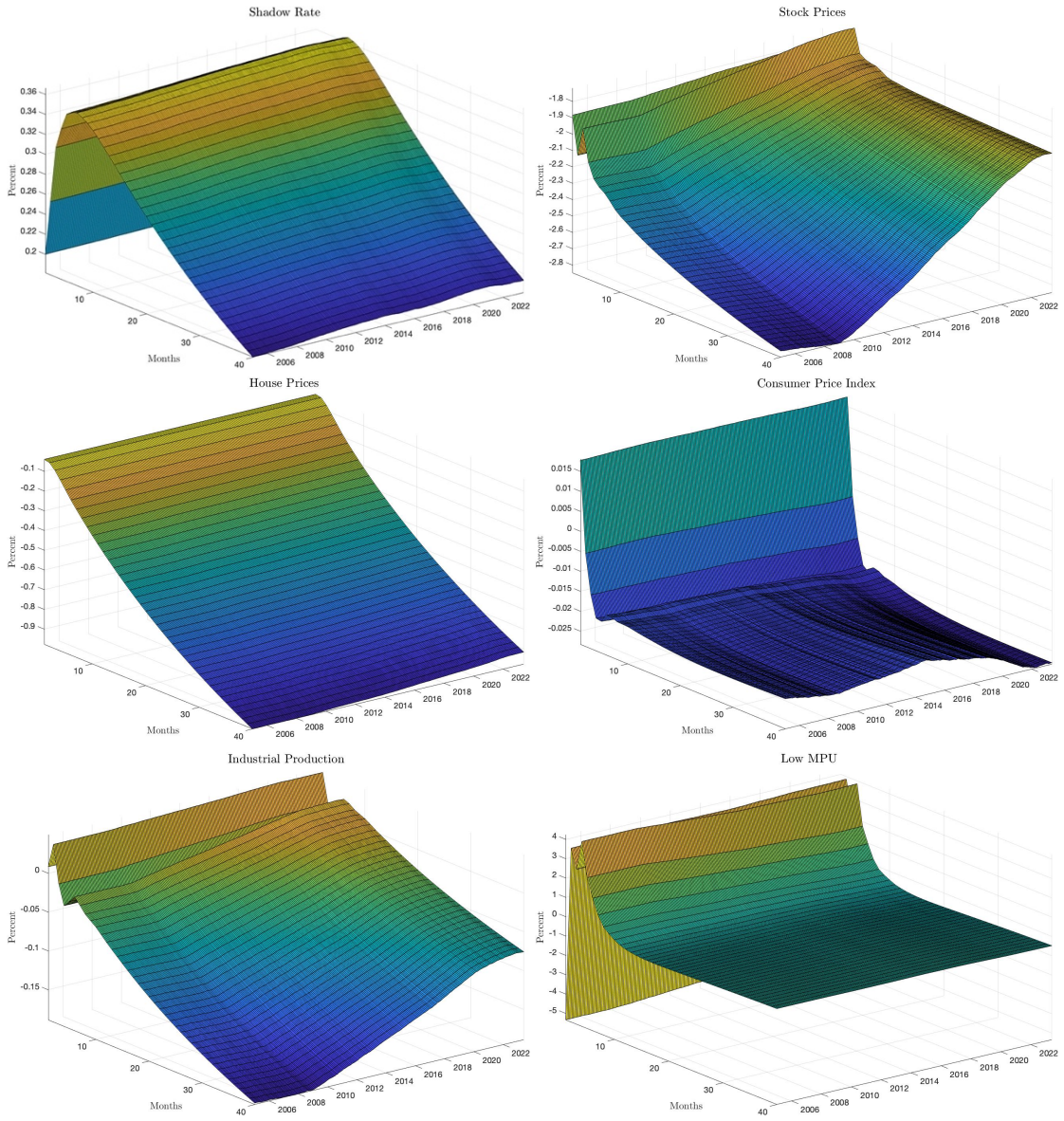



**Fig. 4.** Time-varying impulse responses: Low MPU regime.

*5.3 Sacrifice ratio analysis*

Referencing Ball (1994), the classical sacrifice rate is defined as the cumulative percentage loss in output per percentage change in the broad price index; that is, the output gap required to achieve unit of deflation. Building upon this sacrifice ratio framework proposed by Ball (1994) and following the approach of Paul (2020), we construct an asset price-based sacrifice ratio. Specifically, we replace the broad price index response with the

HP and SP response to measure the policy tradeoff between deleveraging and real economic activity during monetary tightening. Introducing the sacrifice ratio enables us to directly compare the two types of marginal costs of monetary tightening under high/low MPU, the cost of disinflation measured by CPI and the cost of "de-bubbling" measured by SP/HP.

Therefore, we calculate the sacrifice ratio based on the IRF over three-month and one-year time horizons to examine short-term and more prolonged output losses associated with monetary tightening. Figures 5 and 6 illustrate the dynamic paths of sacrifice rates over time (left axis) under high and low MPU regimes. The figures illustrate the cumulative response of IP relative to a 1% cumulative change in SP, HP, and CPI during three-month (dashed line) and one-year (dotted line) forecasting horizons. The right axis is the logarithmic levels of the corresponding price indices. Figure 7 depicts the difference between the sacrifice rate under high- and low-MPU regimes.

The results indicate that the sacrifice ratio under high MPU consistently exceeded that under low MPU throughout nearly the entire sample period. This pattern holds true across all indicators (SP, HP, CPI) and both horizons. This is reflected in Figure 7, where the difference curve remains above zero and relatively stable throughout the entire sample period. This indicates that achieving 1% inflation and asset price correction requires greater cumulative output loss under high MPU. These findings demonstrate that the marginal cost of tight monetary policy for disinflation and deleveraging is higher under high MPU. This

outcome is consistent with the cautionary effect emphasized in Section 2, where uncertainty leads businesses and households to delay spending and investment. When policy transmission is weakened by MPU, the output cost required to achieve the same price adjustment target inevitably rises. This resonates with Brainard's (1967) principle that optimal policy reacts more cautiously under uncertainty. Therefore, when the MPU is elevated, overreliance on substantial interest rate adjustments may not be optimal. Instead, reducing policy transmission frictions requires strengthening communication and forward guidance. Notably, Figures 5 and 6 reveal a long-term trend wherein, as the sample period progresses, sacrifice ratios for various asset prices and CPI exhibit a downward trajectory. This trend indicates that as the policy toolkit expands (e.g., through the application of UMP tools such as forward guidance and large-scale asset purchases), market sensitivity to policy signals gradually rises. The likelihood of achieving price stability and asset price stabilization objectives at a lower economic cost improves over time. This indicates that the cost function of monetary policy may have been dynamically optimized through institutional evolution and tool innovation.

Overall, our findings reveal that the effects of monetary policy shocks exhibit nonlinearity and asymmetry under varying MPU states. When MPU is relatively high, the influence of monetary policy shocks on asset prices and inflation diminishes, aligning with theoretical predictions based on real options effects. Quantitative measures centered on the sacrifice ratio reveal that the costs of inflation suppression and deleveraging become higher

at the real economic level in high MPU environments. For market participants, this implies that risk management should adjust exposure levels according to uncertainty states. For policymakers, it suggests stabilizing uncertainty through clear policy communication and verifiable forward guidance. This study offers new insights into developing a detailed understanding of how monetary policy shocks impact macroeconomic and asset markets under varying MPU environments.

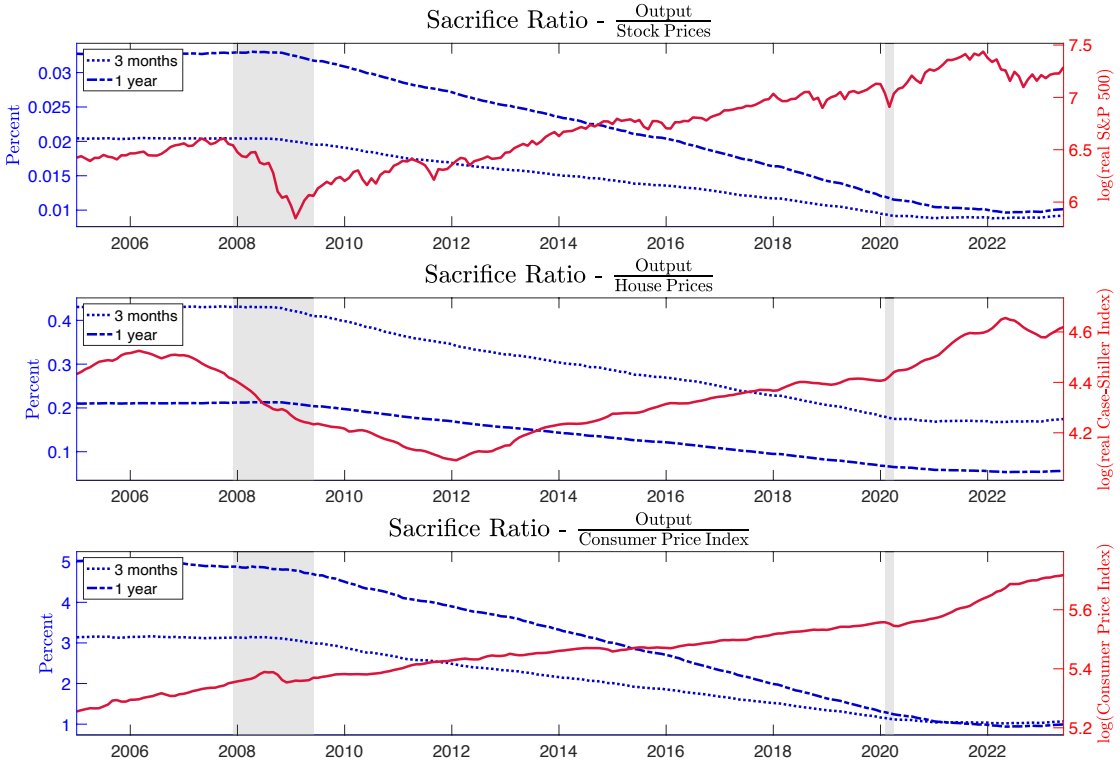



**Fig. 5.** Sacrifice Ratios: High MPU regime.

Notes: Left axis: Percentage change in output per 1% change in stock prices (SP), house prices (HP), and consumer prices (CPI) after three months (dotted) and one year (dashed-dotted). Right axis: SP index, HP index, or CPI in log levels (solid). Gray bars denote NBER recessions.

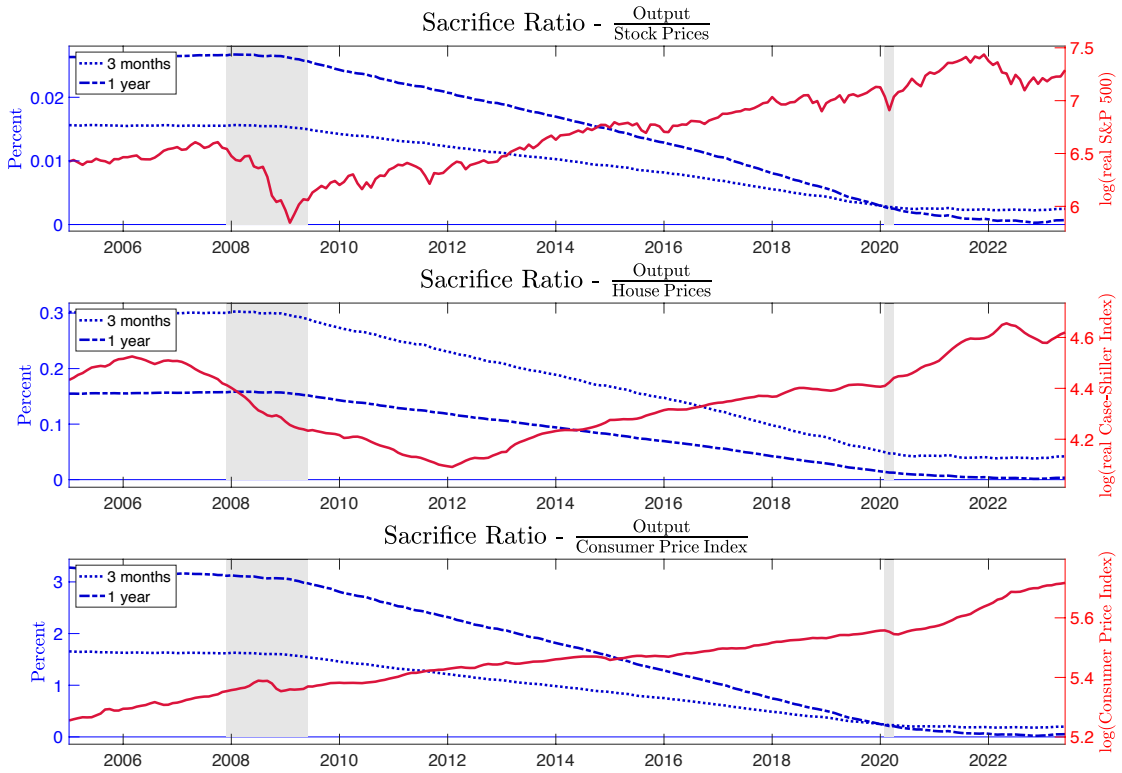



**Fig. 6.** Sacrifice ratios: Low MPU regime.

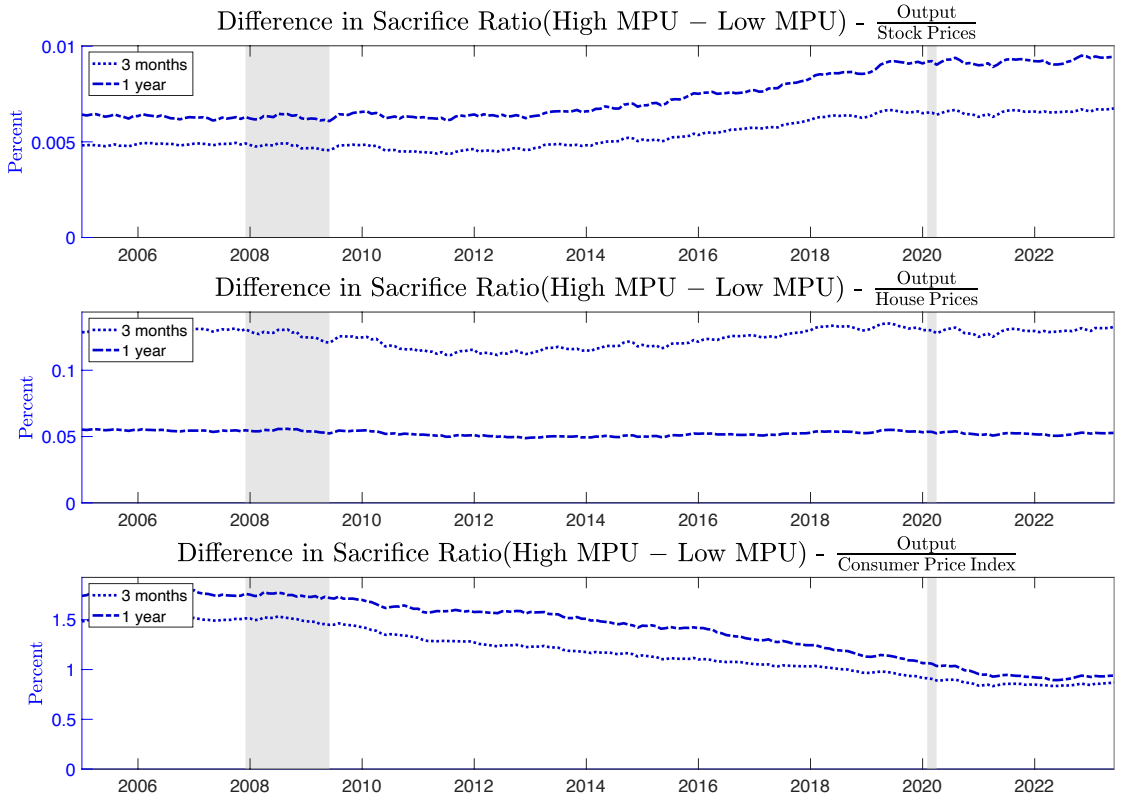



**Fig. 7.** Difference in sacrifice ratios between high and low MPU regimes (high MPU − low MPU).

## 6. Robustness tests

First, to verify that our findings are not sensitive to our choice of MPU proxy, we test the robustness of our baseline results against alternative MPU measures. In the benchmark model, we employ the BBD MPU referencing Baker, Bloom, and Davis (2016). This index is derived from the Access World News database by counting the frequency of articles in hundreds of US newspapers that mention "monetary policy uncertainty," followed by standardization and aggregation of those counts. To test the sensitivity of the findings to different MPU proxies, we employ an alternative version of the BBD MPU index from Baker et al. (2016), which is derived from a balanced sample of 10 major US national and local newspapers such as the Chicago Tribune, the Washington Post, and the Wall Street Journal. Aside from differences in the coverage scope of the newspaper samples, the criteria and scaling methods for identifying reports related to MPU are consistent with the baseline. Appendix Figures A.1–A.5 present the robustness test results, confirming that monetary tightening consistently depresses consumer and asset prices in both regimes, although the effect is slightly stronger when MPU is low. The remaining IRs qualitatively align with our baseline results.

We also test the robustness of our findings to sample length, with the benchmark sample spanning January 2005 to June 2023. In contrast to our benchmark model, Paul (2020) employed a sample ending in September 2017 within a TVP-VARX framework and revealed negative SP and HP responses to tightening monetary policy shocks. Sekandary

and Bask (2023) employed a panel smooth transition regression model with a sample ending in December 2015, demonstrating a negative correlation between monetary policy shocks and SP, although this relationship became less pronounced in periods of heightened uncertainty. Both studies were based on prepandemic samples and did not include the 2020 public health shock or subsequent period of surging inflation. As both studies relied on prepandemic samples, while the period from 2020 to 2023 combined the exogenous pandemic shock with supply chain and energy price disturbances and sharp swings in market liquidity, the TVPVARX model may be overly sensitive to abnormal fluctuations near the end of the sample. Therefore, we reduce the sample endpoint to December 2019 and re-estimate the TVP-VARX model and recalculated the sacrifice ratio under otherwise unchanged settings. The results are presented in Appendix Figures A.6–A.10. The core conclusions remain robust, demonstrating that our baseline results are stable to sample length changes.

## 7. Conclusion

This study investigates whether the state of MPU influences the impacts of monetary policy shocks on inflation and asset prices in the US. Using monthly data from January 2005 to June 2023, we demonstrate that tightening monetary policy shocks induce negative responses in US asset and consumer prices across high and low MPU, and the magnitude of these effects is larger under low-MPU environments, with asset and consumer prices exhibiting deeper and more persistent declines. The sacrifice ratio-based quantitative

measure reveals that the real economic costs of disinflation and deflating asset bubbles are considerably higher under a high-MPU environment. These results remain robust across alternative sample periods and alternative MPU measures. Overall, the findings indicate that elevated MPU diminishes monetary policy effects and increases the associated policy costs. Our findings align with real options theory, which emphasizes the role of fixed adjustment costs. This theory posits that when fixed adjustment costs or partial irreversibility are present, increased uncertainty induces economic agents to postpone decisions until more precise information or stronger demand emerges. This cautionary approach diminishes their responsiveness to economic fluctuations, including interest rate movement, rendering the economy less sensitive to any policy stimulus (Bernanke, 1983; Bloom, 2009; Dixit and Pindyck, 1994). In addition, behavioral and precautionary saving channels may serve as potential theoretical explanations for our results. The finding that monetary policy is less effective under high MPU than low MPU provides empirical support for policymakers to adopt more proactive policies in times of uncertainty.

Our findings have significant implications for monetary policymakers. First, policymakers should reduce MPU by enhancing communication transparency, strengthening forward guidance, and improving information disclosure quality. This will enhance the policy effectiveness and minimize the economic costs required to achieve policy objectives. Second, our evidence does not imply that monetary policy is incapable of supporting economic activity under high volatility. Instead, it indicates that the marginal

impacts of monetary policy weaken in such environments. This interpretation aligns with previous empirical work showing that alternative policy instruments can operate more powerfully under uncertainty. For example, Auerbach and Gorodnichenko (2012) provided evidence that fiscal multipliers rise under high volatility in the US, and Canzoneri et al. (2016) demonstrated that fiscal multipliers are also amplified in such environments using a general equilibrium model with financial frictions. Therefore, fiscal policy may be a comparatively more effective instrument for stimulating the economy in such periods. Third, policy authorities can combine macroprudential instruments such as countercyclical capital buffers, loan-to-value limits, and debt-to-income restrictions with monetary policy, which can contain financial vulnerabilities without raising the sacrifice ratio in high MPU environments (Borio and Zhu, 2012). Overall, our findings demonstrate that MPU reduces policy effectiveness and provides guidance for policymakers to optimize policy design and coordination in complex environments. Our findings point to the need for a deeper understanding of the channels through which MPU influences the monetary policy transmission. In particular, future work could explore bank-level risk-taking behavior, distributional effects, and the role of macroprudential policies using micro-level data.

## Appendix

This appendix presents additional impulse response results and sacrifice ratio estimates for the robustness tests discussed in Section 6. Figures A.1–A.5 present results

using an alternative MPU measure, and Figures A.6–A.10 are results obtained using an alternative sample period.

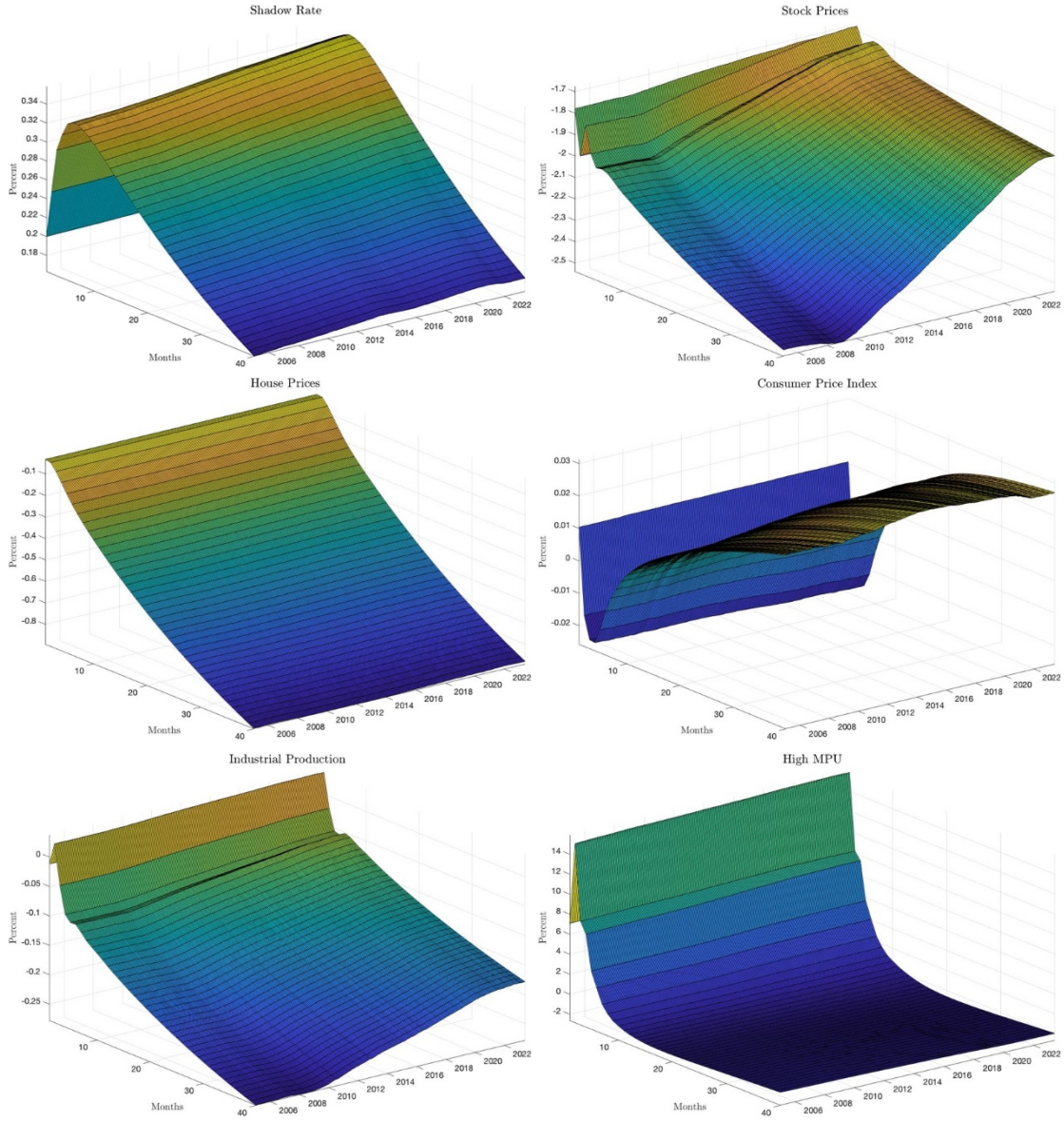



**Fig. A.1.** Time-varying impulse responses: High MPU regime.

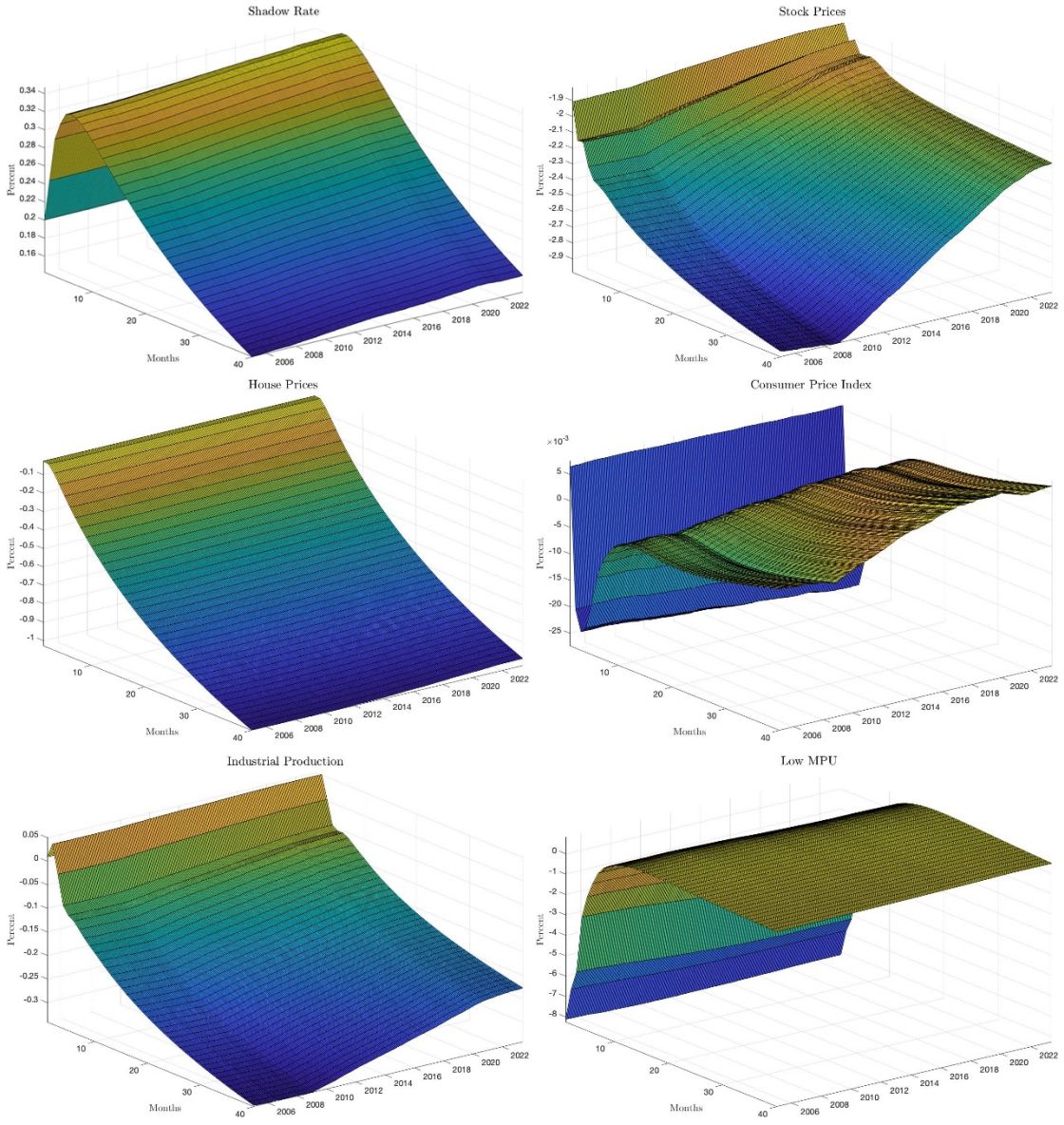



**Fig. A.2.** Time-varying impulse responses: Low MPU regime.

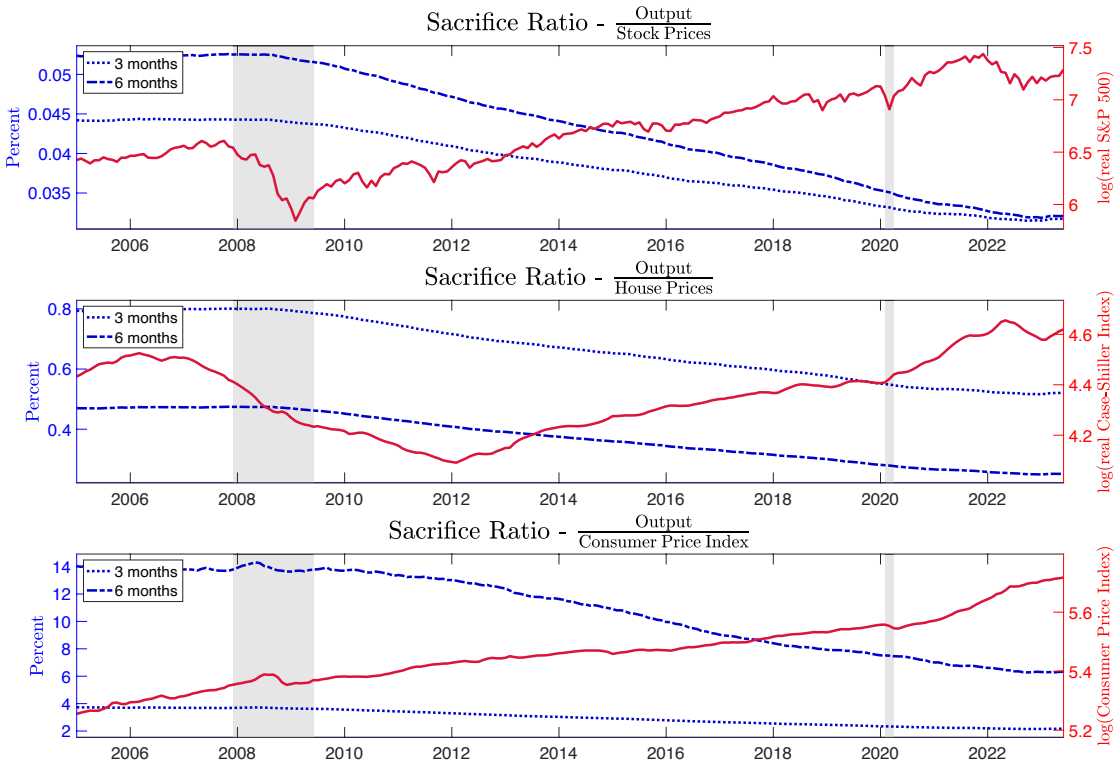



**Fig. A.3.** Sacrifice ratios: High MPU regime.

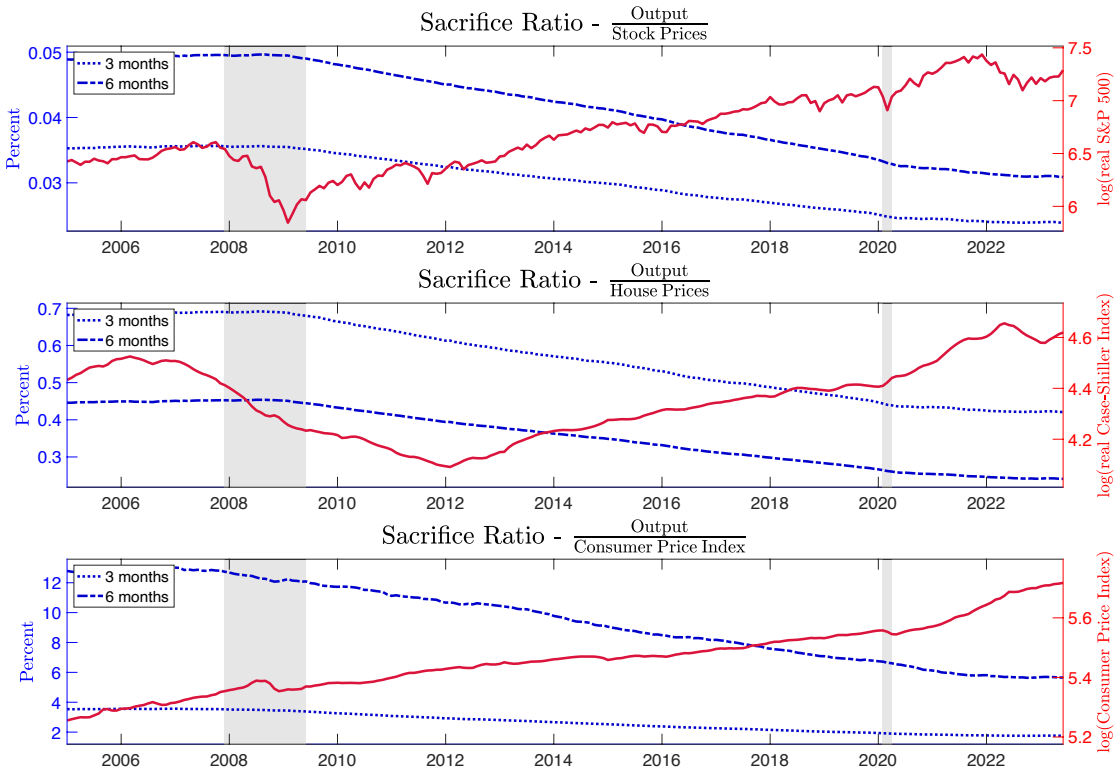



**Fig. A.4.** Sacrifice ratios: Low MPU regime.

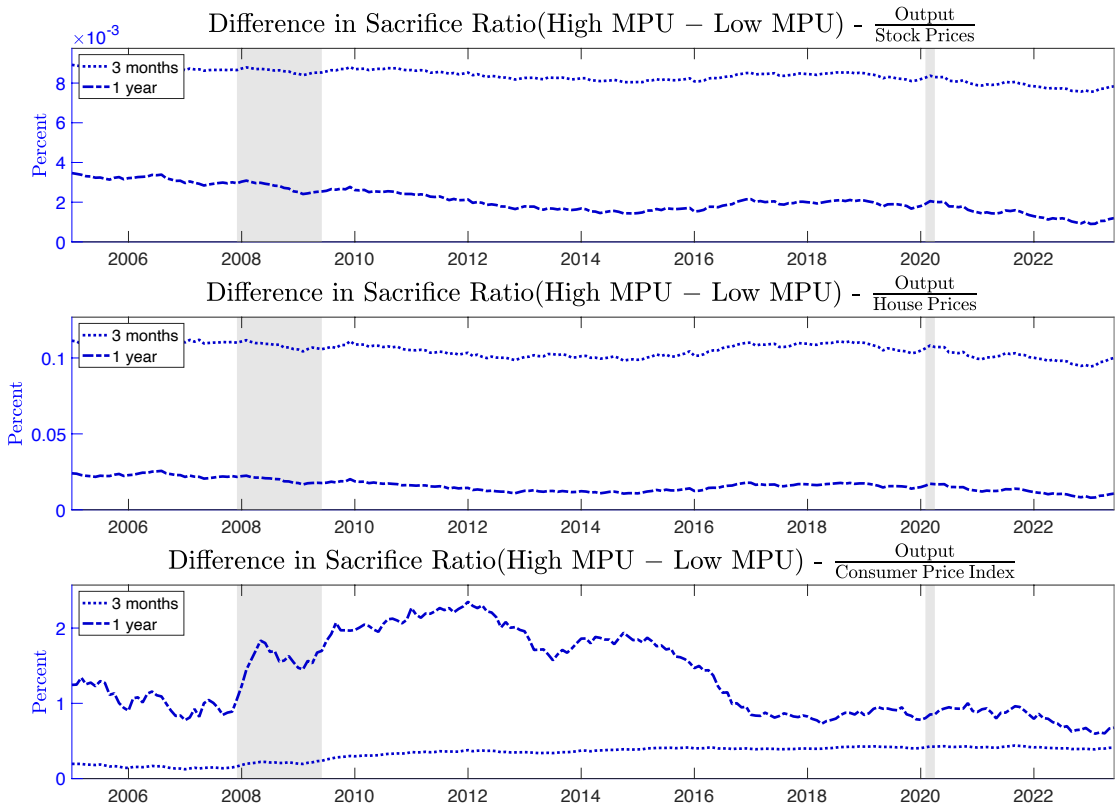



**Fig. A.5.** Difference in sacrifice ratios between high and low MPU regimes (high MPU − low MPU).

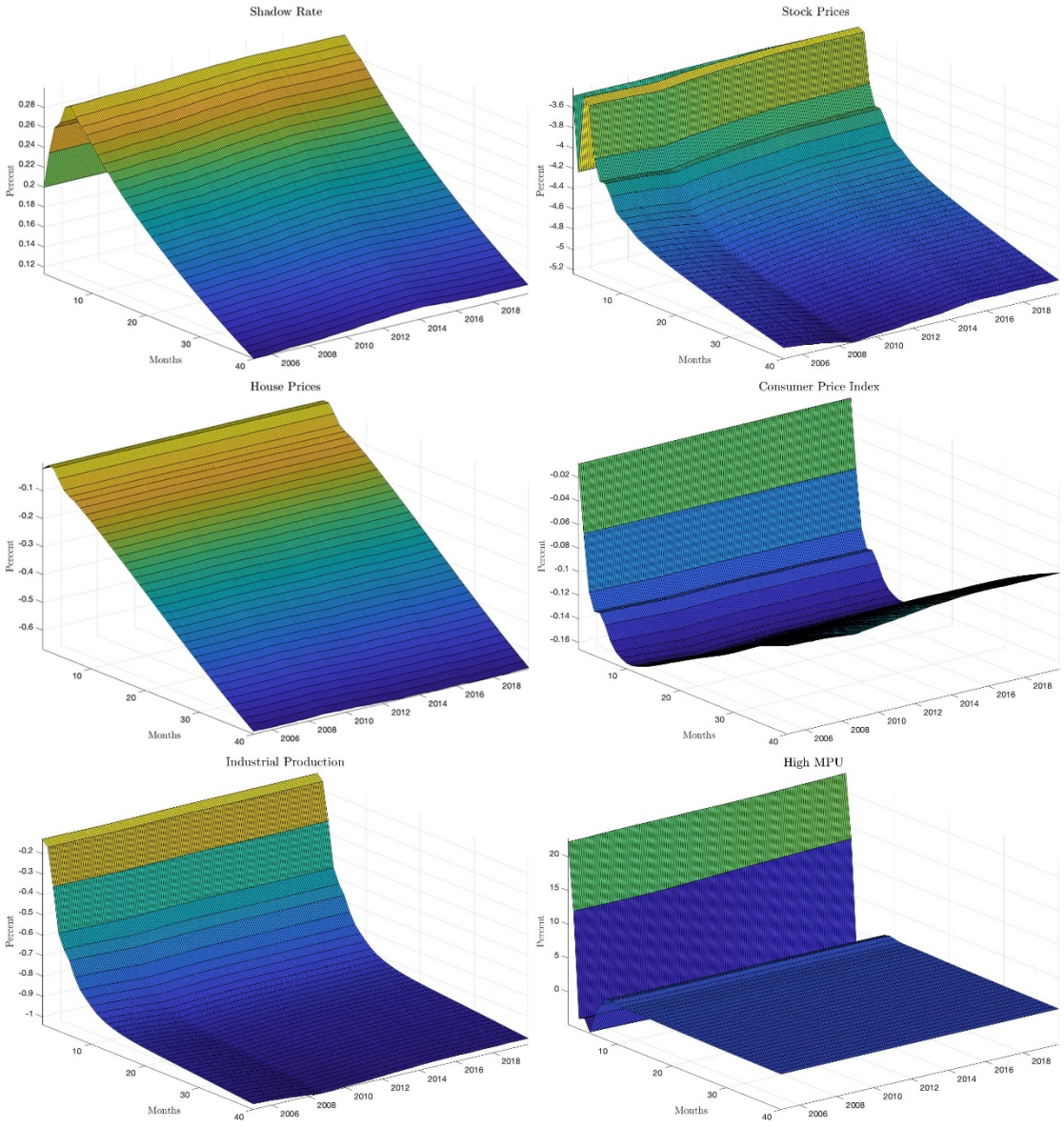



**Fig. A.6.** Time-varying impulse responses: High MPU regime.

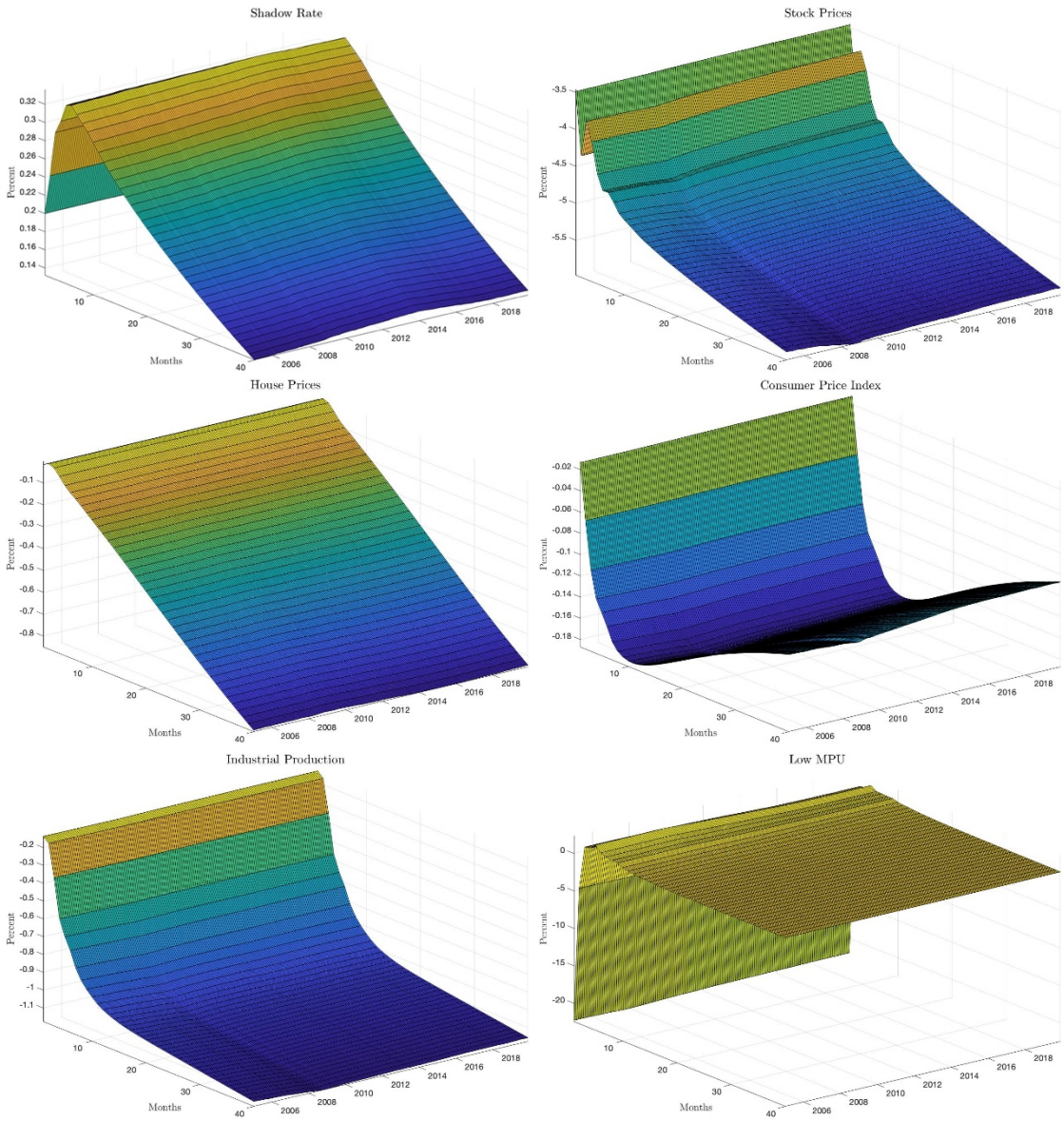



**Fig. A.7.** Time-varying impulse responses: Low MPU regime.

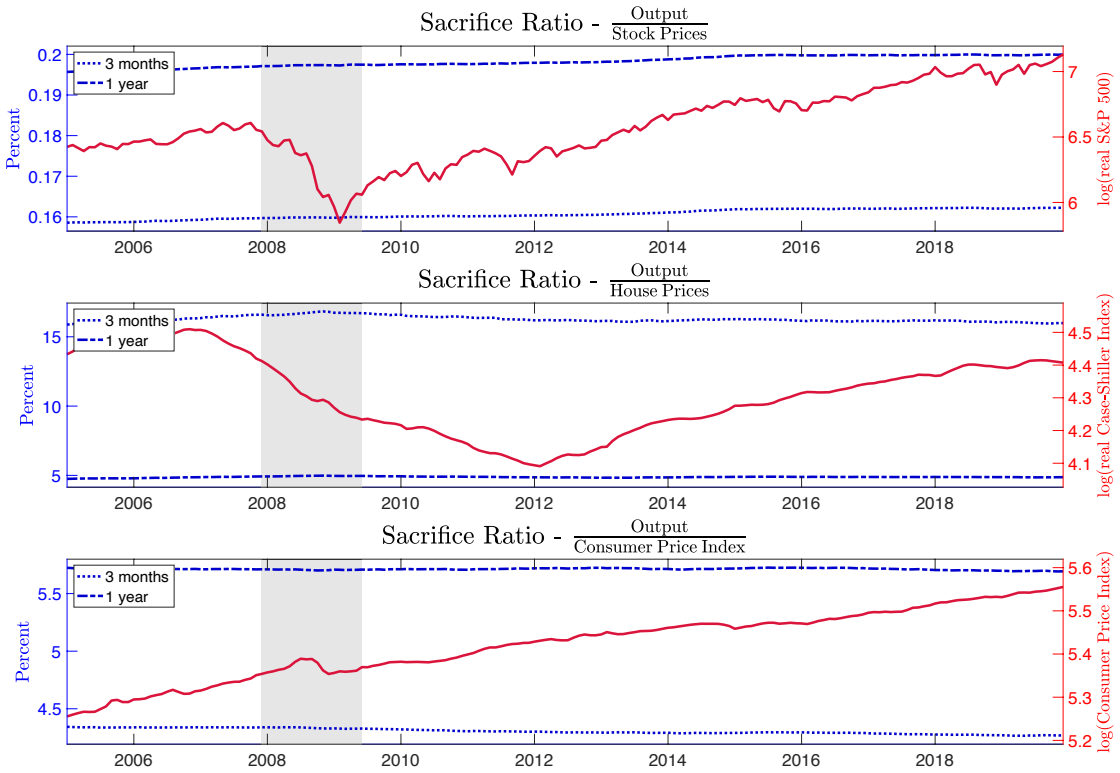



**Fig. A.8.** Sacrifice ratios: High MPU regime.

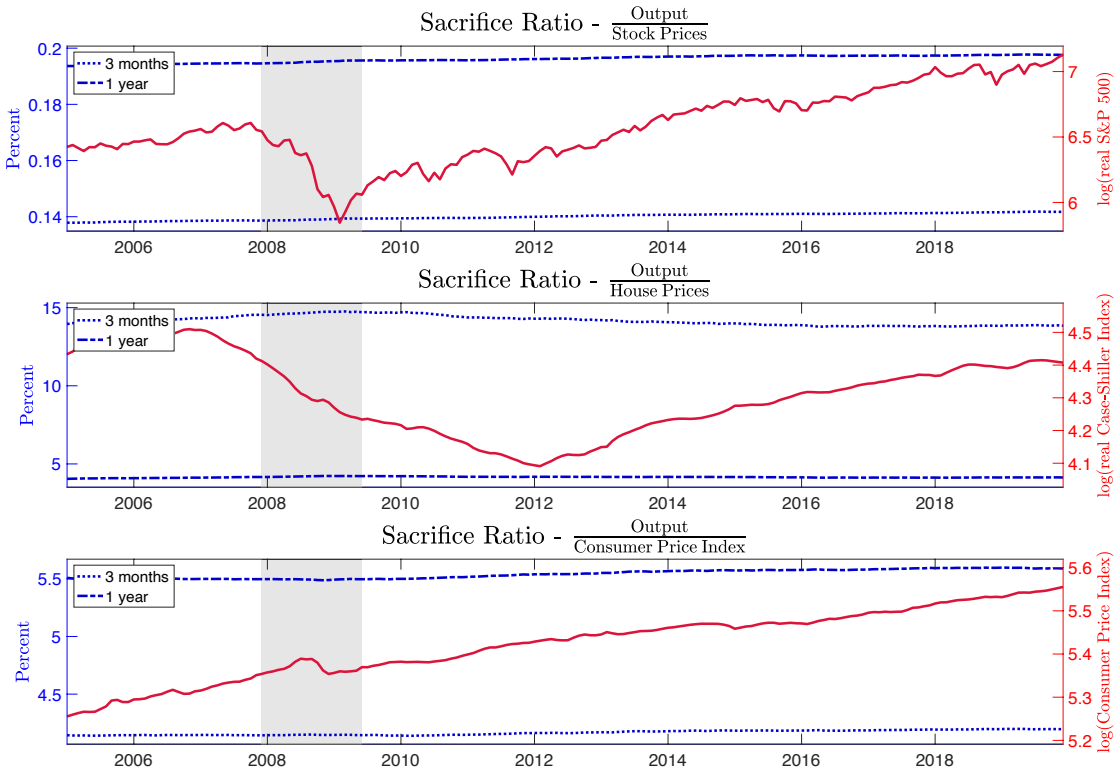



**Fig. A.9.** Sacrifice ratios: Low MPU regime.

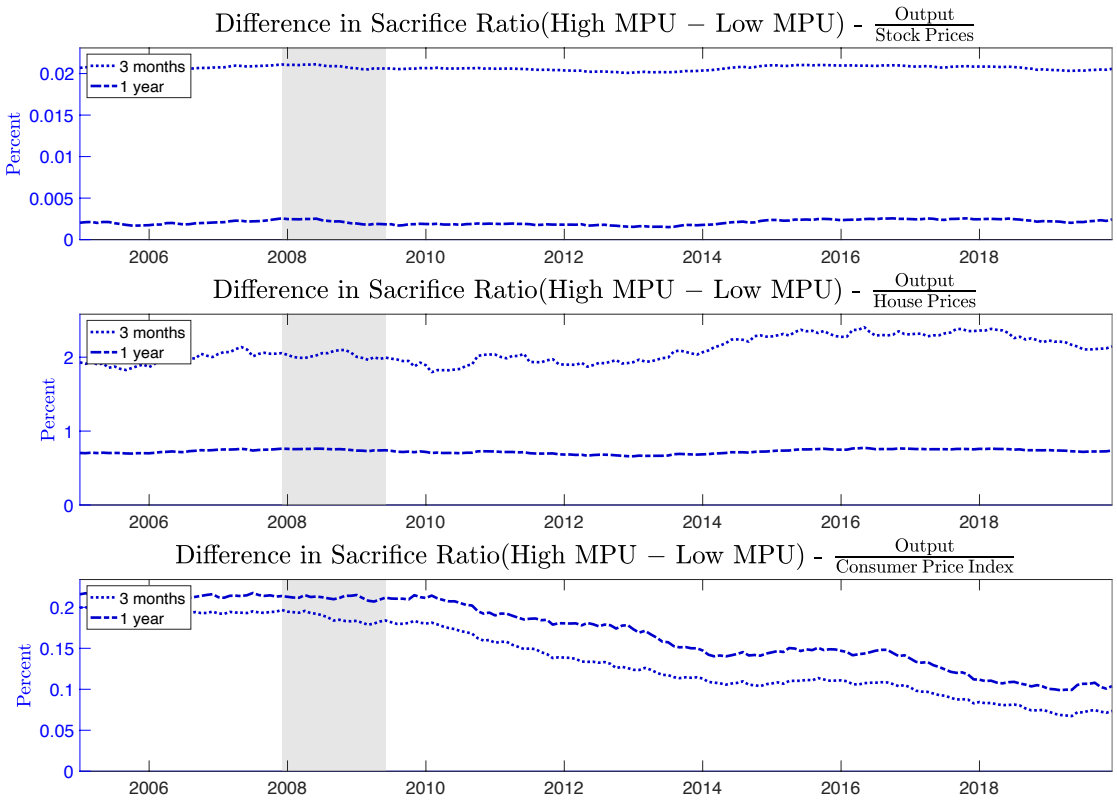



**Fig. A.10.** Difference in sacrifice ratios between high and low MPU regimes (high MPU − low MPU).

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