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Time-Varying Impact of Monetary Policy Shocks on U.S. Stock Returns: The Role of Investor Sentiment

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Abstract

This paper investigates how monetary policy shock affects the stock market of the United States (US) conditional on states of investor sentiment. In this regard, we use a recently developed estimator that uses high-frequency surprises as a proxy for the structural monetary policy shocks, which in turn is achieved by integrating the current short-term rate surprises, which are least affected by an information effect, into a vector autoregressive (VAR) model as an exogenous variable. When allowing for time-varying model parameters, we find that, compared to the low investor sentiment regime, the negative reaction of stock returns to contractionary monetary policy shocks is stronger in the state associated with relatively higher investor optimism. Our results are robust to alternative sample period (which excludes the zero lower bound) and model specification and also have important implications for academicians, investors, and policymakers.

JEL classification: E44; E52; G12; G14

Keywords: Investor sentiment; External instruments; Monetary policy surprises; Time-varying parameter VAR model

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1. Introduction

Theoretically, monetary policy shocks affect stock prices by changing investors' expectation about future cash flows, and by affecting the cost of capital, i.e., the real interest rate which is used to discount the future cash flows and/or the risk premium associated with holding stocks (Bernanke and Kuttner, 2005; Maio, 2014). Given these two channels, a large amount of work has been devoted to studying the impact of monetary policy shocks on the stock prices and/or returns of the United States (see Kishor and Marfatia, 2013, Simo-Kengne et al., (2016), and Caraiani and Călin (2018) for detailed literature reviews), with these studies suggesting that, in general unexpected increase (cut) in the Federal funds rate (FFR) is negatively (positively) related to stock prices and/or returns, and also the fact that the effect is state-dependent, whereby the states are associated with phases (bearish or bullish) of the stock market (Chen (2007)) and the overall macroeconomy involving recessions or expansions (Basistha and Kurov, 2008), pre- or during-crisis periods (Kontonikas et al., 2013), and uncertainty (Marfatia, 2014).

At the same time, behavioral theory of finance and related empirical studies have established the effect of investor sentiment on stock returns (see, Gebka (2014) and Balcilar et al., (2018) for detailed reviews). Given this, the objective of our paper is to analyze whether sentiment-based regimes affect the time-varying response of stock returns to monetary policy shocks, with states of the investor sentiment defined by a Markov-switching model. We hypothesize that the impact of monetary policy shocks on stock market returns is stronger during periods of high sentiment due to the so-called sentiment-mispricing mechanism.[1] The intuition behind what we posit is that the stock market becomes less rational during high sentiment periods due to higher participation of noise traders (Stambaugh et al., 2012), who in turn are subject to animal spirits, fads and fashions, overconfidence and related psychological biases (Abreu and Brunnermeier, 2003), leading to an extended period of market overvaluation. During this phase, stock prices depart from the rationally discounted value of expected cash flows (De Long et al., 1990; Lee, et al., 1991), either due to overestimation of the size of the cash flows or due to underestimation of risk (Mian and Sankaraguruswamy, 2012; Kaplanski et al., 2015). Simultaneously, sentiment-driven overpricing is known to be more prevalent than underpricing due to the limits of arbitrage and short sale constraints (Chung et al., 2012). Hence, a contractionary monetary policy shock during periods of high-sentiment is likely to produce a relatively

[1] In this regard, Kurov (2010) has inter alia shown that monetary policy actions (in bear market periods) have a larger effect on (cross-section of) stocks that are more sensitive to changes in investor sentiment (and credit market conditions).

strong correction back to equilibrium than when sentiment is relatively low.

Note that our hypothesis now adds a behavioural channel to the transmission of monetary policy shocks to equity prices, besides the two above-mentioned theoretical channels through which monetary policy is expected to affect stock prices, with our results providing a test of rationality of the stock market. Understandably, under the null of rationality, the stock price response to monetary policy shocks should not be different across periods of low- and high-sentiment. In addition, from the perspective of a policymaker, if the size of the monetary policy impact is contingent on the level of investor sentiment, then policy authorities need to be aware of this information when undertaking monetary policy decisions aimed to affect the stock market to a certain degree, say, for example, to control the development of ”bubbles”. But it must be realized, that the primary goal of monetary policy is to stabilize fluctuations in output and inflation and keep these variables close to their desired targets. Hence, it is important to study how monetary policy jointly affects the equity prices and the real economy, contingent on the levels of investor sentiment.

In light of this, from an econometric perspective, we use the time-varying vector autoregressive (VAR) model of Paul (2019), which involves an estimator that uses high-frequency surprises (specifically, price changes in federal funds futures around announcements of the Federal Open Market Committee (FOMC)) as a proxy for the structural monetary policy shocks. Then the simultaneous impact of monetary policy shocks on stock prices and the real economy is achieved by integrating the surprises (as a proxy for the structural monetary policy shocks) into the VAR as an exogenous variable, resulting in a VARX model. In this regard, Paul (2019), and also us, use the current short-term rate surprises because these are least affected by a release of a central banks private information.

To the best of our knowledge, this is the first attempt to provide time-varying evidence of the impact of both conventional and unconventional monetary policy shocks on aggregate stock returns of the US over the monthly period of 1978:11 to 2017:09, conditional on the regimes of investor sentiment. A paper that is related to our work is that by Guo et al., (2020), wherein the authors rely on a constant parameter event study-based approach, and hence, unlike us are unable to provide dynamic effects over time jointly on the equity market and macroeconomic variables. Guo et al., (2020) show that the stock returns increase significantly over the pre-FOMC announcement window (known as the pre-FOMC announcement drift) only during periods of high investor sentiment (and low economic uncertainty).[2] The remainder of the paper is organized as follows: Section 2 discusses the data, while Section 3 presents the methodologies

[2] In addition, in a (working) paper Guo et al., (2019) indicate that the impact of FFR surprises negatively impacts stock returns

used, with Section 4 devoted to the empirical results and associate robustness checks. Finally, Section 5 concludes the paper.

2. Data

Our data set includes the federal funds rate (FFR), S&P 500 stock price index (SP), S&P /Case-Shiller national home price index (HP), consumer price index (CPI), industrial production (IP), monetary policy surprises and investor sentiment for the US economy over the monthly period of 1978:11 to 2017:09, with the end date driven by data availability of the monetary policy surprises data. Seasonally-adjusted IP, HP, and CPI data are downloaded from the FRED database of the Federal Reserve Bank of St Louis. Time series of FFR and end of the month price of the SP are obtained from the Bloomberg terminal. The investor sentiment index is based on the work of Baker and Wurgler (2006, 2007). They construct the investor sentiment index using the principal component analysis to aggregate the information from six individual sentiment proxies: the closed-end fund discount, which is the average difference between the net asset value of closed-end stock fund shares and their market prices; New York Stock Exchange (NYSE) share turnover, based on the ratio of reported share volume to average shares listed from the NYSE Fact Book; the number of IPOs; the average first-day returns; the share of equity issues in total equity and debt issues, which is a measure of financing activity and the dividend premium.[3]

Finally, we obtain the monetary policy surprises data from the work of Paul (2019) which is based on the spread between 30-day federal fund futures that are settled at the end of the month t during which a policy decision is made[4]. Since the surprises are given by high-frequency price changes in federal fund futures around announcements of the FOMC, these show unanticipated movements in the monetary policy rate. Put differently, these surprises are computed from difference of the settlement price for the current month's federal fund futures and the settlement price before the FOMC meeting which is measured in a 30-minute window around a FOMC meeting[5].

only when sentiment is high for the period before the zero lower bound (ZLB). Since this paper could only detect a low-sentiment regime over the unconventional monetary policy period (of 2009-2014), the authors could not provide a state-contingent impact of unconventional monetary policies on stock returns.

[3]The six individual investor sentiment proxies, as well as the overall PCA-based sentiment index data, are available from Professor Jeffrey Wurgler's website at `http://people.stern.nyu.edu/jwurgler/`.

[4]We thank Dr. Pascal Paul for sharing his data in this regard.

[5]A narrow window is used to mitigate possible biases because of certain details being released before the policy statement,

3. Methodologies

3.1. Markov-Switching Model for Investor Sentiment Regimes

Following Chen (2007) and Kurov (2010) who apply Markov-switching model to identify states of the stock market, we estimate the probabilities of high and low investor sentiment regimes by also employing a Markov-switching model of investor sentiment:

$$s_t = \mu_{R_t} + \beta_{R_t} s_{t-1} + \epsilon_t \qquad \varepsilon_t \sim i.i.d.N\left(0, \sigma^2_{R_t}\right) \tag{1}$$

where s_t is the investor sentiment index, μ_{R_t} and $\sigma^2_{R_t}$ are the regime specific mean and variance of sentiment, respectively. The transition from one state to the other is characterized by a Markov chain process and based on probabilities of transition between two regimes. The parameters of the model (means, variances, and transitional probabilities) are estimated jointly with the maximum likelihood estimation method. R_t is an unobserved dummy variable that shows high or low sentiment periods. Thus, R_t takes the value of one if the smoothed probability is greater than 0.5 and is zero otherwise. And finally, by multiplying this dummy variable with the investor sentiment index, corresponding high and low investor sentiment indices are constructed.

3.2. Time-Varying Parameter VAR Model (TVP-VAR)

We utilize the time-varying parameter VAR model of Cogley and Sargent (2001), but also follow the exogenous variable approach proposed by Paul (2019). Let y_t be an $n \times 1$ vector of endogenous variables that evolves according to

$$y_t = B_{0,t} + B_{1,t} y_{t-1} + \ldots + B_{k,t} y_{t-k} + A_t z_t + u_t \quad t = 1, \ldots, T \tag{2}$$

$$y_t \equiv \left[ffr_t, \Delta sp_t, s^j_t, \Delta hp_t, \Delta cpi_t, \Delta ip_t\right]' \tag{3}$$

where y_t is a vector of endogenous variables and includes FFR (ffr_t), the log real end of the month stock price index of S&P 500 (sp_t), the log real S&P /Case-Shiller national home price index (hp_t), the log of consumer price index (cpi_t), the log of real industrial production (ip_t), and investor sentiment (s^j_t) alternatively high or low investor sentiment regimes where j = high, low. Furthermore, $B_{0,t}$ 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 with

which may provoke responses from financial markets.

respect to the lagged endogenous variables[6]. The reduced-form innovations are given by the $n \times 1$ vector u_t. The monetary policy surprises are integrated to the model as an exogenous variable z_t with $n \times 1$ vector of time-varying coefficients A_t which is again linked to the structural monetary policy shock, $\epsilon_{1,t}$, but not to any other structural shocks.[7] A further assumption is that z_t is associated with the structural shock $\epsilon_{1,t}$ via:

$$z_t = \phi \epsilon_{1,t} + \eta_t \tag{4}$$

where $\eta_t \sim N\left(0, \sigma_\eta^2\right)$ and η_t orthogonal to all other variables. This means that the identified time-variation in A_t is not because of the time variability in the relation between z_t and $\epsilon_{1,t}$, which is useful in order to generate the impulse responses. Next, we define B_t to be a vector that includes all coefficients on the right-hand side of (3). Then, B_t is assumed to follow a driftless random walk:

$$B_t = B_{t-1} + v_t \tag{5}$$

The model's innovations are assumed to be jointly normally distributed with mean zero and block-diagonal covariance matrix as represented by:

$$V = \text{Var}\left(\begin{bmatrix} u_t \\ v_t \end{bmatrix}\right) = \begin{bmatrix} \Omega & 0 \\ 0 & Q \end{bmatrix} \tag{6}$$

where Ω and Q are positive definite matrices. The history of coefficients B_t is denoted by $B^\tau = \left[B_1', \ldots, B_\tau'\right]'$. We use Bayesian methods and Gibbs sampling to evaluate the posterior distributions of B_t and V. Following Paul (2019), the prior distributions are computed on the basis of a training sample covering the period of 1978:11 to 1990:12. Then, we generate time-varying impulses responses for the sample 1991:01 to 2017:09. According to OLS estimates of the constant parameter VAR model for the training sample, mean and variance of B_0, and degrees of freedom for the inverse - Wishart prior of Ω and Q are determined as

[6] Although, a lag length of k=4 is chosen based on the Akakike Information Criterion (AIC), we reduce the lag length to k=3 to lower dimensions of both B_t and Q.

[7] The interest lies in the identification of impulse responses to one of the structural shocks, represented by $\epsilon_{1,t}$. Put differently, the reduced form innovations u_t are associated with structural shocks $\epsilon_{1,t}$ and the $(n-1) \times 1$ vector $\epsilon_{2,t}$ includes all other structural shocks. While we also suppose that z_t is correlated with the structural monetary policy shock of interest, it is uncorrelated with the rest of the structural shocks.

follows:

$$
\begin{aligned}
&B_0 \sim N\left(\widehat{B}_{OLS}, 4 \cdot V\left(\widehat{B}_{OLS}\right)\right) \\
&\Omega \sim IW\left(I_n, n+1\right) \\
&Q \sim IW\left(\kappa_Q^2 \cdot \tau \cdot V\left(\widehat{B}_{OLS}\right), \tau\right)
\end{aligned} \tag{7}
$$

where $\widehat{B}_{OLS}$ includes the OLS estimates of the constant VAR model and $V\left(\widehat{B}_{OLS}\right)$ their variance, and τ represent the length of the training sample. The parameter κ_Q captures the prior belief regarding the time variation of B_t.[8] The model simulation is based on 5000 Gibbs sampler iterations, although the first 2000 are discarded in order to reach convergence.

Given the estimated model and a structural shock $\epsilon_{1,t}$ that results in a one-unit increase in some variable j in y_t at time t, the contemporaneous relative impulse response of some other variable i in y_t at time t is indicated by:

$$
r_{t,ij} = \frac{\bar{A}_{t,i}}{\bar{A}_{t,j}} \tag{8}
$$

where $\bar{A}_{t,i}$ and $\bar{A}_{t,j}$ are the posterior means of the coefficients for variables i and j, respectively, that are associated with z_t at time t. All resulting impulse reactions are then extracted using the posterior means of the remaining coefficients in B_t. To obtain relative impulses over time, the initial response of one of the endogenous variables must be normalised for a particular period.[9]

4. Empirical Results

4.1. Main Findings

Figure 1 presents the smoothed probabilities of the two-state Markov-switching model for the investor sentiment index. While the upper panel displays the smoothed probabilities of low sentiment regime (regime 1), the lower panel demonstrates the high sentiment regime's smoothed probabilities (regime 2). It can be seen from the Figure 1 that, the low investor sentiment regime coincides with the periods including two oil shocks in the 1970s, the Gulf War in early 1990, the failure of Long Term Capital Management that

[8] Following Paul (2019), we set κ_Q=0.015.

[9] For instance, one may consider a monetary policy shock that leads to fall in output in period t, say, one percent. This shock implies a particular variation in z_t which can be utilized to compute the impulse responses for the remaining periods to provide an accurate comparison over periods, as suggested by Paul (2019).

contributed to the 1998 crisis, the default of the Russian sovereign bonds and the recent global financial crisis. Furthermore, most of the periods classified as low investment sentiment regimes occur in the NBER recessions (the shaded areas).

– Insert Figure 1 about here. –

In Figures 2 and 3, we plot the impulse responses (IRs) obtained from the TVP-VAR model under both low and high sentiment regimes. As previously noted, the key advantage of the TVP-VAR framework is that it allows us to estimate impulse response functions in a time-varying nature. Following the approach of Paul (2019), we normalize the response of the FFR on impact to 20 basis points at the beginning of the sample (1991:01) by putting a specific $\bar{z}$ value to achieve this response.[10] Similarly, in order to to obtain contemporaneous impulse responses for any other variable in 1991:01 or any subsequent period, we utilize the same variation $\bar{z}$.[11] An inspection of Figures 2 and 3 leads to a number of interesting observations:

First, although the FFR's reaction fluctuates over time, as in Figures 2 and 3, the estimated effects suggest that monetary policy shock usually leads to a monetary tightening. However, the response is muted during the recent ZLB. In particular, the response is close to zero since late 2008 resulting in the lack of substantial variation of the monetary policy surprises. This result is consistent with the view that central banks used unconventional policies to provide further monetary stimulus beyond a zero policy rate via direct lending to specific short term credit markets, the large scale of asset purchases of programs, and forward guidance on future policy announcements (See for example, Neely (2015), McKay et al., (2016) and Hagedorn (2019)).

Second, the estimated responses of stock prices to monetary tightening are always negative in both regimes, but the effect is slightly more pronounced under the high investor sentiment regime. As shown in Figure 2, while the stock prices's negative response oscillates between 3.5% to 7% in high investor sentiment regime, the decline ranges from 3% to 6.5% in periods of low investor sentiment regime. Furthermore, the responses of stock markets are statistically significant at the 95% confidence interval in both regimes.[12] The

[10]In particular, we set $\bar{z} = 0.2/\bar{A}_{1991M1,1}$ where $\bar{A}_{1991M1,1}$ is the estimated posterior mean for the federal funds rate at time 1991:01.

[11]While, the contemporaneous impulse response of variable i at time t is defined by $\bar{A}_{t,i} \cdot \bar{z}$, the contemporaneous relative impulse response of any two variables i and j at time t can then be computed from the ratio of their responses $\frac{\bar{A}_{t,i} \cdot \bar{z}}{\bar{A}_{t,j} \cdot \bar{z}} = \frac{\bar{A}_{t,i}}{\bar{A}_{t,j}} = r_{t,ij}$ as defined in the equation (8). See Paul (2019) for more details.

[12]Figure A1 in the Appendix shows posterior credibility intervals based on iterations of the Gibbs sampler for the month of 2003:01.

reason for the higher decline of stock returns in high sentiment regime is in line with our hypothesis of the so-called sentiment-mispricing mechanism, whereby we expect a contractionary monetary policy shock during periods of high-sentiment is likely to produce a relatively strong correction back to equilibrium than when sentiment is relatively low. Figure 2 also shows that the reaction of stock prices to monetary policy surprises tends to display a more sizable reaction since 2008 compared to those of low investor sentiment regime (Figure 3). This implies that when investors have high sentiment and confidence about the future path of monetary policy actions, they tend to take riskier positions before a policy meeting (De Pooter et al., (2018)).

Third, industrial production always responds negatively to a monetary tightening and the same is valid also for the inflation rates over most of the sample. Industrial output declines roughly over one year and a half after the impact in both regimes. In line with the findings of Gertler and Karadi (2015), monetary policy surprise has relatively little impact on inflation due to temporary nominal rigidities that restrict offsetting movements in inflation.

Fourth, the responses of house prices are negative in both high and low sentiment regimes, with their effect being much larger in the high sentiment regime. This finding shows that the reaction of housing prices is likely to be stronger in periods of a high sentiment because of the possible overestimation of the size of rental growth or underestimation of risk, as in the case of stock markets, again due to sentiment-mispricing on asset markets in general (Caraiani et al., forthcoming).

Fifth, although there is an initial increase in investor sentiment in high regime contrary to our expectations in response to a surprise monetary tightening, the effects reverse over time. On the other hand, the effect of monetary tightening on investor sentiment is negative and persistent in the low sentiment regime implying that monetary tightening influences investor sentiment through excess pessimism as proposed by Shiller (2000). However, the effect of the monetary policy shock attenuates and completely dies out after 2008 because of the ZLB. This result shows that investors' responses to monetary tightening are asymmetric depending on the investor regimes.

– Insert Figures 2 and 3 about here. –

Overall, our results highlight the possible asymmetries in the effects of monetary policy surprises on the economy in different states of investor sentiment. Given that monetary policy decisions are closely monitored by investors and are widely reported by financial media, the relation between monetary policy and investor sentiment can have significant implications for both practitioners and policymakers. With the prevalence of bubbles in recent years, indicators of investor behaviour are now being closely monitored by policymakers (Jordà et al., 2015a, 2015b), and our results provide new insights to establish a detailed understanding of the effects of monetary policy surprises on the economy and investor sentiment.

4.2. Robustness Checks

Our sample includes the ZLB covering the periods between the end of 2008 and the end of 2015. During this period, the monetary policy surprises are much smaller in absolute size and do not provide too much information for the estimation of the contemporaneous impulse responses. Put differently, over this period, the surprises with respect to the current month's federal funds rate are essentially zero. Hence, this episode provides little information for the estimation of the contemporaneous impulse responses. However, it is also not an obstacle for the estimation approach since the contemporaneous relative impulse responses are identified from the remaining non-zero observations of the instrument. To address this issue, we repeat the same exercise on a sample that ends in 2007:12 by discarding the ZLB-episode as suggested by Paul (2019). Figures A2 and A3 in the Appendix present the impulse responses under the high and low sentiment regimes respectively. Compared with Figure 2, although the initial reaction of the stock prices is strong in the high sentiment regime as in the full sample, we observe from Figure A2 that this effect decreases in later months. Similarly, the response of industrial production is much smaller than those of the full-sample. While the inflation rate shows a "price puzzle" initially, its reaction turns out to be negative in the long-run. Compared with Figure 3, the negative response of stock prices is more pronounced during the low sentiment periods before the ZLB (Figure A3). Furthermore, house prices always decrease following a monetary tightening but the impact is higher in magnitude. The other impulse responses are qualitatively similar.

We also check the robustness of our results for a different value of κ_Q, since Primiceri (2005) points out that the results may be prone to this parameter as it captures the prior belief. We repeat our exercise by setting $\kappa_Q = 0.01$ (from 0.015) to decrease the time variation in the coefficients B_t. The results are presented in Figures A4 and A5 in the Appendix. In line with the findings of Paul (2019), setting κ_Q to a lower value reduces the time variation of the B_t coefficients which result in less variability over time for some of the impulses, which in our exercise happens particularly to be the case for house prices and industrial production.

5. Conclusion

In this paper, we posit that the impact of monetary policy shocks on stock market returns is stronger during episodes of high sentiment relative to periods of comparatively lower values of the sentiment due to the so-called sentiment-mispricing mechanism. To test this hypothesis, we use a recently developed time-varying VAR model, which involves an estimator that uses high-frequency surprises as a proxy for the structural monetary policy shocks. Then the simultaneous impact of monetary policy shocks on stock prices and the real economy is achieved by integrating the current short-term rate surprises, which are least affected by a release of a central banks private information, into the VAR as an exogenous variable, thus yielding a VARX model. Over the monthly period of 1978:11 to 2017:09, we find evidence of a stronger decline of stock returns following a contractionary monetary policy under the high sentiment regime compared to a period characterized by relatively weaker investor optimism. These results continue to hold under an alternative sample period which excludes the zero lower bound and also prior specifications that are used to estimate the Bayesian time-varying VARX model.

From the perspective of an academician, our results add a behavioral channel through which monetary policy can impact equity returns. As far as an investor is concerned, we provide further evidence that the US equity market is not necessarily rational, and hence, understandably, behavioral factors need to be accounted for to price equities. Finally, from the standpoint of a policymaker, our analysis implies that, while bubbles are more likely to originate due to over-exuberance under higher investor sentiment, the Federal Reserve, if it desires, can also curb the stock market from deviating away from its fundamentals relatively easily under this state of higher optimism of market agents. Alternatively put, the stronger monetary response would be required to move the stock market to the desired degree when sentiments are low.

As part of future research, contingent upon data availability of high-frequency monetary policy instruments, it would be interesting to extend our analysis to other advanced and emerging equity markets to provide a comparative analysis to that of the US.

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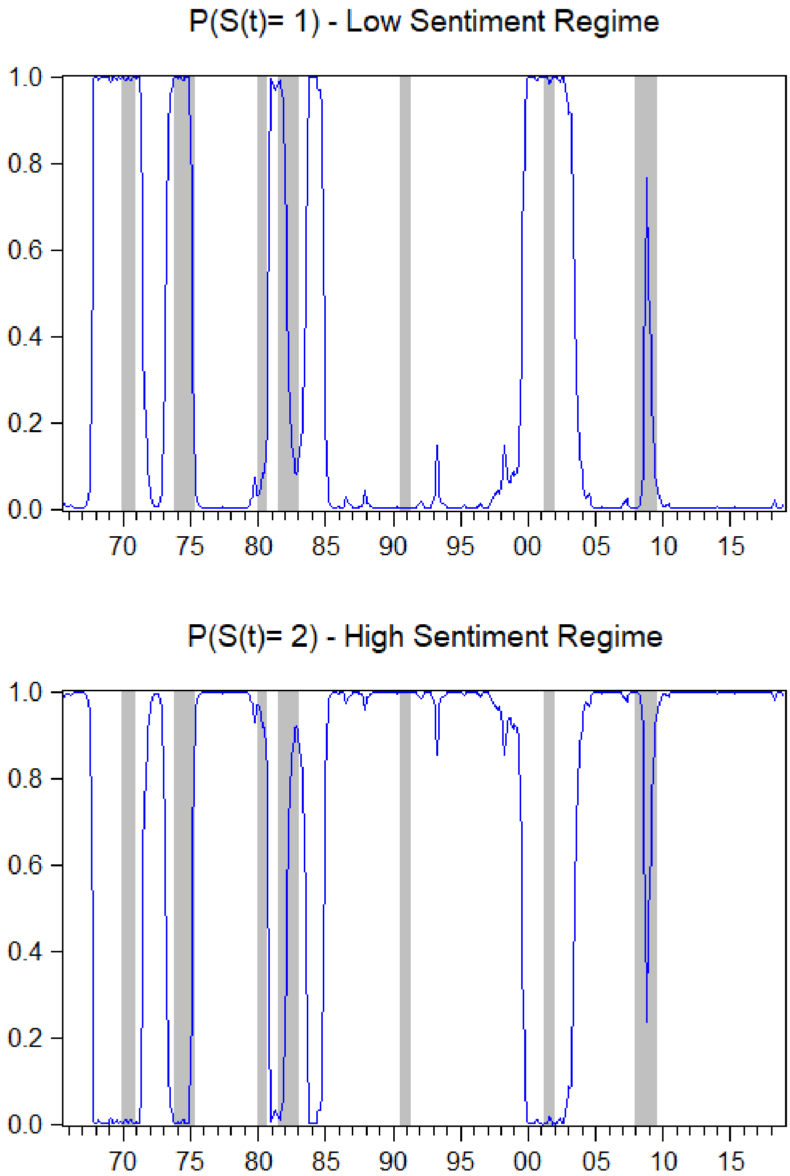
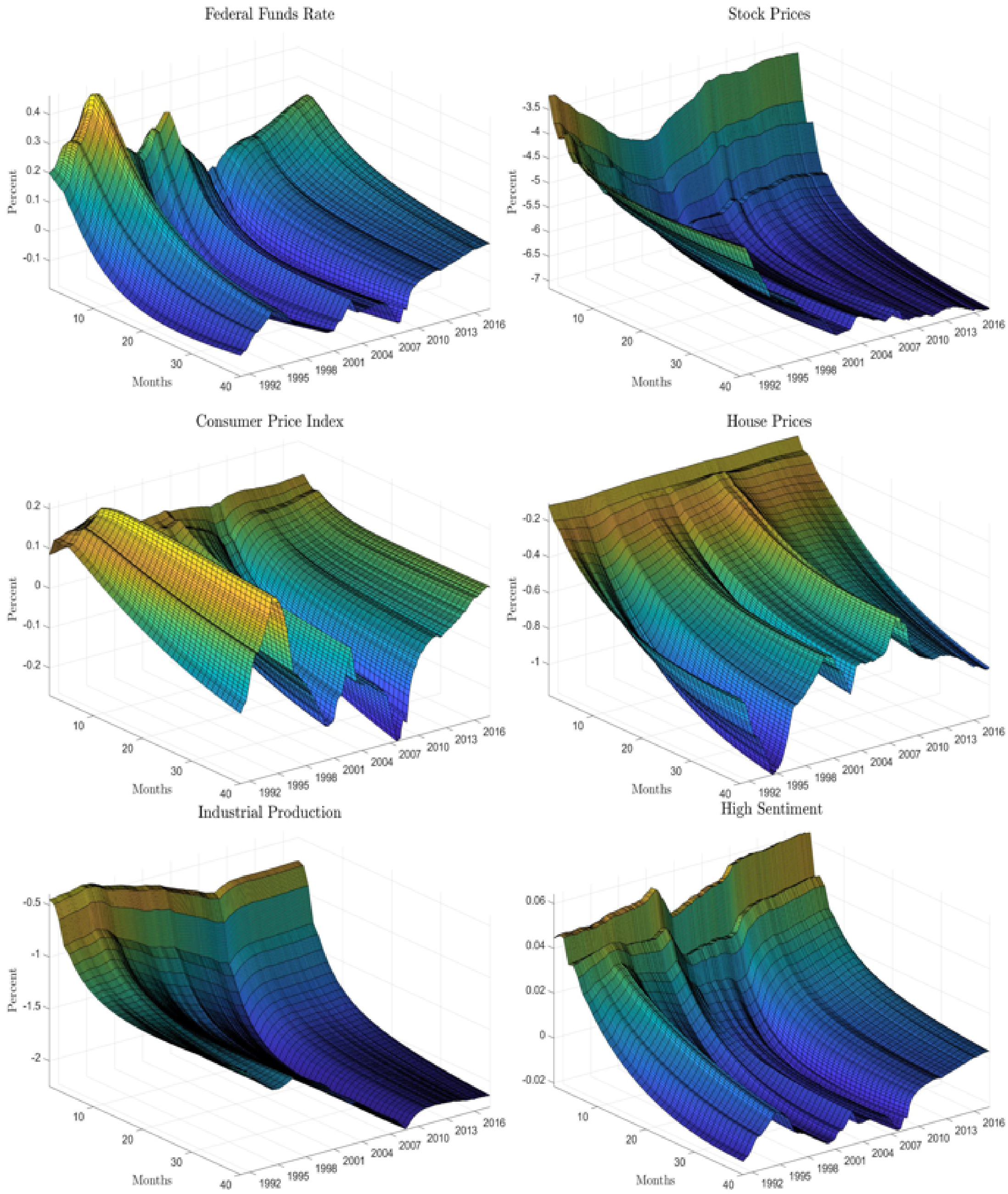
Figure 1: Markov switching smoothed regime probabilities



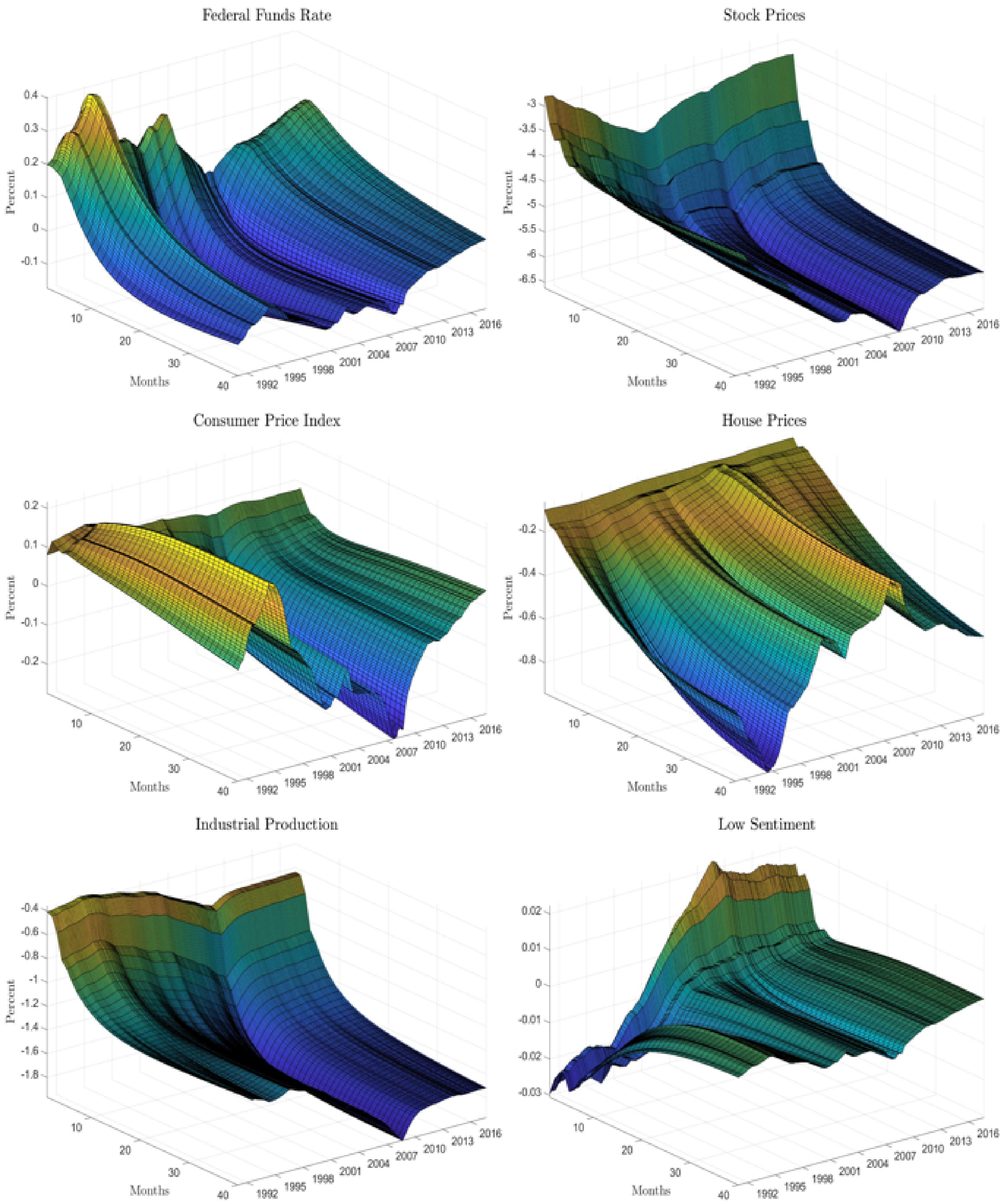
Notes:This figure plots the smoothed probabilities for the two-state Markov-Switching model comprising monthly investor sentiment index. The upper (lower) panel displays the smoothed probabilities of Regime 1 (Regime 2). The shaded areas represent the NBER recessions.

Figure 2: Time varying impulse responses - High investor sentiment regime



Notes: This figure shows the time-varying cumulative impulses responses to a monetary tightening obtained from the TVP-VAR model for the sample 1991:M1 to 2017:M9. Vertical axis: Percantage change. Front axis left: monthly response horizon. Front axis left: Years.

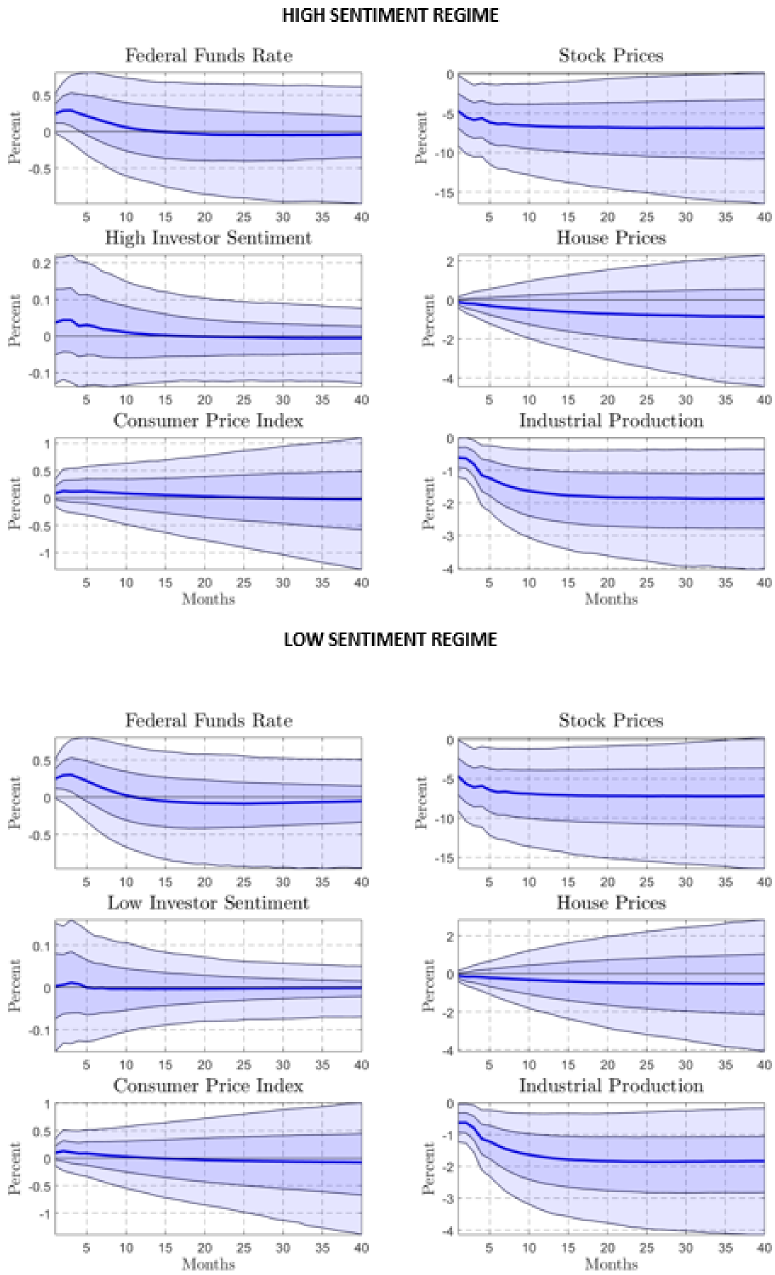
Figure 3: Time varying impulse responses - Low investor sentiment regime



Notes: See notes to Figure 2.

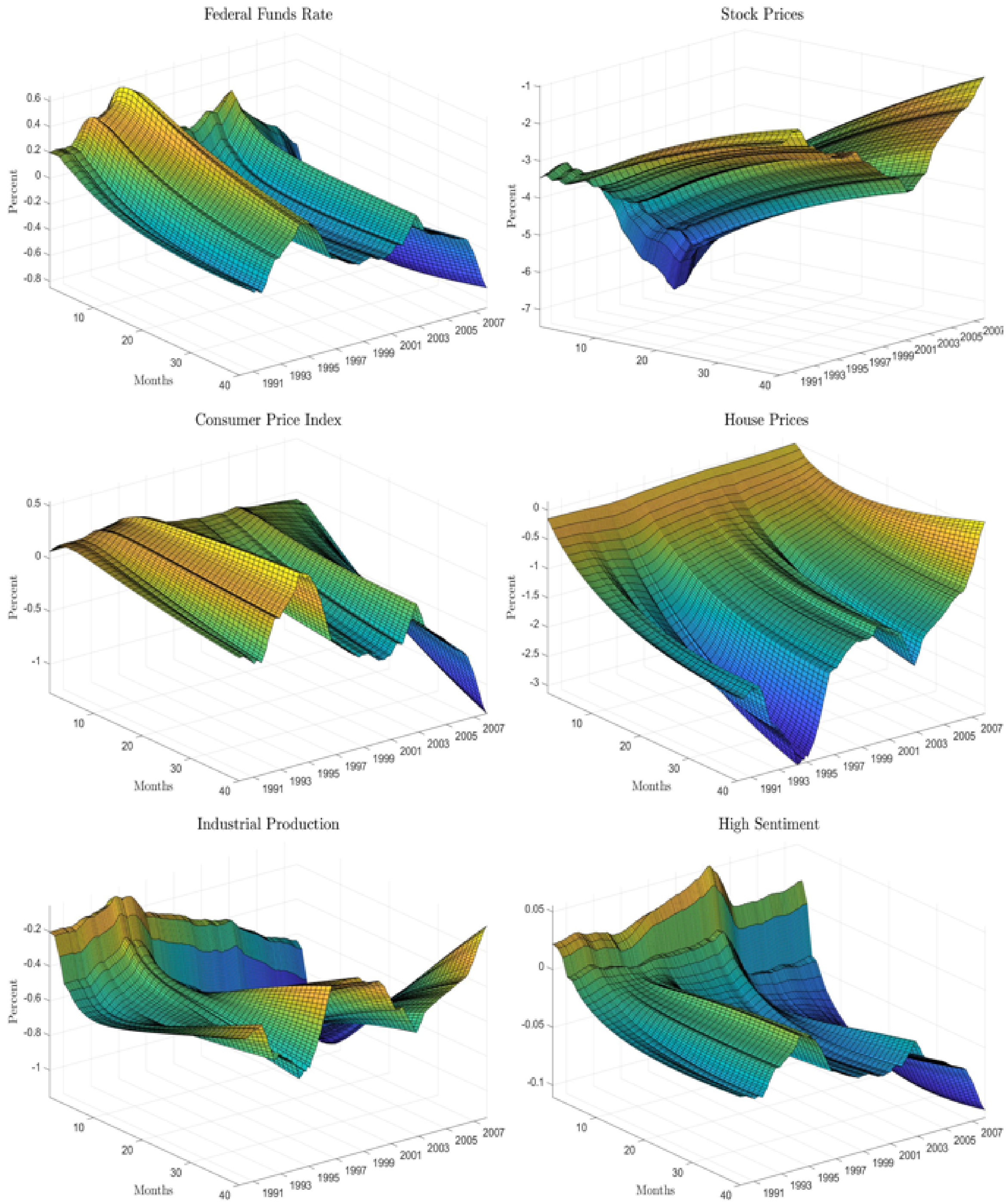
Appendix

Figure A1: Posterior confidence intervals based on Gibbs sampler iteration



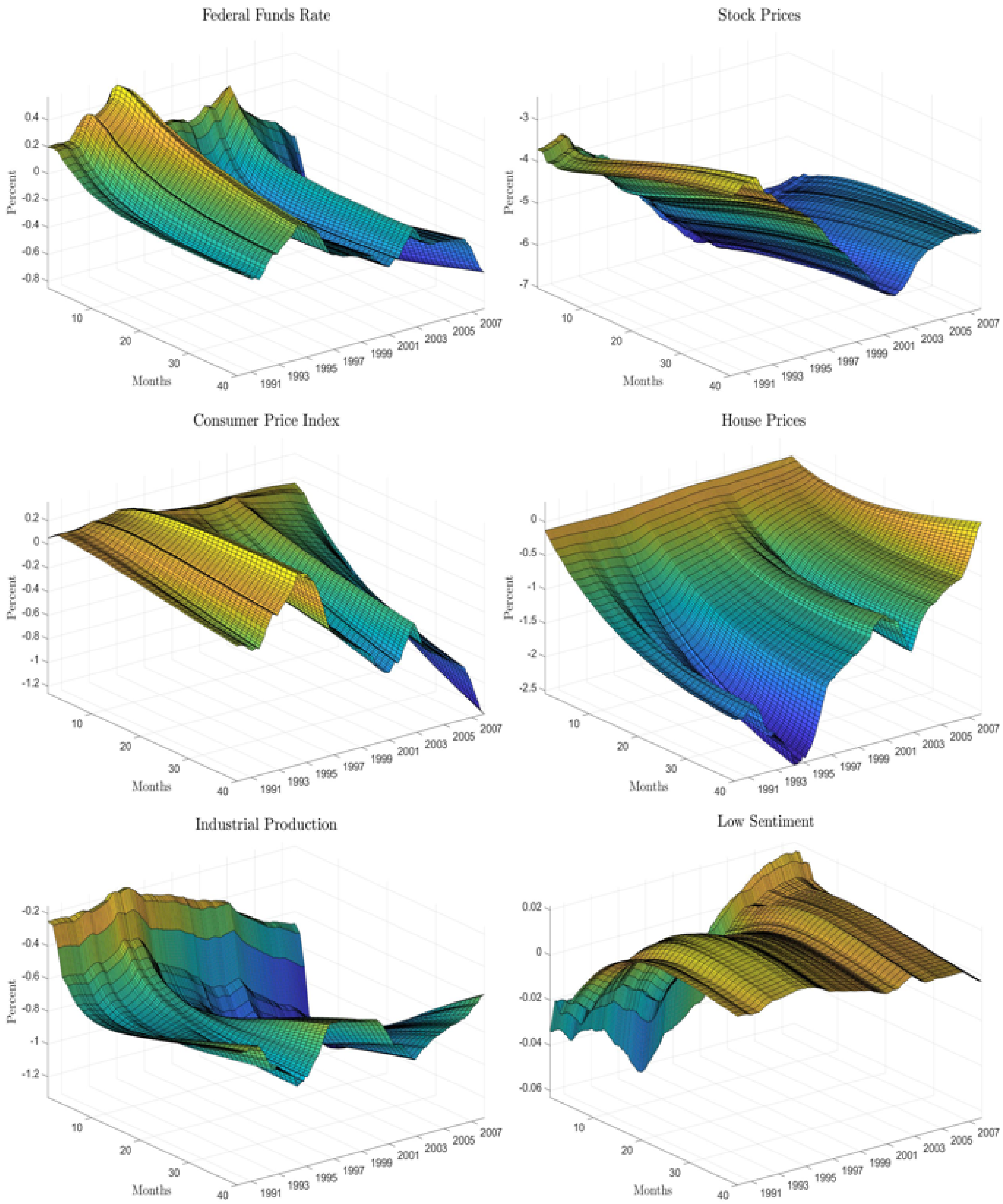
Notes: This figure presents impulse responses based on the TVP-VAR model for 2003:M1. Cumulative impulse responses to a contractionary monetary policy shock are given along with the 68% and 95% confidence interval based on iterations of the Gibbs sampler.

Figure A2: ZLB episode- High investor sentiment regime



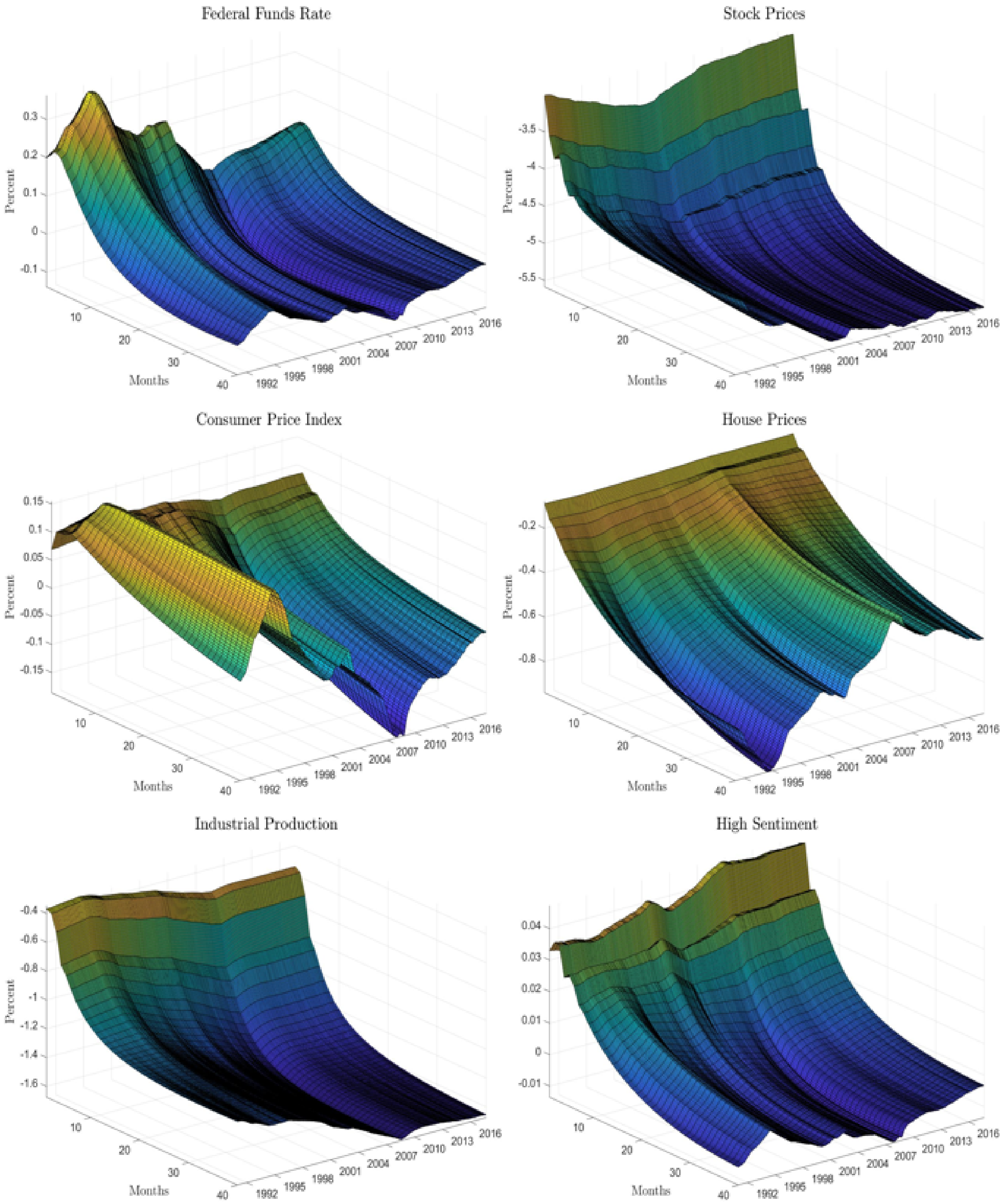
Notes: See notes to Figure 2.

Figure A3: ZLB episode - Low investor sentiment regime



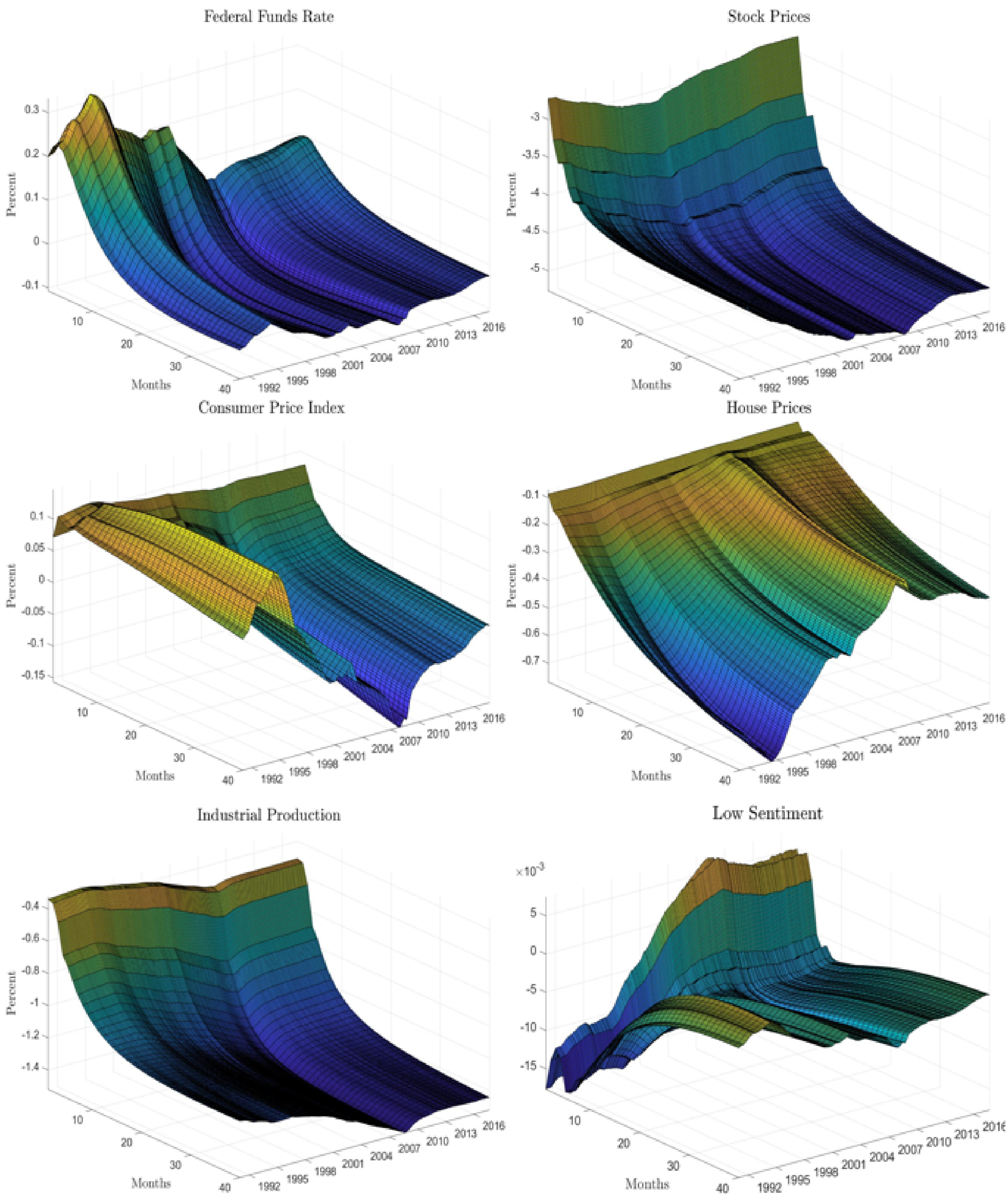
Notes: See notes to Figure 2.

Figure A4: -Impulse responses with different prior - High investor sentiment regime



Notes: See notes to Figure 2.

Figure A5: Impulse responses with different prior - Low investor sentiment regime



Notes: See notes to Figure 2.