Time-varying volatility, financial intermediation and monetary policy*

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Abstract

Is monetary policy less effective in stimulating economic activity during times of high volatility? To answer this question we employ a non-linear VAR and document that expansionary monetary policy shocks are less effective in stimulating output and investment in high volatility periods. We show that the lower effectiveness of monetary policy might be attributed to weaker responses of credit spread measures, suggesting a weaker financial accelerator during times of high volatility. We show that our empirical results are consistent with the predictions of a New Keynesian DSGE model with financial intermediaries in which financial intermediaries endogenously choose the level of leverage.

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1 Introduction

During the Great Recession the Federal Reserve slashed interest rates to near zero per cent, launched large-scale asset purchase programs and used forward guidance to influence economic activity. In spite of this massive monetary intervention, the economic recovery has been very sluggish in the United States. The experience in the years shortly before and during the Great Recession has led to a widespread view that monetary policy is less effective in stimulating economic activity in highly volatile times, and it is thus "pushing on a string".

Against this backdrop, we investigate the state-dependent effects of monetary policy both empirically and from a structural perspective. In the first part of the paper, we estimate a structural threshold vector autoregression (TVAR) for the US economy over the period from 1969 to 2007. This model distinguishes between two recurring regimes of "low" and "high" financial market volatility, which enables us to trace the regime-specific effects of expansionary monetary policy shocks. We identify exogenous policy changes by adapting the external instruments approach proposed by Stock and Watson (2012) and Mertens and Ravn (2013) to our non-linear model. As an external instrument for the underlying structural disturbances we use the monetary policy shock series constructed by Romer and Romer (2004) and Gertler and Karadi (2015).

We find that monetary policy is more effective in stimulating economic activity in periods of low volatility compared to high volatility periods. In the low volatility regime, an expansionary monetary policy shock generates an immediate reduction in the cost of credit for non-financial firms, reflected by a decline in corporate bond spreads. This reduction is accompanied by an increase in investment on impact and by a boom in output after some delay. In contrast, a same-sized expansionary monetary policy shock produces a much less dramatic reduction in the cost of credit in the high volatility regime, which accounts for an increase in investment and output that is substantially weaker, and that builds up only gradually over time.

To dig deeper into the channels underlying the higher effectiveness of monetary policy in low volatility periods, we investigate the regime-specific impact of expansionary monetary policy shocks on indicators of credit frictions. We show that banks' willingness to lend increases more, the excess bond premium constructed by Gilchrist and Zakrajsek (2012) declines more and the leverage ratio of security broker-dealers drops more in the low volatility regime following a surprise monetary expansion. Monetary policy is thus more effective because of its stronger ability to reduce credit frictions and to improve funding conditions in periods of low financial market volatility.

In the second part of the paper, we show that our empirical results can be reconciled with a New Keynesian extension of the structural model proposed by Gertler et al. (2012). A key feature of this framework is that financial intermediaries issue both equity and short-term debt. Hence, they choose leverage endogenously, depending on whether the economy resides in a low volatility or a high volatility state, which in turn depends on the fundamental shocks to the economy. A central implication of the model is a negative relation between financial intermediary leverage and volatility: leverage is high in periods of low volatility and lax funding constraints. This relationship constitutes a salient feature of the US economy present in our data, as also documented by Adrian and Shin (2014). The procyclicality of financial intermediary leverage has important implications for the regime-specific propagation of monetary policy shocks. Consistent with the results from the TVAR, the DSGE model predicts that monetary policy is more effective in low volatility regimes: expansionary monetary policy shocks generate a larger reduction in the cost of credit and a stronger output and investment boom in periods of low volatility compared to high volatility periods.

The model puts the liability structure of banks at the center-stage of the transmission mechanism. Banks increase their leverage in times of low volatility due to the perception of low risk. High leverage makes their balance sheets sensitive to monetary policy induced changes in asset prices. After an expansionary monetary policy shock, highly levered banks experience a strong increase in their net worth, and leverage drops. The improved balance sheet strength allows banks to borrow more and channel more funds into the economy. The credit spread drops leading to an investment and output boom. In contrast, banks hold more equity in times of high volatility because equity shields their net worth from asset price changes. Hence, expansionary monetary policy shocks have relatively less impact on banks' net worth, and the financial accelerator mechanism embedded in the model is weaker during periods of high volatility. Thus, the portfolio choice of banks which generates procyclical leverage can account for the state-dependent effects of monetary policy.

The Great Recession has renewed interest in the effectiveness of monetary policy. According to the "wait-and-see" hypothesis advanced by Bloom (2009) and Bloom et al. (2012), heightened volatility induces firms to delay investment and hiring decisions until the uncertainty associated with high volatility is resolved. Productive firms delay expanding while unproductive firms delay contracting their activity, which dampens productivity growth, resulting in a more modest response of economic activity to a monetary policy expansion in times of high volatility. Vavra (2014) shows that US consumer prices adjust faster in response to shocks in times of high volatility. An Ss price-setting model can reproduce this result due to a "volatility effect" which implies that in high volatility periods changes in productivity exceed menu costs more frequently than in low volatility periods. Vavra (2014) argues that the volatility effect can have large effects on economic activity. One implication of this result is that higher price flexibility reduces the effectiveness of monetary policy in periods of high volatility. Bachmann et al. (2014) confirm higher price flexibility using German micro data. However, using a New Keynesian DSGE model, they argue that the quantitative effect is small. In a recent paper, Berger and Vavra (2015) argue that durable expenditures respond more sluggishly to economic shocks during high volatility periods. Using micro data they show that, while durable adjustment is always infrequent, households are particularly unlikely to adjust their durable holdings during recessions. In addition, using a heterogeneous agent incomplete markets model, they document a strong state-dependence in impulse-responses of durable spending to aggregate shocks. Their findings thus provide another rationale for lower monetary policy effectiveness in periods of high volatility.

There has also been a proliferation in empirical work documenting asymmetries in the monetary policy transmission mechanism. Aastveit et al. (2013) use a small-scale interacted VAR approach, featuring CPI, GDP, consumption, investments, and the short term interest rate, using stock market volatility as main (exogenous) interaction variable. They find that monetary policy shocks affect economic activity weaker in times of heightened volatility. Pellegrino (2014) uses a similar small-scale interacted VAR as the one in Aastveit et al. (2013) but models the interaction variable endogenously in the VAR. He also uses stock market volatility as interaction variable. Using Generalized Impulse Response Functions he finds monetary policy to be less effective in high volatility periods. Caggiano et al. (2014b) take a different approach. Out of a non-linear VAR they use a counterfactual analysis to study the ability of systematic monetary policy to stabilize the economy after uncertainty shocks. Consistent with our findings they show that monetary policy is less effective in stabilizing the economy during periods of high volatility. Finally, Tenreyro and Thwaites (2013) find that in high volatility periods monetary policy tends to be less effective in influencing the economic activity. They do not find evidence that the size and the sign of monetary policy shocks are driving this result.

Relative to the existing literature, our approach offers two distinct contributions. First, our empirical results show that the effect of monetary policy shocks on the cost of credit is highly state dependent. Furthermore, we show that indicators of funding conditions and credit constraints react less to monetary stimuli during periods of high volatility. Our evidence thus suggests that in times of high volatility financial accelerator effects are smaller, providing a new channel that gives rise to state-dependent monetary policy effectiveness. Second, we show that an off-the-shelf model in which banks endogenously choose their capital structure can account for our results: in high volatility periods, banks endogenously choose to hold more capital, which weakens monetary policy transmission through banks' balance sheets.

The remainder of the paper is organized as follows. In Section 2 we present the data. In Section 3 we discuss the econometric methodology. Section 4 provides the key results and the robustness analysis. The model and the simulation results are presented in Section 5. We conclude in Section 6.

2 Econometric methodology

2.1 The threshold vector autoregressive model

Let Y_t be an $n \times 1$ vector of endogenous variables that contains quarterly US data on log real GDP, the log personal consumption expenditure (PCE) deflator, the effective federal funds rate, log realized stock market volatility based on the S&P 500, the log level of nonborrowed reserves, log total private investment (defined as the sum of residential investment, non-residential investment and durable consumption following Berger and Vavra, 2015) and the spread between Moody's seasoned Baa and Aaa corporate bond yield. We assume that the dynamics of Y_t is described by a TVAR model given in reduced form by (see Balke, 2000):

$$Y_t = \sum_{l=1}^{p} \Theta_l^1 Y_{t-l} I_{\{\forall t: sv_t \geq \gamma\}} + \sum_{l=1}^{p} \Theta_l^2 Y_{t-l} I_{\{\forall t: sv_t < \gamma\}} + u_t, \tag{1}$$

where stock market volatility sv_t is a transition variable with delay d. If stock market volatility crosses a threshold value γ, the economy switches from a "low" volatility regime ($sv_t < \gamma$) to a "high" volatility regime ($sv_t \geq \gamma$). $I_{\{.\}}$ is an indicator function which takes the value of one in the assigned regime and it equals to zero otherwise. Θ_l^j is a $n \times n$ coefficient matrix for $l = 1 \ldots p$, where p is the lag length and $j \in 1, 2$ denote the high and low volatility regimes, respectively. For ease of exposition we neglect any deterministic terms in equation 1, however, we include a constant which can differ across regimes. The $n \times 1$ vector u_t represents the reduced-form innovations. We stack all elements of u_t corresponding to regime j into a vector u_t^j for $j \in 1, 2$. The regime-specific errors u_t^j are Gaussian with mean zero and regime-dependent positive definite covariance matrices $\Sigma_u^j = E(u_t^j u_t^{j\prime})$.

Our empirical framework can be considered as a limiting case of the the smooth transition model which has recently gained popularity in studying regime-dependence in macroeconomics (see, e.g., Auerbach and Gorodnichenko, 2012b; Caggiano et al., 2014a). In the smooth transition model transition across regimes is governed by a logistic function which assigns a certain probability to being in each regime. The parameter that determines the shape of the transition function is usually calibrated outside of the model, such that the regimes match some narrative evidence.[1] This approach ensures that the autoregressive coefficient estimates are not sensitive to changes in the parameters

[1] In principle, the parameter governing the smooth transition from one state to another can also be estimated. However, this requires the number of variables in the model to be relatively small. In practice, the parameter is typically set exogenously to allow for smooth transmission from one state to another. However, Auerbach and Gorodnichenko (2012b) state that when estimating the parameter governing the shape of the logistic distribution, the approach seems to favor a model that switches regimes sharply at a certain threshold. In the same vein, Artis et al. (2007) show that the threshold VAR is preferred over a smooth transition specification using model selection criteria. Therefore, we believe that the threshold VAR – although perhaps less general than the smooth transition model – does not constitute a very restrictive data representation in practice.

governing the regimes, as argued by Auerbach and Gorodnichenko (2012b). In the same vein, Granger and Terasvirta (1993) suggest fixing the regime switching parameter exogenously, which amounts to fixing the threshold value in our setup.

Following this line of argument, we prefer not to estimate the threshold level jointly with $\{\Theta^1, \Theta^2\}$. Instead, our approach of identifying the regimes mimics the procedure used in Auerbach and Gorodnichenko (2012b). In particular, we estimate the threshold γ *a priori*, based on a univariate self exciting threshold autoregressive model of order one fitted to sv_t (see Tong and Lim, 1980). We show below that the regimes identified by the threshold autoregressive model match well narrative evidence on the occurrence of financial stress periods. Once the volatility regimes have been identified, we estimate the full TVAR. Conditional on the threshold γ, the TVAR model reduces to a piecewise linear VAR which can be estimated equation-wise by OLS.

2.2 Shock identification

Our objective is to investigate the effects of monetary policy shocks in the low and high volatility regime. The structural shocks of interest ϵ_t^j are related to the the reduced-form residuals according to $u_t^j = A_0^j \epsilon_t^j$, with $E(\epsilon_t^j \epsilon_t^{j\prime}) = I_n$. The impact effects are captured in the orthogonal invertible Gaussian $n \times n$ matrix A_0^j that satisfies $\Sigma_u^j = A_0^j A_0^{j'}$. One way to identify the structural shocks ϵ_t^j is by imposing timing restrictions on the matrix A_0^j. However, the latter are problematic in monetary VARs that include financial variables, as monetary policy and financial markets are likely to affect each other simultaneously. Thus, we identify structural monetary policy shocks using the external instruments approach proposed by Stock and Watson (2012) and Mertens and Ravn (2013). Crucially, our shock identification does not rely on recursive timing restrictions, which constitutes a key advantage over other existing techniques.

Let Z_t^j denote an observable variable that constitutes the monetary policy shock instrument in regime j. We regress the reduced-form residuals associated with the monetary policy equation in the VAR, $u_t^{j,\mathrm{q}}$, on the monetary policy instrument Z_t^j:

$$u_t^{j,\mathrm{q}} = \alpha^j Z_t^j + v_t^j. \tag{2}$$

The fitted value of this regression $\widehat{u_t^{j,\mathrm{q}}} = \widehat{\alpha^j} Z_t^j$ contains only variation that is due to structural monetary policy innovations. In the second step, we use the fitted values to obtain the structural impact effects of all other variables in the VAR. This is done by regressing the remaining VAR residuals $u_t^{j,\mathrm{r}}$ on the fitted values $\widehat{u_t^{j,\mathrm{q}}}$

$$u_t^{j,\mathrm{r}} = \beta^j \widehat{u_t^{j,\mathrm{q}}} + \xi_t^j. \tag{3}$$

The coefficient vector β^j contains the regime-dependent impact effect of all variables in the system to a unit monetary policy shock. That is $\beta^j = \frac{a^{\mathrm{r},j}}{a^{\mathrm{q},j}}$. Using the condition

$\Sigma_u^j = A_0^j A_0^{j'}$ together with equation 3 allows recovering the impact effect of the monetary policy shock on the federal funds rate $a^{\mathrm{q},j}$ and thereby the elements $a^{\mathrm{r},j}$. Specifically, consider partitioning the vector of reduced form residuals as $u_t^j = [u_t^{\mathrm{q},j} u_t^{\mathrm{r},j}]$, and the matrix of structural coefficients as

$$A^j = [A^{\mathrm{q},j} A_2^j] = \begin{bmatrix} a^{\mathrm{q},j} & a_{12}^j \\ a^{\mathrm{r},j} & a_{22}^j \end{bmatrix} \tag{4}$$

and the reduced-form variance-covariance matrix as

$$\Sigma^j = \begin{bmatrix} \Sigma^{\mathrm{q},j} & \Sigma_{12}^j \\ \Sigma^{\mathrm{r},j} & \Sigma_{22}^j \end{bmatrix} \tag{5}$$

Then $a^{\mathrm{q},j}$ is identified up to a sign and can be obtained by the following closed form solution

$$(a^{\mathrm{q},j})^2 \quad = \quad \Sigma^{\mathrm{q},j} - a_{12}^j a_{12}^{j'} \tag{6}$$

where

$$a_{12}^j a_{12}^{j'} \quad = \quad (\Sigma^{\mathrm{r},j} - \frac{a^{\mathrm{r},j}}{a^{\mathrm{q},j}}\Sigma^{\mathrm{q},j})' Q^{j^{-1}} (\Sigma^{\mathrm{r},j} - \frac{a^{\mathrm{r},j}}{a^{\mathrm{q},j}}\Sigma^{\mathrm{q},j}) \tag{7}$$

with

$$Q^j \quad = \quad \frac{a^{\mathrm{r,j}}}{a^{\mathrm{q},j}}\Sigma^{\mathrm{q},j}\frac{a^{\mathrm{r},j'}}{a^{\mathrm{q},j}} - (\Sigma^{\mathrm{r},j}\frac{a^{\mathrm{r},j'}}{a^{\mathrm{q},j}} + \frac{a^{\mathrm{r},j}}{a^{\mathrm{q},j}}\Sigma^{\mathrm{r},j'}) + \Sigma_{22}^j \tag{8}$$

This procedure delivers all elements of the vector associated with the monetary policy shock in the structural impact matrix A_0^j.

We use the monetary policy shock series constructed by Gertler and Karadi (2015) as an external instrument for exogenous policy changes in the TVAR model. Gertler and Karadi (2015) identify monetary policy shocks as surprises in fed funds futures that occur on the days of FOMC policy announcements, along the lines of Guerkaynak et al. (2005). To isolate the impact of news about monetary policy, the surprises in futures rates are usually within a tight window (e.g. thirty minutes) of the FOMC decision. The key identifying assumption is that news about the economy on the FOMC day do not affect the policy choice. Only information available the previous day is relevant. Given this assumption, surprises in fed funds futures on FOMC dates are orthogonal to movements in macroeconomic and financial variables within a period (e.g., a month or a quarter). The Gertler-Karadi series is not available for the period before 1990Q1. Thus, we append to it the exogenous monetary policy shock measure free of systematic responses to information about future economic developments constructed by Romer and Romer (2004). The Romer-Romer measure is the residual from a regression of intended fed funds rate changes around FOMC meetings on the Fed's internal inflation and real activity forecasts.[2]

We conduct inference on the structural impulse response functions using a wild bootstrap. That is, we generate bootstrap residuals as $u_t^b = u_t \omega_t$, where ω_t is a scalar drawn from the Rademacher two-point distribution: $P(\omega_t = 1) = P(\omega_t = -1) = 1/2$. Also, let $Z_t^b = Z_t^b \omega_t$. Based on the point estimates of the VAR parameters and u_t^b we derive the endogenous variables and re-estimate the VAR model. We then identify the monetary policy shocks making use of Z_t^b. The confidence bands are then constructed as the percentile intervals of the resulting bootstrap distribution of the impulse response functions. Throughout the paper we show median impulse responses along with 68% confidence bands.

3 Empirical results

3.1 Identified volatility regimes

We identify volatility regimes based on the realized variance of the S&P 500 index. We compute realized volatility as the quarterly sum of squared daily returns. This variable has a rather high quarter-to-quarter variability that would imply implausibly frequent regime changes. Therefore, following Balke (2000), we use as threshold variable the one-sided moving average of the realized variance series.

Figure 1 shows (smoothed) realized stock market volatility (solid line) together with the estimated threshold (dashed line). The grey shaded areas denote high volatility periods. The regimes match well narrative accounts of financial stress episodes, such as those documented by Lopez-Salido and Nelson (2010). In particular, stock market volatility exceeds the threshold during the 1971 "Nixon-Shock" that effectively abolished the Bretton-Woods system, the first (1973) and second (1979) oil crisis, the 1982 Latin American debt crisis, the 1987 stock market crash, the First Gulf War and capital crunch in the early 1990s and the period between 1998 and 2003 which includes the 1998 LTCM crisis, the Asian and Russian crises, the dot-com crash in the early 2000s, the Sept. 11., 2001 terrorist attacks, the stock market scandals (WorldCom, Enron etc.) of early 2002, and the beginning of the Second Gulf War in 2002-03.

Overall, the identified high volatility regimes overlap with financial crises, periods of political stress and recessions. In a robustness exercise we show that our main conclusions are not sensitive to varying the regime periods.

[2]We use in our benchmark the spliced Romer-Romer/Gertler-Karadi series rather than the pure Romer-Romer shocks mainly because, although our baseline sample ends before the Great Recession, we conduct robustness tests based on a sample until 2012Q2, which is possible with the Gertler-Karadi shock instrument series but not with the Romer-Romer series that ends before the Great Recession. A robustness exercise shows that using the pure Romer-Romer shock series on the baseline sample ending in 2007Q4 yields identical results. We thank Patrick Huertgen for providing us with a Romer-Romer shock series updated until 2008Q4; see also Cloyne and Huertgen (2014).

3.2 Baseline results

Figure 2 shows the results from the baseline seven-variate threshold VAR model. The left panel of Figure 2 shows the impulse response functions to an expansionary monetary policy shock in the low volatility regime. The middle panel presents impulse responses in the high volatility regime. The right panel shows differences between impulse responses in the high and low volatility regime. In both regimes we normalize the impulse responses such that the monetary policy shock is defined as an unexpected 100 basis point reduction in the federal funds rate on impact.

The results in the left panel of Figure 2 reveal that an unexpected monetary policy expansion has a relatively strong stimulative effect in the low volatility regime. The expansionary monetary policy shock induces a hump-shaped behavior of output. GDP increases for two years before peaking at around 2%, it then returns to its baseline value after around four years. The shock also leads to a strong investment boom. Investment increases significantly on impact by about 2%, peaks at 6% after one year and returns to baseline within nearly four years. The monetary policy expansion is followed by a very persistent increase in the price level, peaking at around 3% within 14 quarters after the shock. Nonborrowed reserves rise by about 0.5% in response to the monetary policy shock, remaining significantly positive for about a year. The surprise monetary expansion generates an immediate reduction in the cost of credit, reflected by a significant decline in the credit spread by almost 20 basis points on impact. The response of the cost of credit is very persistent, with the credit spread staying below baseline for nearly two years after the monetary policy shock.

In the high volatility regime the impulse responses draw a different picture. Output peaks at roughly 0.5% after around one and a half years and returns relatively quickly to baseline after three years. The response of investment displays a similar pattern to output, with a maximum increase of roughly 2% after one year, returning to baseline already two years after the shock. Hence, compared to the high volatility regime, the expansion in economic activity induced by the monetary policy shock is more than three times larger in the low volatility regime. Prices decline temporarily after the shock and then turn insignificant. Most strikingly, the credit spread hovers around its regime specific baseline value for about one year after the shock, without a tendency to fall. Five quarters after impact the credit spread displays a moderate, albeit significant, decline of 8 basis points. It then returns to its baseline value after only two years. The right column of Figure 2 shows that the impulse response functions in the two regimes for the main variables of interest are significantly different from each other.

Mertens and Ravn (2013) show that under certain distributional assumptions about the measurement error it is possible to compute the correlation coefficient between the monetary policy shock instrument and the unobserved "true" monetary policy shock (see also Kliem and Kriwoluzky (2013)). In our setting, this correlation equals 0.41 in the low volatility regime and 0.69 in the high volatility regime, which indicates that the shock instrument contains substantial information for identification. Nevertheless, the correlation coefficients are well below unity, which suggests that the shock instrument is not free of measurement error, an issue that we address in a robustness exercise.

3.3 Credit frictions and funding conditions

The baseline results show that both economic activity and credit spreads respond relatively less strongly to monetary policy shocks in high volatility periods. In this section we investigate whether these baseline results can be reconciled with a credit channel of monetary policy transmission, or whether other factors are needed to explain credit spread dynamics after monetary policy shocks. To that end, we add to the baseline model specification one by one various indicators that capture credit frictions in financial markets. We note upfront that none of our key results (i.e., the responses of output, prices, credit spreads and investment) change with the inclusion of the additional variables. Hence, we only present the impulse response functions for the variables that we add to the baseline model specification.

We augment the baseline model specification with the excess bond premium (EBP) developed by Gilchrist and Zakrajsek (2012), the leverage of security brokers and dealers and a survey-based measure for banks' willingness to lend. The EBP is a risk premium that reflects systematic deviations in the pricing of US corporate bonds relative to the issuers' expected default risk. It thus arguably constitutes a good proxy for the effective risk-bearing capacity of the financial sector.[3] We use broker-dealer leverage as an indicator of funding conditions following Adrian and Shin (2009), who argue that "...broker dealers may be seen as a barometer of overall funding conditions in a market-based financial system" (page 600), and they show that fluctuation in broker-dealers assets have an impact on macroeconomic variables.[4] In addition, broker-dealer leverage helps to explain excess returns on a variety of assets, as shown by Adrian et al. (2014). A further reason to include the leverage of broker-dealers is that their business model closely resembles the concept of financial intermediation in DSGE models with banks in that their liabilities are short term and their balance sheets are typically marked to market. Finally, we use information from the Senior Loan Officer Opinion Survey on

[3]The EBP is available from 1973Q1 onwards, and we estimate the model over a shorter sample starting in 1973Q1, replacing the credit spread with the EBP.

[4]Following Adrian et al. (2013), we detrend broker-dealer leverage with the one-sided Hodrick-Prescott filter. This allows us to abstract from secular trends in leverage due to changes in the structure of the financial system and financial regulation. Adrian et al. (2013) use different detrending techniques (among them the Hodrick-Prescott filter), and find that their results do not depend on the technique used. Our results are robust against using the non-filtered leverage series directly.

Bank Lending Practices on the net percentage of banks reporting an increased willingness to make consumer loans.[5]

Figure 3 shows the results for the different credit friction indicators. In the low volatility regime, the EBP responds with a significant decline to an expansionary monetary policy shock. The EBP displays substantial inertia comparable to that of the Baa-Aaa credit spread, staying below baseline for nearly three years. The response of the EBP suggests that most of the movement in the credit spread is related to changes in banks willingness to take credit risk rather than fluctuation in expected default. In addition, broker-dealer leverage drops significantly on impact and the response is very persistent, and the monetary policy shock triggers an immediate and very front-loaded increase in banks' willingness to lend.

In periods of high volatility the effect of monetary policy on credit frictions is substantially weaker. The response of the EBP in the high volatility regime is again similar to the response of the credit spread itself. The EBP is not statistically different from zero for around one year after the shock before turning negative. Bank leverage hardly moves after the monetary policy shock. Banks' willingness to lend increases only marginally on impact; one quarter after the shock, however, the response is not different from zero.

On balance, the results presented thus far highlight that monetary policy is less effective in improving credit conditions in high volatility periods relative to low volatility periods. This might explain the stronger reduction of the credit spread in the low volatility regime, which in turn explains the stronger boom in economic activity. To the best of our knowledge, we are the first to empirically document this aspect of the monetary policy transmission mechanism. The next section outlines a DSGE model that is able to match our main empirical findings. However, before turning to the theoretical rationalization of our results, we first present a series robustness checks.

3.4 Robustness analysis

Omitted variables

If the central bank and the private sector operate using information not captured in the baseline model specification, the impulse responses will give a distorted picture of the monetary policy transmission mechanism. We tackle this issue by augmenting the baseline specification one by one with additional variables that capture potentially relevant omitted information. Specifically, we include the log level of house prices and the log level of the S&P 500 index to account for the asset price channel of policy transmission. Furthermore, to capture forward-looking aspects, we include measures of business and consumer sentiment. Finally, we add the log of total factor productivity

[5] We use banks' willingness to lend to consumers because other willingness-to-lend variables, e.g. the willingness to lend to firms, are not available back to 1968.

because periods of high volatility might reflect future movements in productivity (see Caggiano et al., 2014a; Bachmann and Bayer, 2013).

Figure 4 shows the median impulse responses of the baseline variables obtained from the expanded TVARs and, for better comparability, the confidence band from the baseline model. In all cases the median impulse responses from the expanded model specification lie well within the confidence bands of the baseline model specification. Most importantly, our key result that the credit spread responds more weakly in the high volatility regime is not plagued by omitted variable bias.

3.4.1 Alternative credit spreads

We replace the baseline Baa-Aaa spread with two alternative widely used credit spreads. These are the Baa-rated corporate bond yield minus the 30-year constant maturity Treasury bond yield, and the credit spread recently proposed by Gilchrist and Zakrajsek (2012) (henceforth GZ spread).[6] Figure 5 shows that these alternative credit spreads display similar responses to monetary policy shocks to those obtained with the Baa-Aaa spread, suggesting that our results are not a special feature of the specific credit spread series.

Definition of regimes

We have shown above that our procedure detects regimes which accord well with narrative evidence. Nevertheless, we assess the robustness of our results with respect to the specific timing of the volatility regimes. We consider two alternative volatility regime definitions by excluding potentially controversial periods from the baseline regime specification. The top panel of Figure 9 shows the baseline regime specification, the second panel shows the regime specification that excludes the period surrounding the stock market crash in 1987, while the third panel shows the regime specification that excludes the period surrounding the stock market crash in 1987 and the non-recession period between 1998 and 2003. For comparison, the bottom panel in Figure 9 shows NBER recessions.

Figure 9 shows the impulse responses from the baseline model specification obtained with different volatility regime definitions. Our main conclusions are robust to a more conservative definition of high volatility periods. Specifically, the impulse responses depicted in Figure 9 are within the confidence bands of the baseline model for the

[6] Gilchrist and Zakrajsek (2012) use prices of senior unsecured bonds outstanding, issued by individual nonfinancial firms to calculate a credit spread over a hypothetical risk free security with the same cashflow structure. The GZ spread corresponds to the average of these individual security credit spreads over all bonds of all firms. Gilchrist and Zakrajsek (2012) show that the GZ spread has high predictive ability for economic activity. We do not use the GZ spread in our baseline model because it is only available since 1973Q1. Hence, for the purpose of this robustness exercise, we extend the GZ series backwards using the Baa-Aaa spread. Estimating the model starting in 1973Q1 and using the pure GZ spread delivers qualitatively the same results.

majority of the variables. The only notable, albeit quantitatively small, difference is in the response of the credit spread which responds slightly less on impact to a monetary policy shock than in the baseline case. Nevertheless, the key result that the credit spread falls more in the low volatility regime compared to the high volatility regime continues to hold.

The zero lower bound period

Our baseline sample ends in 2007Q2, and we conduct several robustness checks to account for the Great Recession and zero lower bound period. First, we estimate the baseline model over the period from 1969Q1 to 2012Q2. We allocate the entire period after 2007Q4 to the high volatility regime, while keeping the pre-crisis regimes unchanged. Figure 6 shows the impulse responses of three key variables: output, investment and the credit spread. The impulse responses obtained for the extended sample closely resemble those for the pre-2007 period. The key variables continue to display a substantially weaker responses in the high volatility regime.

Second, we modify our baseline model specification in order to better capture the scope of monetary policy during the Great Recession and zero lower bound period. Following Gertler and Karadi (2015) we replace the federal funds rate with the 1-year government bond rate as the monetary policy indicator. The 1-year rate does still have some room to manoeuvre when short-run nominal interest rates are stuck near zero. Moreover, the 1-year rate incorporates information on forward policy guidance. This aspect seems particularly important during and after the Great Recession since the Federal Reserve made extensive use of forward guidance as an additional monetary policy tool. To maximize the informational content with respect to the effect of forward guidance we also change the monetary policy instrument. We replace (within-quarter averages of) changes in the current month federal funds futures rate with (within-quarter averages of) changes in the three months ahead federal funds futures rate.

In Figure 7 we show the results of the model estimated until 2012Q2 with the 1-year rate as policy indicator instrumented with the three month ahead federal funds futures rate. To ensure comparability of the shock sizes from the different model specifications we also include the federal funds rate into the model with the 1-year rate, and we normalize the shock such that it reflects an increase in the federal funds rate by 100 basis points. We compare the results of the model using the 1-year rate with those of the baseline model estimated on the sample running until 2012Q2. Our main conclusions remain unchanged also when accounting for the Great Recession period.

Alternative external instruments

We also experiment with different external monetary policy shock instruments. First, we use the original Romer-Romer shock series instead of the spliced Romer-Romer/Gertler-

Karadi shock series. Figure 8 shows the key impulse response functions based on instrumenting the federal funds rate with the pure Romer-Romer shock instrument series. Our key results are unaffected. Our outcomes also do not change when we use other external instruments also explored by Gertler and Karadi (2015), which are computed based on the 3-months ahead fed funds futures, the 3-months ahead, 6-months ahead and 9-months ahead Eurodollar futures.

3.4.2 Different identification strategies

Identification using sign restrictions We identify monetary policy shocks by imposing the following sign restrictions on impulse responses: after an expansionary monetary policy shock the response of the federal funds rate is non-positive, while the responses of output, prices and nonborrowed reserves are non-negative. These restrictions are standard in the literature and disentangle monetary policy from aggregate demand and supply shocks (see Faust, 1998; Canova and de Nicolo, 2003; Uhlig, 2005). The restrictions also disentangle monetary policy from financial and uncertainty shocks insofar as the latter may trigger either aggregate demand or supply effects which a central bank that focuses on inflation and output stabilization will attempt to counteract. The restrictions are imposed on impact and over the subsequent two quarters after the shocks. Finally, all other six shocks are required not to have the same characteristics as monetary policy shocks, i.e., they must not satisfy the sign restrictions we impose to identify monetary policy shocks. We implement the sign restrictions following the procedure suggested by Rubio-Ramirez et al. (2010).[7]

Figure 11 depicts the results from the sign identified model. For better comparability the shaded areas represent the confidence bands from the baseline model. Overall, the results from the baseline and the sign identified model are very similar, and confidence bands overlap over most horizons. Prices now rise also in the high volatility regime, as implied by the sign restrictions. However, their reaction is still much weaker than in the low volatility regime, and it does not seem to affect the remaining impulse response functions.

[7] Let $\Sigma_\epsilon^j = P_\epsilon^j P_\epsilon^{j'}$ be the Cholesky decomposition of the regime j reduced form variance-covariance matrix of the VAR. Further, let Ω^j be a $n \times n$ random matrix drawn from an independent standard normal distribution. The QR decomposition of Ω^j delivers $\Omega^j = Q^j R^j$. The regime-specific impact matrix of the structural shocks is then computed as $\tilde{A}_0^j = P_\epsilon^j Q^{j'}$. If the impulse responses generated by the impact matrix $\tilde{A}_0^j$ satisfy the sign restrictions, we keep the matrix, otherwise we discard it. We keep drawing from Ω^j until we obtain 500 impact matrices which satisfies all sign restrictions simultaneously. Sign restrictions do not achieve unique identification of shocks. Instead, all impact matrices that satisfy the sign restrictions are *a priori* equally admissible. To summarize the evidence of the sign-identified VAR we adopt a "mean target" approach along the lines of Fry and Pagan (2011) and Kilian and Inoue (2013). That is, out of all admissible models we pick the one which yields impulse responses of the variables to the shock closest to the mean impulse responses. Hence, the selected model is a representation of the central tendency of the set of all admissible impulse response functions. Given that we focus on mean target responses, confidence bands reflect parameter uncertainty rather than model uncertainty. This procedure is carried out for both regimes $j \in 1, 2$.

Impulse responses by local projection The previously used identification schemes are conditional on the underlying VAR model. Even though we have shown that our results are robust against a battery of model perturbations, the possibility still remains that the model is misspecified and the estimated impulse response functions are misleading. In order to test the robustness of our results against model miss-specification, we compute impulse responses using a variant of the local projection method suggested by Jorda (2005). The local projection approach is free from the dynamic restrictions implied by VARs, which makes it in general less prone to model miss-specification.

In the local projection approach, the monetary policy shock series is treated as observable, rather than an external instrument of the "true" monetary policy innovation. We use a model that closely resembles the smooth transition local projection models employed by Auerbach and Gorodnichenko (2012a) and Tenreyro and Thwaites (2013), which involves estimating univariate regressions of the following form (again, omitting regime-specific constants):

$$y_{t+h} = (\alpha_h^1 X_t + \beta_h^1 Z_t) I_{\{\forall t: sv_t \geq \gamma\}} + (\alpha_h^2 X_t + \beta_h^2 Z_t) I_{\{\forall t: sv_t < \gamma\}} + \zeta_t,$$

where $h \in \{0, H\}$, α_h^j are coefficients corresponding to the control variables $X_t = [Y'_{t-1}, ..., Y'_{t-p}]'$, and β_h^j are coefficients corresponding to the monetary policy shock series Z_t, i.e. the measure we have used as an instrument in our baseline. The coefficient β_h^j on the shock series is the impulse response of variable y at horizon h in regime j to a one standard deviation monetary policy shock. The model is estimated for each h. Standard errors and confidence bands for the local projection regressions are computed using White's heteroscedasticity and autocorrelation consistent covariance estimator (White (1980)).

In Figure 12 we show the impulse responses from the local projection regressions.[8] The right panels show t-statistics of $\beta_h^1 - \beta_h^2$. Whenever the t-statistic falls outside the bands, the null hypothesis that the impulse responses are equal at that particular horizon is rejected at the 90% level against the alternative that they are different. All in all, the impulse responses from the local projection method tell the same story as the baseline model: GDP, investment and the credit spread react less in the high volatility regime compared to the low volatility regime. The test statistic concerning the significance of the difference between impulse responses in the high and low volatility regime confirm that the differences between the two regimes are statistically significant.

[8] While we normalized the monetary policy shocks from the VARs to lower the federal funds rate on impact by 100 basis points in the two regimes, this is not easily feasible in the local projection model employed here. We would need to adopt a system estimation approach. This would, however, involve imposing cross-equation restrictions, which we prefer to avoid. By presenting reactions to one standard deviation shocks, we are on the conservative side, and normalizing the impact on the federal funds rate would rather strengthen our main findings.

4 A macroeconomic model with financial intermediation

In this section we provide a structural interpretation of our empirical results using a macroeconomic model with a financial intermediation sector. The model we use closely follows de Groot (2014), and it constitutes a New Keynesian extension of the model proposed by Gertler et al. (2012). A key feature of this framework is that banks issue both (non-state-contingent risk-free) short-term debt and (state-contingent) equity, which makes leverage an endogenous choice that depends on banks' risk perceptions. The model implies a negative relationship between banks' balance sheet structure and risk perceptions: banks opt for greater leverage when the perceived risk is low. This relationship constitutes a salient feature of the US economy present in our data, as also documented by Adrian and Shin (2014).

The procyclicality of leverage has important implications for the state-dependent effects of monetary policy shocks. The high leverage in low risk periods makes bank balance sheets relatively more sensitive to monetary policy induced changes in asset prices. Hence, highly levered banks experience a strong increase in their net worth after an expansionary monetary policy shock, and leverage drops. The improved balance-sheet strength allows banks to borrow more and channel more funds into the economy. The spread between the expected return on capital and the risk-free interest rate drops, leading to an investment and output boom. In contrast, when the perceived risk is high, banks hold more equity because it shields their net worth from asset price changes. Thus, expansionary monetary policy shocks have relatively less impact on banks' net worth, and the financial accelerator mechanism embedded in the model is weaker in high risk periods.

4.1 The model

Households' preferences are given as

$$\max \mathbb{E}_t \sum_{i=0}^{\infty} \beta^i \frac{1}{1-\zeta} \left(C_{t+i} - hC_{t+i-1} - \frac{\varrho}{1+\upsilon} L_{t+i}^{1+\upsilon} \right)^{1-\zeta}. \tag{9}$$

$\mathbb{E}_t$ is the expectations operator conditional on time t. We formulate the preference function to allow for internal habit formation and to abstract from wealth effects on labor supply.

Households have access to non-contingent, risk-free bank deposits, D_t, paying the risk-free rate R_t, and sate-contingent bank equity, E_t, that is priced at $Q_{E,t-1}$, and pays $R_{E,t}$. The households' budget constraint is given as:

$$C_t = W_t L_t + R_t D_t + Q_{E,t-1} R_{E,t} E_t - D_{t+1} - Q_{E,t} E_{t+1}. \tag{10}$$

Perfectly competitive entrepreneurs produce intermediate goods with a constant return to scale production function. Intermediate goods are sold to retailers. At the end of period t the entrepreneur purchases capital, K_{t+1}, at the price Q_t, using funds obtained from banks. The entrepreneur uses capital and labor, L_t to produce output Y_t. The production process is subject to capital quality shocks, $\epsilon_{K,t}$.

$$Y_t = (\exp(\epsilon_{K,t})K_t)^{\alpha} L_t^{1-\alpha}. \tag{11}$$

At the end of each period, capital producers buy depreciated capital from entrepreneurs, repair depreciation, and build new capital. The repaired and new capital is then sold back to entrepreneurs. Production of capital involves convex investment adjustment costs. The objective function of capital producers is given by:

$$\max \mathbb{E}_t \sum_{i=0}^{\infty} \Lambda_{t,t+1} \left(Q_{K,t+1} I_{t+1} - \left(1 + \frac{\rho_I}{2} \left(\frac{I_{t+i}}{I_{t+i-1}} - 1 \right)^2 \right) I_{t+i} \right). \tag{12}$$

The economy's capital stock evolves as:

$$K_{t+1} = (1-\delta)\exp(\epsilon_{K,t})K_t + I_t. \tag{13}$$

Monopolistically competitive retailers buy intermediate goods from entrepreneurs, and costlessly differentiate them to produce their output $Y_{t,r}$. Final output, Y_t, is a CES aggregator of unit mass of output from differentiated retailers, $Y_{r,t}$:

$$Y_t = \left(\int_0^1 Y_{r,t}^{\frac{\varepsilon-1}{\varepsilon}} dr \right)^{\frac{\varepsilon}{\varepsilon-1}}. \tag{14}$$

From the cost minimization of users of final output we can derive the demand schedule for the output of retails and the aggregate price level:

$$Y_{r,t} = \left(\frac{P_{r,t}}{P_t} \right)^{-\varepsilon} Y_t \text{ and } P_t = \left(\int_0^1 P_{r,t}^{1-\varepsilon} dr \right)^{\frac{1}{\varepsilon-1}}. \tag{15}$$

Retailers face price adjustment costs as in Rotemberg (1982) when setting prices. Their objective is to maximize profits:

$$\max \mathbb{E}_t \sum_{i=0}^{\infty} \Lambda_{t,t+1} \left(\frac{P_{t+i}}{P_{t+i-1}} Y_{t+i} - X_{t+i} Y_{r,t+i} - \frac{\rho_\pi}{2} \left(\frac{P_{t+i}}{P_{t+i-1}\pi} - 1 \right)^2 Y_{t+i} \right). \tag{16}$$

Costs associated with price and investment adjustment are paid in real terms. The economy's budget constraint is therefore given as:

$$\left(1 - \frac{\rho_\pi}{2} \left(\frac{\pi_t}{\pi} - 1 \right)^2 \right) Y_t = C_t + \left(1 - \frac{\rho_I}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 \right) I_t. \tag{17}$$

Monetary policy is characterized by a Taylor rule with monetary policy shocks, ϵ_M:

$$\frac{R_{n,t}}{R_n} = \left(\left(\left(\frac{\pi_t}{\pi}\right)^{\mu_\pi} \left(\frac{X_t}{X}\right)^{\mu_X}\right)\right)^{1-\mu_{R_n}} \left(\frac{R_{n,t-1}}{R_n}\right)^{\mu_{R_n}} \exp(\epsilon_M), \tag{18}$$

and nominal interest rates $R_{n,t}$ relate to real interest rates R_t according to the Fisher relation:

$$R_{n,t} = R_t \mathbb{E}_t \pi_{t+1}. \tag{19}$$

Banks issue deposits and outside equity to finance the funds they provide to entrepreneurs. Banks also have inside equity - their own net worth, N_t accumulated through past earnings. In each period the banks finance the entire capital stock K_t valued at the price Q_t. The banks earn the entire return on capital R_{kt}.

For the banks the flow-of-funds constraint states that the value of loans given out, $Q_t K_t$, is equal to the sum of banks net worth, deposits issued to households, and the value of outside equity issued to households:

$$Q_t K_t = N_t + Q_t^E E_t + D_t. \tag{20}$$

Net worth N_t at time t is the payoff from assets financed one period ago in $t-1$ less the return paid to depositors and outside equity holders:

$$N_t = R_{kt-1} Q_t K_{t-1} - R_{et} Q_{t-1}^E E_{t-1} + R_t D_{t-1}. \tag{21}$$

The key feature of outside equity is that is allows the bank to hedge against fluctuations in the return on assets: Movements in the return on assets will be absorbed by concurrent movements in the return on equity. It is this hedging value which makes outside equity valuable for banks, especially so in times of heightened volatility. This will become clear shortly.

The objective of the bank at the end of period t is to maximize its franchise value:

$$V_t = \mathbb{E}_t \left(\sum_{i=t+1}^{\infty} (1-\sigma)\sigma^{i-t-1} \Lambda_{t,i} N_i \right). \tag{22}$$

Because banks are financially constrained, it is optimal for banks to retain earnings until the financial constraint no longer binds. To limit the bankers' ability to become unconstrained we assume that in each period, with probability $(1-\sigma)$, a banker exits the financial sector, transfers the accumulated earnings to the household and becomes a member of the household.

An agency problem limits the ability of the bank to obtain funds: After a bank obtains funds, the banker may transfer a fraction of assets to her family. Households recognize this and endogenously limit the amount of deposits and outside equity they provide to banks. Also, the fraction of assets a bank can divert depends on the liability structure of the bank. As in Calomiris and Kahn (1991), deposits serve as a disciplining device for the banker: Short-term deposits require to meet a non-state dependent payment, while the return on outside equity depends on the bank's performance, which is difficult for the equity holder to monitor. Therefore, we assume that at the margin it is easier to divert assets funded by outside equity than by deposits.

This argument suggests that the fraction of assets the bank can divert, Θ, is a function of the share of assets funded by outside equity $x_t = {}^{Q^E_{t-1}E_{t-1}}/_{Q_{kt}K_t}$. The function $\Theta(x)$ is convex in x:

$$\Theta(x) = \theta(1 - \epsilon_1 x_t + \frac{\epsilon_2}{2} x_t^2). \tag{23}$$

Because households are aware of the banks' incentive to divert funds, they will restrict the amount they lend to banks, generating an external financing constraint. Let $V_t(K_t, N_t, x_t)$ be the maximized franchise value for a given asset-liability configuration at the end of period t. The incentive constraint ensuring that the bank does not divert funds is given by:

$$V_t \geq \Theta(x) Q_{kt} K_t. \tag{24}$$

Equation (24) states that for the household to be willing to supply funds to the bank, the bank's franchise value must be at least as large as the gain from diverting funds and closing down the bank.

Inserting Equation (20) into Equation (21) yields the evolution of bank net worth as a function of K_{t-1}, x_{t-1}, and N_{t-1}:

$$N_t = (R_{kt} - x_{t-1} R_{et} - (1 - x_{t-1}) R_t) K_{t-1} Q_{kt} + R_t N_{t-1}. \tag{25}$$

Banks' franchise value at the end of period $t-1$ satisfies the Bellman equation:

$$V_{t-1}(K_{t-1}, N_{t-1}, x_{t-1}) = \mathbb{E}_{t-1} \Lambda_{t-1,t} \left((1 - \sigma) n_t + \sigma \max_{K_t, x_t} [V_t(K_t, N_t, x_t)] \right) \tag{26}$$

In each period t the bank chooses K_t, and the liability structure x_t to maximize $V_t(K_t, N_t, x_t)$ subject to the law of motion of net worth (25), and the incentive constraint (24).

4.2 Calibration and solution method

Table 1 summarizes the values assigned to the structural parameters. Our calibration of the model follows as close as possible the parametrization of Gertler et al. (2012). For the parameters related to the nominal rigidities and monetary policy we choose standard values from the literature. The price elasticity of demand ϵ is set at 4.17 as in Gertler and Karadi (2011) and de Groot (2014). The Rotemberg price adjustment parameter ρ_I is set at 48.8 (de Groot (2014)). The monetary policy parameters are set at 1.5, 0.125

and 0.8 for the parameters governing the inflation response, the markup response and the interest rate smoothing.

The key feature of the model is that the bank chooses the capital structure endogenously. A meaningful portfolio choice between debt and equity requires taking into account risk in the solution of the model. We do so by working with second order approximations of the model where perceptions about future volatility matter: We employ the concept of the stochastic or risk-adjusted steady state (Collard and Juillard (2001), Schmitt-Grohe and Uribe (2004), Coeurdacier et al. (2011), Juillard (2011), Kliem and Uhlig (forthcoming). The stochastic state state differs from the non-stochastic steady state by second order terms, i.e. variance and covariances of the endogenous variable in the model. It is the point of the state space where, in absence of shocks in that period, agents would choose to remain although they take future volatility into account. As is well known, in the non-stochastic steady state the portfolio decision of banks is not determined, and the second order terms in the stochastic steady state pin down bank liability structure. In the Appendix we provide a detailed discussion and presentation of the solution method.

4.3 Simulation results

We conduct simulations which illustrate how the model helps explaining the key empirical regularities uncovered above. We consider two different regimes characterized by high volatility and low volatility, and study the implication of the model concerning the dynamics of the economy to a monetary policy shock. We use the capital quality shock to trigger the time variation in the volatility, e.g. the high and low volatility regime. We assume that the high volatility regime is generated by large exogenous shocks to the quality of capital, while the low volatility regime features small exogenous capital quality shocks. The capital quality shock can be thought of as a form of economic obsolescence. Periods of high capital quality shocks thus represent the model analog to high volatility periods in the empirical analysis.

In Table 2 we show the steady state values for some selected variables in the high and low volatility states. We note upfront that the steady state results are qualitatively identical to those presented in Gertler et al. (2012). The key result we want to stress is that the inside leverage ratio of banks drops when moving from the low volatility regime to the high volatility regime. This is consistent with the data used in the empirical section. Figure 13 documents the negative relation between volatility and broker-dealer leverage born out in the data. The model provides an explanation for this pattern: In the high volatility regime banks aim at increasing the share of outside capital on the liability side. This is because in high volatility times outside equity has greater hedging value. The more extensive use of outside equity however intensifies the agency problem between banks and the providers of funds (see Equation (24)). For households to be willing to provide additional outside equity the bank needs to build up additional inside equity. Net worth of banks is therefore higher in the high volatility state relative to the low volatility state, and banks are less levered in the high volatility state.

This procyclicality in the leverage ratio across regimes has implications for the propagation of monetary policy shocks in the high and low volatility regime. In both volatility states we feed in monetary policy shocks of same size. In Figure 14 we show the response of some selected variables to a monetary policy shock in the low and the high volatility regimes. The expansionary monetary policy shock generates a substantially stronger boom in output and investment in the low volatility regime, which is in line with the findings from the TVAR analysis. Also in line with our empirical findings, the reduction in the credit spread and the drop in inside leverage is larger in the low than in the high volatility state.

The mechanism behind these results is intuitive. In the low volatility regime banks lever up because they perceive the economic environment as less risky. The highly levered balance sheet however makes banks inside equity very sensitive to changes in asset prices and returns induced by the monetary policy shock. The expansionary monetary policy shock increases net worth, and inside leverage drops strongly. This loosens banks' incentive constraint. Consequently, banks increase borrowing, allowing them to channel more funds into the economy. The credit spread drops strongly generating the investment and output boom. This financial accelerator mechanism is weaker in the high volatility regime because banks are better capitalized.

Overall, the theoretical model just outlined shows that our empirical results can be rationalized within a standard general equilibrium model with financial frictions. Different from the existing literature on asymmetric dynamics of the economy to policy shocks, our theory stresses the role of banks' endogenous leverage decision on the effectiveness of monetary policy to stimulate the economy and is able to match the key empirical regularities uncovered in this paper.

5 Conclusions

In this paper we show that monetary policy is less effective in stimulating the economy in regimes of heightened volatility. A key robust result emerging from our empirical analysis is that monetary policy is more effective in stimulating the economy in periods of low volatility because credit frictions react more strongly.

We use a standard general equilibrium model featuring financial intermediaries to explain our results. The model stresses the importance of banks' liability structure in the transmission of monetary policy shocks: Monetary policy stimuli are more effective when banks are highly levered, and banks have an incentive to lever up in periods of low volatility.

We want to stress here that the results in this paper do not imply that monetary policy is *in*effective in stimulating the economy. Rather, monetary policy makers should be aware that in times of heightened volatility they will get ”less-bang-for-the-buck”. At the same time, recent empirical evidence for the US provided by Auerbach and Gorodnichenko (2012b) suggests that the aggregate fiscal multiplier is larger in these periods of heightened volatility. Accordingly, fiscal policy stimuli might be a more effective tool in stimulating the economy in these periods.

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6 Tables

Table 1: Parameter values

	Standard parameter	
α	Capital share	0.33
β	Discount factor	0.99
ζ	Risk aversion	2
ϱ	Labor weight in utility	0.25
υ	Frisch elasticity (inverse)	1/3
δ	Depreciation rate	0.025
h	Habit parameter	0.75
ρ_I	Investment adjustment parameter	1
ρ_π	Price adjustment parameter	48.8
ε	Price elasticity of demand	4.17
μ_π	Taylor rule inflation response	1.5
μ_X	Taylor rule mark-up response	0.125
μ_{R_n}	Taylor rule interest rate smoothing	0.8
	Banking sector	
σ	Survival rate of bankers	0.9685
ξ	Transfer to new bankers	0.0289
θ		0.264
ϵ_1		-1.24
ϵ_2		13.41

Table 2: Steady state results

	Low volatility	High volatility
Output	6.23	5.92
Consumption	5.18	4.94
Labor	2.43	2.34
Kapital	42.11	39.12
Net worth	5.49	5.78
Risk free rate	4.10	4.09
(outside) Equity ratio	0.10	0.14
(inside) Leverage ratio	7.68	6.77
SD capital quality shock	0.69	2.07

7 Figures

Figure 1: **Stock market volatility and high and low volatility regimes**

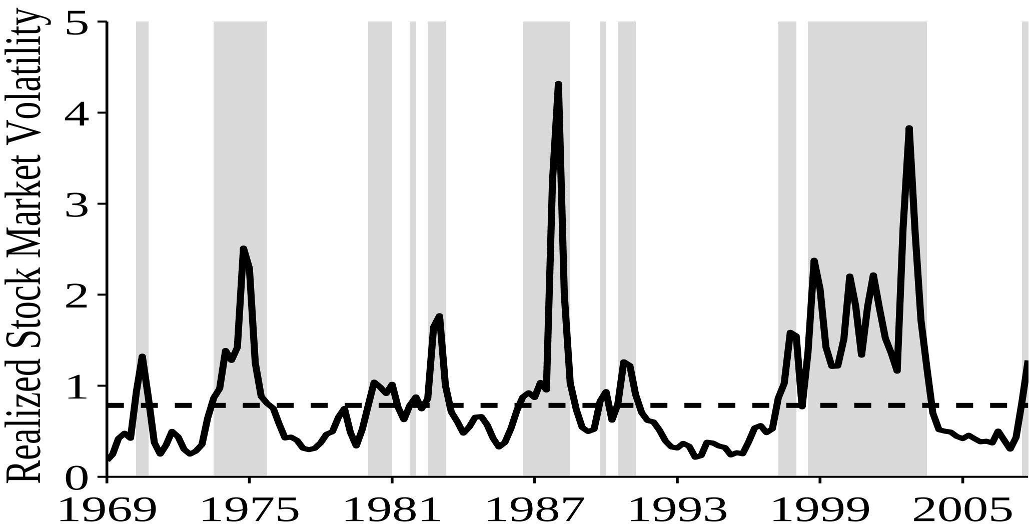

Figure 2: **Effect of monetary policy shocks - baseline model**

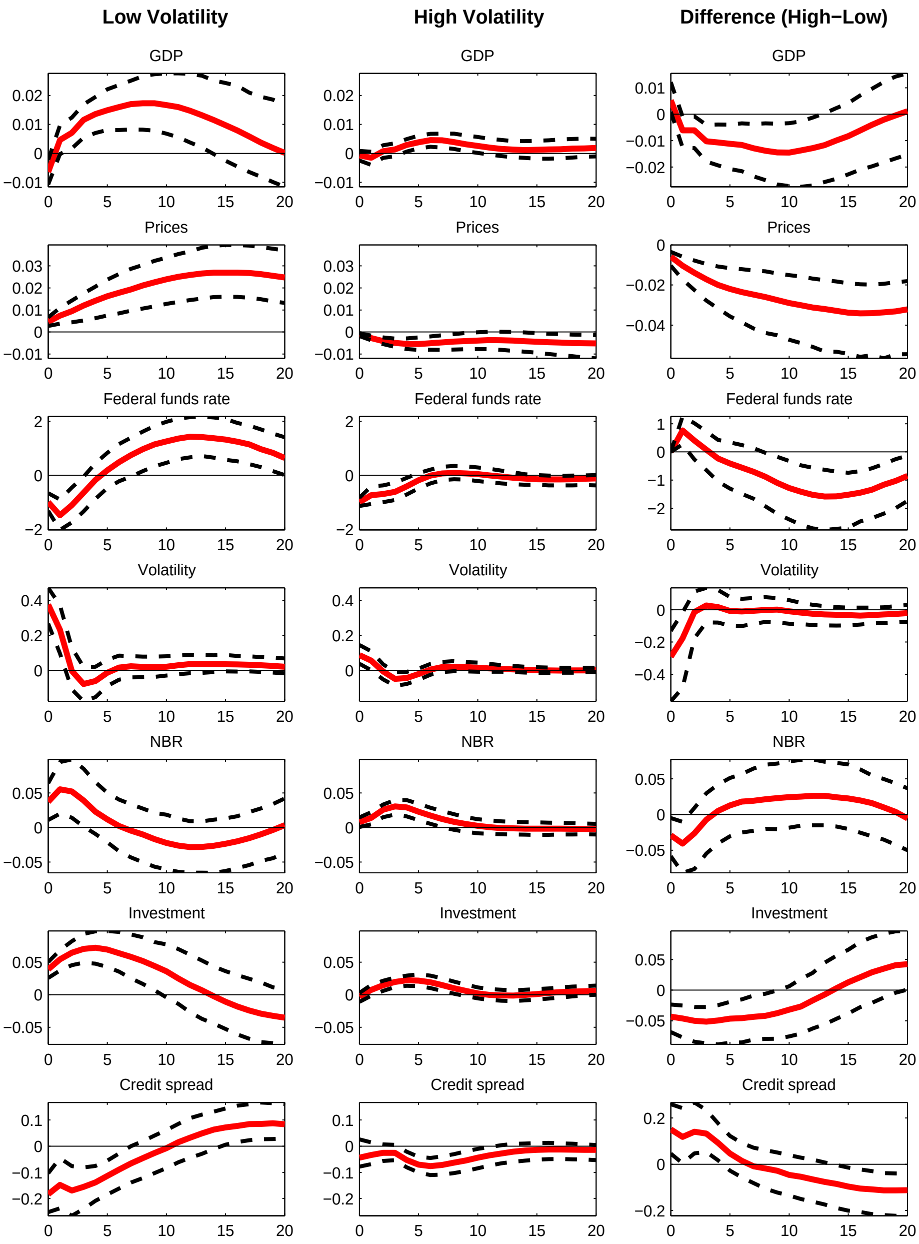

Figure 3: **Effect of monetary policy shocks - credit supply effects**

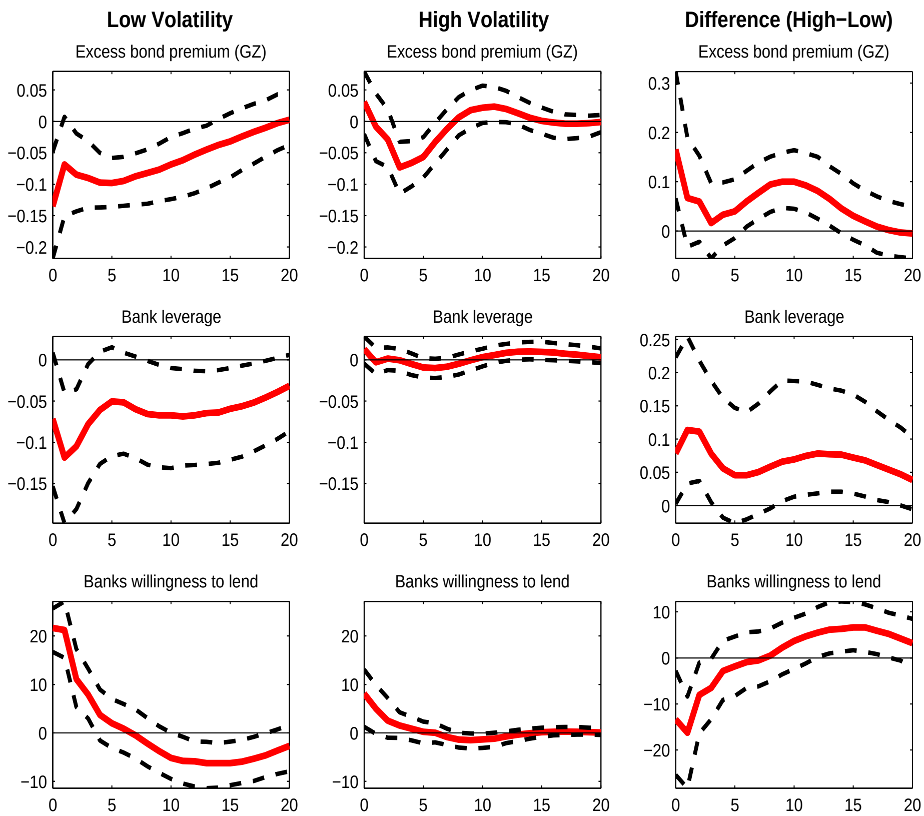

Figure 4: **Effect of monetary policy shocks - omitted variables**

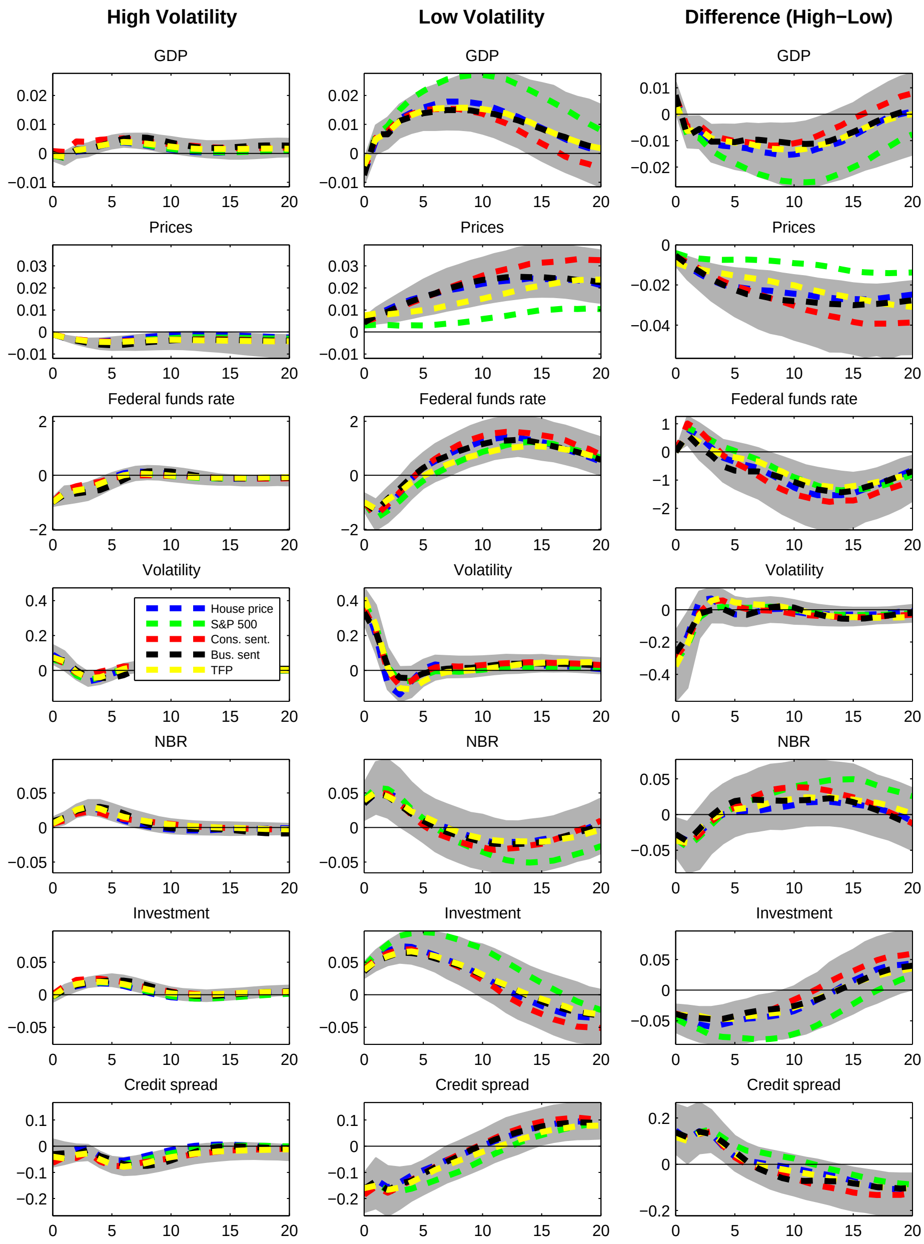

Figure 5: **Effect of monetary policy shocks - alternative credit spreads**

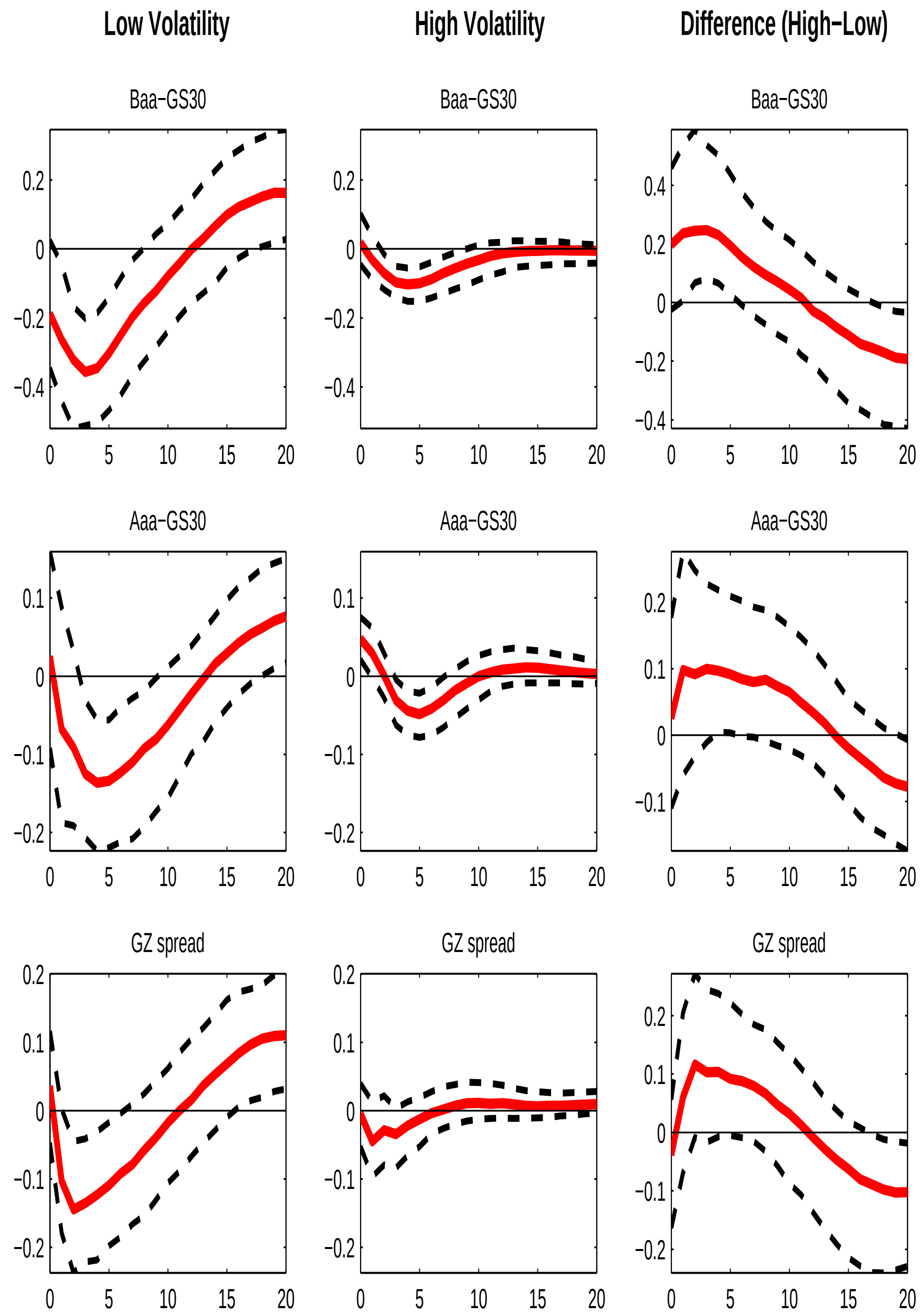

Figure 6: **Effect of monetary policy shocks - 1969-2012**

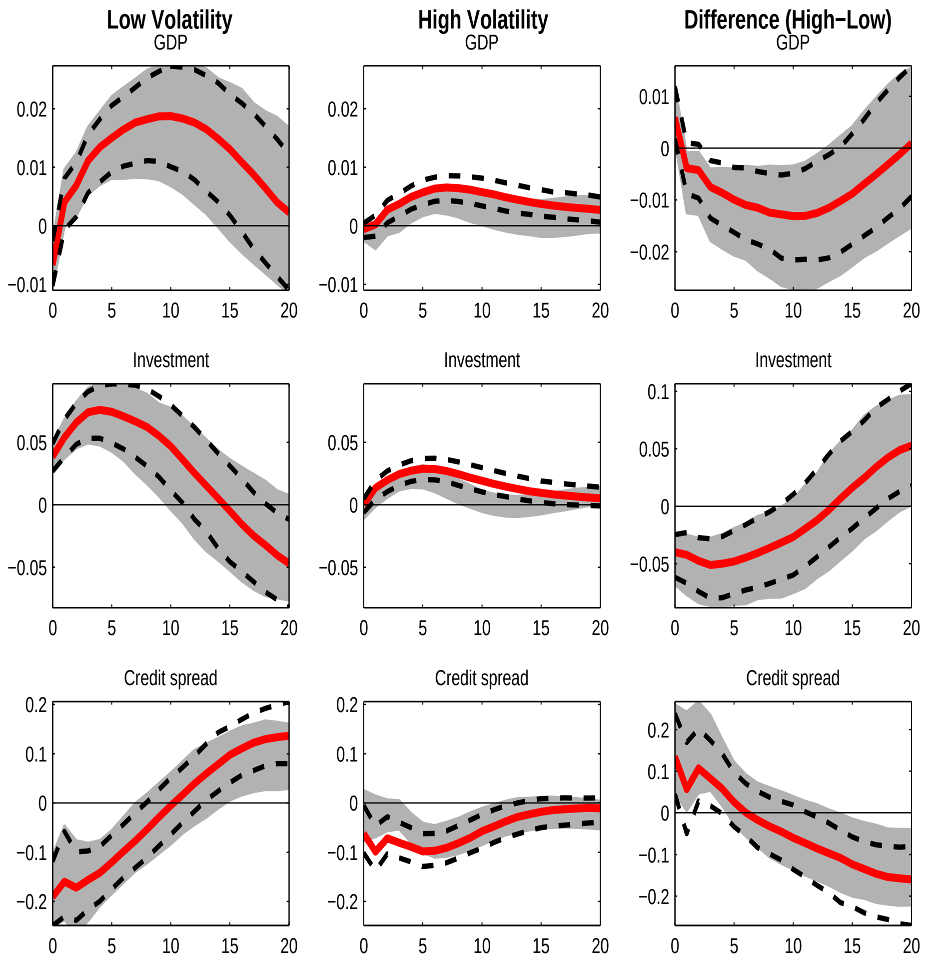

Figure 7: **Effect of monetary policy shocks - 1969-2012 accounting for forward guidance**

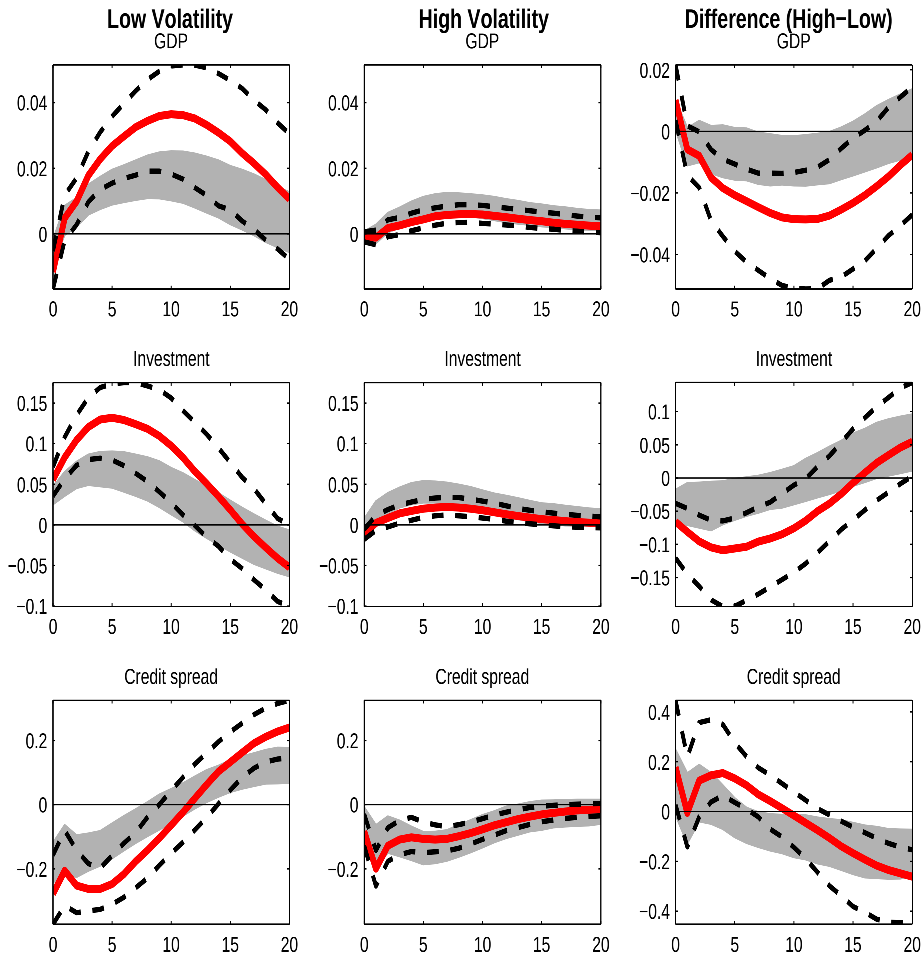

Figure 8: **Effect of monetary policy shocks - pure Romer-Romer shock measure**

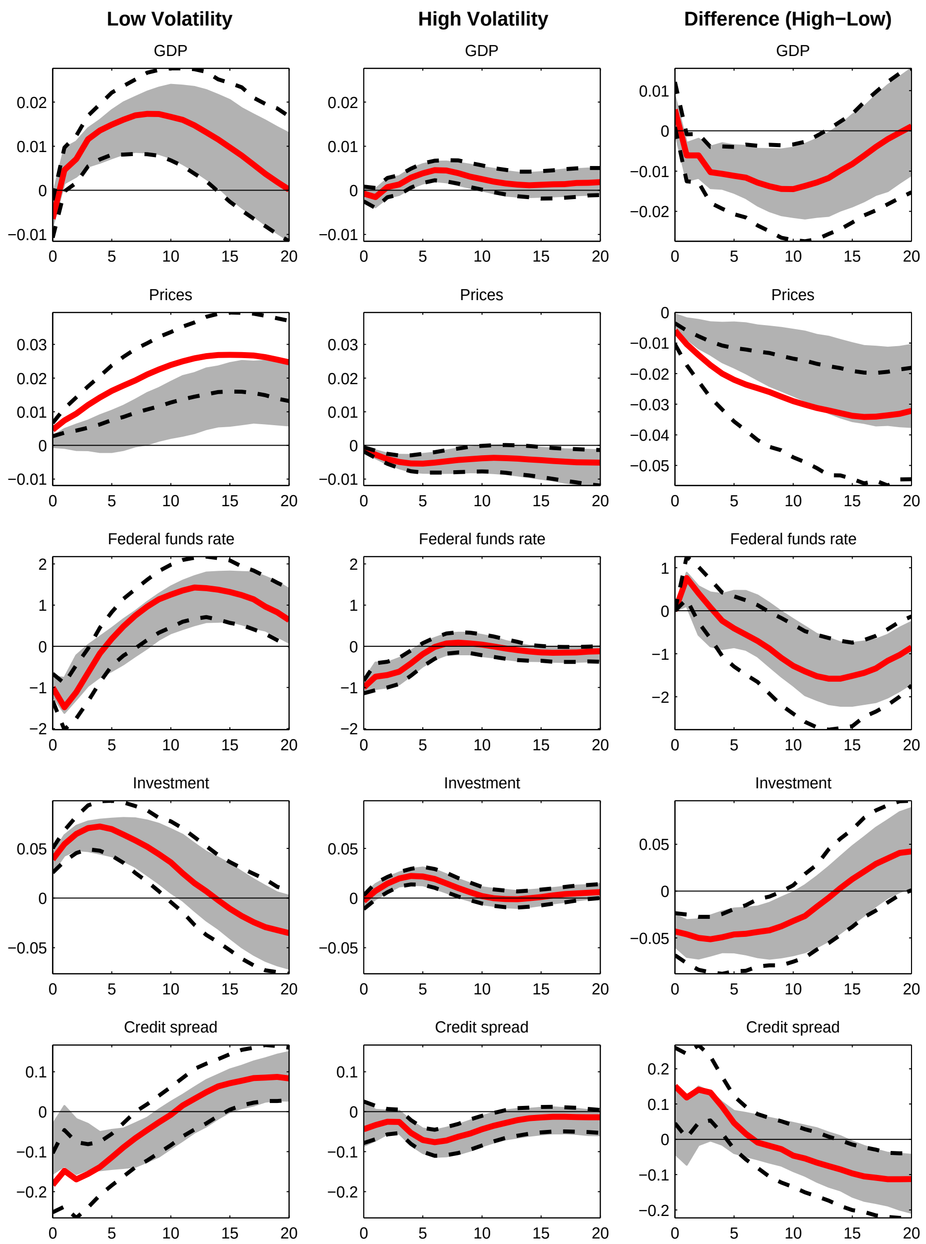

Figure 9: **Different regime definitions**

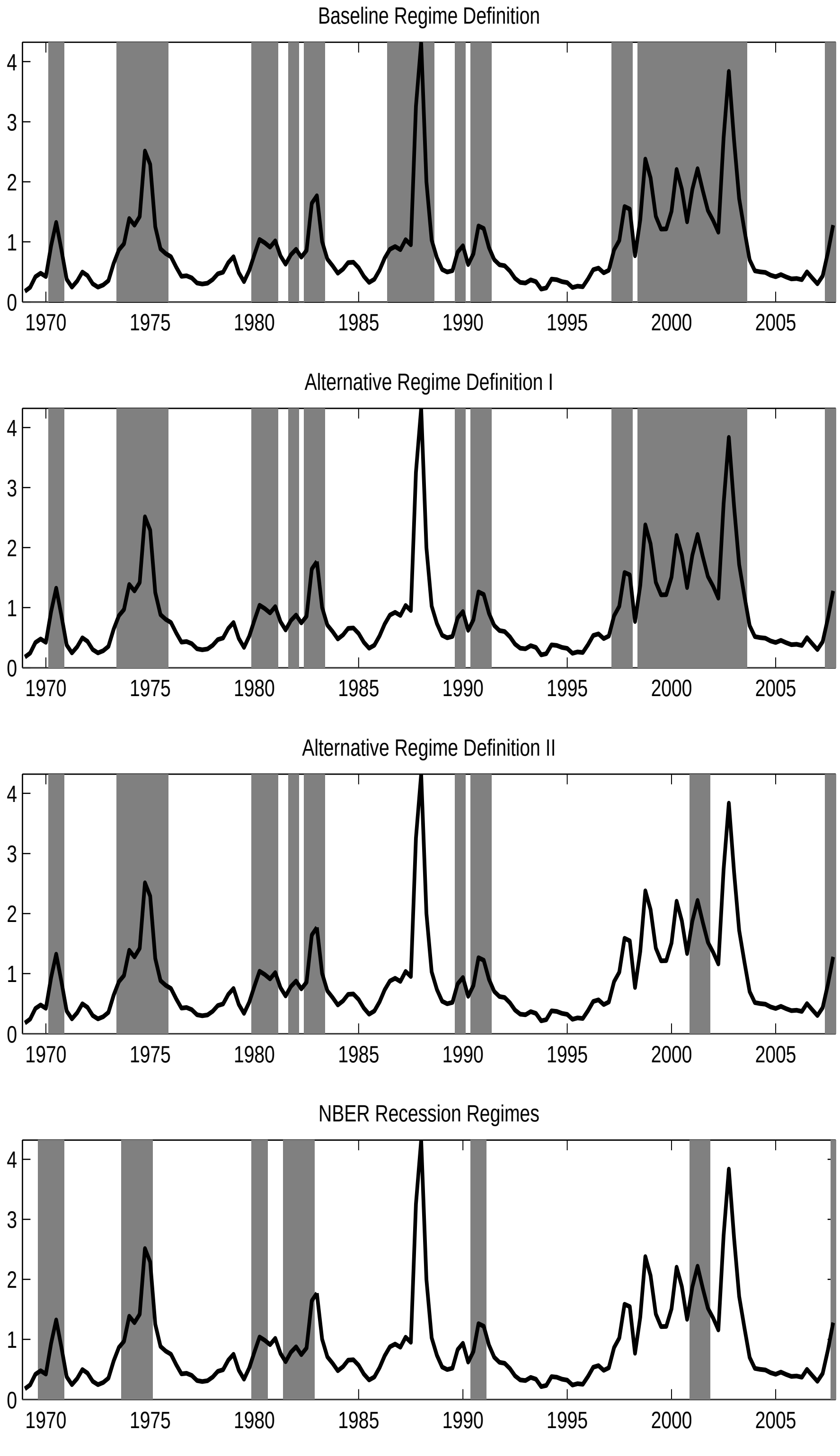

Figure 10: **Different regime definitions**

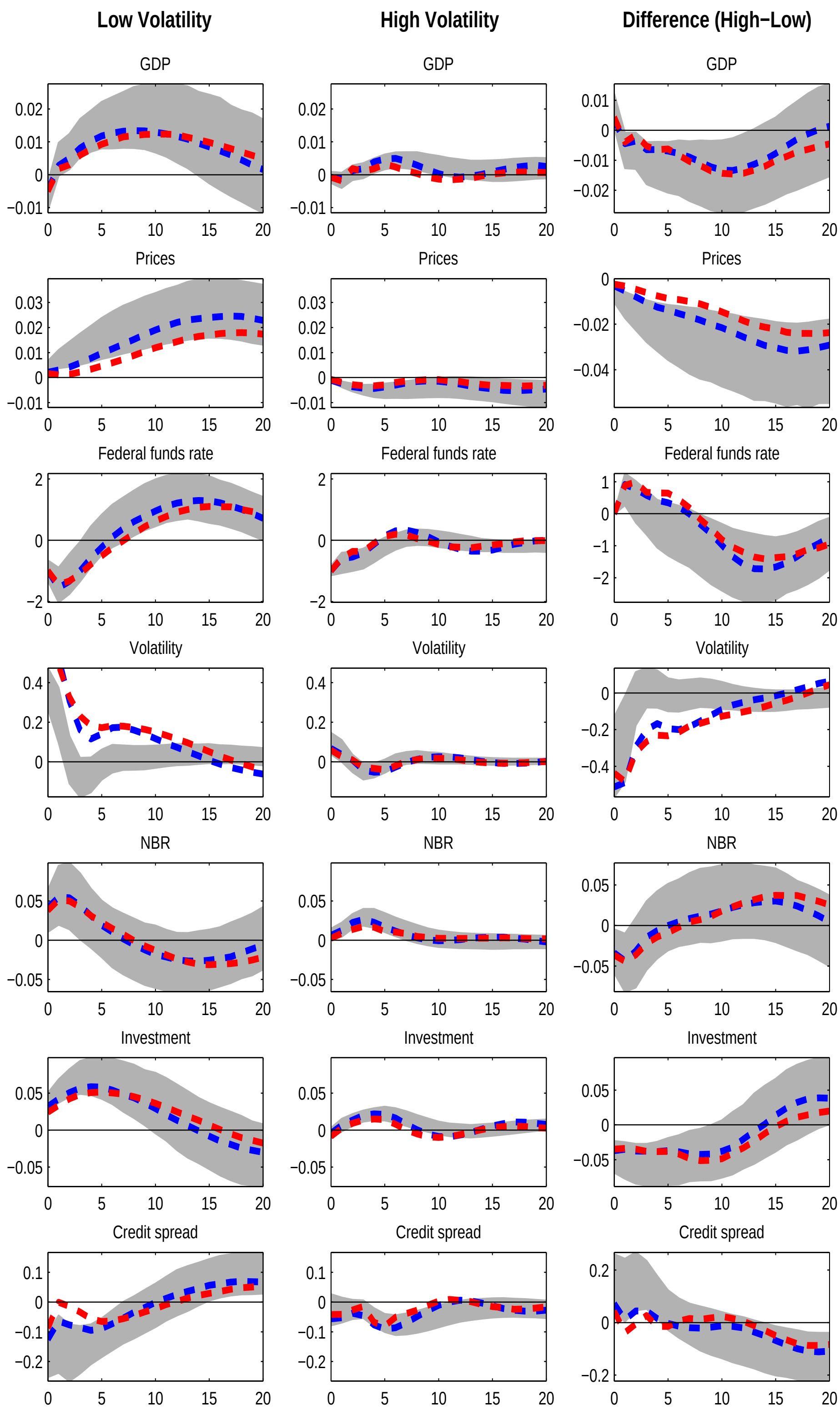

Figure 11: **Effect of monetary policy shocks - sign-identified VAR**

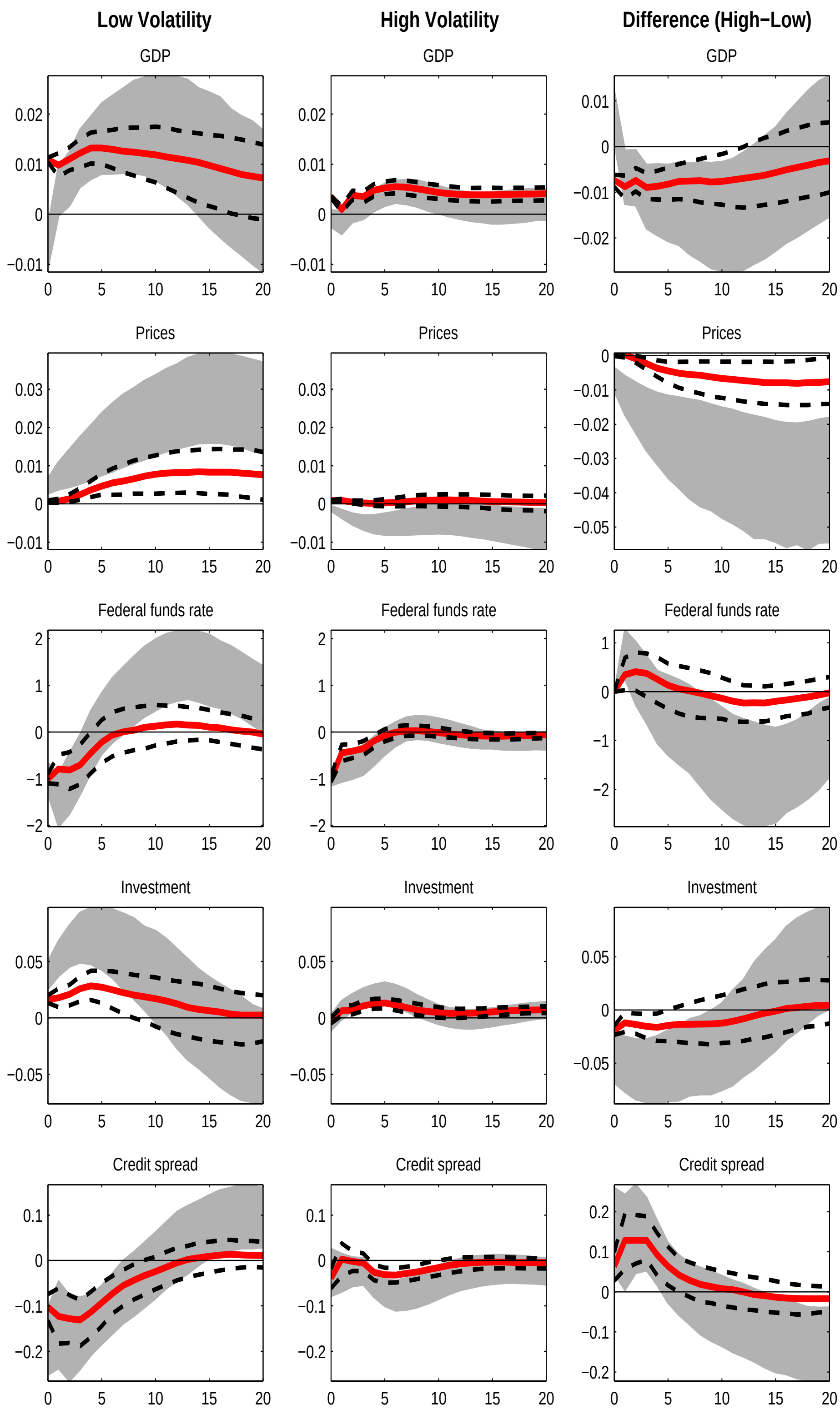

Figure 12: **Effect of monetary policy shocks - local projection approach**

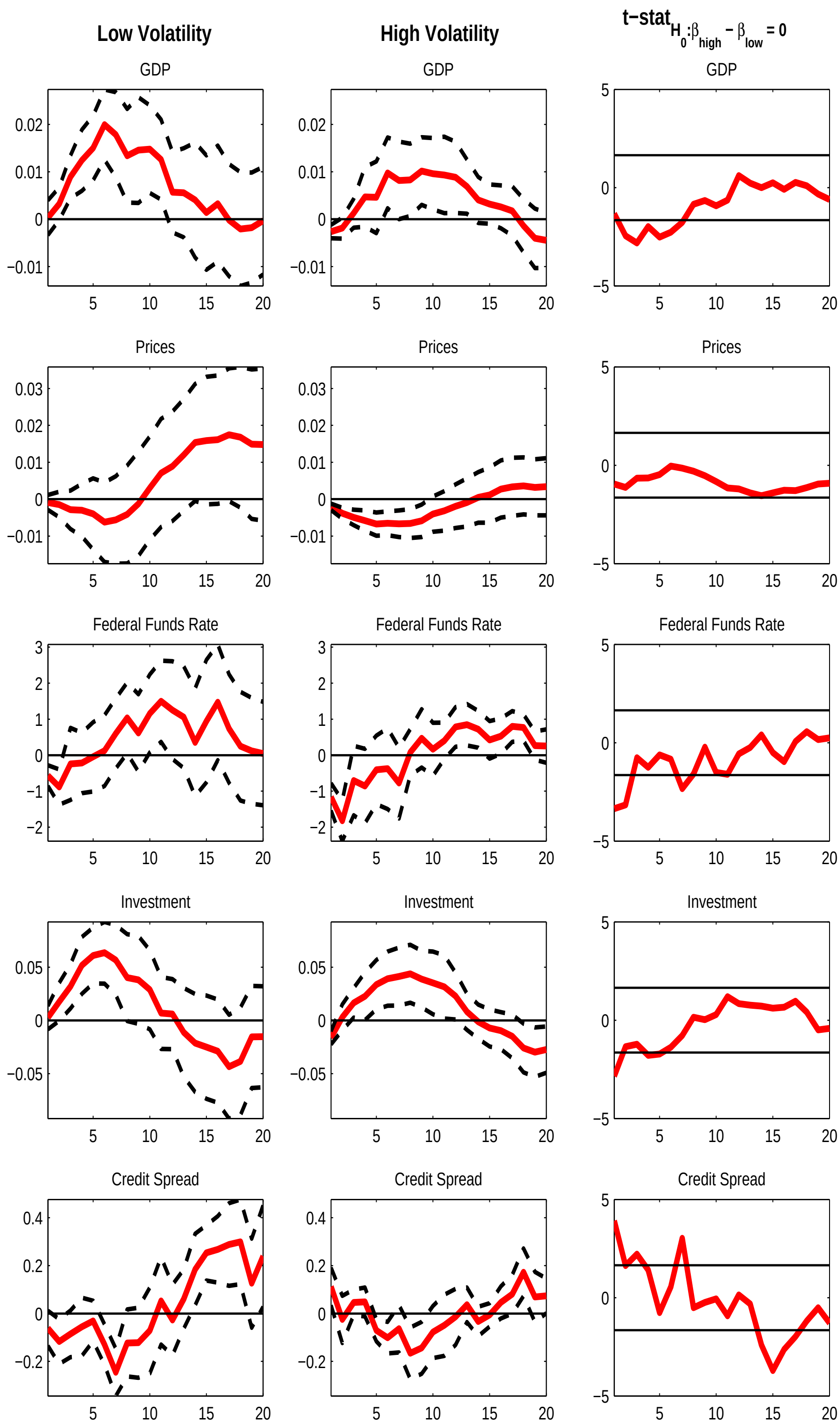

Figure 13: **Volatility and leverage**

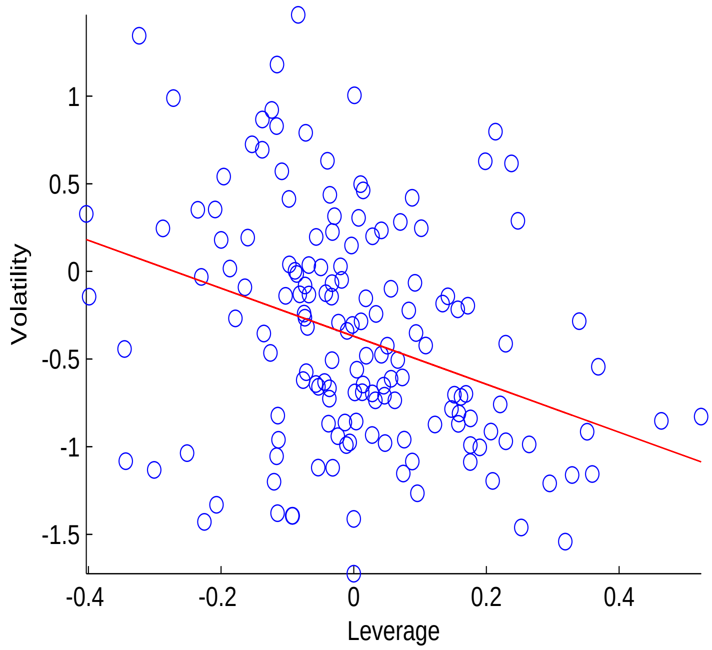

Figure 14: **Effect of monetary policy shocks - Model implication**