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Theory Ahead of Measurement? Assessing the Nonlinear Effects of Financial Market Disruptions*

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Abstract

An important, yet untested, prediction of many macro models with financial frictions is that financial market disruptions can have highly nonlinear effects on economic activity. This paper presents empirical evidence supporting this prediction, and in particular that financial shocks have substantial (i) asymmetric and (ii) state dependent effects. First, negative shocks to credit supply have large and persistent effects on output, but positive shocks have no significant effect. Second, credit supply shocks have larger and more persistent effects in periods of weak economic growth.

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1 Introduction

A large literature aims at better understanding the macroeconomic implications of financial frictions and the effects of financial shocks.

Building on earlier theoretical contributions,[1] a set of recent papers showed numerically that financial constraints can lead to highly nonlinear dynamics in the economy's response to shocks.[2] In particular, financial frictions can lead to (i) asymmetric impulse responses to financial shocks if the financial constraints are occasionally binding, and (ii) state dependent impulse responses as financial disruptions can have larger effects in recessions when firms have little net worth and are more sensitive to credit shortages. In such cases, adverse credit supply shocks can take the economy far away from the steady state for a long time, so that a small shock can generate large and long-lasting effects on output.

Surprisingly, while the existence of such non-linearities can provide an important diagnostic for models of financial frictions, these predictions have never been evaluated empirically. Instead, empirical studies have focused exclusively on the linear effects of financial market disruptions, whether credit shocks or financial crises.[3]

This paper fills this gap by using a novel econometric technique to estimate the nonlinear effects of shocks to the supply of credit. We find strong evidence of nonlinear dynamics consistent with theoretical predictions. First, contractionary shocks to credit supply have large and persistent adverse effects on output, but expansionary shocks have no significant effect, consistent with the presence of occasionally binding financial constraints. Second, negative shocks to credit supply have larger and more persistent adverse effects during recessions than during expansions, consistent with the idea that net worth influences the effect of a credit shock. Also consistent with that idea, we find that positive shocks to credit supply can have a positive and significant effect on output growth, but only if the shock takes place during a recession.

An important reason for the lack of studies on the possibly asymmetric and state dependent nature of the financial shocks is methodological. Standard techniques are often linear, which makes the exploration of nonlinearities difficult. In particular, VARs (or factor-augmented VARs), as used by Gilchrist and Zakrajsek

[1] In particular, Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Bernanke, Gertler and Gilchrist (1999)

[2] See Mendoza (2010), He and Krishnamurthy (2013), and Brunnermeier and Sannikov (2014).

[3] For studies of the effects of credit supply shocks, see Helbling et al. (2010), Gilchrist, Yankov, and Zakrajsek (2009), Gilchrist and Zakrajsek (2011, 2012), and Boivin et al. (2013). For studies of the effects of financial crises, see Cerra and Saxena (2008), Reinhart and Rogoff (2009), Jorda et al. (2010), Bordo and Haubrich (2012), Ball (2014), Blanchard, Cerutti, and Summers (2015), Krishnamurthy and Muir (2015), Romer and Romer (2015).

(2011, 2012) and Boivin et al. (2013), cannot allow the impulse response to depend on the sign of the shock.[4] The "narrative approach," which isolates financial crisis episodes and studies the economy's behavior around these episodes,[5] is more flexible and could be extended to allow for nonlinearities using Autoregressive Distributed Lag models (ADL) or Local Projection (LP, Jorda, 2005). However, it suffers from two limitations: (i) shock identification and (ii) low efficiency. First, the financial crisis dates isolated through the narrative approach need not identify shocks originating in the financial markets, so that the approach is mostly aimed at measuring correlations rather than at identifying the causal effect of a financial crisis on economic activity.[6] Second, because of their nonparametric nature, ADL and LP methods are limited by efficiency considerations, which makes inferences on a rich set of nonlinearities (e.g., asymmetry and state dependence) difficult.

To overcome these technical challenges, we use a new method that combines the strength of the VAR for shock identification with the flexibility of ADL and LP models to allow for nonlinearities, in particular asymmetry and state dependence. The method consists in (i) directly estimating the impulse response function (i.e. the moving average representation) from the data while simultaneously identifying the structural shocks, and (ii) using mixtures of Gaussian functions to parametrize the impulse response functions, which offers efficiency gains and allows for the exploration of a rich set of nonlinearities. Such "Gaussian Mixture Approximations" (GMA) build on two premises: (i) any mean-reverting impulse response function can be approximated by a mixture of Gaussian basis functions, and (ii) a small number (one or two) of Gaussian functions can already capture a large variety of impulse response functions, and notably the typical impulse responses found in empirical or theoretical studies. For instance, the impulse response functions to credit supply shocks are often found (or theoretically predicted) to be monotonic or hump shaped.[7] In such cases, a single Gaussian function can already provide

[4] Regime-switching VAR models can capture certain types of nonlinearities such as state dependence (whereby the value of some state variable affects the impulse response functions), but they cannot capture asymmetric effects of shocks (whereby the impulse response to a structural shock depends on the sign of that shock). With regime-switching VAR models, it is assumed that the economy can be in a finite number of regimes, and that each regime corresponds to a different set of VAR coefficients. However, if the true data-generating process features more general asymmetric impulse responses, a new set of VAR coefficients would be necessary each period, because the (nonlinear) behavior of the economy at any point in time can depend on all structural shocks up to that point. As a result, such asymmetric data-generating process cannot be well approximated by a small number of state variables such as in threshold VARs or Markov-switching models.

[5] Reinhart and Rogoff (2009) and all references in Footnote 3.

[6] An exception is Romer and Romer (2015), who use real-time narrative accounts to identify surprises originating in the financial markets.

[7] See e.g., Gilchrist and Zakrajsek (2012) for empirical evidence or Bernanke, Gertler, and Gilchrist (1999), Gertler and Kiyotaki (2010), Gertler and Karadi (2011) for theoretical predic-

an excellent approximation of the impulse response function. Thanks to the small number of free parameters allowed by our Gaussian mixture approximation, it is then possible to directly estimate impulse response functions from the data using Maximum Likelihood or Bayesian methods. A more technical companion paper (Barnichon and Matthes, 2016) provides details on the technical aspects of the GMA methodology as well as Monte-Carlo simulations to assess its (good) performances in finite samples.

To measure conditions in financial markets, we follow a long tradition in economics and focus on credit spreads.[8] However, credit spreads do not only reflect conditions in financial markets and credit supply[9] but also variations in the default probability of borrowers (Bernanke et al. 1999, Philippon, 2009). In an important recent paper, Gilchrist and Zakrajsek (GZ, 2012) isolate variations in the credit spread driven solely by fluctuations in the risk-bearing capacity (or willingness) of the financial sector. They use a large sample of US corporate bonds to decompose the credit spread into two components: one component capturing the expected default risk of borrowers and a residual component - the excess bond premium (EBP). The EBP tells us how much risk the financial sector is able (or willing) to take on and thus reflects the supply of credit. We use the EBP together with a recursive identification scheme as in GZ to identify structural credit supply shocks.

The remainder of the paper is structured as follows. Section II presents our empirical model, our method to approximate impulse responses using Gaussian basis functions and our strategy to identify structural shocks to credit supply; Section III presents our results; Section IV presents robustness checks using an alternative econometric technique. Section V concludes and lays out possible paths for future research.

2 Empirical Model

Our goal in this paper is to study to what extent the effects of a credit shock depend on the sign of the shock as well as on the state of the business cycle at the time of the shock.

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tions.

[8]This focus is in part motivated by theory emphasizing the importance of credit spreads, most notably Blinder (1987), Bernanke et al. (1989), and Kiyotaki and Moore (1997) and in part by the literature documenting the substantial predictive power of credit spreads. See e.g. Gertler and Lown (1999), Mody and Taylor (2004) and King et al. (2007), Gilchrist et al. (2009) and Faust et al. (2012).

[9]Credit spreads are believed to convey important information about the availability of credit from financial intermediaries (see e.g. Gertler and Karadi, 2009) and the risk sentiment of financial intermediaries (Heaton and Lucas, 1997; Fernanded-Villaverde et al. 2009; Kim, 2009; Christiano et al., 2010).

To capture these possibilities, we need a model that allows the impulse response functions to depend on the sign of the shock or on the state of the economy at the time of the shock.[10] Our empirical model is thus a (nonlinear) structural moving-average model, in which the behavior of a vector of macroeconomic variables is dictated by its response to past and present structural shocks.

Specifically, denoting $\boldsymbol{y}_t$ a vector of stationary macroeconomic variables, the economy is described by

$$\boldsymbol{y}_t = \sum_{k=0}^{K} \boldsymbol{\Psi}_k(\boldsymbol{\varepsilon_{t-k}}, z_{t-k})\boldsymbol{\varepsilon_{t-k}}, \tag{1}$$

where $\boldsymbol{\varepsilon_t}$ is a vector of structural shocks with $E(\boldsymbol{\varepsilon_t}) = 0$, $E(\boldsymbol{\varepsilon_t}\boldsymbol{\varepsilon_t'}) = \boldsymbol{I}$, K is the number of lags, which can be finite or infinite, and z_t is a stationary variable that can be a function of past values of $\boldsymbol{y_t}$ or of exogenous variables. $\boldsymbol{\Psi}_k$ is the matrix of lag coefficients, i.e., the impulse response functions to shocks.

Note that is a nonlinear moving average model, because the coefficients of $\boldsymbol{\Psi}_k$ can depend on the values of the structural innovations $\boldsymbol{\varepsilon_{t-k}}$ and on the value of the macroeconomic variable z_{t-k}.

With $\boldsymbol{\Psi}_k$ a function of $\boldsymbol{\varepsilon_{t-k}}$, the impulse response functions to a given structural shock depend on the value of the shock at the time of shock. For instance, a positive shock may trigger a different impulse response than a negative shock.

With $\boldsymbol{\Psi}_k$ a function of z_{t-k}, the impulse response functions to a structural shock depend on the value of the macroeconomic variables z at the time of that shock. For instance, the response function may be different depending on the state of the business cycle (recession or expansion) at the time of the shock.

Importantly, our empirical model is *not* a structural Vector AutoRegression (VAR). While the use of a VAR is a common way to estimate a moving-average model, it relies on the existence of a VAR representation. However, in a nonlinear world where $\boldsymbol{\Psi}_k$ depends on the sign of the shocks $\boldsymbol{\varepsilon}$ as in (1), the existence of a VAR is compromised, because inverting (1) is difficult. Thus, in this paper, we work with an empirical method that side-steps the VAR and instead directly estimates the vector moving average model (1).

2.1 Gaussian Mixture Approximations (GMA) of impulse responses

Estimating a moving-average model is notoriously difficult, because the number of free parameters $\{\boldsymbol{\Psi}_k\}_{k=0}^{K}$ in (1) is very large or possibly infinite. To address this

[10]As we argue in a few paragraphs, a VAR is ill-suited to capture such nonlinearities.

issue, we follow Barnichon and Matthes (2016) and use Gaussian Mixture Approximations (GMAs) of the impulse responses, which consists in parameterizing the impulse response functions using Gaussian basis functions. We first discuss linear GMA models and then present nonlinear GMA models.

2.1.1 The Linear Case: One-Gaussian Approximation

As a first example, consider a linear version of (1), i.e.

$$\boldsymbol{y}_t = \sum_{k=0}^{\infty} \boldsymbol{\Psi}_k \boldsymbol{\varepsilon}_{\boldsymbol{t-k}}. \tag{2}$$

Denote $\psi(k)$ the representative element of matrix $\boldsymbol{\Psi}_k$, so that $\psi(k)$ is the value of the impulse response function ψ at horizon k. If we parametrize the impulse response function ψ with one Gaussian function, we have that

$$\psi(k) = ae^{-\left(\frac{k-b}{c}\right)^2} \qquad \forall k > 0, \tag{3}$$

where a, b, and c are the parameters to be estimated. For additional flexibility, we can let the contemporaneous impact coefficient $\psi(0)$ be a free parameter. Note that a one-Gaussian approximation implies a much smaller set of free parameters than one would typically have in a corresponding VAR. With a system of four variables and six lags, a structural VAR has $6 * 4^2 + 4 + 4^2 = 116$ (lag coefficients + constants + contemporaneous effects) free parameters while the one-Gaussian approximation has only $3 * 4^2 + 4 + 4^2 = 68$ free parameters. Note that the number of parameters in a GMA model is independent of the lag length, in contrast to a VAR. This parsimony has two important advantages. First, it will allow us to directly estimate the impulse responses from the moving-average representation (2). Second, it will allow us to add more degrees of freedom and introduce (and estimate) asymmetric or other nonlinear effects of shocks.

Figure 2 plots a typical Gaussian function and describes how the three parameters a, b, and c govern the shape of a one-Gaussian approximation: a captures the peak response of a variable to a given shock, b is the point in time when the peak effect occurs, and c captures the persistence of the effect.[11]

2.1.2 The Linear Case: Gaussian Mixture Approximation

In order to capture more complex shapes of impulse responses, one can approximate the impulse response functions with a sum –a mixture– of Gaussian functions. A GMA of order N, or GMA(N), is of the form

[11]The amount of time τ required for the effect of a shock to be 50% of its maximum value is given by $\tau = c\sqrt{\ln 2}$.

$$\psi(k) = \sum_{n=1}^{N} a_n e^{-\left(\frac{k-b_n}{c_n}\right)^2} \qquad \forall k > 0. \tag{4}$$

For instance, one might want to add a second Gaussian function in order to capture overshooting or oscillating patterns in the impulse response function of a variables. Figure 3 describes how the sum of Gaussian functions can be used to capture such a pattern. In this GMA(2) example, the first Gaussian captures the first-round effect of the shock, while the second Gaussian captures the strength of the second-round effect, that (partially) compensates the first-round effect one. For the nth Gaussian basis function, the parameters a_n, b_n, and c_n capture the magnitude, location and persistence of the nth effect of the shock.

2.1.3 Asymmetric Effects

We can now generalize the model by allowing $\boldsymbol{\Psi}_k$ to depend on the sign of the shock such that

$$\boldsymbol{y}_t = \sum_{k=0}^{\infty} \boldsymbol{\Psi}_k^{+} 1_{\boldsymbol{\varepsilon} \geq \mathbf{0}} \boldsymbol{\varepsilon}_{\boldsymbol{t-k}} + \sum_{k=0}^{\infty} \boldsymbol{\Psi}_k^{-} 1_{\boldsymbol{\varepsilon} < \mathbf{0}} \boldsymbol{\varepsilon}_{\boldsymbol{t-k}}, \tag{5}$$

where $\boldsymbol{\Psi}_k^{+}$ and $\boldsymbol{\Psi}_k^{-}$ are the impulse responses to positive and negative shocks, respectively.

In our case of interest, denoting $\psi_i^{c+}(k)$, the impulse response of variable i at horizon k to a *positive* shock to credit supply and similarly for $\psi_i^{c-}(k)$, a GMA(N) model of the impulse response function ψ_i^{c+} would write

$$\psi_i^{c+}(k) = \sum_{n=1}^{N} a_{i,n}^{+} e^{-\left(\frac{k-b_{i,n}^{+}}{c_{i,n}^{+}}\right)^2}, \ \forall k > 0 \tag{6}$$

with $a_{i,n}^{+}$, $b_{i,n}^{+}$, $c_{i,n}^{+}$ some constants to be estimated. A similar expression would hold for $\psi_i^{c-}(k)$.

2.1.4 Asymmetry and State dependence

With asymmetry and state dependence in response to credit shocks, the matrix $\boldsymbol{\Psi}_k^{+}$ becomes $\boldsymbol{\Psi}_k^{+}(z_{t-k})$, i.e., the impulse response to a positive shock depends on some indicator variable z_t, capturing for instance the state of the business cycle. And similarly for $\boldsymbol{\Psi}_k^{-}$.

To construct a model that allows for both asymmetry and state dependence while preserving parsimony, we build on the asymmetric GMA(N) model (6) and allow $a_{i,n}^{+}$, the loading on each Gaussian function, to be a linear function of the state, i.e.

$$\begin{cases} \psi_i^{c+}(k, z_{t-k}) = \sum_{i=1}^{N} a_{i,n}^{+}(z_{t-k}) e^{-\left(\frac{k-b_{i,n}^{+}}{c_{i,n}^{+}}\right)^2} \\ a_{i,n}^{+}(z_{t-k}) = \alpha_{i,n} + \beta_{i,n}^{+} z_{t-k} \qquad \forall k > 0 \end{cases}, \tag{7}$$

where now $\alpha_{i,n}$, $b_{i,n}$, $c_{i,n}$, and $\beta_{i,n}$ are the parameters to be estimated. An identical functional form holds for ψ_i^{c-}.

Note that in specification (7), the state of the cycle is allowed to expand/shrink the loading on each Gaussian basis function, but the Gaussian basis functions are themselves fixed (the b and c parameters do not depend of z_t). While one could allow for a more general model in which all parameters a, b and c depend on the indicator variable, specification (7), with limited sample size, it is necessary to impose some structure on the data. Imposing fixed basis functions is a reasonable and parsimonious starting point.[12]

2.2 Data and Identifying Assumption

Our baseline specification uses four endogenous variables: (i) the log-difference of industrial production, (ii) CPI inflation, (iii) the excess bond premium, and (iv) the effective federal funds rate.

$$\boldsymbol{y_t} = [\Delta log(IP_t), \Delta log(CPI_t), EBP_t, FFR_t]$$

We use monthly data covering 1973 to 2015 - the longest time span for which the excess bond premium is available. Our choice of variables corresponds closely to Mueller (2007), Gilchrist and Zakrajsek (2011), and the SVAR analysis in Boivin et al. (2013). The Gilchrist-Zakrajsek excess bond premium (EBP) serves as our measure of credit supply conditions. Figure 1 plots the evolution of the excess bond premium from 1973 to 2015. Intuitively, the excess bond premium can be thought of as a credit spread net of expected defaults, liquidity risk, and prepayment risk. It captures the effective risk bearing capacity of the financial sector and hence credit supply. The Appendix provides a more detailed description of the EBP and its construction.

To identify credit supply shocks, we follow Mueller (2007), Gilchrist and Zakrajsek (2012), Boivin et al. (2013), and we use the short-run restriction that macroeconomic variables can only react with a lag to credit supply shocks while the fed funds rate can react contemporaneously.

To make use of post-2008 data, we must address the fact that the federal funds rate is at the zero lower bound and therefore no longer captures variations in

[12]Importantly, this assumption is easy to relax or to evaluate by model comparison using posterior odds ratios.

the stance of monetary policy: While the Federal Reserve engaged in expansionary policies through forward guidance and quantitative easing (starting in March 2009), the federal funds rate remained unchanged at zero, therefore (wrongly) signaling no change in the monetary policy stance. We address this issue in two ways. First, we use the shadow federal funds rate of Wu and Xia (2014) as a measure of the monetary policy stance.[13] Second, we check the robustness of our results by estimating our specifications using only data from 1973 to 2007 to avoid the zero lower bound period.

2.3 Estimation

We now briefly describe how we use Bayesian methods to estimate a multivariate linear GMA(N) model with a short-run restriction. More details (especially on the straightforward extension to nonlinear models) are available in Barnichon and Matthes (2016).

The key to estimating a moving-average model (1) is the construction of the likelihood function $p(\boldsymbol{y}^T|\boldsymbol{\theta}, z^T)$ of a sample of size T for a moving-average model with parameter vector $\boldsymbol{\theta}$ and where a variable with a superscript denotes the sample of that variable up to the date in the superscript. For the indicator vector z_t, we will consider here that it is a function of lagged values of $\boldsymbol{y_t}$ (as will be the case in the empirical application).

We use the prediction error decomposition to break up the density $p(\boldsymbol{y}^T|\boldsymbol{\theta}, z^T)$ as follows:[14]

$$p(\boldsymbol{y}^T|\boldsymbol{\theta}) = \prod_{t=1}^{T} p(\boldsymbol{y}_t|\boldsymbol{\theta}, \boldsymbol{y}^{t-1}). \tag{8}$$

Then, to calculate the one-step-ahead conditional likelihood function $p(\boldsymbol{y}_t|\boldsymbol{\theta}, \boldsymbol{y}^{t-1})$, we assume that all innovations $\{\boldsymbol{\varepsilon_t}\}$ are Gaussian with mean zero and variance one, and we note that the density $p(\boldsymbol{y}_t|\boldsymbol{y}^{t-1}, \boldsymbol{\theta})$ can be re-written as $p(\boldsymbol{y}_t|\boldsymbol{\theta}, \boldsymbol{y}^{t-1}) = p(\boldsymbol{\Psi}_0\boldsymbol{\varepsilon_t}|\boldsymbol{\theta}, \boldsymbol{y}^{t-1})$ since

$$\boldsymbol{y}_t = \boldsymbol{\Psi}_0\boldsymbol{\varepsilon}_t + \sum_{k=1}^{K} \boldsymbol{\Psi}_k\boldsymbol{\varepsilon}_{t-k}. \tag{9}$$

[13]The shadow rate is the hypothetical level of a federal funds rate not constrained by the zero lower bound, given the level of asset purchases and forward guidance. Wu and Xia (2014) construct an estimate of the shadow rate from the observed Treasury yield curve, i.e., by finding the level (positive or negative) of the policy rate that would generate the observed yield curve. See also Krippner (2014).

[14]To derive the conditional densities in decomposition (8), our parameter vector $\boldsymbol{\theta}$ thus implicitly also includes the K initial values of the shocks: $\{\boldsymbol{\varepsilon}_{-K}...\boldsymbol{\varepsilon}_0\}$. We will keep those fixed throughout the estimation and discuss our initialization below.

Since the contemporaneous impact matrix is a constant, $p(\boldsymbol{\Psi}_0\boldsymbol{\varepsilon}_t|\boldsymbol{\theta}, \boldsymbol{y}^{t-1})$ is a straightforward function of the density of $\boldsymbol{\varepsilon_t}$.

To recursively construct $\boldsymbol{\varepsilon_t}$ as a function of $\boldsymbol{\theta}$ and $\boldsymbol{y}^t$, we need to uniquely pin down the value of the components of $\boldsymbol{\varepsilon_t}$, that is we need that $\boldsymbol{\Psi}_0$ is invertible. We impose this restriction by only keeping parameter draws for which $\boldsymbol{\Psi}_0$ is invertible. It is also at this stage that we impose the identifying restriction: We order the variables in $\boldsymbol{y}$ such that the EBP is ordered third – after output growth and inflation, but before the fed funds rate – and we impose that for the last two columns of $\boldsymbol{\Psi}_0$ the elements above the diagonal are filled with zeros.[15] Finally, to initialize the recursion, we set the first K values of $\boldsymbol{\varepsilon}$ to zero.[16,17]

We use flat (improper) priors, and to explore the posterior density, we use a Metropolis-within-Gibbs algorithm (Robert and Casella, 2004) with the blocks given by the different groups of parameters in our model; a, b, and c. Using a flat prior allows us to interpret our results as outcomes of a maximum likelihood estimation. To initialize the Metropolis-Hastings algorithm in an area of the parameter space that has substantial posterior probability, we follow a two-step procedure: first, we estimate a standard VAR using OLS on our data set, calculate the moving-average representation, and we use the impulse response functions implied by the VAR as our starting point.[18] In the nonlinear models, we initialize the parameters capturing asymmetry and state dependence at zero (i.e., no nonlinearity). This approach is consistent with the starting point (the null) of this paper: shocks have linear effects on the economy, and we are testing this null against the alternative that shocks have nonlinear effects.

3 Results

This section presents our empirical results. We begin by looking at the effects of credit supply shocks in a linear model to derive some intuition and to use as a benchmark for what follows. In the next step, we allow for asymmetry and let credit supply shocks generate different impulse responses depending on the sign of the shock. We then add state dependence to the model and allow the effect of a credit supply shock to depend on the state of the business cycle at the time of

[15]Note that all our results are robust to interchanging the ordering of the financial variables, i.e. ordering the EBP last.

[16]Alternatively, we could use the first K values of the shocks recovered from a structural VAR.

[17]When K, the lag length of the moving average (1), is infinite, we truncate the model at some horizon K, large enough to ensure that the lag matrix coefficients $\boldsymbol{\Psi}_K$ are "close" to zero. Such a K exists since the variables are stationary.

[18]Specifically, we set the parameters of our GMA model (the a, b, and c coefficients) to minimize the discrepancy (sum of squared residuals) between the impulse responses implied by the GMA and those implied by the estimated VAR.

the shock. Finally, we check the robustness of our results to using an alternative econometric technique that combines the use of a VAR with Jorda's (2005) Local Projection.

3.1 The Linear Benchmark

As a natural benchmark for our results, we first look at the *linear* effects of credit supply shocks. To do so, we estimate a standard structural VAR using OLS. Following Mueller (2007), Gilchrist and Zakrajsek (2011), and the SVAR analysis in Boivin et al. (2013), we use six lags on our endogenous variables (this is also the lag length implied by the Bayesian information criterium). As discussed above, we use the short-run restriction that macroeconomic variables can only react with a lag to credit supply disturbances while the fed funds rate can react simultaneously. Figure 4 plots the impulse responses to a 1 standard-deviation shock to the EBP - about 0.25 percentage point. Note that although we estimate the model using IP growth rate, for clarity of exposition, we report the impulse response of the level of IP.

As found by Gilchrist and Zakrajsek (2011), an unanticipated increase in the EBP leads to a substantial reduction in output, to a decline in the price level, and to a decline in the federal funds rate. In terms of dynamics, output bottoms out two years after the shock, reaching -1.6 percentage points below trend, and then starts to slowly revert back to its pre-shock level. Three years after the credit supply shock, the effect on output is no longer significantly different from zero. In other words, from our linear estimates we cannot reject that the effect of a credit supply shock is transitory.

3.2 Asymmetric Effects of Credit Supply Shocks

We now study whether credit supply contractions and expansions have asymmetric effects on the economy. To do this, we directly estimate the moving-average representation (5) and parametrize the impulse responses with a GMA. We use a GMA(2) model –two Gaussian functions per impulse response– as a likelihood-ratio test favors a GMA(2) over a GMA(1) (Table 1) or a GMA(3) (not shown). A GMA(2) is particularly relevant here, because it allows us to capture the mean-reverting pattern of output. As a illustration, Figure 5 shows that a GMA(2) achieves a very good approximation of the linear VAR-based impulse responses, and Figure 6 describes how we combine the two Gaussian functions to achieve the GMA(2) parametrization of the impulse responses. This fit to the VAR-based impulse responses is used as initial guess in our Metropolis-Hastings algorithm. We truncate the moving-average process after $K = 100$ months and use a recursive identification scheme as described in Section II. B.

Allowing for asymmetric effects of credit shocks leads to a large improvement in the goodness of fit of the model. Table 1 summarizes the log likelihood of alternative GMA models, and we can see that allowing for asymmetric effects substantially increases the log likelihood (comparing columns (1) and (2)). Since the GMA models are nested, we can compare them with likelihood-ratio tests, and we can reject the symmetric GMA model in favor of the asymmetric GMA model.

Figure 7 presents the estimated impulse responses of credit supply shocks. The thick lines are posterior mode estimates and the shaded areas cover 90% of the posteriors probability, and the thick dashed lines are the VAR-based impulse responses plotted as a benchmark. The left panel shows the impulse responses following a credit supply contraction (an increase in the EBP), and the right panel shows the impulse responses following a credit supply expansion (a decrease in the EBP). When comparing impulse responses to positive and negative shocks, it is important to keep in mind that the impulse responses to expansionary credit shocks (a decrease in the EBP) were multiplied by -1 in order to ease comparison across impulse responses. With this convention, when there is no asymmetry, the impulse responses are identical in the left panel (responses to a contractionary credit shock) and in the right panel (responses to an expansionary credit shock). Finally, in order to facilitate the interpretation of the results, the magnitude of the credit shock is chosen to generate the same initial effect on EBP regardless of the sign of the shock.

Credit supply shocks have strongly asymmetric effects. A *contractionary* credit supply shock leads to a large and persistent decline in industrial production. While the linear estimate suggests that output starts to revert back to its initial level two years after the shock, our estimate suggests that output keeps dropping until six years after the shock, eventually stabilizing around -2.2 percentage points below its pre-crisis level. We find no sign that output reverts back to the pre-crisis level, and our confidence bands reject the null of no long-run effect. In contrast, an *expansionary* credit supply shock has no significant effect on output, both in the short run and in the long run. Interestingly, the impulse responses of the EBP to positive and negative shocks are similar, so that the asymmetry does not appear to be driven by different impulse responses of EBP to positive and negative credit shocks.

3.3 Effects on Other Selected Variables

To get a more nuanced perspective on the effects of credit supply shocks on the economy, we now explore the asymmetric impulse response functions of four additional macroeconomic variables: personal consumption expenditures (C), business fixed investment (I), the unemployment rate (U), and business investment in research and development (R&D).[19]

To study the effects of credit supply shocks on variables not included in $\boldsymbol{y_t}$, we proceed as follows. First, we extract the structural shocks to credit supply, denoted $\{\hat{\varepsilon}_t^c\}$, that we identified from our baseline specification.[20]

Second, we directly estimate a univariate model - a univariate GMA - capturing the impulse response of our selected variables. Denoting y_t a variable of interest, we estimate

$$y_t = \sum_{k=0}^{K} \psi^c(k)\hat{\varepsilon}_{t-k}^c + u_t, \tag{10}$$

where $\psi^c(k)$ captures the impulse response functions to the credit supply shock and u_t is the residual. Since the u_ts are likely to be serially correlated, in order to improve efficiency, we will allow for serial correlation in u_t by positing that u_t follows an AR(1) process. Then, we use Gaussian Mixture Approximations as in equation (4) to parametrize the impulse responses. We again estimate a GMA(2) model - to have enough flexibility to capture the (potentially) mean-reverting pattern of our variables - and truncate the moving-average process after $K = 100$ months. As a linear benchmark, we estimate a linear GMA(2) model.

Figure 8 summarizes our results and again shows very asymmetric impulse responses to credit supply shocks. The effect of a credit supply contraction on consumption, investment, R&D spending, and unemployment is larger than implied by the linear estimates. It is also very persistent, with the responses of consumption, investment, and R&D spending displaying no mean-reverting pattern. In contrast, credit supply expansions have no significant effect on all four variables, and the response of consumption and investment display a mean-reverting pattern.

The strong and persistent adverse effect of credit supply contractions on R&D spending is interesting and deserves further exploration. While the response of R&D spending could be driven solely by the strong decline in output, the behavior of R&D also provides a natural link from business cycle fluctuations to long-term economic performance. For instance, it has been argued that adverse transitory shocks that lower R&D spending can inhibit economic performance in the long run (see e.g. Comin and Gertler, 2006; Bianchi and Kung, 2015). In this context, a decline in R&D spending could cause a persistent decline in output.

3.4 Excluding the Zero Lower Bound period

As a robustness check, we re-estimate our model excluding data from the global financial crisis and the period in which the nominal interest rate was at the zero

[19] We use private domestic investment in research and development.

[20] More specifically, the Bayesian estimation of the vector-GMA model described by equation (5) and (6) delivers a posterior distribution of the $\{\hat{\varepsilon}_t^c\}$ shocks.

lower bound. That is, we estimate our same benchmark specification using data over 1973-2007 only.[21]

Our key results remain unchanged, and the impulse responses are very similar. The only quantitative difference (not shown) is that the decline in output following a credit supply contraction is smaller; being about 0.5 percentage point lower in the linear model or in the asymmetric GMA(2) model.

3.5 Credit Supply Shocks and State Dependence

We now extend our model by allowing the effect of credit supply shocks to also depend on the state of the business cycle. That is, we estimate the vector moving average (5) using a GMA model with asymmetry and state dependence as in (7). For our cyclical indicator, z_t, we use the 12-month moving average growth rate of industrial production (see Figure 9).[22]

Table 1 shows that adding state dependence to the model significantly improves the goodness of fit, and a likelihood-ratio test favors the model featuring both asymmetry and state dependence against a model with asymmetry only.

To visualize how the state of the business cycle affects the response of the economy to credit shocks, Figure 10 shows how the peak response of output growth and inflation depend on the (annual) growth rate of Industrial Production (IP) at the time of the shock.[23] To understand intuitively the effect captured by Figure 10, it is useful to go back to Figure 3 that illustrates an impulse response with an oscillating pattern, which is typical of the response of output growth: following an adverse shock, output growth is initially negative and then turns positive as output reverts (at least partially) to its pre-shock level. Figure 10 plots how the minimum of the first Gaussian (the red line in Figure 3) changes with the state of the business cycle. The first Gaussian can be interpreted as capturing the first-round (or short-run) effect of the credit shock, and Figure 10 shows how the magnitude of the short-run effect of a shock varies with the state of the cycle.

The peak effects of contractionary credit shocks are plotted in the left panels and the peak effects of expansionary credit shocks in the right panels. In addition, the bottom panels of Figure 10 plot the histograms of the distributions of respec-

[21]We do this for two reasons. First, the 2007-2008 financial crisis constituted an exceptional disruption in the credit markets, which could be driving our results. Second, after December 2008 the federal funds rate no longer captures the stance of monetary policy. While we addressed this problem using Wu and Xia's (2014) shadow federal funds rate as our measure of the monetary policy stance, this approach has its own limitations (Krippner, 2014).

[22]In our sample, the mean growth rate of industrial production is 2.6% with a standard deviation of 4.1%.

[23]To be specific, for a variable i with impulse response $\psi_i^c(k,z)$ at horizon k when the indicator variable takes the value z, we plot the function defined by $f_i(z) = \max_{k\in[0,K]} |\psi_i^c(k,z)|$.

tively contractionary shocks and expansionary shocks over the business cycle. This information is meant to get a sense of the range of our indicator variable (annual IP growth rate) over which we identify the coefficients capturing state dependence.

Our main conclusions are (i) regardless of the sign of the shock, the effect of credit shocks on output is stronger in recessions, and (ii) contractionary credit shocks always have stronger effects than their expansionary counterparts. Regarding the response of inflation, we find no significant effect of the state of the cycle.

Looking at the left upper panel of Figure 10, we can see that contractionary credit supply shocks have very severe effects on output growth during recessionary periods but have only mild effects during expansionary periods. In fact, the posterior probability bands show that we cannot reject that negative credit supply shocks have no effect on output growth during large expansions, i.e. if annual IP growth surpasses 5%. Similarly, the right upper panel shows that an expansionary credit supply shock has a larger effect if the economy is in a recession but has no significant effect on output growth during "normal" times. The asymmetry between positive and negative shocks is still present however, and expansionary shocks always have smaller effects than their contractionary counterparts. For instance, while an expansionary credit supply shock does have a significant positive impact on economic activity if the economy is in a recession, the effect remains limited. Even during severe recessionary periods (IP growth lower than -4%), the peak effect of an expansionary shock on output growth (of about 1 percent) remains lower than implied by the average effect implied by (linear) VAR estimates (about 1.4 percent), and substantially (and significantly) lower (in absolute value) than the effect of a contractionary shock (about 2 percent in absolute value).

To illustrate the effects of state dependence from a different angle, Figure 11 shows how the impulse response of output depends on the state of the business cycle. Compared to Figure 10 (focused on the first-round effect of the shock), Figure 11 plots the cumulative impulse response of output growth, so that we can also visualize how the longer-run effects of a credit shock depend on the state of the cycle. Again, the impulse responses to expansionary credit shocks (right-hand panels) were multiplied by -1 in order to ease comparison across impulse responses.

Our main conclusion is that contractionary credit shocks have strong and persistent effects on output during recessionary periods. The top panels show the impulse responses of output to a shock occurring during a recessionary period, i.e. when output growth is -2%. During recessions, contractionary credit shocks have particularly large and persistent effects on output. The posterior probability bands comfortably exclude zero, indicating that output does not revert to its pre-crisis trend five years after the shock. Expansionary credit shocks have a significant effect on output when the shock occurs during a deep recession, although the effect remains smaller than that of the corresponding contractionary shock and one cannot reject that output mean-reverts to its pre-shock level.

The bottom panels show the impulse responses of output to a shock occurring during a large economic expansion, i.e. when annual IP growth is at 5%. The effects of the credit shock on output are now muted: Credit supply contractions no longer have a significant adverse effect on output in the longer run. Credit supply expansions have no effect on output during large expansions.

4 Robustness Check: Local Projections

To the best of our knowledge, the GMA approach used in this paper is the only operational way of identifying structural shocks when the Data Generating Process (DGP) is nonlinear with asymmetric impulse responses.[24]

However, since our approach relies on the parametrization of the impulse response functions with Gaussian basis functions, in this section, we examine the robustness of our results to this parametrization. The idea of the robustness check is to not rely on a GMA but instead to use a nonparametric method –Jorda's (2005) Local Projections (LP)– which imposes little structure on the data-generating process (DGP) and is thus more robust to misspecification than a GMA model (at the cost of efficiency). The drawback of this approach is that it requires a series of previously identified credit shocks.

We thus use an "hybrid VAR-LP" procedure that proceeds in two steps: First, we estimate a standard structural VAR as described in Section V.A. to identify structural shocks to the supply of credit, denoted $\{\widehat{\varepsilon}_t^c\}$. Second, we estimate the dynamic effects of these shocks using Local Projections, possibly allowing for sign-dependence and state dependence. While such a hybrid VAR-LP procedure is flawed (in fact, not internally consistent since the VAR shocks are identified under

[24]While VARs can accommodate certain types of non-linearities, the asymmetric effect of a shock cannot be answered within a VAR framework. In particular, regime-switching VARs can capture state dependence (whereby the value of some state variable affects the impulse response functions), but they cannot capture asymmetric effects of shocks (whereby the impulse response to a structural shock depends on the sign of that shock). Indeed, with regime-switching VAR models, it is assumed that the economy can be in a finite number of regimes, and that each regime corresponds to a different set of VAR coefficients. However, if the true data generating process features asymmetric impulse responses, a new set of VAR coefficients would be necessary each period, because the (non-linear) behavior of the economy at any point in time depends on all structural shocks up to that point. As a result, such asymmetric data generating process cannot be approximated by a small number of state variables such as in threshold VARs or Markov-switching models. In contrast, by working directly with the structural moving-average representation, GMA models can easily capture asymmetric impulse response functions (as well as state dependence).

the assumption that the DGP is linear), we see it as a useful robustness check of our results based on GMAs. We come back to this point at the end of the section.

To first have a linear benchmark for the effects of credit shocks, we run linear Local Projections, i.e. we estimate H equations

$$y_{t+h} = \alpha_h + \beta_h \widetilde{\varepsilon}_t^c + \gamma' x_t + u_t^h, \qquad h = 0, 1, ..., H \tag{11}$$

where y_{t+h} is the variable of interest, x_t contains 12 lags of y_t, and $\widetilde{\varepsilon}_t$ is our VAR-based estimate of the credit shock at time t. The impulse responses are then given by $\beta^0, \beta^1, ..., \beta^H$. We use an horizon of $H = 60$ months (or 5 years).

To allow for asymmetric effects of credit shocks, we allow for sign dependence in β_h, that is we estimate the H equations

$$y_{t+h} = \alpha_h + \beta_h^+ \widetilde{\varepsilon}_t^{c+} + \beta_h^- \widetilde{\varepsilon}_t^{c-} + \gamma' x_t + u_t^h, \qquad h = 0, 1, ..., H \tag{12}$$

where β_h^+ is the response to a positive credit supply shock $\widetilde{\varepsilon}_t^{c+}$, and β_h^- is the response to a negative credit supply shock $\widetilde{\varepsilon}_t^{c-}$ at horizon h. We estimate (11) and (12) for all the variables considered so far, and Figure 12 summarizes our results for industrial production, the price level (CPI), the excess bond premium, and the federal funds rate, while Figure 13 shows the results for consumption, investment, RD spending, and the unemployment rate.

Overall, the results are very similar to the results obtained with GMA models: the effects of credit supply contractions are larger than implied by linear estimates and highly persistent. Credit supply expansions, on the other hand, have no significant effects on our variables. Quantitatively, we find that our results obtained with Gaussian Mixture Approximations are the more conservative ones, since the hybrid VAR-Local Projection method points to even stronger asymmetries.

We can also add state dependence to the model. As a cyclical indicator we use NBER recession dates,[25] and we estimate the following H equations:

$$y_{t+h} = \alpha_h + \beta_h^{+,R} \widetilde{\varepsilon}_t^{c+,R} + \beta_h^{-,R} \widetilde{\varepsilon}_t^{c-,R} + \beta_h^{+,B} \widetilde{\varepsilon}_t^{c+,B} + \beta_h^{-,B} \widetilde{\varepsilon}_t^{c-,B} + \gamma' x_t + u_t^h, \qquad h = 0, 1, ..., H \tag{13}$$

where B stands for boom and R for recession. Figure 15 summarizes our results for state dependence using the hybrid VAR-LP approach. Again, we find that the results are very similar to the results we obtained from estimating the nonlinear moving average with Gaussian Mixture Approximations: the adverse effects of contractionary shocks are very pronounced during recessions and very mild during expansions.

[25] We use a binary indicator (instead of a continuous indicator as was the case with GMAs) for efficiency reasons.

Figure 15 confirms these results and shows impulse response functions that are similar to the ones reported in Figure 11 using GMAs. Note, however, that the error bands are considerably larger with Local Projection, which reflects the lower efficiency of this approach (see e.g., Ramey, 2012).

We conclude from this robustness exercise that a) nonlinearities in the effects of credit supply shocks are important, and b) our previous conclusions on the asymmetric and state dependent effect of credit shocks do not seem to be driven by the parametric restrictions imposed by Gaussian Mixture Approximations.

As a final remark, note that while the hybrid VAR-LP approach is attractive because it relies only on standard linear regression techniques, it is flawed for two reasons. First, to perform the Local Projection exercise laid out above, one needs to know the structural shocks. Here, we take the shocks identified from the structural VAR as given. They are, however, the result of a first stage estimation and therefore the standard errors obtained from Local Projections are incorrect. Second, if the data are generated by a nonlinear process, a linear model to identify the structural shocks is misspecified and we can not estimate consistently the true structural shocks. To do so, one must explicitly account for the nonlinearities in the data-generating process. These two drawbacks can however be overcome with Gaussian Mixture Approximations.

Despite its shortcomings, we think of the hybrid VAR-Local Projection approach as a useful tool. First, it can be used as a quick test for nonlinearities in the impulse response functions to shocks estimated from a linear VAR. Therefore, one might see it as (visual) test for misspecification in terms of omitted nonlinearities. Second, once structural shocks are estimated from any model (for instance from a VAR or GMAs), Local Projections can be used to examine whether relaxing the dynamic structure (i.e., the parametric restrictions) imposed by the model alters the results substantially.

5 Conclusion

Using a novel econometric technique, we assess whether credit shocks have nonlinear effects, notably asymmetry and state dependence, that have been predicted theoretically but never considered empirically.

We obtain two main results. First, negative shocks to credit supply have large and persistent effects on output, but positive shocks have no significant effect. Second, credit supply shocks have larger and more persistent effects in periods of weak economic growth.

These findings are consistent with the presence of occasionally binding financial constraints and provide important empirical support for the predictions of mainstream models of financial constraints.

With the existence of nonlinearities established from both a theoretical and an empirical perspective, an interesting avenue for future research is to explore the policy implications of such nonlinearities. For instance, as highlighted in a speech by Federal Reserve Governor Jeremy Stein (2014), exploring the implications of the asymmetric effects of financial market disruptions for the conduct of monetary policy is an important goal for research.

Appendix

Credit Spreads and the Excess Bond Premium

A crucial ingredient for our analysis is how we measure conditions in financial markets. Throughout the recent financial crisis credit spread - the difference in yields between corporate debt instruments and government securities with the same maturity - served as a crucial instrument to assess the level of distress in the financial system. This focus is in part motivated by theory[26] and in part by the large literature documenting the substantial predictive power of credit spreads for real economic activity.[27] Credit spreads are believed to convey important information about the availability of credit from financial intermediaries (see e.g. Gertler and Karadi, 2009) and the risk sentiment of households and financial intermediaries (Heaton and Lucas, 1997; Fernanded-Villaverde et al. 2009; Kim, 2009; Christiano et al., 2010). However, a crucial caveat is that traditional credit spreads do not only reflect changes in credit supply: (iii) prepayment and liquidity risk (Duca, 1999), (ii) variations in the net worth of the borrower (Bernanke et al. 1999), and (iii) anticipation of defaults (Phillippon, 2009), are also reflected.

In an important recent paper, Gilchrist and Zakrajsek (2012, henceforth GZ) address these issues by using a bottom-up approach. GZ use a large panel of corporate bonds issued by US non-financial firms[28]. They make a careful selection of corporate bonds that do not have embedded options or are highly illiquid, thus eliminating (i) prepayment risk and liquidity risk from their credit spread index. For each corporate bond, they construct a hypothetical risk free counterpart that mimics precisely the cash flow of the the corporate bonds and is discounted using continuously compounded zero-coupon Treasury yields. The bond spread of bond k of firm i at time t is then simply the difference in yield between the corporate bond and its risk free counterpart, i.e.

$$S_{it}(k) = y_{it}(k) - y_{it}^{f}(k).$$

In the next step, GZ exploit the micro-level aspect of their data to distinguish between changes that can be attributed to either variations in credit supply conditions or (i) variations in the net worth of borrowers and (ii) the anticipation of

[26] Most notably Blinder (1987), Bernanke et al. (1989), and Kiyotaki and Moore (1997).

[27] Gertler and Lown (1999), Mody and Taylor (2004), and King et al. (2007) show that credit spreads based on "junk" corporate bonds do well in predicting output growth during the 1990s. Gilchrist et al. (2009) construct 20 monthly credit spreads indexes for different maturity and credit risk categories and show that they have significant predictive power for output both in the short and the longer run. Faust et al. (2012) build on Gilchrist et al. (2009) and come to similar conclusions about the predictive content of credit spreads.

[28] The final sample consists of 5882 individual securities issued by 1112 firms.

defaults. They decompose the credit spread into two components: one component capturing default risk and a residual component - the excess bond premium. Using Merton's distance-to-default framework (1974), they obtain a predicted credit spread that captures the default risk of firms. The excess bond premium (EBP) is then simply the difference between the actual and the predicted credit spread, i.e.

$$EBP_{it,t} = S_{it}(k) - \hat{S}_{it}(k).$$

To get an aggregate measure of credit supply conditions, we take the arithmetic average over all spreads.

The EBP can be understood as a credit spread net of i) and ii). Changes in the EBP may reflect 'search-for-yield' - when investors are willing to take on higher risk - and 'flight-to-quality' mechanisms - when investors become more cautious (see. e.g. Fernandez-Villaverde et al., 2009; Kim, 2009). Therefore, it tells us about how much risk financial intermediaries are willing (or able) to take on. Or in other words, it reflects the general risk sentiment and the capacity of financial intermediaries to take on risk. Changes in the risk attitude or the risk-bearing capacity are then likely to lead to adjustments in credit supply (Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2013; Gertler and Karadi, 2011; Brunnermeier and Sannikov, 2014).

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Table 1: Log likelihood of alternative models

	GMA(2) Symmetric	**GMA(1) Asymmetric**	**GMA(2) Asymmetric**	**GMA(2) Asymmetric State Dep.**
	(1)	**(2)**	**(3)**	**(4)**
log likelihood	-3680	-3055	-3029	-3015
LR test		(2) vs (1)	(3) vs (2)	(4) vs (3)
p-value		<0.01	<0.01	<0.01

Note: GMA model with $\Delta log(IP), \Delta log(CPI), EBP, FFR$ estimated with data from 1973 to 2015. (1) is a symmetric model using a two Gaussian parametrization (GMA(2)) of the impulse responses. (2) is a model that allows for asymmetric effects of credit supply shocks using a one Gaussian parametrization (GMA(1)) of the impulse responses. The LR test is between (2) and (1). (3) is a model that allows for asymmetric effects using a two Gaussian parametrization (GMA(2)). The LR test is between (3) and (2). (4) is identical to (3) but also allows for state dependent effects of credit supply shocks.

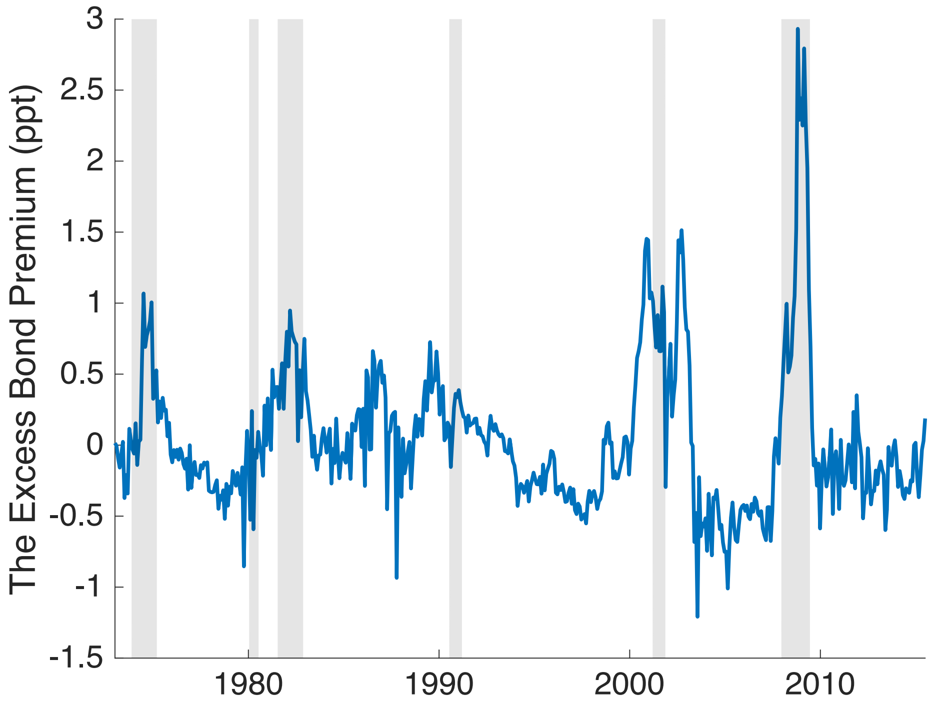

Figure 1: The Excess Bond Premium. Shaded areas mark NBER recession dates.

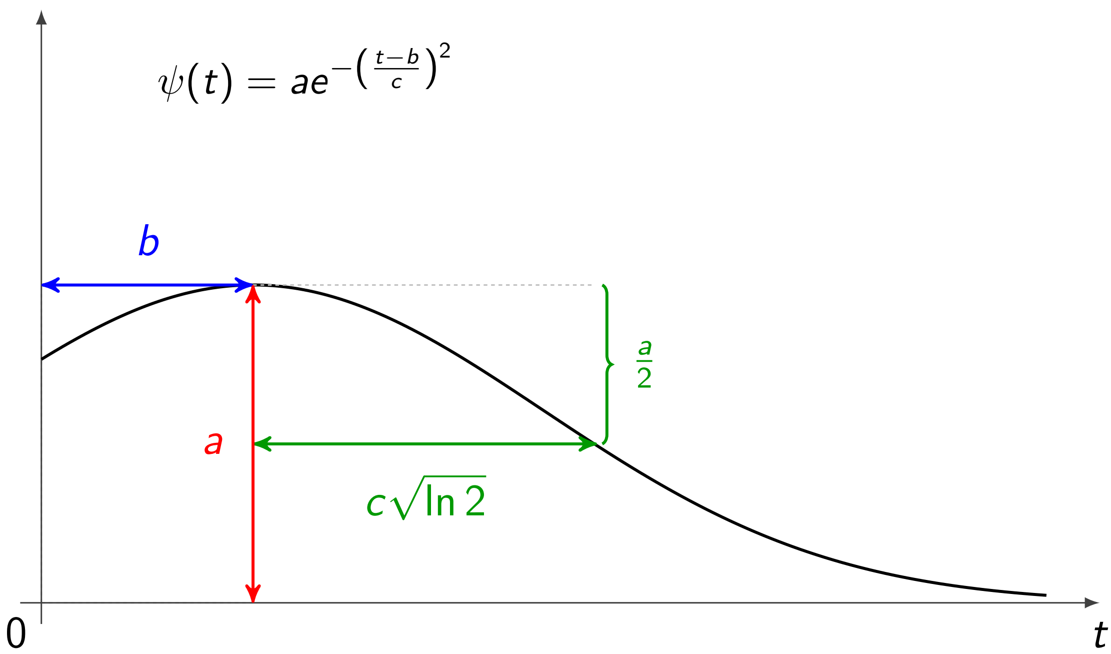

Figure 2: Interpreting an impulse response function with a GMA(1) model.

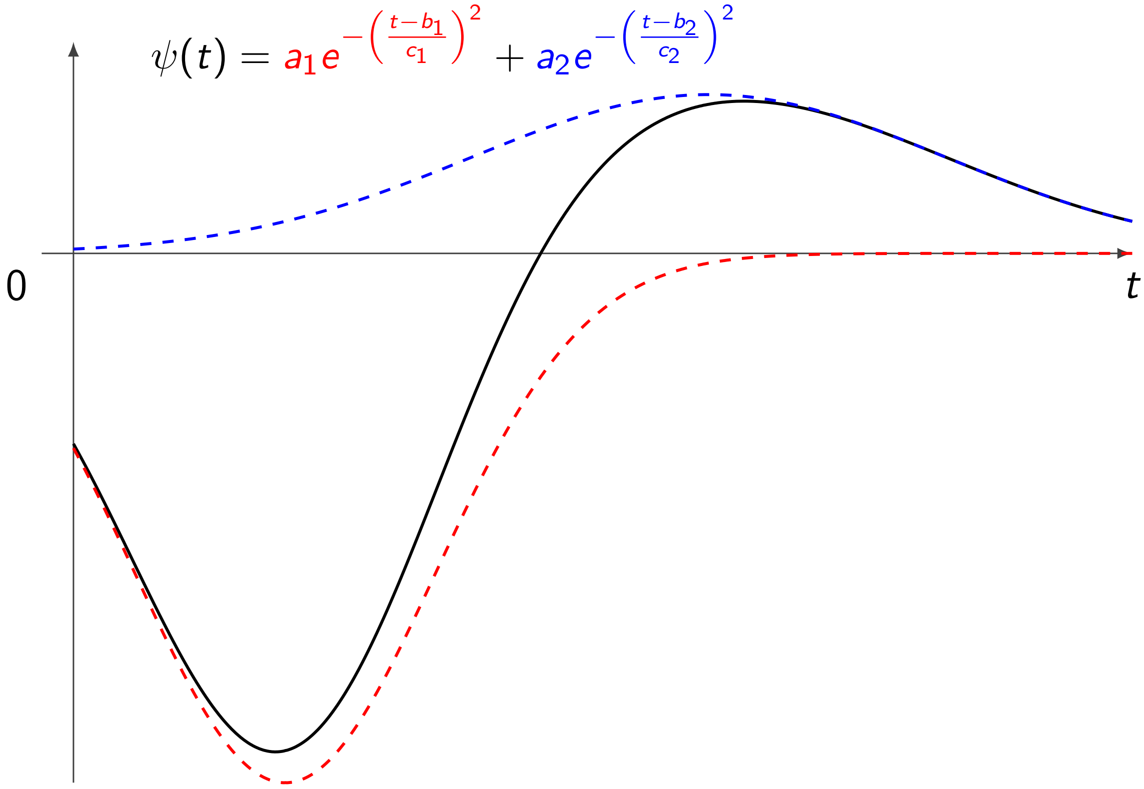

Figure 3: Example of how a GMA(2) model can capture oscillating (or overshooting) patterns.

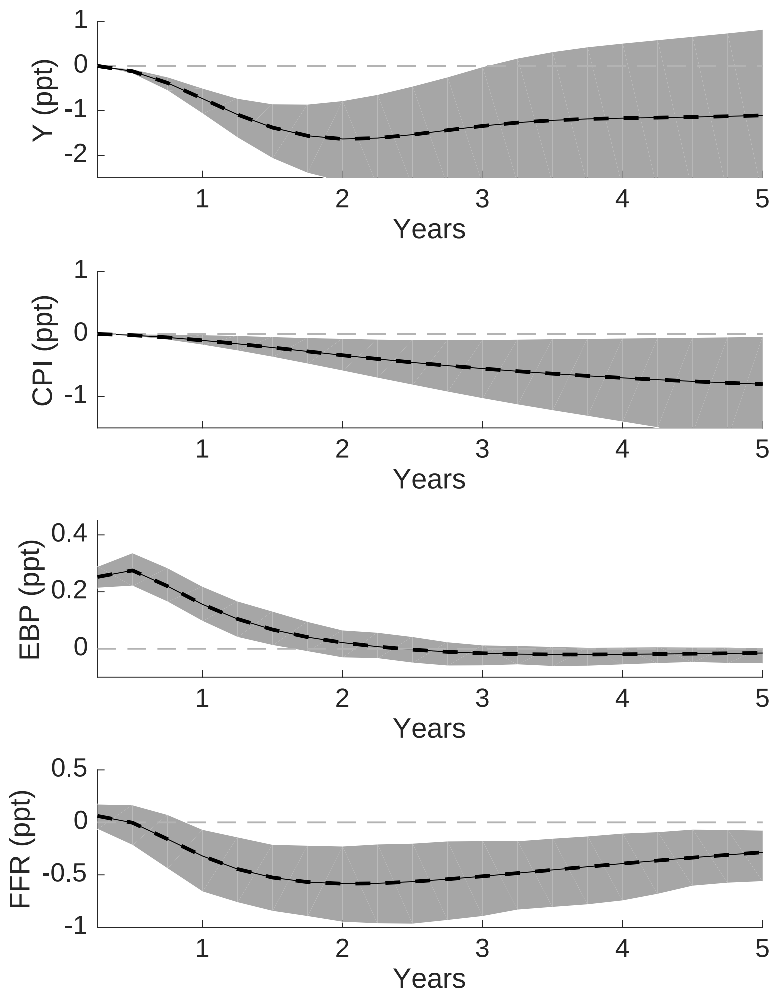

Figure 4: Impulse response function of output (industrial production), the price level (CPI), the excess bond premium (EBP) and the federal funds rate to a one standard-deviation shock to the EBP. Estimation from a structural VAR with recursive identification using data from 1973 to 2015. Shaded areas are 90% confidence bands based on 2000 bootstrap replications.

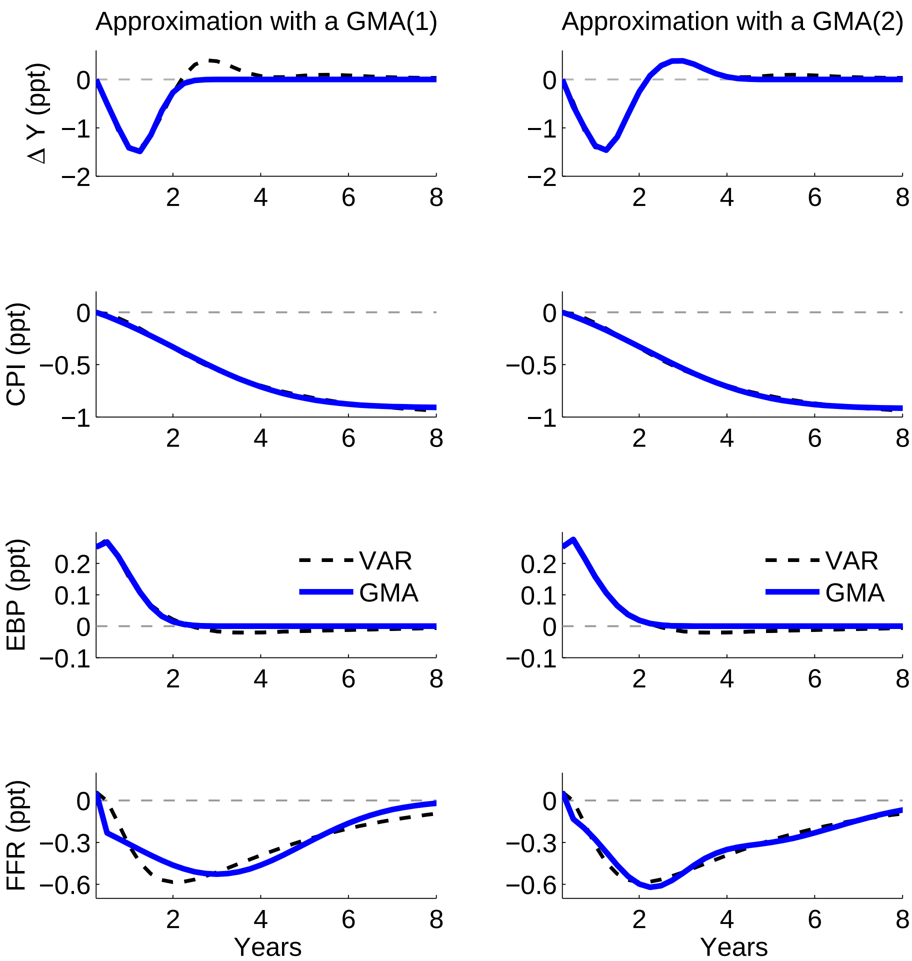

Figure 5: Impulse response function of output (industrial production), the price level (CPI), the excess bond premium (EBP) and the federal funds rate to a one standard-deviation shock to the EBP. Impulse responses estimated with a VAR (dashed line) or approximated using one Gaussian basis function (GMA(1), left panel, thick line) or two Gaussian basis functions (GMA(2), right panel, thick line). Estimation using monthly data from 1973 to 2015.

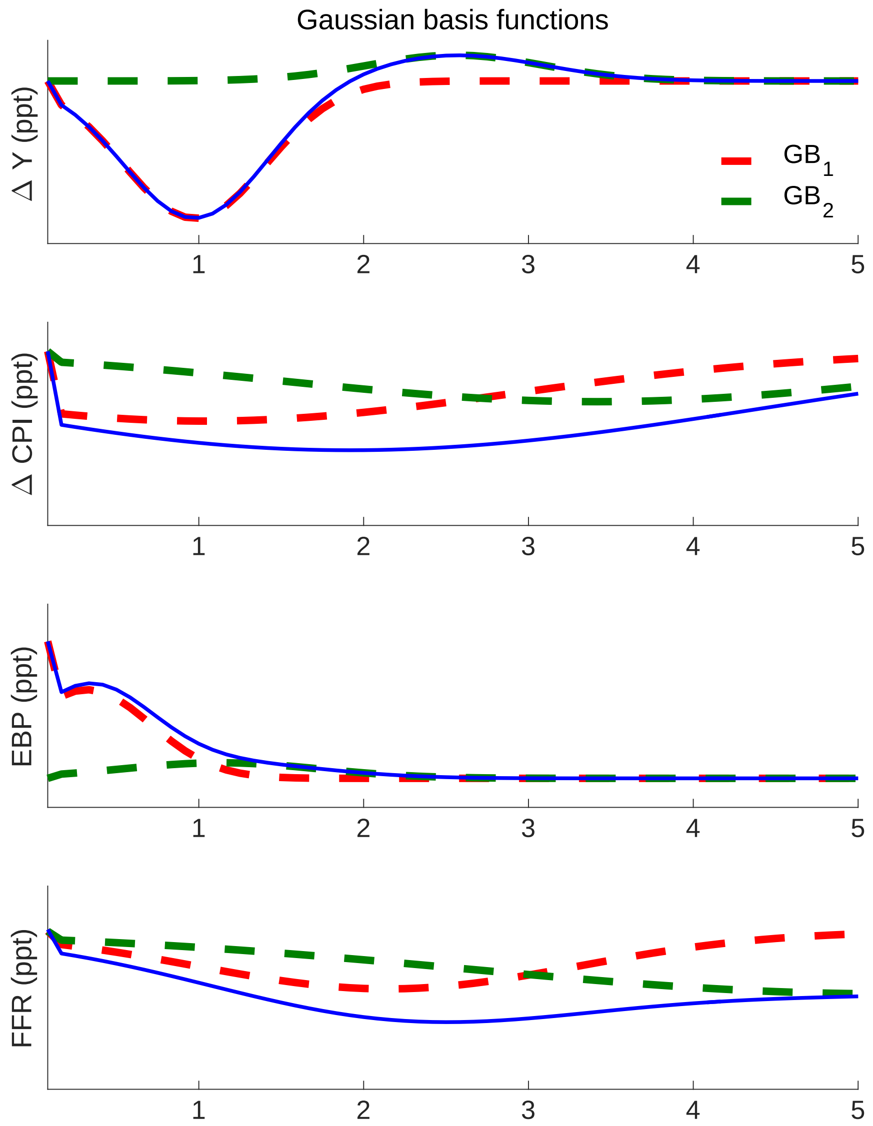

Figure 6: Gaussian basis functions (dashed lines) used by a GMA(2) to approximate the responses of output growth, inflation, the excess bond premium and the fed funds rate to a credit supply shock. The basis functions are appropriately weighted so that their sums gives the GMA(2) parametrization of the impulse response functions (solid lines).

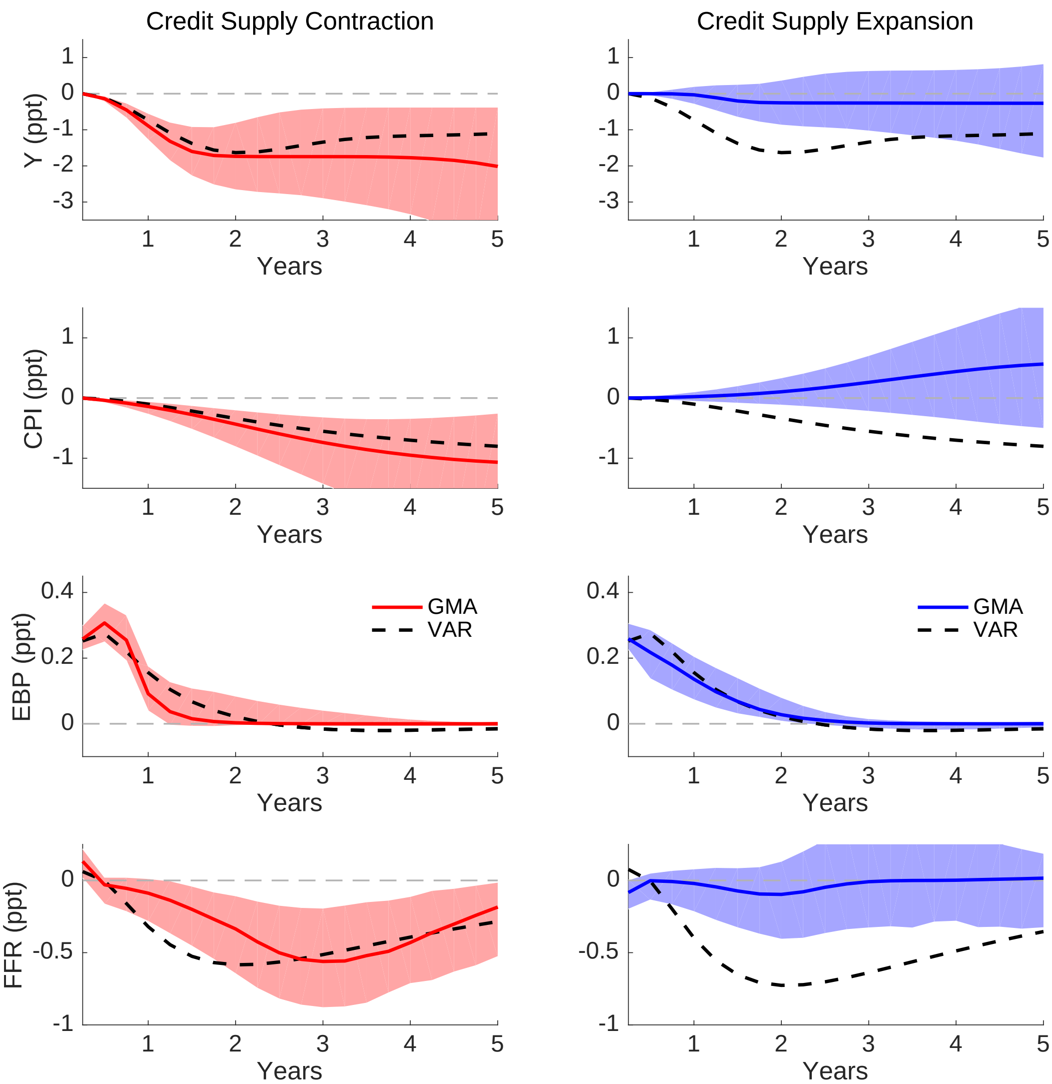

Figure 7: Impulse response functions of output (industrial production), the price level (CPI), the excess bond premium and the federal funds rate to a one-standard deviation shock to the excess bond premium. Estimation from a standard VAR (dashed line) or from a GMA(2) (plain lines). The shaded bands cover 90% of the posterior probability. For ease of comparison between the left and right panels, the responses to an expansionary credit shock (a decline in EBP) are multiplied by -1 in the right panels. Estimation using monthly data covering 1973-2015.

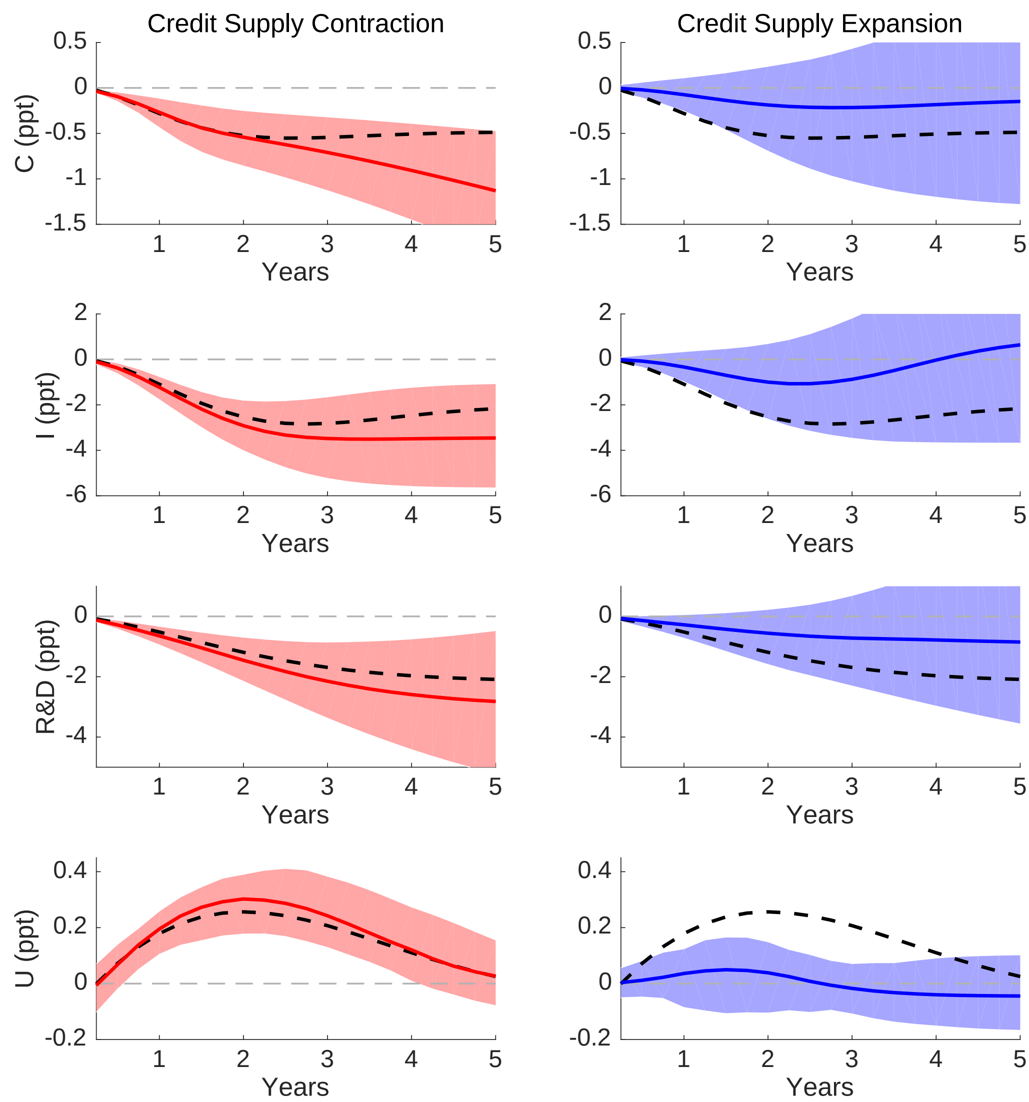

Figure 8: Impulse response functions of business fixed investment (I), personal consumption expenditures (C), business spending in R&D, and the unemployment rate (U) to a one standard deviation shock to the EBP. Estimation from a linear GMA(2) (dashed line) or from an asymmetric GMA(2) (plain lines). The shaded areas cover 90% of the posterior probability. For ease of comparison between the left and right panels, the responses to an expansionary credit shock (a decline in EBP) are multiplied by -1 in the right panels. Estimation using data from 1973 to 2015.

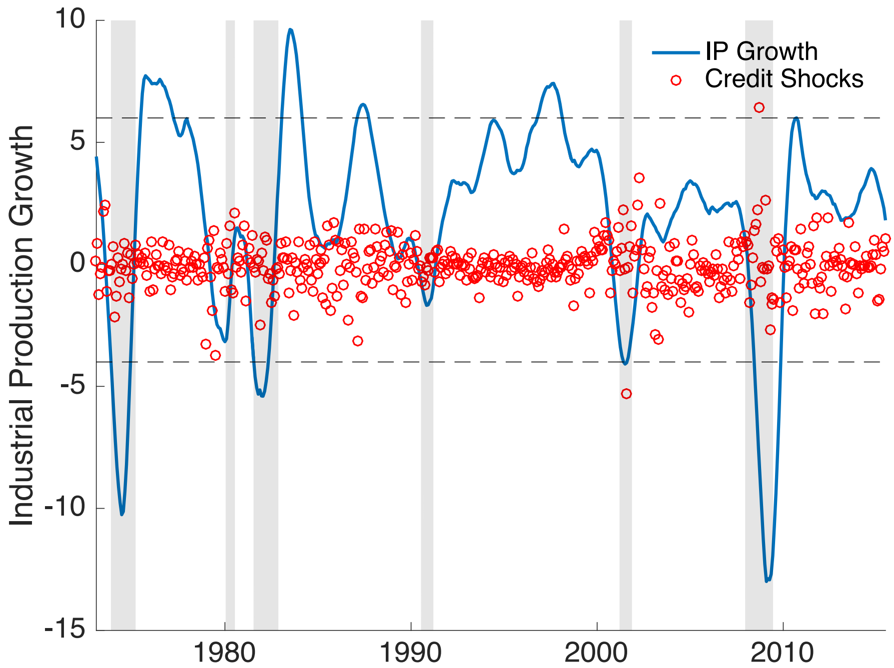

Figure 9: Industrial Production growth rate and Credit Shocks. Credit shocks are multiplied by 10. The dashed lines mark the cutoffs for our state dependence results. Shaded areas mark NBER recession dates.

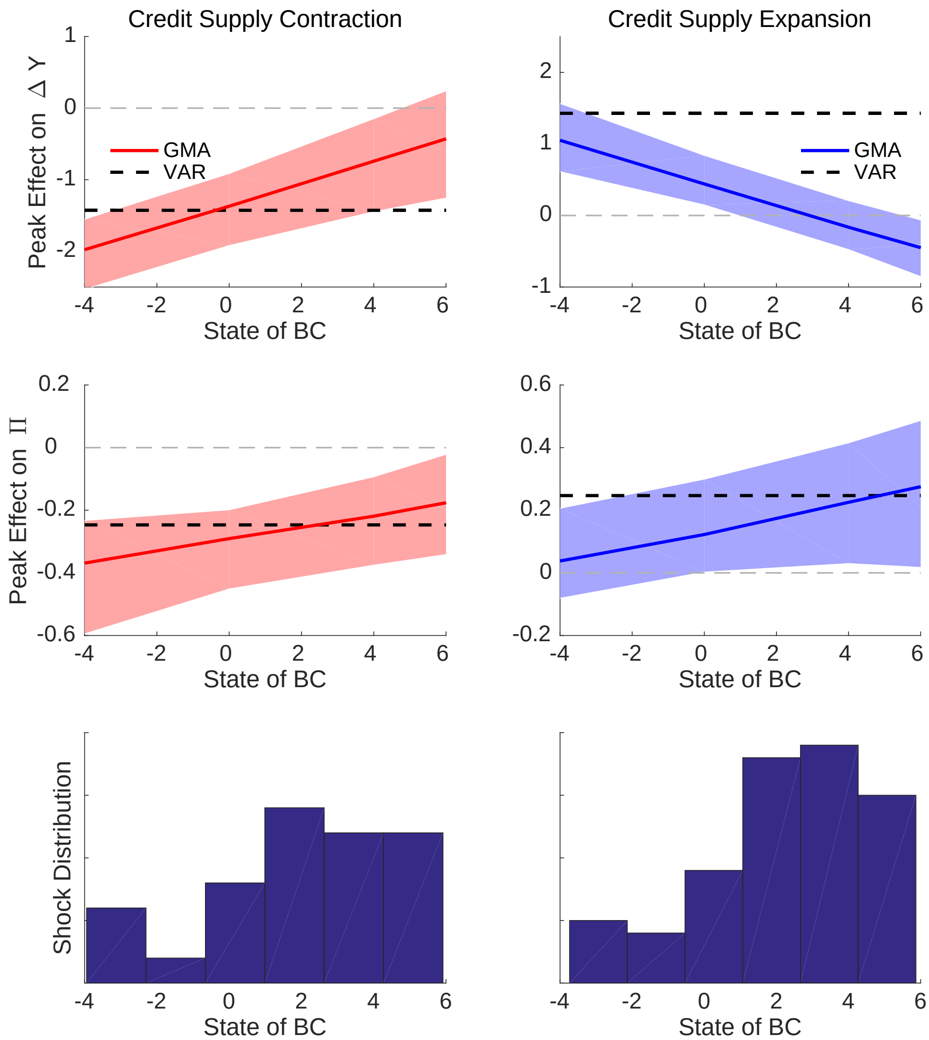

Figure 10: Peak effect of credit supply shocks on output growth (industrial production) and inflation (CPI) as a function of the state of the business cycle (in units of annualized IP growth rate) to a shock to the excess bond premium. Estimation from a standard VAR (dashed line) or from a GMA(2) with asymmetry and state dependence (thick lines). The shaded areas cover 90% of the posterior probability. Estimation using data covering 1973 to 2015.

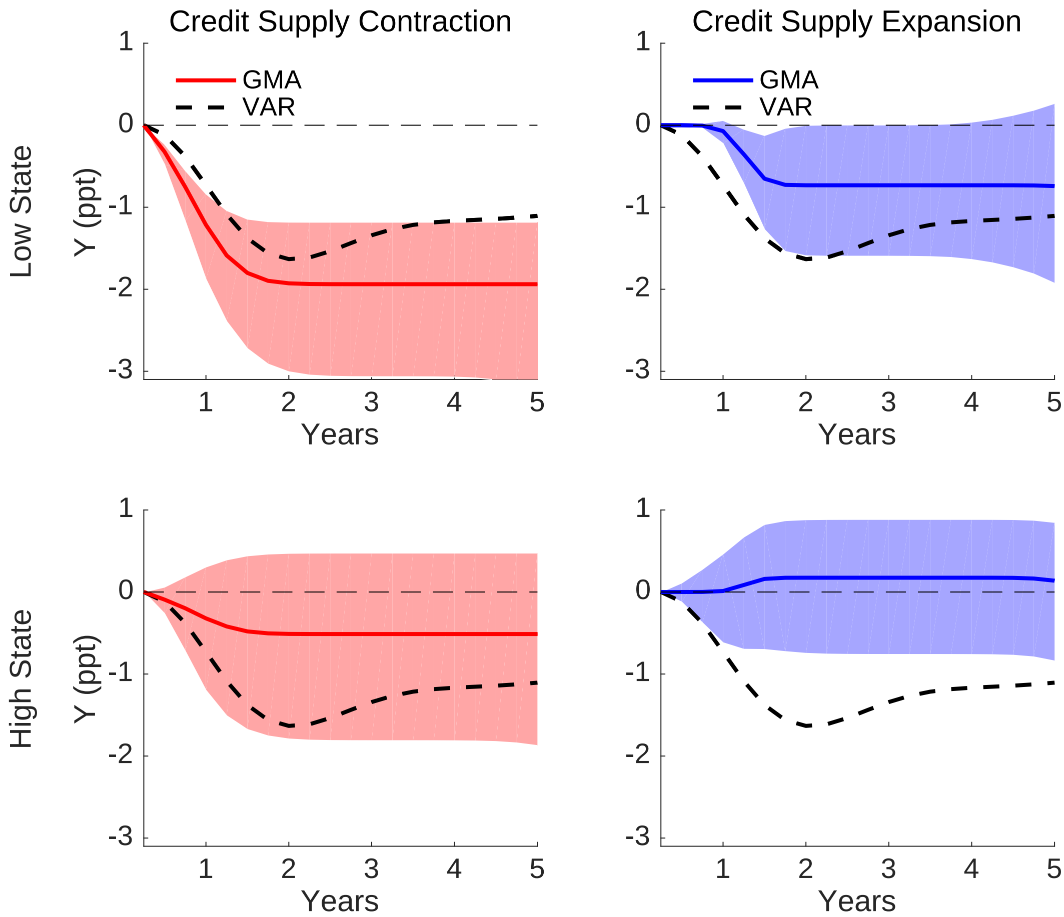

Figure 11: Impulse response functions of industrial production to a one standard deviation shock to the EBP as a function of the state of the business cycle. The top panel plots the impulse responses during recessionary periods (-2% average annual output growth). The lower panel plots the impulse responses during expansionary periods (5% average annual output growth) The shaded areas cover 90% of the posterior probability. The dashed plain black lines depict the estimates from a standard VAR. For ease of comparison between the left and right panels, the responses to an expansionary credit shock (a decline in EBP)– are multiplied by -1 in the right panels. Estimation using data covering 1973 to 2015.

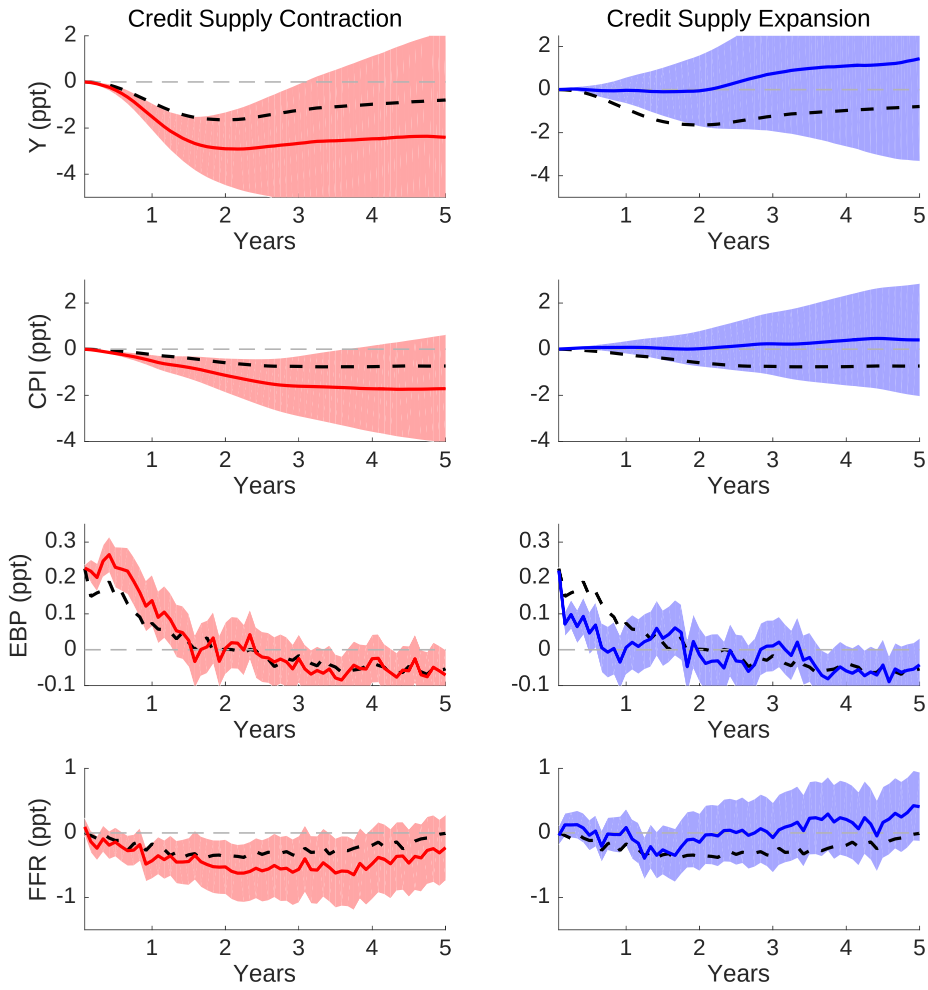

Figure 12: Estimates from hybrid VAR-LP: Impulse response functions of industrial production, the price level, the excess bond premium and the fed funds rate to a one standard deviation shock to the EBP. Results from a symmetric model (dashed line) and from a model allowing for asymmetry (plain lines). The shaded areas span 90% confidence bands calculated using Newey-West standard errors. For ease of comparison between the left and right panels, the responses to an expansionary credit shock (a decline in EBP) are multiplied by -1 in the right panels. Estimation using data covering 1973 to 2015.

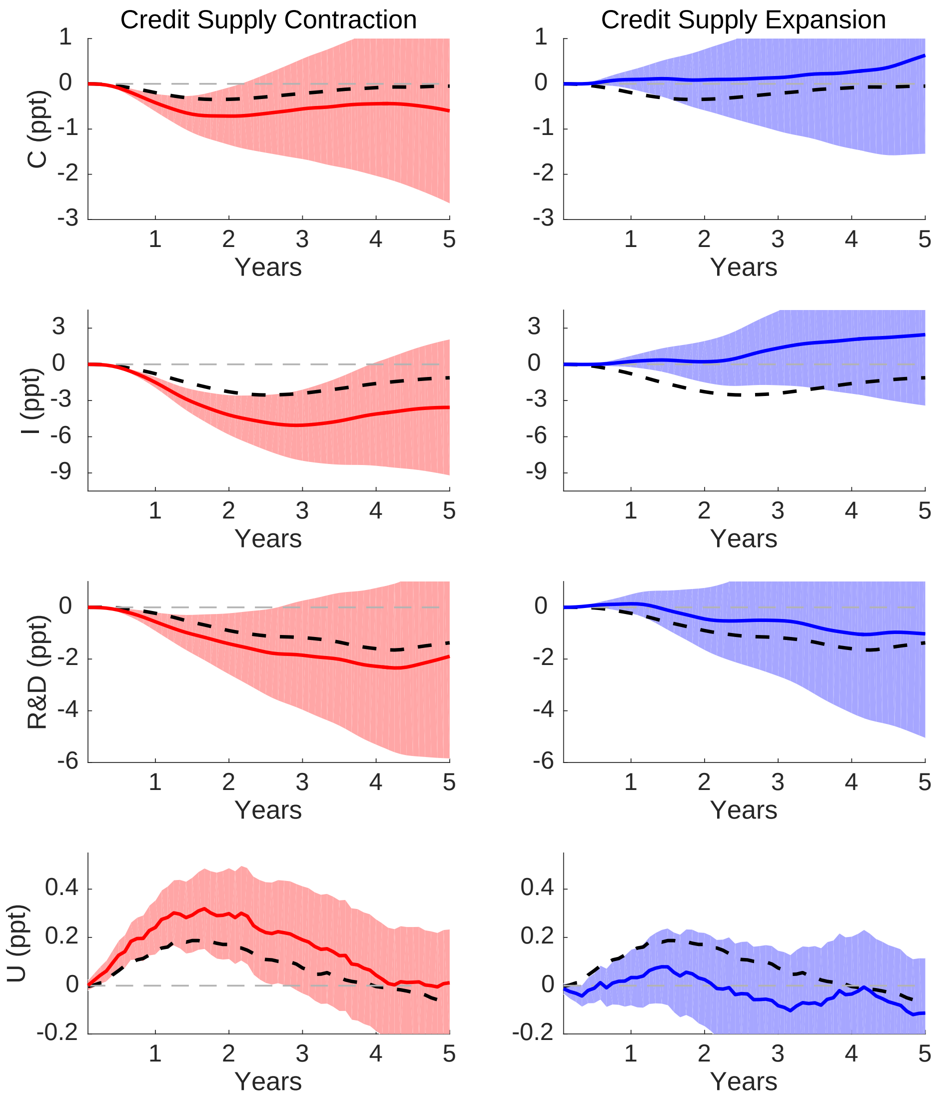

Figure 13: Estimates from hybrid VAR-LP: Impulse response functions of business fixed investment (I), personal consumption expenditures (C), business spending in R&D, and the unemployment rate (U) to a one standard deviation shock to the EBP. Results from a symmetric model (dashed line) and from a model allowing for asymmetry (plain lines). The shaded areas span 90% confidence bands calculated using Newey-West standard errors. For ease of comparison between the left and right panels, the responses to an expansionary credit shock (a decline in EBP) are multiplied by -1 in the right panels. Estimation using data covering 1973 to 2015.

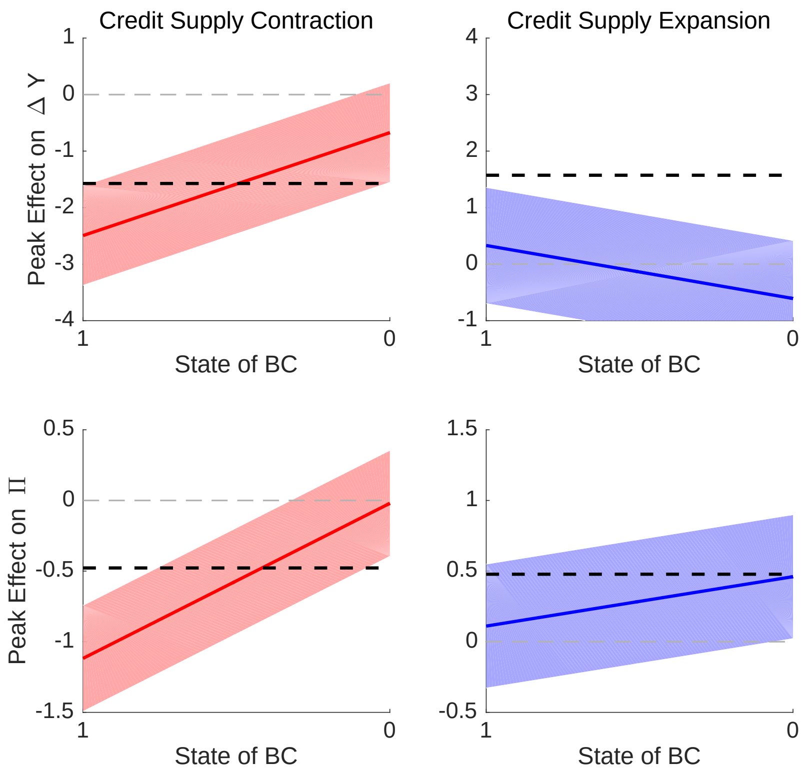

Figure 14: Estimates from hybrid VAR-LP: Peak effect of credit supply shocks on output growth (industrial production) and inflation (CPI) as a function of the state of the business cycle ("1" denotes an NBER recession state, and "0" denotes a non-recession state) in units of annualized IP growth rate) to a shock to the excess bond premium. Results from a linear model (dashed lines) and from a model allowing for asymmetry and state dependence (plain lines). The state of the business cycle are NBER recession dates. Estimation using data covering 1973 to 2015.

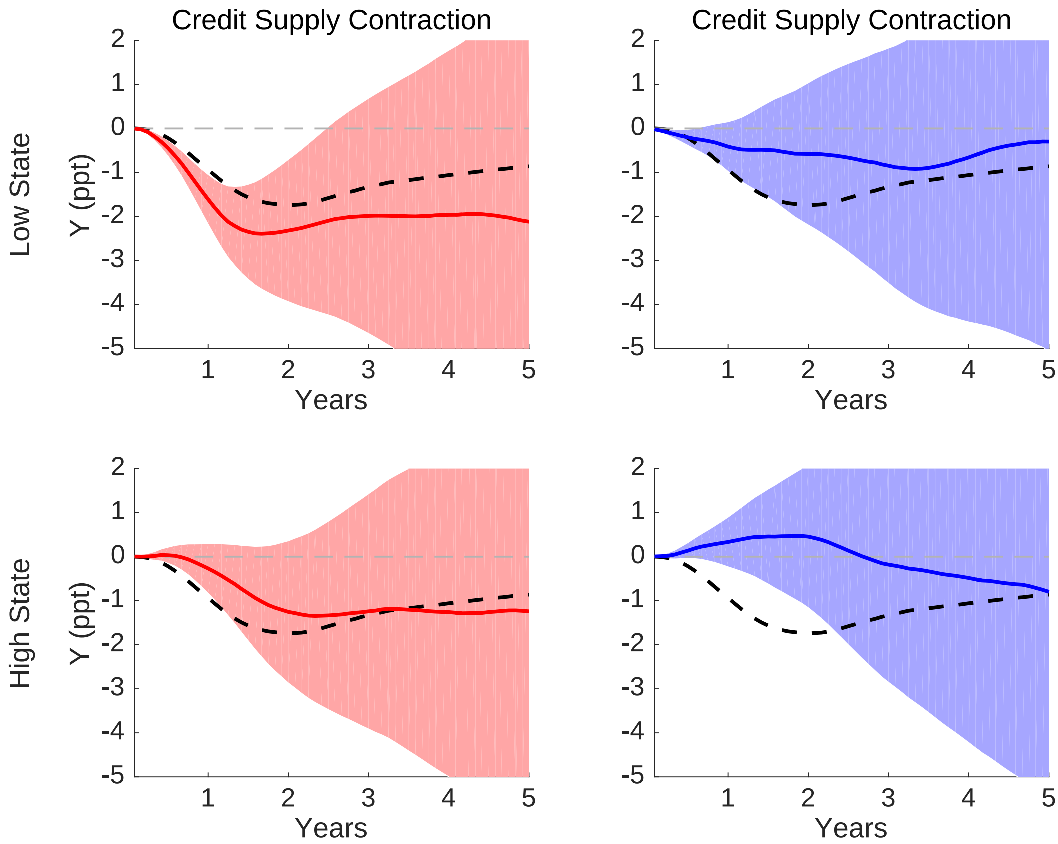

Figure 15: Estimates from hybrid VAR-LP: Impulse response functions of industrial production to a one standard deviation shock to the EBP as a function of the state of the business cycle. The top panel plots the impulse responses during recessionary periods (NBER recessions).The lower panel plots the impulse responses during expansionary periods (non NBER recessions). The shaded areas are 90% confidence bands calculated using Newey-West standard errors. The dashed plain black line depicts the estimate from a symmetric Local Projection. For ease of comparison between the left and right panels, the responses to an expansionary credit shock (a decline in EBP) are multiplied by -1 in the right panels. Estimation using data covering 1973 to 2015.