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Credit Growth, Monetary Policy, and Economic Activity in a Three-Regime TVAR Model*

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Abstract

We employ a threshold vector autoregression (TVAR) methodology in order to examine the nonlinear nature of the interactions among credit market conditions, monetary policy, and economic activity. We depart from the existing literature on the subject along two dimensions. First, we focus on a model in which the relevant threshold variable describes the state of economic activity rather than credit market conditions. Second, in contrast to the existing TVAR literature, which concentrates exclusively on single-threshold models, we allow for the presence of a second threshold, which is overwhelmingly supported by all relevant statistical tests. Our results indicate that the dynamics of the interactions among credit market conditions, monetary policy and economic activity change considerably as the economy moves from one phase of the business cycle to another and that single-threshold TVAR models are too restrictive to fully capture the nonlinear nature of those interactions. The impact of most shocks tends to be largest during periods of sub-par economic growth and smallest during times of moderate economic activity. By contrast, credit risk shocks have the largest impact when output growth is considerably above it long-term trend.

Keywords: threshold vector autoregression, regime switching, nonlinearity, business-cycle asymmetry, credit shock

JEL classification: E32, E51, C32

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1 Introduction

The notion that credit market developments affect cyclical fluctuations in macroeconomic activity can be traced all the way back to Fisher (1933) and Keynes (1936). Due to a combination of factors, this idea lost prominence among mainstream economists for most of the second half of the twentieth century. Over the last couple of decades, however, it has been gradually revived by a significant body of theoretical (e.g., Kiyotaki and Moore (1997), Bernanke *et al.* (1999), Christiano *et al.* (2010)) and empirical (e.g., Whited (1992), Gertler and Gilchrist (1994), and Calvo *et al.* (2006)) research on the topic. The recent global financial crisis and the ensuing worldwide recession have once again put the study of the interaction between credit market conditions and the real economy at the top of the list of challenges facing the economics profession.

Until recently, most of the empirical literature on the subject (e.g., Stock and Watson (1989), Friedman and Kuttner (1992, 1993), Kashyap *et al.* (1993), and Ramey (1994)) focused exclusively on evidence based on linear regressions or linear vector autoregressions (VARs). Nevertheless, in the last decade, a growing body of empirical research (e.g., Balke (2000), Atanasova (2003), Calza and Sousa (2005), and Li and St-Amant (2006)) has demonstrated the existence of a nonlinear relationship among credit market conditions, monetary policy, and real economic activity in a number of major developed economies. The evidence in the above papers is based on the results of Threshold Vector Autoregression models (TVARs), which change "structure" if a given variable (the threshold variable) crosses a certain estimated threshold. In particular, the threshold variables in their models are related to the state of the credit market. As a result, the interactions among the endogenous variables in the above models are examined in two separate regimes whose boundaries are defined by the state of the credit market at each point in time— a "tight" credit regime and a "normal" credit regime. Virtually all of above-mentioned papers conclude that the impact of economic shocks, especially credit shocks, tends to be substantially larger when the economy is in a "tight" credit regime than when it is in a "normal" credit regime.

In this paper, we contribute to the above TVAR literature by examining how the nonlinear interactions among credit market conditions, monetary policy, and real economic activity change as the economy moves through three different phases of the business cycle. In order to do that, we estimate a structural two-threshold (three-regime) TVAR model with five variables: real output growth, inflation, the federal funds rate, real credit growth, and the interest rate spread between Baa-rated corporate bonds and US Treasury bonds.

We depart from the existing literature on the subject along two dimensions. First, we focus on a model in which the relevant threshold variable (output growth) describes the state of economic activity rather than the state of the credit market. This modification is inspired by the seminal contribution of Potter (1995), who estimates a threshold autoregressive model for US GNP and finds evidence of asymmetric effects of shocks over the business cycle. Conditioning on the level of economic activity allows us to investigate how the dynamics of our benchmark system change conditional on the stage of the business cycle that the economy is in. Moreover, the fact that the thresholds in our TVAR model are determined endogenously allows us to examine how macroeconomic, monetary and credit shocks affect the probability of regime switching.

Second, in contrast to the existing TVAR literature, which concentrates exclusively on single-threshold models, we allow for a second threshold in our TVAR system. The results of the statistical tests proposed by Hansen (1999) overwhelmingly point to the presence of two thresholds in our benchmark system. As a consequence, an important contribution of our paper is to demonstrate that a single-threshold TVAR model would be too restrictive to fully capture all nonlinearities in the data. Furthermore, by estimating the two-threshold (three-regime) model, we can examine the effects of the model's shocks on real economic conditions in three distinct phases of business cycles. These three regimes roughly correspond to (1) subpar economic growth, (2) moderate economic growth, and (3) high economic growth. To the best of our knowledge, our paper is the first to apply the methodology originally proposed by Hansen (1999) in order to study a problem of any kind while allowing for the existence of more than one threshold in a multivariate setting.[1]

Our results suggest that the dynamics of the interactions among credit market conditions, monetary policy and economic activity change considerably as the economy moves from one stage of the business cycle to another. More specifically, the impulse responses of all shocks in the TVAR system exhibit a considerable degree of regime-dependence. In accordance with the findings of the kinked Phillips curve literature, shocks to real output and credit growth tend to have the largest impact in the subpar growth regime. Meanwhile, credit spread shocks are most potent in the high growth regime. We argue this result is mainly driven by the fact that, since financial institutions tend to be highly leveraged during economic booms, even small adverse credit risk shocks can trigger vicious deleveraging spirals, which can have a considerable negative impact on real economic activity. Finally, we also demonstrate that negative output shocks have larger and more persistent effects on credit quantities and credit spreads than the positive ones. We explain this finding with the asymmetric nature of debt contracts and the effect that it has on the behavior of financial intermediaries.

Our findings also reveal that the response of output to monetary policy shocks is largest when economic growth is below par. This result adds to the literature that examines the degree to which the effectiveness of monetary policy varies over the business cycle. Using a logistic smooth transition vector autoregression (LSTVAR) model, which is a generalized version of the TVAR model used in this paper, Weise (1999) demonstrates that increasing money supply is more effective in stimulating output during an economic bust than during an economic boom. Similarly, using a Markov regime switching model of US real output, Garcia and Schaller (2002) find that the effects of monetary policy actions tend to be larger when they are implemented during recessions than during expansions. Using the same methodology, Peersman and Smets (2001) show that similar results hold for the euro area as well. Our results take the evidence from the above papers a step further by demonstrating that monetary policy is significantly more effective when economic growth is sluggish than

[1] Chen *et al.*(2012) examine multiple-threshold auto-regressive models, but do not extend their framework to a multivariate setting.

it is during periods of either moderate or high economic growth. Last but not least, we also find that monetary policy reacts more aggressively to output, inflation, and credit shocks when the economy is in a recession than in the other two phases of the business cycle.

Furthermore, we exploit the fact that our methodology allows us to measure the sensitivity of the regime switching probabilities to the model's shocks. Our results indicate that output shocks have the greatest marginal impact on the regime switching probabilities. Moreover, in accordance with the results from our impulse response analysis, the marginal impact of credit spread shocks is greatest when the economy is in the high growth regime. We also demonstrate that the regime switching probabilities are much less sensitive to monetary policy shocks and credit shocks in the subpar growth regime than in the other two regimes.

Finally, using a nonlinear historical decomposition approach, we examine the contributions of each of the model's shocks to changes in the forecasts of real output growth and credit growth. We find that there are significant differences among the historical decompositions implied by the three-regime TVAR model, the two-regime TVAR alternative, and the linear VAR model. More specifically, the non-idiosyncratic shocks identified by the two-regime TVAR and the linear VAR models do not exhibit much interaction with output shocks, and as a result, do not contribute meaningfully to fluctuations in real GDP growth. By contrast, the three-regime TVAR attributes a considerable share of the observed fluctuations in output growth to monetary policy shocks and credit shocks— a result that the other two specifications fail to capture.

In addition to the papers discussed above, our paper is also related to the strand of literature that uses nonlinear VAR models to study the asymmetric behavior of macroeconomic variables over the different phases of the business cycle. For instance, using a fixed-transition probability Markov-switching model, Hamilton (1989) demonstrates that quarterly real GNP exhibits significant asymmetries over the business cycle. Filardo (1994) generalizes the method of Hamilton (1989) by allowing for time-varying transition probabilities in his Markov-switching model and documents the existence of a high correlation between the evolution of the model-implied phases and traditional reference cycles for monthly output data. He further shows that many of the economic variables that determine the time-varying probabilities have significant predictive power for turning points in the business cycle.

The rest of the paper is organized as follows. In the next section, we present the details of our benchmark TVAR model. In Section 3, we go over the estimation of the model's threshold values and the tests for their statistical significance. In Section 4, we describe the procedure for generating the nonlinear impulse response functions implied by the estimates of our benchmark TVAR model and discuss the most intriguing among them. We examine how each of the structural shocks in our model affects the regime switching probabilities in Section 5. In Section 6, we perform nonlinear historical decompositions in order to assess the contributions of the structural shocks to realized movements in the observable variables. We conclude in Section 7.

2 The Three-Regime Threshold Model

A standard (non-structural) two-threshold TVAR can be expressed using the following equation:

$$Y_t = B_1(L)Y_{t-1}I\left(y_{t-d} \leq \gamma_1\right) + B_2(L)Y_{t-1}I\left(\gamma_1 < y_{t-d} \leq \gamma_2\right) + B_3(L)Y_{t-1}I\left(y_{t-d} > \gamma_2\right) + e_t, \tag{1}$$

where Y_t is a vector of endogenous variables, $B_1(L)$, $B_2(L)$, and $B_3(L)$ are lag polynomial matrices, e_t is a vector of innovations to the non-structural TVAR, and y_{t-d} is the threshold variable, which determines what economic regime the system is in, given threshold values γ_1 and γ_2. $I(\cdot)$ is an indicator function; for example, $I\left(y_{t-d} \leq \gamma_1\right)$ equals 1 when $y_{t-d} \leq \gamma_1$, and 0 otherwise. The threshold values γ_1 and γ_2 are estimated along with the coefficient matrices.

We estimate the above TVAR model using quarterly US data that runs from 1955:1

to 2012:4. In our benchmark model, Y_t consists five variables: (1) real GDP growth; (2) inflation (calculated using the GDP implicit price deflator); (3) the effective federal funds rate; (4) aggregate credit volume (calculated as the sum of real total credit market liabilities of nonfinancial businesses and households); and (5) the interest rate spread between Baa-rated corporate bonds and 10-year Treasury bonds. Following the approach of Balke (2000), we use the four-quarter moving average of real GDP growth as the threshold variable, y_{t-d}, due to the relative volatility of the raw quarterly real GDP growth series[2]. The number of lags in the VAR is set at four.

Even though there is a single threshold variable in our model, having a vector of endogenous variables allows economic regimes to switch as a result of shocks to any of the other variables in the TVAR. In the context of the TVAR described in equation (1), a shock to any element in e_t could result in regime switching. Therefore, unlike in a linear VAR, an identification of the innovation vector e_t could potentially affect the model estimation.

Using ε_t to denote a vector of orthogonal shocks, a structural TVAR can be written as:

$$\begin{aligned} Y_t &= [A_1 Y_t + B_1(L) Y_{t-1}]\, I\left(y_{t-d} \leq \gamma_1\right) + [A_2 Y_t + B_2(L) Y_{t-1}]\, I\left(\gamma_1 < y_{t-d} \leq \gamma_2\right) \\ &\quad + [A_3 Y_t + B_3(L) Y_{t-1}]\, I\left(y_{t-d} > \gamma_2\right) + \varepsilon_t, \end{aligned} \tag{2}$$

where A_1, A_2, and A_3 reflect the structural contemporaneous relationships in the three regimes, respectively. We assume that they have a recursive structure as in much of the recent VAR literature (e.g., Balke (2000), Christiano, *et al.* (2005), and Gilchrist and Zakrajsek (2011)). In our benchmark model specification we impose the following ordering: (1) output growth, (2) inflation, (3) credit (quantity) growth, (4) credit spread, and (5) the effective federal funds rate. The ordering of real output and inflation before the credit variables is conventional and in line with much of the monetary VAR literature. Based on the "broad credit view," where the decision on issuing bank loans is directly affected by the size of the

[2] Note that real GDP growth enters the vector autoregression directly in its original form, not as a moving average.

external finance premium which depends on the creditworthiness of borrowers, we order credit quantity growth before the credit spread, which quantitatively measures the risk premium. Finally, following Balke and Zeng (2013), we order the federal funds rate last, implicitly assuming that monetary policy responds contemporaneously to output, inflation, and credit market conditions.

In addition to the benchmark model described above, we also estimate several alternative specification in order to check the robustness of our results. First, we estimate the "structural" model using alternative orderings for the endogenous variable [3]. More specifically, we estimate a version of the model that features a more traditional ordering in which monetary policy responds contemporaneously only to output and inflation as in Taylor (1993). In addition, we examine a specification in which the credit quantity variable is ordered before real output growth as in Lown and Morgan (2006). Finally, in order to check the extent to which our results are affected by the zero-lower-bound constraint (which was binding in the last 17 quarters of our sample), we also estimate our model on a sub-sample of the data that runs from 1955:1 to 2008:3. It turns out that the estimated thresholds are robust to both, alternative structural orderings and the time span of the data sample. As a consequence, in the rest of the paper, we focus exclusively on the results of the benchmark model specification.

3 Threshold Value Estimation

We estimate the threshold values, thus endogenizing regime switching. To estimate the pair of thresholds $\gamma \equiv (\gamma_1, \gamma_2)$ in the three-regime TVAR (TVAR(3)) model given in equation (2), we adopt the "one-step-at-a-time" approach proposed by Bai (1997), Bai and Perron (1998), and Hansen (1999).

[3] The alternatives include a more traditional ordering in which monetary policy only responds to output and inflation contemporaneously as in Taylor (1993). In addition, we examined a specification in which the credit quantity variable is ordered before real output growth as in Lown and Morgan (2006).

First, we estimate a two-regime TVAR model (TVAR(2)) that can be expressed as:

$$Y_t = [A_1 Y_t + B_1(L) Y_{t-1}]\, I\,(y_{t-d} \leq \gamma_1) + [A_2 Y_t + B_2(L) Y_{t-1}]\, I\,(y_{t-d} > \gamma_1) + \varsigma_t, \qquad (3)$$

and obtain the estimated delay $\hat{d}$ and the threshold value $\hat{\gamma}_1$. The estimates are those that maximize the log determinant of the "structural" residuals, ς_t. Next, we estimate γ_2 by enforcing that $d = \hat{d}$ and that one of the elements in vector γ equals $\hat{\gamma}_1$. The second-stage estimate $\hat{\gamma}_2$ is consistent for the other element of γ. Bai (1997) shows that this one-step-at-a-time method yields consistent estimates of $\hat{d}$ and $\hat{\gamma} = (\hat{\gamma}_1, \hat{\gamma}_2)$, which have the same asymptotic distribution as estimates obtained from a grid search over (γ, d), if this method is iterated at least once. That is, once we obtain $\left(\hat{\gamma}, \hat{d}\right)$, we repeat the second step by enforcing that $d = \hat{d}$ and that one element of γ equals $\hat{\gamma}_2$, yielding a refined estimate $\hat{\gamma}_1$.

To examine if and how the threshold structure enters the model, we follow Hansen (1999) and test the hypotheses that there is no difference between (i) the linear model and the TVAR(2) model, (ii) the linear model and the TVAR(3) model, and (iii) the TVAR(2) model and the TVAR(3) model. Given threshold values γ_1 and γ_2, a Wald statistic can be calculated to test each of the three hypotheses. However, the distributions of the Wald statistics depend on the unknown threshold values which need to be estimated. To implement the test, we estimate the threshold model for all possible threshold values, and compute the Wald statistic for each possible threshold value (in the TVAR(2) case) or each possible pair of threshold values (in the TVAR(3) case). For example, to test the 2-regime model against the 3-regime model, the TVAR(2) is estimated for all possible $\hat{\gamma}_1$, and the TVAR(3) is estimated for all possible $\hat{\gamma}_2$ that are larger than $\hat{\gamma}_1$. A Wald statistic is calculated for each combination of $\hat{\gamma}_1$ and $\hat{\gamma}_2$. Following Hansen (1996) and Balke (2000), we compute three different Wald test statistics over all possible threshold values: the maximum Wald (sup-Wald) statistic; the average Wald (avg-Wald) statistic; and the sum of exponential Wald (exp-Wald) statistic. To prevent overfitting, we follow the approach of Hansen (1996) and limit the possible threshold values so that each regime includes at least 15% of the observations plus the number of parameters for each individual equation in the VAR.

We simulate the empirical distributions of sup-Wald, avg-Wald, and exp-Wald statistics and calculate the p-values using a bootstrap approximation as in Hansen (1996, 1999). The algorithm involves the following steps. First, we generate a random sample, ε_t^*, by sampling with replacement from the estimated residuals, $\hat{\varepsilon}_t$. Then we simulate a sample, Y_t^*, by feeding the model with the random residuals ε_t^*, the estimated coefficient matrices, and the fixed initial conditions $(Y_0,\ Y_{-1},\ Y_{-2},\ ...,\ Y_{-p+1})$, where p is the number of lags in the VAR. Based on the simulated series Y_t^*, the Wald statistics can be obtained using the method described above. This simulation is repeated 1000 times. The bootstrap p-value is equal to the share of simulated Wald statistic values which exceed the observed Wald statistic value.

Table 1 reports the estimated threshold values, $\hat{\gamma}_1$ and $\hat{\gamma}_2$, and delay, $\hat{d}$, and the results of the tests of three hypothesis discussed above. They reveal that one can reject all null hypotheses, and thus present strong evidence of the existence of two thresholds for real GDP growth. The test results and the estimated thresholds are robust to alternative recursive restrictions on the coefficient matrices.

Figure 1 displays a plot of the estimated threshold values against real GDP growth and its four-quarter moving average (i.e., the threshold variable), along with NBER recessions (shaded areas). The estimated lower and upper threshold values, 1.80% and 4.28%, respectively, split our sample into three regimes which roughly correspond to three distinct phases of the business cycle. The first regime is active when the threshold variable (i.e., the four-quarter moving average of real GDP growth) is below the lower estimated threshold, 1.80%. It captures the dynamics which govern the relationships among the endogenous variables when output growth is below par (i.e., when output growth is either negative or positive, but considerably below its long-term trend). In turn, the second regime includes periods during which the economy is growing at a moderate pace (i.e., at a rate between 1.80% and 4.28%). Finally, the third regime captures the dynamics that govern the economy when it is growing significantly faster than its long-term trend. In the time period that we focus on, 24% of observations fall in the *subpar growth regime*, 48% are in the *moderate growth regime*, and 28% belong to the *high growth regime*. Unsurprisingly, Figure 1 shows that all of the periods that fall into our subpar growth regime appear to be either slightly leading or contemporaneous with NBER recessions.

4 Nonlinear Impulse Responses

In order to allow the system to change regimes during the simulation period, we compute the Generalized Impulse Response Functions (GIRFs) proposed by Koop, Pesaran and Potter (1996). More specifically, for a pre-specified forecast horizon, k, we examine the changes in the conditional expectations of Y_{t+k}, given a shock to the ith variable, $\epsilon_t^{(i)}$ and the past information set Ω_{t-1}:

$$GIRF_k^{(i)} = E\left[Y_{t+k}|\epsilon_t^{(i)}, \Omega_{t-1}\right] - E\left[Y_{t+k}|\Omega_{t-1}\right], \text{ for } k = 0, 1, ..., \tag{4}$$

where the initial condition Ω_{t-1} determines the regime that the system is initially in. In the first term in the right-hand side of equation (4), the conditional expectation of Y_{t+k} depends on the particular initial condition and the realized shock, $\epsilon_t^{(i)}$, while the one in the second term is made in the absence of a shock. Since $\epsilon_t^{(i)}$ could trigger a regime switch, different initial conditions, as well as different shock sizes and signs, can result in asymmetric impulse responses.

The conditional expectations of Y_{t+k} are calculated by simulating the model using randomly drawn shocks. To compute $E\left[Y_{t+k}|\Omega_{t-1}\right]$, we generate a random sample u_{t+k} by taking bootstrap samples from the estimated model residuals $\hat{\varepsilon}_t$; then we simulate the model using u_{t+k}, conditional on the initial regime Ω_{t-1}. In order to eliminate any asymmetry that may arise from sampling variation in the draws of u_{t+k}, the simulation is repeated for $-u_{t+k}$. The same simulation process is used to calculate $E\left[Y_{t+k}|\epsilon_t^{(i)}, \Omega_{t-1}\right]$, by feeding the model with the shock $\epsilon_t^{(i)}$. The details of the computation procedure for the GIRFs are provided in Appendix A.

The most interesting nonlinear impulse response functions that the above procedure generates are summarized in Figures 2-4. To capture the potential asymmetry, we simulate the responses by letting each "structural" shock enter the model with different sign (positive or negative) and different size (one- or two-standard-deviations). Taken as a group, the nonlinear impulse response functions provide compelling evidence that the relationship among credit conditions, monetary policy, and economic activity changes considerably as the economy moves from one stage of the business cycle to another.

4.1 Responses of Real GDP Growth

Figure 2 shows the responses of real GDP growth to output growth shocks, monetary policy shocks, as well as shocks to aggregate credit quantities, and credit spreads, conditional on the regime the system is in. Qualitatively, the effects of these shocks on output growth are all conventional across all three regimes. A rise (fall) in the federal funds rate decreases (increases) real GDP growth. A positive credit quantity shock raises real GDP growth, and vice versa. Finally, an unanticipated increase in credit spreads lowers output growth.

The response of output growth to the model's shocks is heavily regime dependent. The response of real GDP growth to its idiosyncratic shocks is considerably smaller and more persistent in the moderate growth regime than in the other two regimes (Figure 2, first column). Furthermore, in the case of two-standard-deviation shocks, the effect of the negative output shock appears to be more persistent than the effect of the positive one. This asymmetry is particularly obvious when the economy is in the high growth regime, where bad news about economic activity has longer-lasting effect than good news.

The impact of monetary policy shocks on output growth is substantially larger when the economy is in the subpar growth regime than when it is in the other two regimes (Figure 2, second column). The response of output growth to a two-standard-deviation monetary shock in the subpar growth regime peaks at 1.50%, compared to 0.95% in the moderate growth regime and 0.82% in the high growth regime. This finding is consistent with the results in Garcia and Schaller (1995) and Weise (1999), who conclude that monetary shocks have stronger effects on output during period of low economic growth. Intuitively, a fall in the federal funds rate increases liquidity, thus and boosting the supply of credit. This effect tends to be stronger during recessions, when economic agents are more likely to be credit and liquidity constrained. As a consequence, monetary policy shocks have the largest impact when economic growth is below par.

Credit quantity shocks have a much smaller impact on output when economic growth is high than in recessions and during periods of moderate economic growth (Figure 2, third column). This result is consistent with the findings of the kinked Phillips curve literature (Stiglitz (1997) and Laxton *et al.* (1999)). Intuitively, a positive credit quantity shocks is more effective in stimulating aggregate demand when the economy is operating below full-capacity (i.e., in the subpar growth regime and in the moderate growth regime) than when it is overheating (in the high growth regime). In the former case, the additional aggregate demand triggered by the positive credit quantity impulse can be accommodated by employing the economy's idle resources. By contrast, in the latter case, there are few idle resources in the economy to be employed and the additional aggregate demand created by the expansion of credit volumes leads to higher inflation rather than to higher output growth[4].

The impulse responses of output growth to the credit spread shocks appear to be even more regime dependent than the respective responses to the credit quantity shocks and the monetary policy shocks (Figure 2, fourth column). In contrast to the other shocks in our benchmark VAR, the credit spread shock has a much larger impact when economic growth is exceptionally high than in the other two regimes. In the high growth regime, the response of output growth to a two-standard-deviation credit spread shock peaks at 2.83%, which is more than twice as high as the peak response in the low growth regime (1.24%), and more

[4]The GIRFs of inflation to the credit quantity shocks, which are available upon request, provide further evidence in support of this hypothesis.

than five times higher than the one in the moderate growth regime (0.56%).

One possible explanation for the above result is that when the economy is growing at an exceptionally high rate, economic agents, in general, and financial institutions, in particular, tend to be highly leveraged (see, for example, Borio and Disyatat (2011) and Borio (2012)). As a result, even a minor exogenous increase in credit risk (reflected in a slight initial rise in credit spreads) could have a significant negative impact on the healthiness of financial institutions' balance sheets (through its impact on asset valuations). As argued by Gilchrist and Zakrajsek (2012), a decline in the financial capital of these institutions reduces their risk-bearing capacity and causes them to start acting in a more risk-averse manner. In turn, this leads to a reduction in credit supply and to second-round increases in credit spreads, thus generating a vicious deleveraging spiral, which depresses consumption and investment in the real economy. When interpreted in such fashion, this finding provides empirical support for recent macroeconomic models (Gertler and Kiyotaki (2010), Gertler and Karadi (2011), and Gertler *et al.* (forthcoming)), in which shocks to the value of financial intermediaries' assets have adverse effects on real economic activity by reducing credit supply.

4.2 Responses of the Federal Funds Rate

Figure 3 displays the impulse responses of the federal funds rate to shocks to output growth, inflation, aggregate credit volumes, and credit spreads. All impulse responses have the expected signs in all three model regimes. Namely, monetary policy is tightened in response to unanticipated increases in output growth, inflation, and aggregate credit volume. By contrast, an unanticipated increase in interest rate spreads causes loosening of monetary policy (similarly to the findings of Gilchrist and Zakrajsek (2012)).

The impact of output shocks on the federal funds rate is greatest in the subpar growth regime, and smallest in the high growth regime (Figure 3, first column). This suggests that the Fed reacts more aggressively to output shocks when the economy is in a recession than when it is overheating. Furthermore, the responses of the federal funds rate to large (two-standard-deviation) output shocks exhibit some asymmetry: in the high growth regime, negative output shocks have a larger effect on the federal funds rate than positive output shocks. Interestingly, the exact opposite happens in the subpar growth regime, in which monetary policy reacts more aggressively to positive output shocks than to negative output shocks. This result is surprising, given that the conventional wisdom suggests that, all else the same, the Fed should be less willing to tighten monetary policy in response to positive output shocks during a recession out of fear of disrupting a nascent economic recovery while the economy is still fragile.

The responses of the funds rate to the other shocks in the model also appear to be heavily regime dependent. An inflation shock of a given size has a much larger impact on the federal funds rate in the low and the moderate growth regimes than in the high growth regime (Figure 3, second column). Meanwhile, the Fed appears to respond to credit growth more quickly and aggressively when the economy is in the lower growth regime (Figure 3, third column). In response to the two-standard-deviation credit quantity shock, the percentage deviation of the funds rate peaks at 1.10% within less than 2 quarters in the subpar growth regime, compared to the 0.63% in at least 6 quarters in the moderate growth regime, and the 0.30% in at least 4 quarters in the high growth regime. Finally, the response of monetary policy to the credit spread shock is slightly stronger when the economy is in the high growth regime than when it is in the other two regimes (Figure 3, fourth column).

4.3 Responses of Credit Variables

Figures 4 displays the impulse responses of aggregate credit volumes and the interest rate spreads. Once again, the impulse responses have the expected signs in all three regimes. As expected, an increase in output growth causes a rise in total credit and a decline in credit spreads. Meanwhile, an increase in the federal funds rate lowers aggregate credit volumes and increases credit spreads.[5]

[5] Recall that in our benchmark TVAR model the federal funds rate is ordered last, and therefore, the interest rate spread does not respond to the federal funds rate shock contemporaneously. We also examined

The impact of output shocks on both, credit volumes and credit spreads, is strongest in the subpar growth regime (Figure 4, first and second column). Intuitively, when the economy is growing at a slower pace, the balance sheets of economic agents tend to be in bad shape. A positive output shock helps with the balance sheets repair process via a couple of channels. First, it raises the net worth of consumers and businesses, which increases their creditworthiness and, ultimately, leads to a decline in credit spreads and an increase in credit volumes. In addition, a positive output shock increases the profitability of financial institutions, which, in turn, enhances their capitalization levels. This allows them to expand their balance sheets through new lending, thus boosting total credit growth and lowering credit spreads.

Furthermore, the responses of the two credit variables to output shocks also exhibit some sign asymmetry. Negative output shocks appear to have larger and more persistent effects on credit quantities and credit spreads than the positive ones. This asymmetry is particularly obvious in the case of large (two-standard-deviation) output shocks. We argue that this result could largely be explained with the asymmetric nature of debt contracts. More specifically, negative output shocks decrease economic agents' net worth, thus bringing them closer to the point of insolvency. This reduces the incentive of the financial institutions to issue credit. The contraction of credit supply results in higher credit spreads and lower credit volumes. Of course, a positive output shock triggers the opposite chains of events. However, due to the asymmetric nature of debt contracts (i.e., lenders suffer losses when borrowers' net worth falls below zero, but do not make any additional gains regardless of how much borrowers' net worth rises above zero), the magnitude of the impact can be larger on the way down (i.e., in response to negative output shocks) than on the way up (i.e., in response to positive output shocks).

Overall, the strength of the effects of monetary policy shocks on credit market conditions

an alternative ordering where the interest rate spread does respond to the funds rate contemporaneously. In that case, the rise in the funds rate has a direct impact on the 10-year Treasury rate; the resulting increase in the Treasury rate mechanically reduces the spread for the first two quarters following the shock. After that, the increase in the 10-year Baa corporate yield pushes the interest rate spread back up.

is similar across all three regimes (Figure 4, first and second column). This result lends credence to the hypothesis that the effectiveness of monetary policy in stimulating credit markets is stable over the different phases of the business cycle. Nevertheless, the initial response of credit volumes to a monetary policy shock does appear to be larger in the high growth regime than in the other two regimes.

5 Probability of Regime Switching

In a threshold model such as the one in this paper, each exogenous shock has the potential to cause a switch of regimes. In order to examine the marginal impact that each shock has on the probability of the system switching from one regime to another, we compute the impulse responses of the indicator functions to various types of exogenous shocks, $E\left[I\left(y_{t-d} \leq \gamma_1\right)|\epsilon_t^{(i)}, \Omega_{t-1}\right]$, $E\left[I\left(\gamma_1 < y_{t-d} \leq \gamma_2\right)|\epsilon_t^{(i)}, \Omega_{t-1}\right]$, and $E\left[I\left(y_{t-d} > \gamma_2\right)|\epsilon_t^{(i)}, \Omega_{t-1}\right]$, which are equal to the ex-ante probabilities of regime switching.

The four rows of Figure 5 show the probabilities of regime switching due to output, monetary, credit quantity, and interest rate spread shocks. The four columns of Figure 5 display the probabilities of the four types of regime switching that we are particularly interested in: the probabilities of the subpar growth regime (such as a recession) ending, the probabilities of the high growth regime (such as an economic boom) ending, and the probabilities of switching from a moderate to a high growth regime as well as from a moderate to a subpar growth regime.[6] For comparison, the probabilities of regime switching in the absence of a shock are also provided.

Output shocks appear to have a considerably larger impact on the regime switching probabilities than other shocks. Conditional on economic activity initially being in the subpar growth regime, the first panel plots the probabilities of the economy switching to

[6]The probability of switching from the subpar to a higher regime (i.e., the subpar regime ending) equals the sum of the probability of switching from subpar to moderate regime and the probability of switching from subpar to high growth regime. The probability of switching from the high to a lower regime is calculated using the same method.

an upper regime— either moderate or high growth. As expected, a positive output shock substantially increases the probabilities of the subpar growth regime ending: a one-standard-deviation positive output shock raises the probability from 60% to 80% within three quarters, and a two-standard-deviation positive output shock brings this probability up to more than 92%.

The second and third columns display the probabilities of switching from the moderate growth regime to the high growth and subpar growth regimes, respectively. The changes in these two probabilities due to output shocks are roughly the same— a positive (negative) two-standard-deviation output shock raises the probability of switching to the high (subpar) regime by 39 percentage points. However, our results also suggest that there is a considerable degree of asymmetry between the responses of the regime switching probabilities to shocks with different signs. The increase in the probability of moving from the moderate growth to the subpar growth regime induced by a two-standard-deviation negative output shock is much larger than the reduction in the same probability triggered by a positive shock with the same magnitude. Meanwhile, the probability of switching to the high growth regime is more sensitive to positive output shocks than negative output shocks.

Finally, the last panel shows the probabilities of switching from the high growth regime to any of the other two lower regimes. The contributions of output shocks are substantial in this case as well. A positive two-standard-deviation output shock can reduce the probability of high growth regime ending from 49% to 13%, while a negative one would increase it to 91%.

The second row of Figure 5 displays the probabilities of regime switching in response to monetary policy shocks. A reduction in the federal funds rate lowers the cost of borrowing, expands investment and production, and raises the probability of switching to an upper regime while reducing the probability of switching to a lower regime. This effect appears to be relatively short-lived when the economy is initially in the subpar growth regime. Conversely, the effect is much larger and more persistent when the economy starts in the moderate or high growth regimes.

The third and fourth rows of Figure 5 display the probabilities of regime switching in response to credit quantity shocks and credit spread shocks, respectively. An exogenous increase in aggregate credit volumes and a decrease in interest rate spreads both raise the likelihood of switching to a higher economic regime by stimulating consumption, investment, and output. Similarly to monetary policy shocks, credit quantity shocks have the largest impact on the probability of regime switching when the economy is initially in the moderate growth regime. By contrast, their impact is much more modest when the economy starts in the high growth regime. The marginal impact of credit spread shocks, on the other hand, is much larger when the economy is in the high growth regime than in the other two regimes.

6 The Contributions of Shocks: A Nonlinear Historical Decomposition

In order to assess the contributions of the model's exogenous shocks to fluctuations in the observable variables, we examine how the forecasts of the observable variables would change if one conditions on the realizations of the exogenous shocks. As in Balke (2000), given the forecast horizon k, the change of forecast of Y_{t+k} due to the ith realized shock over the entire forecast horizon is given by:

$$E\left[Y_{t+k}|\epsilon_t^{(i)}, \epsilon_{t+1}^{(i)}, ..., \epsilon_{t+k}^{(i)}, \Omega_{t-1}\right] - E\left[Y_{t+k}|\Omega_{t-1}\right].$$

The conditional forecast without realized shocks, $E\left[Y_{t+k}|\Omega_{t-1}\right]$, is computed using the same simulation method as the one described above, while $E\left[Y_{t+k}|\epsilon_t^{(i)}, \epsilon_{t+1}^{(i)}, ..., \epsilon_{t+k}^{(i)}, \Omega_{t-1}\right]$ is simulated by feeding the model a series of realized shock ϵ_{t+j} ($j = 1$ to k) to the ith variable taken from the estimated residuals. The forecast horizon is set to be 12 quarters. Appendix B summarizes the technical details of computing the changes of the forecast functions.

6.1 The Contributions of Shocks in the Three-Regime TVAR Model

Figures 6 and 7 display the decompositions of the fluctuations in output growth and credit growth, respectively. Each figure shows the contributions of the "structural" shocks to the changes in the forecast of the observed variable. The sum of all the individual forecast changes attributed to each shock is also displayed. Note that due to the nonlinear structure of our threshold VAR, the total contribution of all shocks is not necessarily identical to the actual forecast error, $Y_{t+k} - E\left[Y_{t+k}|\Omega_{t-1}\right]$, as in a linear model. Formally, we define a remainder term as the difference between the actual forecast error and the sum of all the individual forecast changes. We show the estimates of that term in the last panels of Figures 6 and 7. Although we compute the contributions of the shocks by taking potential regime switching into account,[7] the remainder term partially captures the contribution of switching regimes to the nonlinear propagation of shocks.

Figure 6 shows that the idiosyncratic shocks contribute substantially to the fluctuations in real GDP growth over the entire sample, and especially in the period before 2000. Besides output shocks, the Great Recession starting in late 2007 appears to be also attributable to monetary, credit quantity, and interest rate spread shocks. The two credit shocks also play a significant role in the second recession of the 1980s, which, according to the conventional wisdom, was triggered by the savings and loan crisis. Credit quantity shock contributed considerably to the 1960-1961, 1973-1975, and 2001 recessions, as well. As expected, shocks to the federal funds rate appear to have a significant impact on economic activity during the Volker period, but not in the most recent recessionary period.

The remainder term in Figure 6 is also worth mentioning. Recall that this term would be zero for a linear model, and therefore captures the extent to which regime switching exacerbates the effects of individual shocks. This term contributes significantly to the fluctuations in nearly all recessionary periods.

[7] More specifically, in every period t, the set of estimated factor loadings and error terms that is used to simulate the current changes of forecast functions is determined by the regime that the previously simulated Y_{t-d} falls into.

The two credit shocks are the most important drivers of changes in the forecast of credit growth, especially after 1980 (Figure 7). The credit expansions of the 1990s and mid-2000s are also partially attributable to output and monetary shocks. Interestingly, the credit crunch in the late 1970s is mainly captured by the monetary and inflation shocks, while the one in late 1980s was primarily driven by shocks to real output.

6.2 Comparing the Contributions of Shocks across Models

In sections 4 and 5, we showed that the responses of output growth, credit growth, and monetary policy to the same shock can be heavily regime-dependent. In addition, the effects of a positive and a negative shock can be asymmetric due to the possibility of regime switching triggered by the shocks. This asymmetry across regimes would remain undetected if one only examines a linear or a two-regime model. In this subsection, we show that besides the asymmetric shock effects, there are shock contributions to the fluctuations in output growth that can be captured by the three-regime model, but not by the linear or the two-regime model specifications.

Each column of Figure 8 displays the changes in the forecast of real GDP growth triggered by the five exogenous shocks identified in the three alternative model specifications. The contributions of the idiosyncratic shock (i.e., the output shock) are similar across three model alternatives— all of them suggest that this shock is the most important driver of output fluctuations. By contrast, shocks to inflation, monetary policy, credit growth, and interest rate spreads do not explain the majority of the fluctuations in real GDP growth according to the linear VAR model and the two-regime TVAR model. This indicates that the non-idiosyncratic shocks identified by these two models do not show much interaction with the output shock.

The three-regime TVAR model, on the other hand, is able to detect significant contributions from the non-idiosyncratic shocks. According to the results of that model, monetary policy shocks contributed substantially to the back-to-back recessions during the Volker's period. In addition, the shocks to credit growth and interest rate spreads play a significant role in explaining the economic contraction in the 2007-09 period and the back-to-back recessions of the early 1980s.

7 Conclusion

In this paper, we examine how the nonlinear relationship among credit market conditions, monetary policy, and real economic activity changes as the economy moves through different business cycle phases. We do that by estimating a structural TVAR model with five variables: real GDP growth, inflation, the federal funds rate, real credit growth, and the spread between Baa-rated corporate bonds and 10-year Treasury bonds. We depart from the existing literature on the subject along two dimensions. First, we focus on a model in which the relevant threshold variable describes the state of economic activity rather than the state of the credit market. Second, in contrast to the existing TVAR literature, which concentrates exclusively on single-threshold models, we allow for the presence of a second threshold in our TVAR system.

Our results provide strong evidence that the interactions among credit market conditions, monetary policy, and economic activity change significantly as the economy moves from one stage of the business cycle to another. We find that shocks to output growth and credit growth have the largest impact when economic growth is below par. Similarly, the effect of monetary policy shocks is strongest when economic activity is sluggish. Furthermore, monetary policy reacts to output, inflation, and credit shocks more aggressively when the economy is in a recession. By contrast, real output growth is most sensitive to credit risk shocks when the economy is booming. We also demonstrate that the regime switching probabilities are most sensitive to output shocks. Last but not least, using a nonlinear historical decomposition approach, we examine the contributions of the model's exogenous shocks to changes in the forecasts of output growth and credit growth. Our results indicate that the three-regime TVAR model captures important contributions of the non-idiosyncratic shocks to output growth fluctuations, despite the fact that these contributions remain undetected by both the two-regime TVAR model and the linear VAR model.

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Appendix

A Computation of Nonlinear Impulse Responses

The steps of simulating the GIRFs can be summarized as follows:

1. Choose an initial condition $\Omega_{n,t-1}$, where $n = 1, 2, ..., N$. The initial condition is the actual value of the lagged variables on a particular date n. The number of initial conditions, N, for a specific regime is the number of the observations fall in the regime that the GIRF is conditional on.

2. Generate a random sample u_{t+k}, where k is the GIRF horizon, by taking bootstrap samples (with replacement) from the estimated residuals $\hat{\varepsilon}_t$ of the model.

3. Simulate a series of Y_{t+k} based on the proposed TVAR model using u_{t+k}, the nth initial condition, the estimated coefficient matrices, the estimated delay $\hat{d}$, and the estimated threshold values $\hat{\gamma}_1$ and $\hat{\gamma}_2$. This gives us $Y_{t+k}\left(u_{t+k}, \Omega_{n,t-1}\right)$.

4. This step is similar to the previous step, except we simulate a series of Y_{t+k} by feeding a shock $\epsilon_t^{(i)}$ to the ith variable of the sampled residual u_{t+k}. Then feed the model with the negative shock $-\epsilon_t^{(i)}$ and simulate a series of Y_{t+k} again. The average of the two series of Y_{t+k} gives us $Y_{t+k}\left(\epsilon_t^{(i)}, u_{t+k}, \Omega_{n,t-1}\right)$.

5. Repeat steps 2 to 4 M times to get M estimates of $Y_{t+k}\left(u_{t+k}, \Omega_{n,t-1}\right)$ and $Y_{t+k}\left(\epsilon_t^{(i)}, u_{t+k}, \Omega_{n,t-1}\right)$. Averaging over the difference of these estimates yields the expectation of Y_{t+k} for the nth initial condition, $E\left[Y_{t+k}|\epsilon_t^{(i)}, \Omega_{n,t-1}\right] - E\left[Y_{t+k}|\Omega_{n,t-1}\right]$. We set the number of simulation M to be 500 as in Balke (2000).

6. Repeat steps 1 to 5 for all possible $\Omega_{n,t-1}$ (all observations in each regime) that the impulse response has to be conditioned on. Averaging over N initial conditions yields

the estimates of the generalized impulse responses, $E\left[Y_{t+k}|\epsilon_t^{(i)}, \Omega_{t-1}\right] - E\left[Y_{t+k}|\Omega_{t-1}\right]$, for a given regime.

B Computation of the Nonlinear Historical Decompositions

We describe the steps of computing the changes in forecast functions as follows:

1. The forecast starts from time period t. Given forecast horizon K and initial conditions $(Y_{t-1},\ Y_{t-2},\ ...,\ Y_{t-p})$ where p is the number of lags of the VAR, we can simulate $E\left[Y_{t+k}|\Omega_{t-1}\right]$ (where $k = 1, 2, ..., K$) similarly to how we simulate the conditional mean to calculate GIRFs. That is, we draw K numbers of bootstrap samples $(\hat{u}_t,\ \hat{u}_{t+1},\ ...,\ \hat{u}_{t+K})$ from the estimated residuals of the model, and simulate $(Y_t,\ Y_{t+1},\ ...,\ Y_{t+K})$ based on the random drawn shocks and the estimated coefficient matrices. In our model, we set the forecast horizon as 12. This step is repeated for 500 times. Then averaging over the total number simulations yields $E\left[Y_{t+k}|\Omega_{t-1}\right]$ for each k.

2. Given the simulated forecast $E\left[Y_{t+k}|\Omega_{t-1}\right]$, we can calculate the forecast errors $Y_{t+k} - E\left[Y_{t+k}|\Omega_{t-1}\right]$. We will calculate the contributions of each shock to the forecast errors.

3. Now using the first p forecast errors, $Y_{t+k} - E\left[Y_{t+k}|\Omega_{t-1}\right]$, as initial conditions, we can feed the model with the estimated residuals $\left(\hat{\varepsilon}_t^{(i)},\ \hat{\varepsilon}_{t+1}^{(i)},\ ...,\ \hat{\varepsilon}_{t+K}^{(i)}\right)$ of the ith variable (one at a time) to simulate $E\left[Y_{t+k}|\Omega_{t-1}, \hat{\varepsilon}_t^{(i)},\ \hat{\varepsilon}_{t+1}^{(i)},\ ...,\ \hat{\varepsilon}_{t+K}^{(i)}\right] - E\left[Y_{t+k}|\Omega_{t-1}\right]$, which is the change in forecast functions due to the ith shock. For each ith variable, save the Kth change in forecast function.

4. Move on to time period $t+1$ and repeat steps 1 to 3, until the end of the sample.

Table 1. Wald Tests for Threshold Effects in the Benchmark VAR

Threshold Variable: MA(4) of Real GDP Growth

Estimated Threshold Value: $\hat{\gamma}_1 = 1.8001$, $\hat{\gamma}_2 = 4.2818$.*Estimated Delay:* $\hat{d} = 2$

Tests	Sup-Wald Statistics	Avg-Wald Statistics	Exp-Wald Statistics
Linear against 2-regime Model	365.8549 (0.000)	223.8872 (0.000)	178.1437 (0.000)
Linear against 3-regime Model	629.6655 (0.000)	475.7057 (0.047)	310.8255 (0.000)
2-regime against 3-regime Model	359.9791 (0.000)	229.8949 (0.004)	175.9824 (0.000)

Note:

1. Data sample runs from 1955:1 to 2012:4.
2. MA(4) denotes a moving average of length of four.
3. P-values based on the simulation method as in Hansen (1996, 1999) are in parentheses.

Figure 1. The Threshold Variable and Estimated Threshold Values

Figure 2. The Nonlinear Impulse Responses of Output Growth

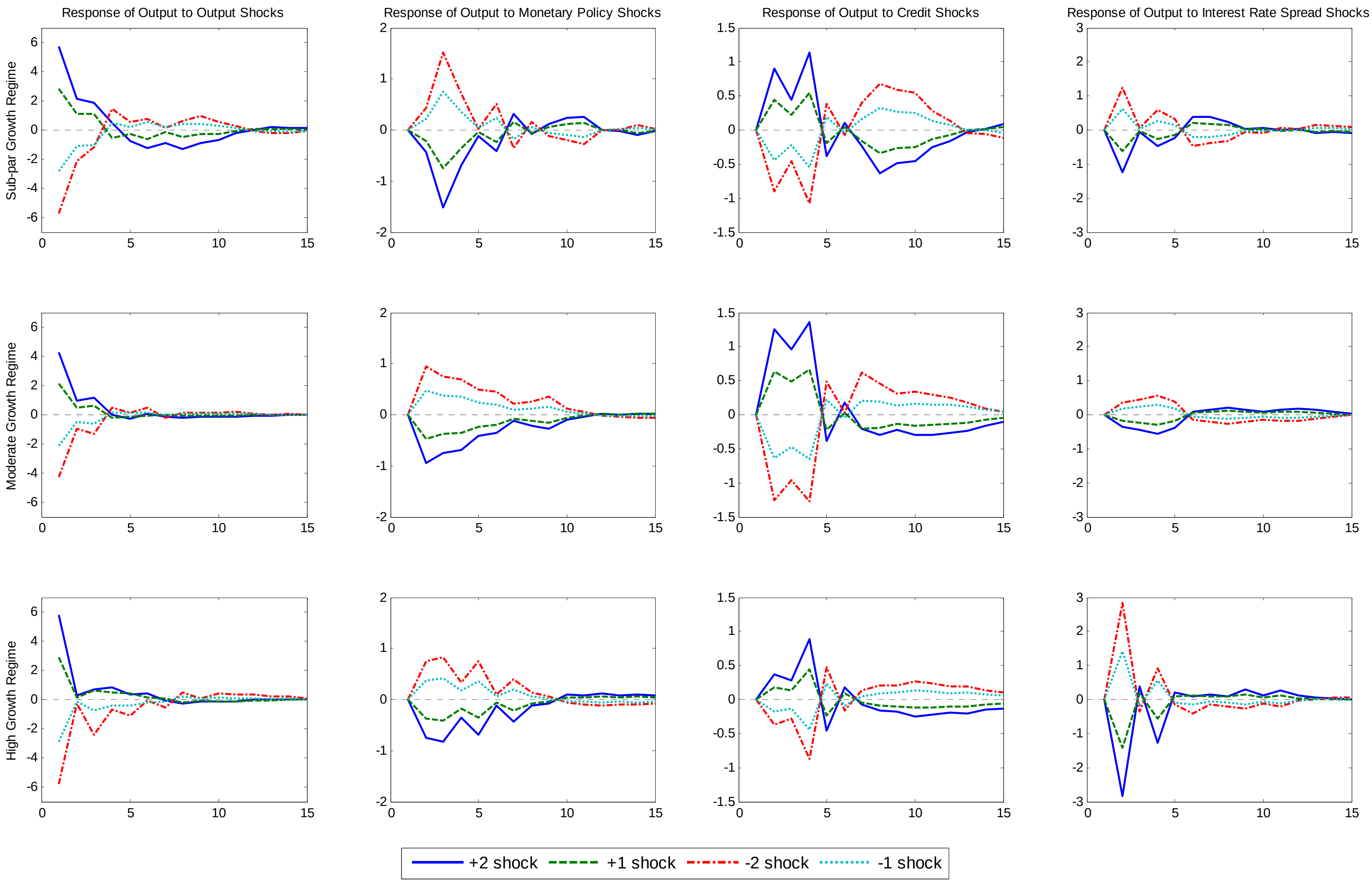

Figure 3. The Nonlinear Impulse Responses of Fed Funds Rate

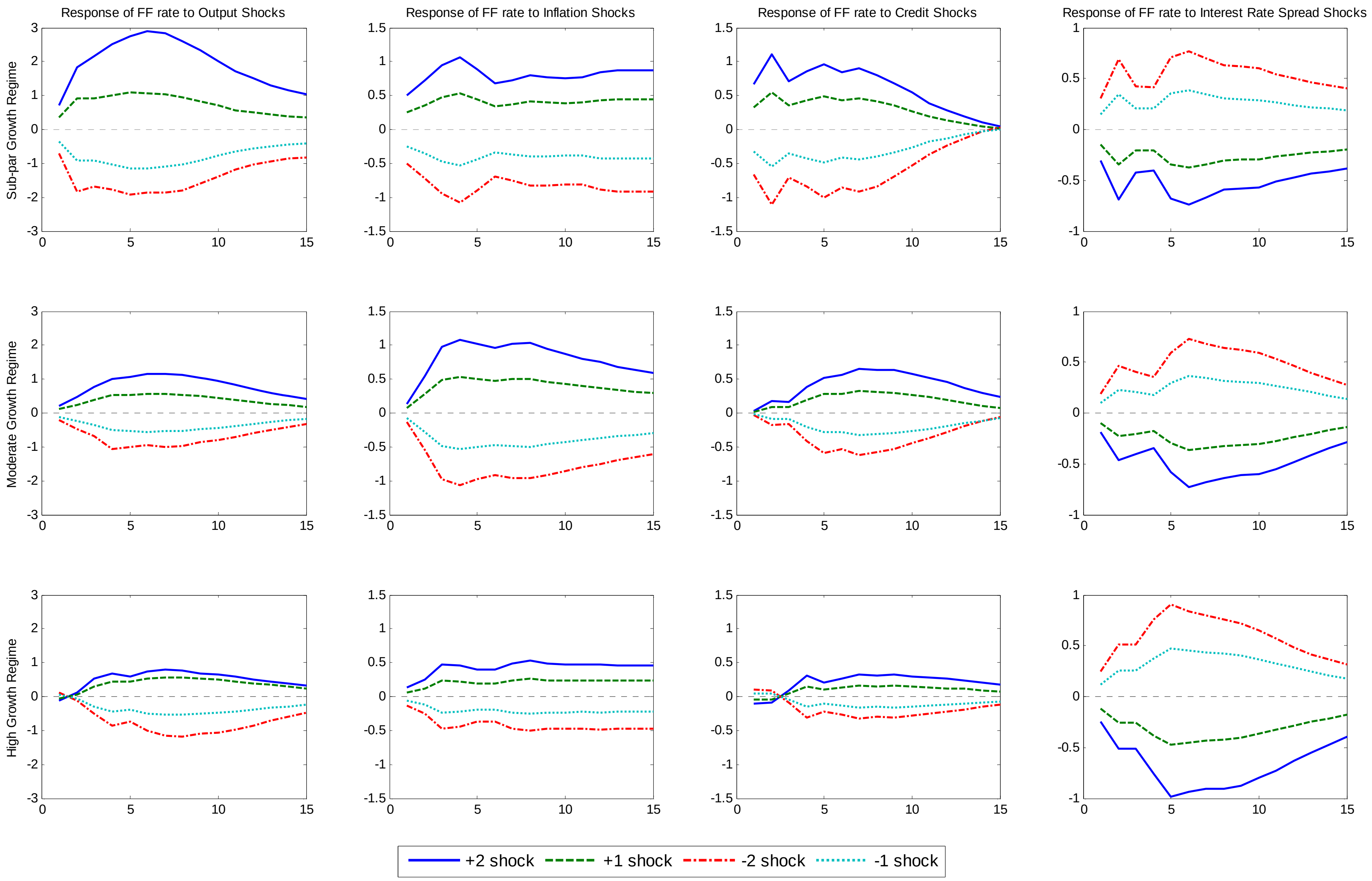

Figure 4. The Nonlinear Impulse Responses of Total Credit Liabilities and Interest Rate Spread

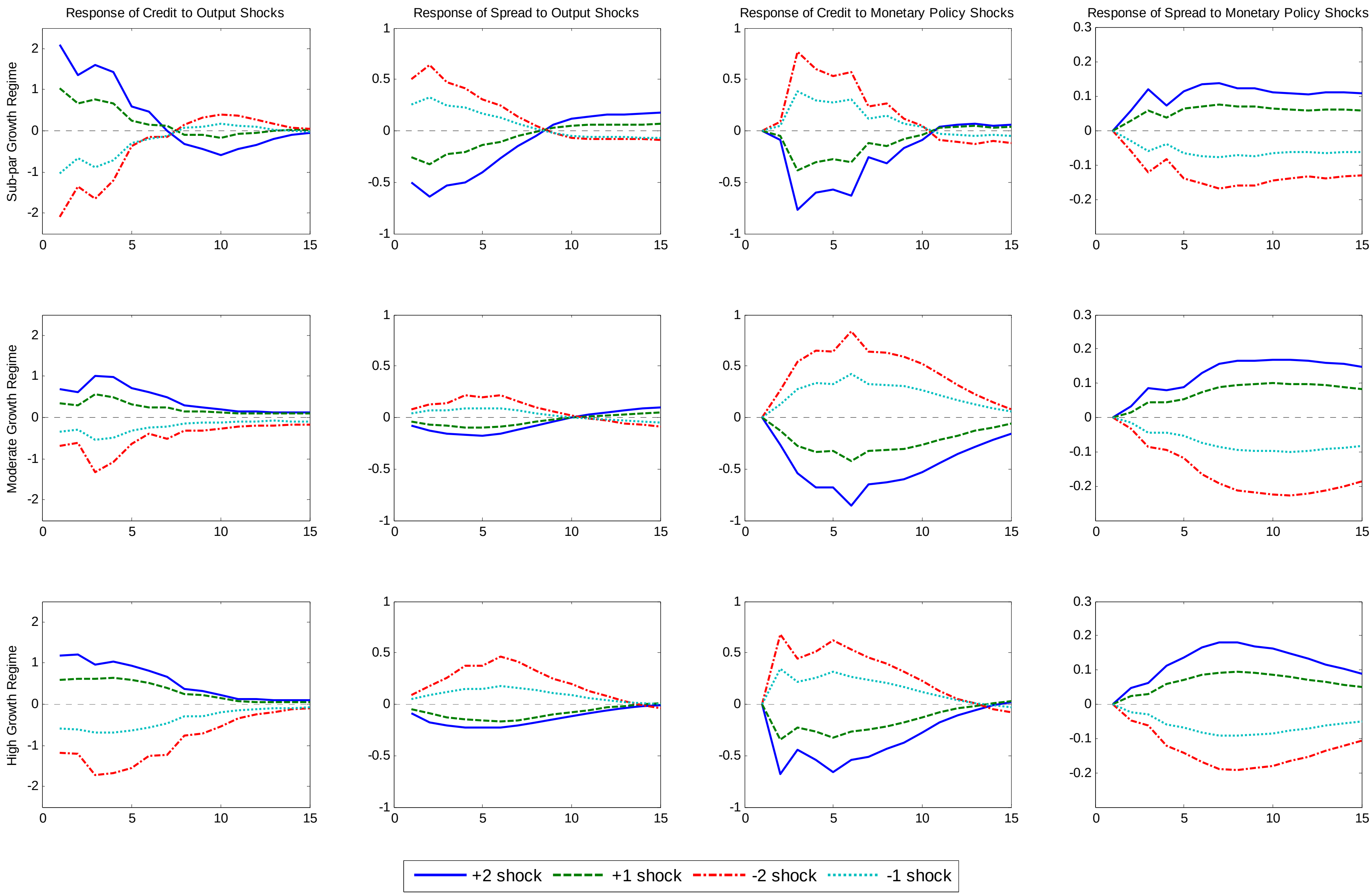

Figure 5. Probability of Regime Switching in Response to Shocks

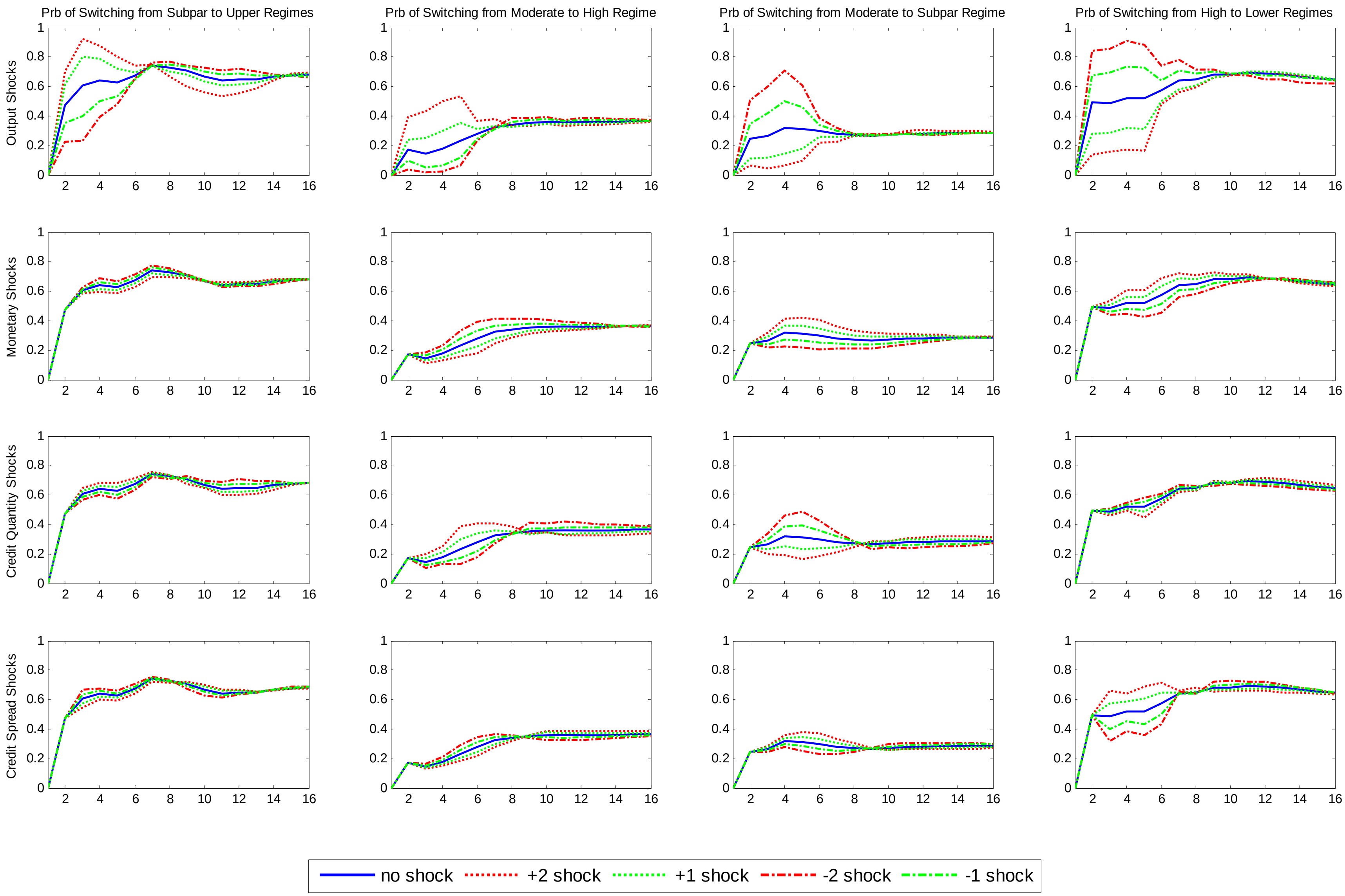

Figure 6. Changes in Forecast of Output Growth as a Result of Shocks

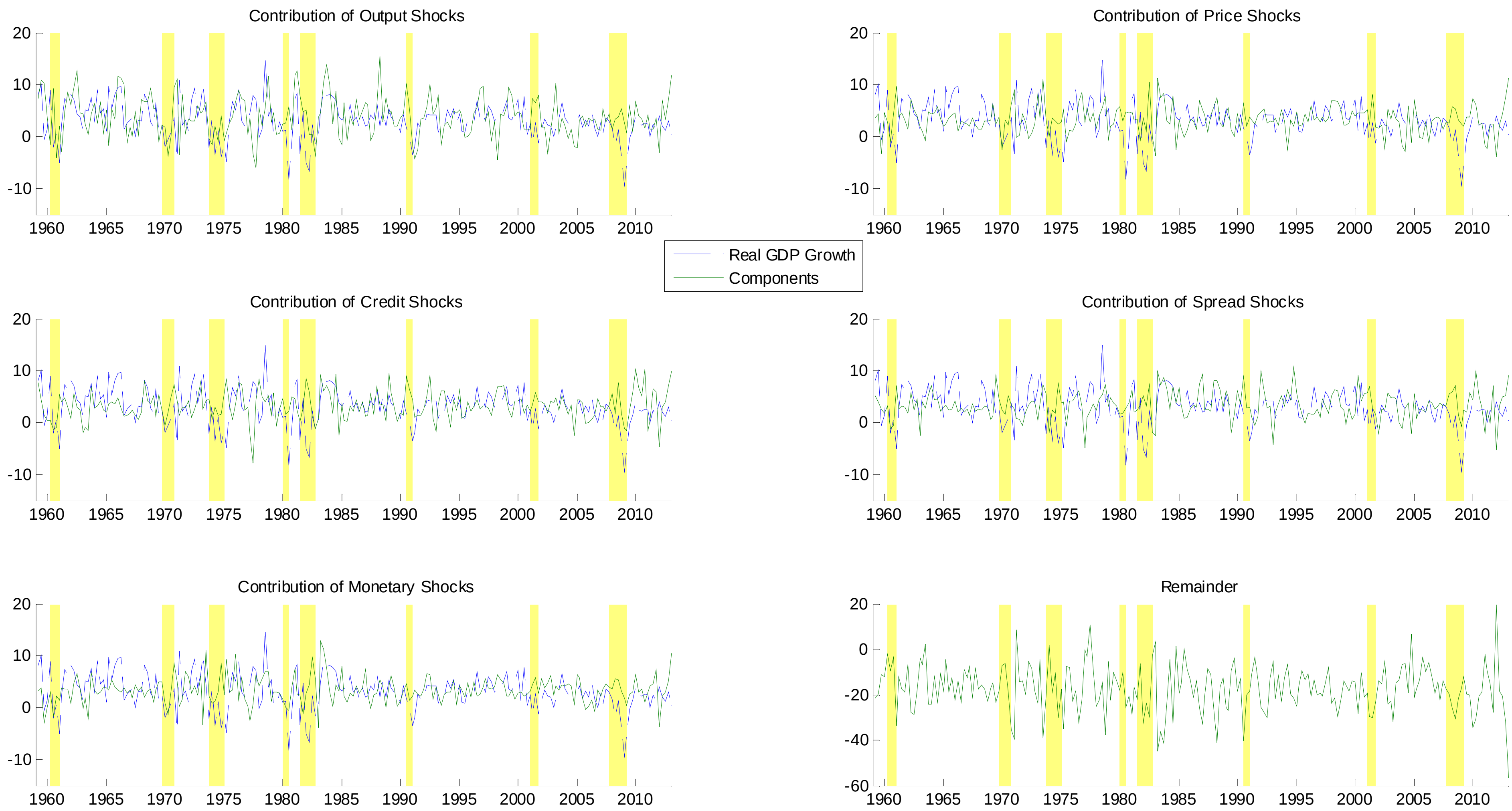

Figure 7. Changes in Forecast of Credit Growth as a Result of Shocks

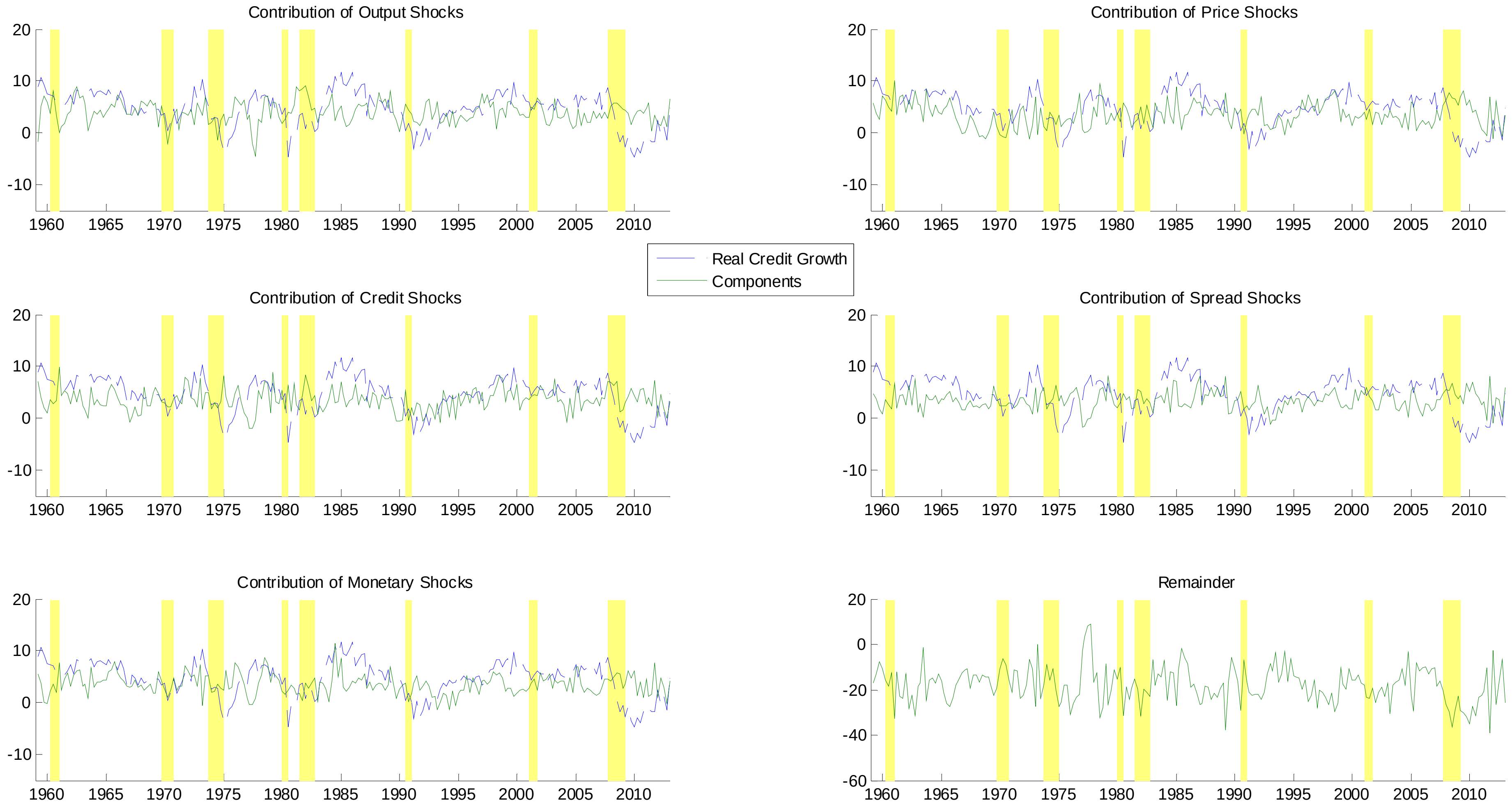

Figure 8. Comparing Changes in Forecast of Output Growth across Models