Department of Economics
Working Paper No. 288

The Impact of Credit Market Sentiment Shocks – A TVAR Approach

Maximilian Böck
Thomas O. Zörner

July 2019

WIRTSCHAFTS UNIVERSITÄT WIEN VIENNA UNIVERSITY OF ECONOMICS AND BUSINESS

EFMD EQUIS ACCREDITED

AACSB ACCREDITED

ASSOCIATION OF MBAs ACCREDITED

The Impact of Credit Market Sentiment Shocks - A TVAR Approach

MAXIMILIAN BÖCK* and THOMAS O. ZÖRNER

Vienna University of Economics and Business

Abstract

This paper investigates the role of credit market sentiments and investor beliefs on credit cycle dynamics and their propagation to business cycle fluctuations. Using US data from 1968 to 2019, we show that credit market sentiments are indeed able to detect asymmetries in a small-scale macroeconomic model. By exploiting recent developments in behavioral finance on expectation formation in financial markets, we are able to identify an unexpected credit market news shock exhibiting different impacts in an optimistic and pessimistic credit market environment. While an unexpected movement in the optimistic regime leads to a rather low to muted impact on output and credit, we find a significant and persistent negative impact on those variables in the pessimistic regime. Therefore, this article departs from the current literature on the role of financial frictions for explaining business cycle behavior in macroeconomics and argues in line with recent theoretical contributions on the relevance of expectation formation and beliefs as source of cyclicity and instability in financial markets.

Keywords: Credit cycles, Belief formation, Threshold VARs.

JEL Codes: C34, E32, E44, E71, G41

1 Introduction

The Great Financial Crisis (GFC) of 2008 to 2009 revived the interest among economists and policymakers about the role of credit expansion and investor beliefs for the subsequent financial crisis. For instance, Rajan (2006) already recognized before the beginning of the GFC that the financial system is admittedly more resilient against small shocks through diversified risks, but more prone to systemic shocks through stronger linkages. A few years after the crisis, Stein (2014) emphasis in a speech at the Federal Reserve Board that policy makers should think about incorporating financial market risk in monetary policy decisions to account for these linkages. By stressing financial instability leading scholars brought back the narrative proposed by Minsky (1977) which gained popularity again.

He provides arguments that crises are endogenous phenomena and inherently tied to financial markets. The mechanism starts with an expansion of credit and investment leading to prosperous times. However, a speculative euphoria sets off which eventually ends in a crisis when optimism abates. Thus, the emergence of crises is endogenized by the incorporation of market sentiments in this approach. In the present article, we see those sentiments as crucial dynamic driver and exploit a belief formation mechanism with microfounded expectations to identify unexpected movements in the sentiment of the credit market. We argue that this unexpected news shock is exogenous to the economy and show empirically within a stylized model of the US macroeconomy that a credit market sentiment shock leads to asymmetric effects on credit and business cycle fluctuations.

Therefore, we depart from the literature relying on financial frictions in explaining instability in the credit cycle. Those theories typically endow their agents with rational expectations (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997) who cut back on investment and reduce borrowing when their ability to borrow is being constrained. Since agents are not fully aware what their borrowing decisions trigger in the aggregate economy, they are confronted with externalities in leverage choice. Through the identification of leverage as variable capturing the fragility of the system, a plethora of empirical studies using balance-sheet measures as predictors of recessions has been initiated (Schularick and Taylor, 2012; Jordà *et al.*, 2016; Mian *et al.*, 2017; Baron and Xiong, 2017). In summary, according to this strand of literature the driving force behind fluctuations can be traced back to some sort of market imperfections.

On the contrary, behavioral theories stressed the importance of overoptimism in the wake of a credit boom, starting with the seminal contributions of Minsky (1977) and Kindleberger (1978). Similar findings emerge from the literature in behavioral finance, thereby stressing the time-varying component of credit conditions when relaxing the assumption of updating beliefs via rational expectations. The literature introduces behavioral elements in the expectation formation mechanism of agents. For instance, Greenwood and Hanson (2013) show that credit quality of corporate debt issuers deteriorates when the credit market is overheating and is thus a better predictor for recessions than rapid aggregate credit growth. Another example, contributed by Gilchrist and Zakrajšek (2012), finds that an excess bond premium (EBP) is also able to predict recessions. In a similar vein, López-Salido *et al.* (2017) find that low credit spreads predict both a rise in credit spreads and a downfall in economic activity linking it to some sort of market sentiments.

Following Simon (1957), many scholars have criticized the unrealistically strong informational and computational requirements upon individual behavior imposed by strict rationality. As an answer, several

branches of literature arose relaxing this assumption and paying attention to *bounded rationality*. One branch is the literature on learning in the expectation formation process (Sargent, 1993; Evans and Honkapohja, 1999), another one forming the rational inattention literature (Sims, 2003; Gabaix, 2014) and finally the behavioral literature using simple psychological heuristics (Tversky and Kahneman, 1974). In a learning-to-forecast experimental study, Anufriev and Hommes (2012) find several robust heuristics when agents forecast asset prices and develop a behavioral model of heterogeneous expectations. In a different set-up, Assenza *et al.* (2011) find that the results also hold in a macroeconomic context. In a more recent contribution by Bordalo *et al.* (2018) the representativeness heuristic (Kahneman and Tversky, 1972) was operationalized and presented as a new belief formation mechanism, called *diagnostic expectations*, to explain credit cycles.

While the financial frictions approach assumes exogenous shocks and rational expectations in order to explain fluctuations, the latter theories provide endogenous explanations without relying on the assumption of strict rationality. However, Matsuyama *et al.* (2016) proposes a model of endogenous credit cycles in an overlapping-generations set-up without leaving the realm of rational expectations utilizing the limited pledgeability of collaterals as a parsimonious friction specification (Tirole, 2010). The authors acknowledge that their process resembles the mechanism proposed by Minsky (1977) but state that „[t]he model [...] does not rely on any form of irrationality" (Matsuyama *et al.*, 2016, p. 528). A recent contribution by Kubin *et al.* (2019) takes this as starting point and extend the model by endogenizing the pledgeability parameter and allowing it to vary over time. The pledgeability ratio is then determined by a simple heuristic rule: if the net worth as a proxy for the current state of the economy is above or below some threshold, the agents' sentiment switches between an 'optimistic' and 'pessimistic' credit market regime reflecting the psychological state of the lenders. This translates in varying degrees of what lenders are willing to accept as collateral and thus provide an endogenous behavioral explanations how the general, or in particular the business, mood is anchored in the perceptions about agency problems.

We take this theoretical approach as a starting point and propose an empirical macroeconomic model that accounts for both an endogenous explanation of credit cycles and switching dynamics resulting from periods of optimism and pessimism on the credit market. Therefore, we examine the conjecture that credit market sentiments can exert disruptive forces on the credit and business cycle. Hereby, we differentiate between optimistic and pessimistic credit market conditions and expect more severe effects when the financial system is already under distress. Furthermore, we argue that if agents receive bad news about the state of the economy, a deterioration of the sentiments towards the credit market sets in and subsequently credit spreads rise. Consequently, this translates to the real sphere of the economy and we expect a decline of credit, investment and finally output. To investigate the proposed relationship we employ a nonlinear VAR using monthly data covering the period between January 1968 and December 2014 of the US economy. This set-up allows us to investigate the impact of a credit market sentiment shock, which corresponds in our view to an unexpected news shock on the credit market.

Moreover, our paper is also related to the literature on structural identification in VARs. While the structural VAR literature has made great advancements in identifying monetary policy shocks (Gertler and Karadi, 2015), the literature looking at the feedbacks on financial markets or modeling financial shocks in an explicit manner is rather scarce. Studies have mostly focused on single-equation models (Krishnamurthy and

Muir, 2017; López-Salido *et al.*, 2017) and reduced form multi-equation models (Gilchrist and Zakrajšek, 2012). A recent contribution by Caldara and Herbst (2019) adds credit spread variables into a structurally identified multivariate framework, but confine themselves to monetary policy shocks. To our knowledge there are only two other contributions dealing with the identification of a credit spread shock. Brunnermeier *et al.* (2017) use the identification-via-heteroscedasticity approach and identify a monetary policy shock and two „stress" shocks, which originate in the financial sector and propagate to the real economy. However, Carriero *et al.* (2018) is closer to our application where they develop a variant of a smooth transition VAR model employing a Cholesky identification strategy to identify a credit conditions shock among others.

To summarize, our contribution is threefold. First, we use a non-linear specification to disentangle phases of optimism and pessimism on the credit market. It is a rather well-established fact in the literature on credit activity that financial markets operate and react quite different when under distress than in periods of tranquility (see, for example Balke (2000) or for a more recent contribution regarding uncertainty shocks Alessandri and Mumtaz (2019)). Second, we use a sophisticated shrinkage prior setup utilizing recent developments in the Bayesian literature on VARs (Huber and Feldkircher, 2019). Third, we propose a novel identification mechanism inspired by the literature on identification via external instruments (Mertens and Ravn, 2013; Gertler and Karadi, 2015) based on diagnostic expectations as belief formation mechanism (Bordalo *et al.*, 2018). In order to robustify our results we use also other behavioral belief formation mechanism discussed in Anufriev and Hommes (2012). With this strategy, we are able to identify a credit market sentiment shock, where unexpected news leads to dynamics of optimism and pessimism on the credit market.

Our results show that a credit market sentiment shock has two distinct features. First, there are strong asymmetries across different credit market regimes. If the credit market is calm, an unexpected news shock of the credit market sentiment induces short-lasting and low to muted effects on the credit and business cycles. On the contrary, in rather turbulent times when a pessimistic mood is already prevailing in the economy, a credit market sentiment shock engenders severe negative effects to the business and credit cycle and, in addition, leads to a drop in prices. The economy recovers approximately after one year.

The remainder of the article is organized as follows. After looking in more depth at our credit market sentiment indicator and the issue of belief formation in macroeconomics in Section 2, which displays the main identifying assumption in the model, we introduce our nonlinear VAR framework and the technical details on our identification strategy in Section 3. Our main results and further robustness analyses are discussed in Section 4 and Section 5 concludes.

2   Expectation formation in macroeconomics

The causes for recurring economic recessions and instabilities is subject to a variety of explanations. There exists a plethora of studies finding the source of instabilities in an exogenous shock to the economy. As our model relies on endogenous explanations backed by behavioral arguments, we focus on endogenous explanations and the role of expectation formation as origin of instabilities. Following Minsky's idea, a prominent example explaining credit market fluctuations was put forward by Matsuyama *et al.* (2016). However, their model rests on the assumption of rational expectation as belief formation mechanism.[1] The

---

[1] Note that we will use the term 'belief' and 'expectation' in our context interchangeably.

underlying idea is that financial frictions cause and amplify instability and recurring fluctuations. In a recent extension, Kubin *et al.* (2019) relax the assumption of rational expectation and incorporate empirical findings from the behavioral finance literature that credit market sentiments play indeed a role in driving aggregate fluctuations (Greenwood and Hanson, 2013; López-Salido *et al.*, 2017). Behavioral elements are introduced to the model to account for a time-varying perception of risk. Thus, beliefs about the state of the economy are directly incorporated and raise the question of how people perceive the state of the economy. While Kubin *et al.* (2019) model the perception-dependent pledgeability parameter in a deterministic fashion depending on the agents' net worth, we are opting for a different approach here.

We make use of the credit spread between yields on seasoned long-term Baa-rated corporate bonds and yields on long-term treasury securities (Baa spread) as our realized credit market sentiment indicator. Based on this sentiment indicator we raise the question of how agents form their expectation about it. Henceforth the sentiment on the credit market is denoted as a time series process $\{\omega_t\}_{t=1}^T$. This time series exhibits financial anomalies, which should not be present according to the efficient market hypothesis (Fama, 1970).[2] For example, a prominent anomaly was put forward by Bordalo *et al.* (2018). Using survey data, they were able to show that forecast errors (and interestingly, also forecast revisions) may be predictable which contradicts the efficient market hypothesis. In general, they found that a path of high returns triggers agents to overestimate the probability of high returns in the future ('excessive optimism') while bad returns yield lower forecasts of future returns ('excessive pessimism'). Therefore, we depart from the agents' net worth as sentiment indicator and argue that the Baa spread is indeed a good operationalization for the sentiment on the credit market.

As we rely on a specific belief formation mechanism to identify our model, some words about the evolution of this literature are in order. There exist a broad branch of contributions which explores optimal behavior under situations where agents' rationality is somehow bounded (see, e.g., Adam and Marcet (2011) for asset pricing topics, Cogley and Sargent (2008), Eusepi and Preston (2011) and Malmendier and Nagel (2016) for macroeconomic issues). All those approaches have the internal rationality or, in Simon's (1955) words, *bounded rationality* in common. This concept is based on the fact that agents have limited computational abilities and no perfect foresight at all; they make use of simple heuristics or 'rules of thumb' for their decisions. Other reasons might include that the agents are not fully informed (external influences), or have some internal misconceptions (see Kahneman (2003) for an introduction to fallacies, biased heuristics and cognitive misunderstandings in general) or other issues which might occur when agents apply their heuristics in the real world. In summary, the literature deviating from rational expectations using some form of bounded rationality is far from having reached a consensus. While behavioral theories are built on some kind of bounded rationality relaxing the assumption of rational expectations, rational structural uncertainty theories tend to accept the rationality assumption but neglect the assumption of complete information. However, Brav and Heaton (2002) show that it is actually quite difficult to distinguish between those approaches. In particular, they consider a model with a one-period risky asset paying an uncertain dividend at the end of the period. They then show that both their models, one with an agent endowed with rationality but incomplete information and the other with a behavioral agent, who behaves according to a simple heuristic, are able to

---

[2] We follow here Brav and Heaton (2002, p. 575) in defining a 'financial anomaly' as „a documented pattern of price behavior that is inconsistent with the predictions of traditional efficient markets, rational expectations asset pricing theory".

replicate financial anomalies (i.e. overreaction and underreaction in asset prices) frequently found in financial markets.

By arguing that decisions in financial market activities have to be made in a fast and accurate manner, we prefer an approach relying on some sort of heuristics to explain specific and observed behavior. We are thus not following the branches of the learning literature (Sargent, 1993; Evans and Honkapohja, 1999) or rational inattention literature (Sims, 2003; Gabaix, 2014). Agents may be backed by forecasts based on rational expectations, but they are part of a complex system of human interactions, which shape their thinking and „what investors and corporate managers think is what drives their actions. And some psychologists would say that what people think derives from how they feel, which is influenced by their interactions with others"(Nofsinger, 2005, p. 144).

For studying agents' actual expectation formation routine, laboratory experiments are the method of choice. Those experiments mainly try to elicit how human behavior tends to form expectations by putting them into controlled situations and monitor their actions. Wagener (2014), for example, discusses experimental results of learning-to-forecast experiments in economics and analyses the implications for the rational expectations hypothesis. A typical characteristic of the employed models concerns a group formation depending on the expectation formation routine including a potential switching between the heuristics according to the past performance. In an experimental setting, the subjects can choose between different expectation formation hypotheses and observe their performance. Due to some evolutionary switching agents try to find the 'true' expectation equation which minimizes their forecast error. Most interestingly, Hommes (2009) and Hommes *et al.* (2017) show in learning-to-forecast experiments that a few number of simple heuristics – combined with an evolutionary switching between them – is sufficient to describe expectation formation of economic agents.

For our purpose, Assenza *et al.* (2011) and Anufriev and Hommes (2012) provide valuable experimental insights on what heuristics agents actually use for forecasting asset prices or macroeconomic variables. Based on this set of heuristics they propose a behavioral model of how heterogeneous expectations are formed, where evolutionary selection takes place among the expectation formation rules. In learning-to-forecast experiments (LtFEs) participants have to forecast a risky asset price for 50 consecutive periods. They knew that the price of the risky asset is in each round determined by market clearing as an aggregation of the individual forecasts, but they only got displayed the realized price, their forecast and their past own earnings. Thus, in the experiment, there exists a positive feedback from the individual price forecast to the realized market price on which the agents' earnings depend. Although the price movements varied across different experimental sessions, a striking result of the LtFEs is that in all sessions participants managed to coordinate their forecasting behavior. They can be boiled down to four different heuristics, which participants used to predict the asset price: the adaptive heuristic (ADA), the weak and strong trend-following heuristic (WTR and STR) and the anchoring and adjustment heuristic with and without learning (AA and LAA). If the price tends to slowly converge to its fundamental value, all participants tend to use the adaptive heuristic. In the limiting case without any weight on their own past prediction, this heuristic collapses to the case of naive expectations.[3] The second and third heuristic uses the last price observation and adjusts it in the

---

[3] Basically, they utilize the random walk, $\mathbb{E}_t^{RW}(\omega_{t+1}) = \omega_t$, for predicting future values. Essentially, this means that the best forecast of tomorrow is the realized value of today.

direction of the last price change. The differentiation in weak and strong trend-followers is according to some extrapolation coefficient. If this compared to the strong trend-following case with a parameter value exceeding unity. With the last heuristic, the anchoring and adjustment heuristic, agents extrapolate the last price change from a reference point (anchor), which they believe to be the „long-run" price level. In the case without learning this reference point is the fundamental value of the asset price, which is then replaced in the case with learning with the sample average of past prices. In Tab. 1 the exact expectation formation mechanisms laid out in Assenza *et al.* (2011) and Anufriev and Hommes (2012) can be found.[4]

Finally, a recent contribution by Bordalo *et al.* (2018) introduces an expectation formation mechanism called *diagnostic expectations* which rests on Kahneman and Tversky's (1972) representativeness heuristic. This heuristic states that agents judge a trait or attribute of a certain population as more common when the relative frequency of this attribute in a certain population appears to be much higher than in a reference population. Therefore, people overestimate certain traits of a certain population which are then diagnostic for this population.[5] When using this heuristic in a dynamic perspective, the reference group is formed on the absence of information at time point t. Bordalo *et al.* (2018) formulate a probability distribution of the sentiment ω_t, which is inflated by a term representing representativeness,

$$p_t^{DE}(\hat{\omega}_{t+1}) = p(\hat{\omega}_{t+1} \mid \omega_t = \hat{\omega}_t) \times \left[\frac{p(\hat{\omega}_{t+1} \mid \omega_t = \hat{\omega}_t)}{p(\hat{\omega}_{t+1} \mid \omega_t = \phi\hat{\omega}_{t-1})} \right]^\theta \frac{1}{Z}, \tag{2.1}$$

where the normalizing constant Z ensures that the probability distribution integrates to unity and $\theta \in [0, \infty]$ measures the severity of judging by representativeness. Note that if $\theta = 0$ the distortionary term vanishes meaning that agents use all information, which corresponds to the assumption of rational expectations. The first term is the conditional distribution using rational expectations by using current news $\hat{\omega}_t$ for predicting $\hat{\omega}_{t+1}$. The second term is the ratio of using current news and using the prediction from news at $\hat{\omega}_{t-1}$, assumed to follow an AR(1) process with parameter ϕ. Thus, the probability of the most representative states is inflated. This represents memory limits, as beliefs inflate the probability of representative states and vice versa. Therefore, as long as $\theta > 0$ memory is limited. Tab. 1 provides the expectation formulation of this term. Bordalo *et al.* (2018) assume a standard AR(1) model with homoscedastic errors. However, we extend this to a stochastic volatility specification, because periods of financial turmoil crucially affect this specific memory. In turbulent phases, a variety of events occurs contemporaneously limiting the memory and leading to biases. Details and derivations are provided in Appendix C. Note that we use for our analysis only the first moment of the diagnostic expectation. Concerning the parameter θ, Gennaioli and Shleifer (2018) refer to values within 0.7 and 1.0 where we stick to the value provided in Bordalo *et al.* (2018), $\theta = 0.91$.

We will use the heuristics given in Tab. 1 to predict the Baa spread, which is our credit market sentiment indicator. However, we abstain from using the AA heuristic with fixed anchor since there is not really a fundamental value of a credit market sentiment. For the heuristic with a learning anchor the moving average

---

[4] For a detailed treatment of heterogeneous expectation formation and bounded rationality in finance and macroeconomics, we refer the interested reader to Hommes (2006) and Hommes (2009) for excellent surveys.

[5] For clarification we refer to the example given in Bordalo *et al.* (2018). Assume that you try to predict the share of red-haired Irish people. Most probably you will overestimate the share of red-haired Irish people since this trait is diagnostic for the Irish and occurs much more frequently than in your reference population. Except you are an Irishwoman or -man.

Table 1: Set of heuristics

ADA	adaptive rule	$\mathbb{E}_t^{ADA}(\omega_{t+1}) = 0.65\omega_{t-1} + \mathbb{E}_{t-1}^{ADA}(\omega_t)$
WTR	weak trend-following rule	$\mathbb{E}_t^{WTR}(\omega_{t+1}) = \omega_{t-1} + 0.4(\omega_{t-1} - \omega_{t-2})$
STR	strong trend-following rule	$\mathbb{E}_t^{STR}(\omega_{t+1}) = \omega_{t-1} + 1.3(\omega_{t-1} - \omega_{t-2})$
LAA	anchoring and adjustment rule with learning anchor	$\mathbb{E}_t^{LAA}(\omega_{t+1}) = 0.5(\omega_{t-1}^{av} + \omega_{t-1}) + (\omega_{t-1} - \omega_{t-2})$
AA	anchoring and adjustment rule with fixed anchor	$\mathbb{E}_t^{AA}(\omega_{t+1}) = 0.5(\omega^f + \omega_{t-1}) + (\omega_{t-1} - \omega_{t-2})$
DE	diagnostic expectations	$\mathbb{E}_t^{DE}(\omega_{t+1}) = \mathbb{E}_t(\omega_{t+1}) + \theta[\mathbb{E}_t(\omega_{t+1}) - \mathbb{E}_{t-1}(\omega_{t+1})]$

Notes: While ω^f denotes the fundamental value, it can be learned by the sample average ω_{t-1}^{av} dependent on the information set up to time point t.

of the last 24 months is employed. Since Bordalo *et al.* (2018) is in a theoretical and practical manner much more related to our work, we will use the diagnostic expectations as workhorse model and provide robustness checks for the other heuristics.
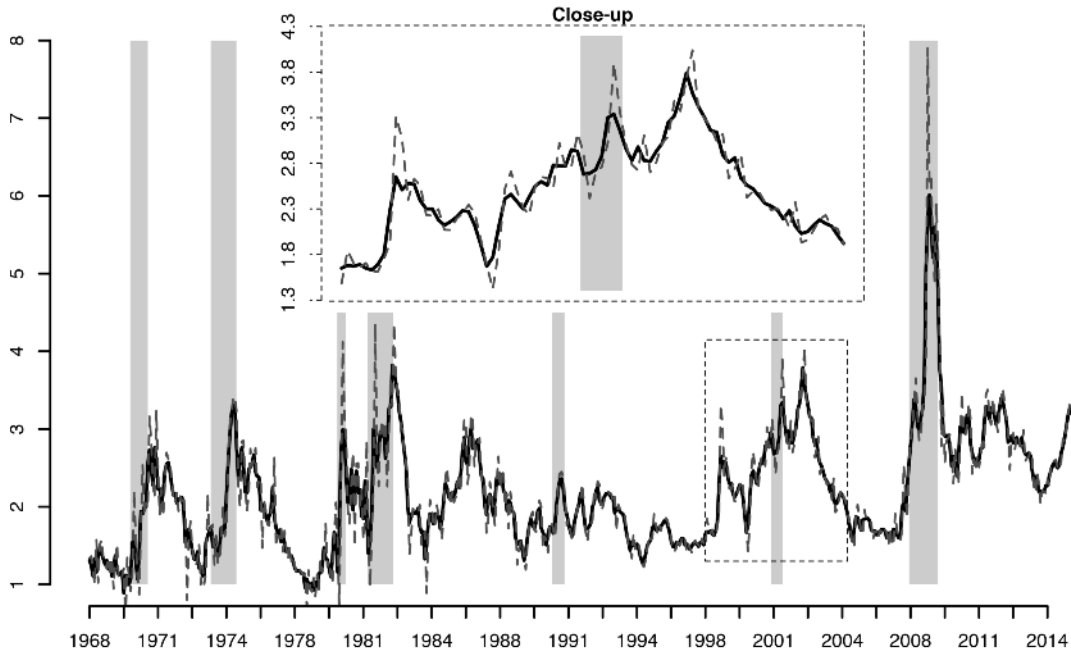

Figure 1: Baa bond - Treasury credit spread and its diagnostic expectations.
Notes: The black line indicates the Baa spread, while the dashed line its corresponding diagnostic expectations. Gray shaded areas denote the NBER recession dates.

In Fig. 1 we plot the original Baa spread along with its diagnostic expectations. The black solid line denotes the credit spread while the dashed gray lines report the diagnostic expectations of the credit spread in each time period. The light gray shaded areas are the NBER recession dates. For the sake of clarity, we zoom in the plot between January 1998 and December 2004. Since we use credit market sentiments and credit spreads synonymously (but with a reversed direction of impact; high or optimistic credit market sentiments imply low credit spreads), we clarify that we actually mean the expected return to bearing credit risk when talking about credit market sentiments. From Fig. 1 the high correlation between recessions and

elevated credit spreads is rather easy to see. Looking closer at the plot, we see the effect of diagnostic expectations. After a few periods of going up/down, rational expectations and diagnostic expectations are closely in line with each other. But after a reversal, diagnostic expectations overshoot in both directions due to the representativeness heuristic. Agents believe that those actions happening in the previous period also have the highest probability in the current period (i.e. go further up/down) and thus underestimate the tail risk of a reversal. It is thus an easy exercise to compute the diagnostic forecast error, which we assume to be an unexpected news shock. Agents employ the representativeness heuristic and forecast sentiments according to diagnostic expectations and are thus overweighting past information pointing further up or down. Later on we will use this diagnostic forecast error, or unexpected news or sentiment shock, for identifying our model.

3 A VAR with credit market regimes

The next subsections introduce our nonlinear VAR model and describe the estimation and identification approach. Since we rely on an external instruments approach for identification, we provide a detailed discussion on our identification strategy related to diagnostic expectations.

3.1 Structure of the model

Empirical macroeconomic analysis is nowadays strongly based on linear VAR models (Sims, 1980), but they fail to capture non-linear dynamics such as regime-switching or asymmetric responses to shocks. When looking at credit cycle dynamics, the applied models are usually specified in a nonlinear fashion. This allows to capture that shocks are propagated differently in different credit regimes (Balke, 2000; Atanasova, 2003). Our set of $M = 5$ endogenous variables consists of

$$Y_t = \{BAAT10_t, INDPRO_t, BUSLOANS_t, CPIAUCSL_t, FFRWXSR_t\}, \tag{3.1}$$

where $BAAT10_t$ denotes the credit market sentiment, $INDPRO_t$ the industrial production growth, $BUSLOANS_t$ business loans growth, $CPIAUCSL_t$ consumer price inflation and $FFRWXSR_t$ a short-term interest rate. We will characterize the credit market sentiment with a the aforementioned credit spread, namely the spread between yields on seasoned long-term Baa-rated corporate bonds and yields on long-term treasury securities (10y government bond yield). Therefore, when the sentiment is elevated this is equivalent in saying that the expected return to bearing credit risk is low and thus the spread is narrow. As short-term interest rate we use the federal funds rate and also its shadow rate provided by Wu and Xia (2016). Except of the aforementioned, all data comes from the FRED database (McCracken and Ng, 2016), is on a monthly frequency and growth rates are computed as annualized log-differences. Details can be found in Appendix A.

Thus, the multivariate time series model runs from $t_0 = 1968 : M01$ and ends in $T = 2014 : M12$ with regimes $\{S_t = i\}_{i=1,2}$ and reads as follows:

$$Y_t = \begin{cases} c_1 + \sum_{j=1}^{p} A_{1j} Y_{t-j} + \Lambda_1 e_t, & \text{if } S_t = 1, \\ c_2 + \sum_{j=1}^{p} A_{2j} Y_{t-j} + \Lambda_2 e_t, & \text{if } S_t = 2, \end{cases} \tag{3.2}$$

where A_{ij} are the regime-specific $M \times M$ coefficient matrices for each lag $j = 1, \ldots, p$. The intercept is denoted by c_i and Λ_i is the lower-triangular Cholesky factor, thus $\Sigma_i = \Lambda_i \Lambda_i^T$ holds. Furthermore, e_t is an $M \times 1$ vector of structural shocks with $\mathbb{E}(e_t) = 0$, $\mathbb{E}(e_t e_t^T) = I$ and $\mathbb{E}(e_t, e_s^T) = 0$ for $s \neq t$ where I denotes the identity matrix.

Our modeling framework thus allows for the occurrence of regime shifts, where the two sets of parameters $\{c_i, A_{ij}, \Sigma_i\}_{i=1,2}$ describe the different dynamics of the economy depending on whether the economy is in an optimistic or pessimistic credit market regime. Our line of reasoning here is that agents behave differently when confronted with a positive or negative atmosphere at the financial markets. Therefore, the credit market sentiment indicator serves as a threshold variable,

$$
\begin{aligned}
S_t = 1 &\iff CS_{t-d} \leq \gamma, \\
S_t = 2 &\iff CS_{t-d} > \gamma,
\end{aligned}
\tag{3.3}
$$

where both, the threshold parameter γ and the delay parameter d are treated as unknown parameters. Note that all parameters are allowed to change across regimes. We use $p = 13$ lags due to monthly data and fix the delay parameter $d = 1$ as financial markets react rather quick. Concerning the covariance matrix of the residuals, we factorize

$$
\Sigma_i = H_i^{-1} D H_i^{-1T},
\tag{3.4}
$$

where H_i is a lower triangular matrix with ones on the main diagonal and $D = \text{diag}(d_1, \ldots, d_M)$ is a diagonal matrix with regime-invariant variances.

Estimation is based on a Bayesian framework and an MCMC algorithm is employed to sample from the joint posterior distribution. Since the joint posterior density is not tractable, we use a Gibbs sampler to draw from the conditional posterior densities iteratively. The whole algorithm is described in detail in Appendix B of the paper.

Some discussion of additional prior choices and algorithm sketches are in order. We impose on each element of A_{ij}, which is denoted as $a_{ij,kl}$, where $k = 0, \ldots, M$ starts at 0 when we include the intercept (only if $j = 1$) and otherwise $k, l = 1, \ldots, M$, a variant of the Normal-Gamma (NG) shrinkage prior. For the sake of brevity, we refrain from postulating the prior on the intercept, but treat it as an element of A_{i1}. This prior is strongly centered on a zero mean, but features also fat tails. Therefore, coefficients are shrunk towards zero if they entail no information inducing sparsity to the system. The NG prior has an idiosyncratic shrinkage component τ_{ik} allowing for an individual degree of shrinkage and a lagwise shrinkage parameter λ_{ij} that shrinks all elements of α_i towards zero while punishing for a higher lag order. Following Huber and Feldkircher (2019) the lagwise NG prior per regime i reads

$$
a_{ij,kl} \mid \tau_{ij,kl} \sim \mathcal{N}(\underline{a}_{ij,kl}, 2/\lambda_{ij}^2 \tau_{ij,kl}), \quad \tau_{ij,kl} \sim \mathcal{G}(\vartheta_{\tau,j}, \vartheta_{\tau,j}),
\tag{3.5}
$$

with $\underline{a}_{ij,kl} = 0$. Furthermore, we put a prior on $\vartheta_{\tau,ij} \sim Exp(1)$, which centers $\vartheta_{\tau,ij}$ a priori on unity translating into the Bayesian LASSO (Park and Casella, 2008) but allowing for additional flexibility through

the hyperprior. For the lagwise specification, we impose an additional prior on λ_{ij}^2 for each A_{ij},

$$\lambda_{ij}^2 = \prod_{g=1}^{j} \zeta_{ig}, \tag{3.6}$$

with independent Gamma priors on each $\zeta_{ig} \sim \mathcal{G}(c_0, d_0)$. Those hyperparameters are set equal to $c_0 = d_0 = 0.01$. As long as ζ_{ig} exceeds unity, this prior shrinks coefficients associated with higher lags more towards zero through a more severe global shrinkage component λ_{ij}^2. This implies that the coefficient matrix A_{ij} becomes increasingly sparse for higher lags. We proceed by imposing also a NG prior on the free off-diagonal elements $h_{i,kl}$ of H_i,

$$h_{i,kl} \mid \phi_{i,kl} \sim \mathcal{N}(\underline{h}_{i,kl}, 2/\xi_i^2 \phi_{i,kl}), \quad \phi_{i,kl} \sim \mathcal{G}(\vartheta_\phi, \vartheta_\phi), \tag{3.7}$$

with $\underline{h} = 0$ and again a hyperprior on $\vartheta_\phi \sim Exp(1)$ allowing for additional flexibility. Similar to the lagwise specification, we also put a Gamma prior on $\xi_j^2 \sim \mathcal{G}(c_0, d_0)$. The remaining prior choices are rather standard.

The main intuition behind the algorithm to estimate our model can be summarized as follows. First, we sample the threshold parameter γ via an adaptive random-walk Metropolis-Hastings step and due to the adaptive nature of the algorithm (Haario *et al.*, 2001) we achieve acceptance probabilities between 20% and 40%. Applying the idea of data-augmentation we can split the data into regime-specific observations and can then sample the regime-specific coefficients. For details, we refer to Appendix B.

3.2   Identification

We are interested in computing impulse response functions of a credit market sentiment shock. In order to identify the shock we rely on external instruments using the methodology developed by Mertens and Ravn (2013) and Gertler and Karadi (2015). After estimating the model we obtain the reduced form errors, denoted by ϵ_t and which are related to the structural shocks as follows

$$\epsilon_{S_t} = \Lambda_i e_{S_t}, \qquad \text{if } S_t = i, \tag{3.8}$$

where $\mathbb{E}(\epsilon_{S_t} \epsilon_{S_t}^T) = \mathbb{E}(\Lambda_i \Lambda_i^T) = \Sigma_i$ for $i = 1, 2$. Denoting $Y_t^p \in Y_t$ the credit market sentiment variable and with e_t^p its associated structural shock with exogenous variation, we are able to identify this structural shock through an external instrument Z_t without taking an identifying stance on all other structural shocks. Let e_t^q be a vector structural shock other than the identified credit market sentiment shock. A valid instrument Z_t for the sentiment shock has then to be correlated with e_t^p and orthogonal to e_t^q, such that:

$$\begin{aligned} \mathbb{E}(Z_t e_t^{pT}) &= \Phi, \\ \mathbb{E}(Z_t e_t^{qT}) &= 0. \end{aligned} \tag{3.9}$$

We proceed in a two-stage manner: first, we regress the reduced form error $\epsilon_{S_t}^p$ on the instrument Z_{S_t} to isolate the variation in the reduced form residual for the sentiment that is due to the news shock in a regime-wise manner. Similar to a two stage least squares procedure, we form the fitted values $\hat{\epsilon}_{S_t}^p$ and regress

them in the second stage regression on the other reduced form residuals

$$\epsilon_{S_t}^q = \frac{\lambda_i^q}{\lambda_i^p} \hat{\epsilon}_{S_t} + \nu_{S_t} \qquad \text{if } S_t = i, \tag{3.10}$$

where $\hat{\epsilon}_{S_t}$ is orthogonal to the error term ν_{S_t}, given that the assumption in Eq. (3.9) that Z_{S_t} is orthogonal to all the structural shocks other than the shock to the sentiment indicator $e_{S_t}^p$. Thus, λ_i^q denotes the response of $\epsilon_{S_t}^q$ to a unit increase in the sentiment shock $e_{S_t}^p$. Using the reduced form variance-covariance matrix Σ_i, an estimate for λ_i^p can be derived which finally enables us to identify the responses to a structural shock in $e_{S_t}^p$. For details we refer to Appendix D.

As we discussed in Section 2, the forecast errors of the diagnostic expectation of the credit market sentiment to its realized value is employed as instrument Z_{S_t}. As pointed out by Bordalo *et al.* (2018) diagnostic expectations have the nice property to be forward-looking and are thus immune to the Lucas critique. In our interpretation, the forecast errors are unexpected news shocks; agents do not forecast according to rational expectations, but with diagnostic expectations and are simply not able to spot sentiment reversals such that expectations tend to overshoot. After periods of elevated credit spreads agents would predict a further surge of credit spreads since their memory is limited and assess the probability of a further increase larger than it actually is.

Concerning the validity criterion in Eq. (3.9) we argue that unexpected movements in the credit market sentiment have a strong correlation with the sentiment itself due to empirical findings of Bordalo *et al.* (2018). They show that even prediction errors are forecastable making it indeed a valid instrument but are decoupled from macroeconomic fundamentals. This states that a sentiment shock is strongly correlated with the structural innovation in the credit market. Furthermore, we argue that the instrument is orthogonal to all the other structural innovations. In this regard, exogenous shocks to macroeconomic fundamentals, i.e. an unexpected oil price shock due to the discovery of new technical possibilities for oil production, terrorist attacks or natural disasters, are neither caused nor contemporaneously correlated with the prevalent sentiment on the credit market.

4 Results

This section is dedicated to the discussion of the results. First, we discuss the estimated credit market regimes while the second subsection presents the results of the impulse response analysis when shocking the credit market sentiment across the estimated regimes. In the third subsection we provide a sensitivity analysis using alternative expectation formation mechanisms, identification schemes or variables. We use $p = 13$ lags due to monthly data and all our estimations are based on sufficient MCMC draws.

4.1 Credit market regimes

In Fig. 2 we report the Baa spread along with the associated probabilities of being in one of the two regimes. The probabilities are calculated by looking at how often the threshold variable has surpassed the estimated threshold parameter γ. Note that the scaling of the plot is different compared to Fig. 1 since we scaled all
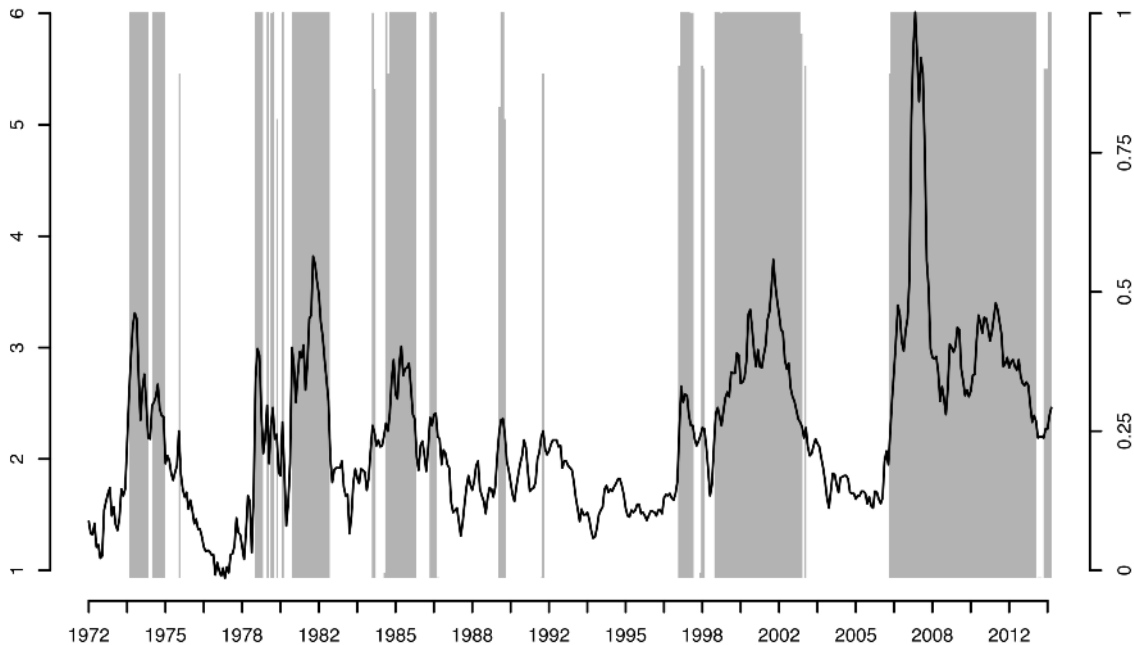
Figure 2: Credit market sentiment regimes.

Notes: Gray shaded areas represent the periods when the US economy is estimated to be in a pessimistic credit market regime (right scale), defined as a state where the Baa spread exceeds the critical threshold in the TVAR of Section 3.

variables to exhibit zero mean and a standard deviation of unity prior to the estimation. By fixing the delay parameter to unity, we assume that the credit sentiment in the month before is crucial in determining the credit market regime in time point t. We label the two credit market regime as either optimistic or pessimistic credit market sentiment regime.

After inspection we notice that the pessimistic credit market sentiment regime approximately coincides with the NBER recession dates, but cover a much longer period of time. This states that the credit market sentiment is still elevated although the recession may gone through the depression point and the economy is already recovering. This can be traced back to the fact that 'bad' experiences are still in the memory of the economic agents which are still too cautious switching to the optimistic regime. Apart from this observation, our regimes resembles the experienced business cycles of the US economy.

4.2 The impact of a credit market sentiment shock

We now turn to the impulse response analysis of the impact of a credit market sentiment shock. As already pointed out and discussed in light of Eq. (3.9) we intend to look at an exogenous shock to the credit market sentiment variable. In our main specification this is the Baa spread, defined as the spread between yields on seasoned long-term Baa-rated corporate bonds and yields on long-term treasury securities. The shock is defined as an 100 basis point increase in the Baa spread, which is a medium deprivation of the sentiment. For instance, during the last financial crisis the US economy experienced a surge of the Baa spread of almost 400 basis points. In Fig. 3 we report the impulse response functions over the horizon of 24 months. For each regime the figure reports the median impulse response and the associated 84%, 90% and 95% confidence
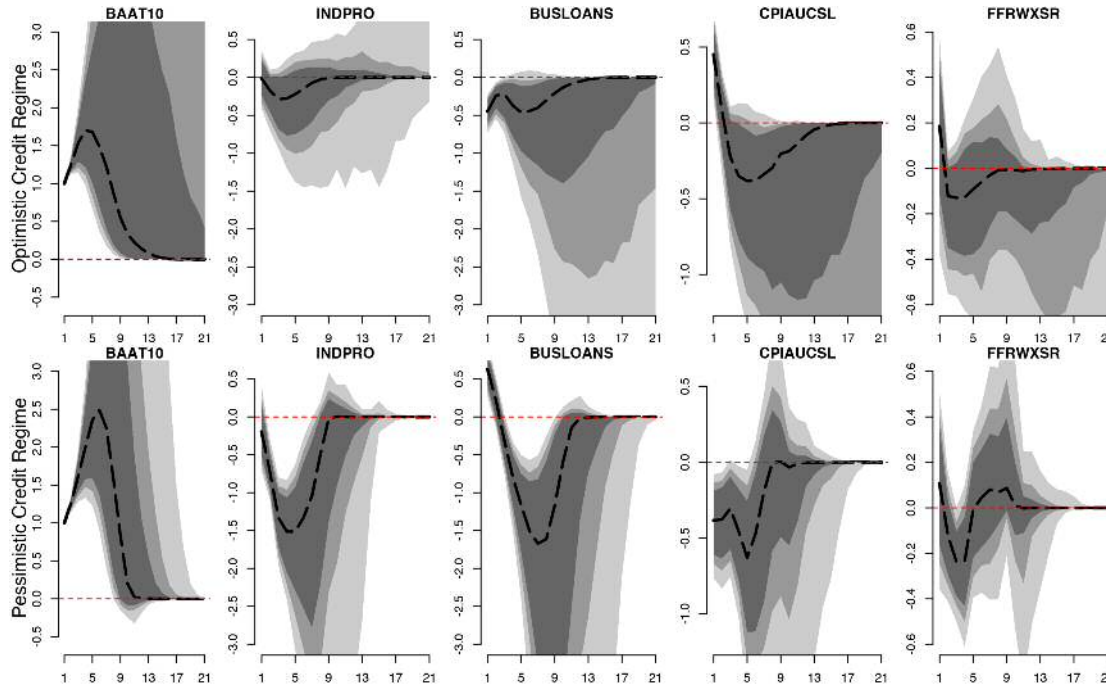
Figure 3: Impulse responses of a credit market sentiment shock (diagnostic expectations).

Notes: Identification via diagnostic expectations. The black dashed line is the median response per regime, while the gray shaded areas depict the 95%, 90% and 84% credible set interval.

bands. In both regimes, after a negative sentiment shock hits the economy, the sentiment tends to deteriorate further unless mean-reversion starts after about one year. In both panels the uncertainty bands tend to be rather big accounting for relatively high uncertainty. However, the responses are still significant. The upper panel depicts the optimistic credit market sentiment regime, whereas the lower panel exhibits the pessimistic one. Generally, the impacts in an optimistic credit market regime are rather muted across all variables. There is a slight reaction on industrial production and business loans along with relatively high uncertainty concerning the reaction of prices and short-term interest rates. This is consistent with our expectations and the theoretical models. For instance, the model developed by Kubin *et al.* (2019), would also predict a rather small to negligible effect on the business and credit cycle in an optimistic regime.

However, the picture reverses when looking at the impact of the credit market sentiment shock in the pessimistic regime. The responses are much more pronounced: the contraction is relatively abrupt and the peak fall in output is about five times larger (-0.27% versus -1.51%). When looking at impulse response of business loans, we interestingly find a positive shock on impact, which turns negative quite fast. Peak fall in credit is about four times larger in the pessimistic than in the optimistic credit market regime (-0.39% versus -1.71%) and stronger than the fall in output. Furthermore, we observe a drop in prices. The effect is rather short lasting and tends to smooth out quickly after a few months. Besides the positive shock on impact (we call it the 'credit puzzle'), the responses are in line with theory. We find a stronger impact on business loans than on output and both react quite strong due to a shock on credit market sentiments. Furthermore, both variables tend to reverse and finally fade after some time. It takes about three quarter of a year that output recovers and a whole year for credit. The initial positive reaction of business loans can be traced back to

some sort of liquidity considerations by entrepreneurs. Expecting or foreseeing a credit crunch due to some economic disruption may cause precautionary loans to ensure liquidity over the whole recessionary period.

Other intriguing empirical results arise from this figure. First, strong asymmetries across credit market regimes are visible. A medium-sized drop in the sentiment leads to obviously distinct effects depending on the general, prevailing mood in the economy. If the general vibe is good, a drop may cause some small disturbances. After the dust has settled, agents realize that the general mood is still good and go back to normal. On the contrary, if the general mood is already bad, another drop in the sentiment exhibits adverse and strong effects. This is comparable to the Minsky-moment, or in our case the realization of the tail risks, which are completely neglected by a forecasting rule like diagnostic expectations.

Moreover, we can relate the above described results to the idea of *corridor stability*, originally brought up by Leijonhufvud (1973) and qualitatively adopted in the light of the GFC by Rajan (2006). Such a phenomenon sees the economic or financial system as rather resilient against small shocks while large shocks have an irreversible and catastrophic effect on the system. In our system, the degree of confidence may influence this corridor, such that in an optimistic regime shocks hit a rather resilient economy. However, turning to a pessimistic regime, this corridor is rather small such that a shock has severe impacts on the whole economy.

4.3 Sensitivity

This section is dedicated to a sensitivity analysis to check whether our results are robust to other specifications. First, we are experimenting with other expectation formation mechanisms based on different heuristics
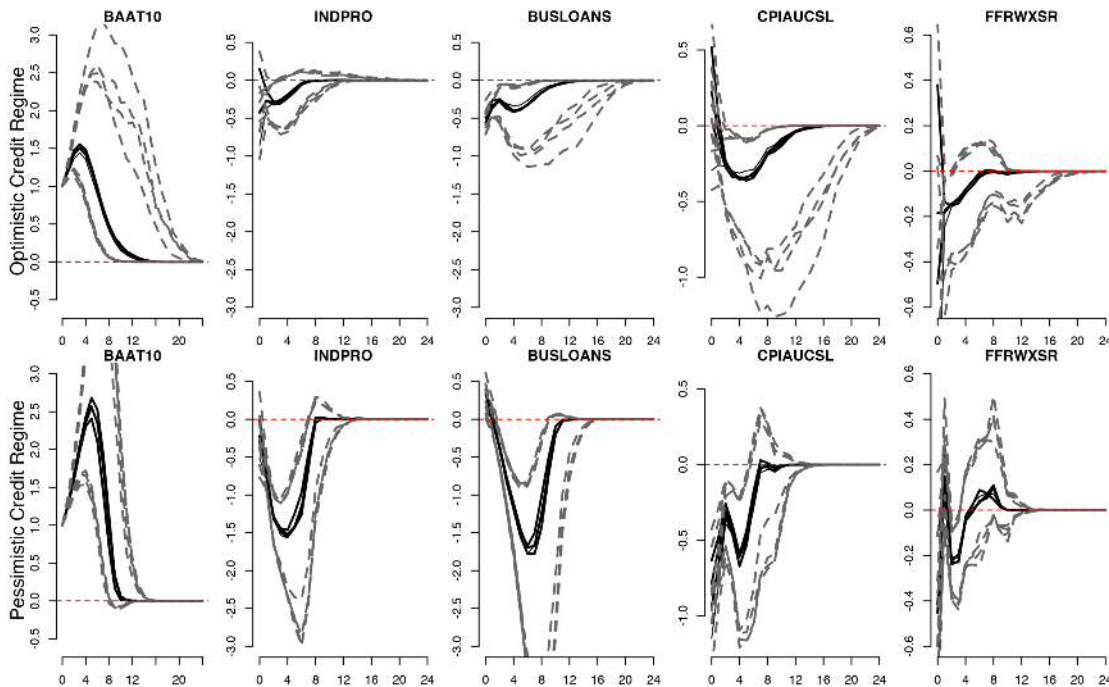

Figure 4: Impulse responses of a credit market sentiment shock (different heuristics).

Notes: Identification via different heuristics depicted in Tab. 1. The black bold lines are the median responses per regime, while the gray dashed lines represent the 84% credible set interval.

depicted in Tab. 1. Second, we apply a Cholesky identification scheme with the Baa spread ordered first. This translates into the assumption that all variables react contemporaneously.

When using forecast errors of the other heuristics in Tab. 1 (excluding the anchoring and adjustment heuristic with fixed anchor), the impulse responses are generally similar to each other as Fig. 4 reveals. Moreover, they are not only qualitatively, but also quantitatively comparable to those computed when using diagnostic expectations. This is not surprising since those heuristics are mainly developed to capture financial time series anomalies. Again, in the optimistic credit market regime rather small responses are visible. Business loans react slightly and after some periods a significant price reaction is perceptible. The pessimistic credit market regime has a strong negative reaction on the business and credit cycle variable and also a rather strong price decrease is in the set of responses. Again, we observe kind of a credit puzzle; however not significant for the used heuristics.

Turning to the identification via Cholesky ordering, where the Baa spread is ordered first, the qualitative interpretation is similar as depicted in Fig. 5. The small negative reaction of business loans in the optimistic credit market regime is not identifiable any more, but instead there appears a rather long-lasting negative reaction of prices. In the pessimistic credit market regime the price reaction is more attenuated than in the identification based on the external instrument. However, we see again a rather fast and strong drop in real activity with fairly fast recovery while the negative reaction of business loans is more persistent. On the contrary to our earlier results, the amplitude of the shocks is different. At the peak of the shock we observe an about one third smaller reaction. Changing the ordering of the variables in the identification process does not change the results qualitatively.[6]
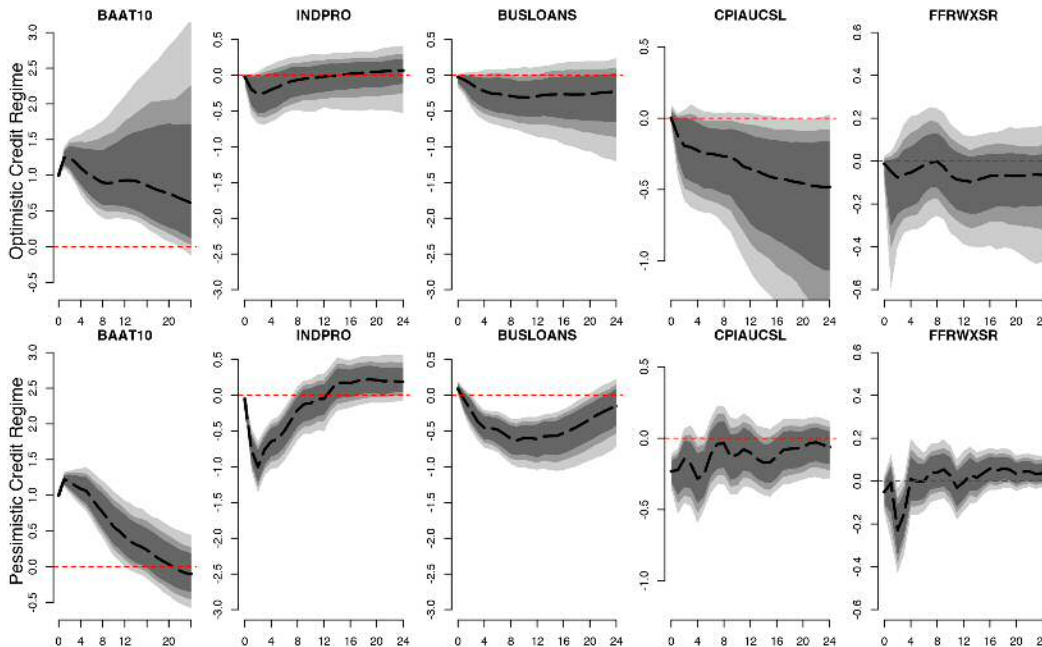

Figure 5: Impulse responses of a credit market sentiment shock (Cholesky identification).

Notes: Identification via Cholesky scheme with Baa spread ordered first. The black dashed line is the median response per regime, while the gray shaded areas depict the 95%, 90% and 84% credible set interval.

[6] Results are available upon request by the authors.

5 Concluding remarks

In this paper, we present a macroeconomic model of the US economy which is capable of controlling for asymmetries at the credit market. Furthermore, we provide a novel identification strategy to analyze a sentiment shock at the credit market. We are not only able to empirically confirm the theoretical predictions of a model dealing with the endogenous explanations of cyclicity using sentiments (Kubin *et al.*, 2019), but also draw on recent developments in the behavioral finance literature, which embeds behavioral arguments grounded in psychology within probability theory (Bordalo *et al.*, 2018).

We estimate a structural threshold vector autoregression model (TVAR) with the credit spread as threshold variable capturing the idea of switching sentiments. The estimated threshold separates the model space in an optimistic and pessimistic credit market sentiment regime. Our identification strategy rests on the forecast error agents make when using a heuristic to predict future values of a variable of interest. In our specific approach, we use an operationalization of the psychologically backed representativeness heuristic to forecast with diagnostic expectations according to Bordalo *et al.* (2018). The resulting forecast error can be thus interpreted as news or sentiment shock on the credit market. This captures the idea that agents face a difficulty in forecasting mean reversals, or sentiment changes on the credit market.

The estimated regime allocation fairly coincides with the NBER recession dates with slightly prolonged pessimism after a recession. The results of a credit market sentiment shock (unexpected news shock) show rather low to muted responses in the optimistic credit market regime, while the reaction of the business and credit cycle variable in the pessimistic credit market regime is rather strong.

We thus provide a framework to embed advancements in the literature on expectation formation from a behavioral tradition in recent achievements on structural identification in VAR models. Our results indicate that it pays off to further strengthen the ties between behavioral studies mostly found in microeconomics and macroeconometric analysis. Evidence from microeconomic studies and laboratory experiments are thus a valuable source for easing strict assumptions frequently found in macroeconomics.

References

Adam K, and Marcet A (2011), "Internal rationality, imperfect market knowledge and asset prices," *Journal of Economic Theory* **146**(3), 1224–1252. [5]

Alessandri P, and Mumtaz H (2019), "Financial regimes and uncertainty shocks," *Journal of Monetary Economics* **101**, 31–46. [4]

Anufriev M, and Hommes C (2012), "Evolutionary selection of individual expectations and aggregate outcomes in asset pricing experiments," *American Economic Journal: Microeconomics* **4**(4), 35–64. [3, 4, 6, 7]

Assenza T, Heemeijer P, Hommes C, and Massaro D (2011), "Individual Expectations and Aggregate Macro Behavior," CeNDEF Working Papers 11-01, Universiteit van Amsterdam, Center for Nonlinear Dynamics in Economics and Finance. [3, 6, 7]

Atanasova C (2003), "Credit market imperfections and business cycle dynamics: A nonlinear approach," *Studies in Nonlinear Dynamics & Econometrics* **7**(4). [9]

Balke NS (2000), "Credit and economic activity: credit regimes and nonlinear propagation of shocks," *Review of Economics and Statistics* **82**(2), 344–349. [4, 9]

Baron M, and Xiong W (2017), "Credit expansion and neglected crash risk," *The Quarterly Journal of Economics* **132**(2), 713–764. [2]

Bernanke BS, and Gertler M (1989), "Agency Costs, Net Worth, and Business Fluctuations," *American Economic Review* **79**, 14–31. [2]

Bordalo P, Gennaioli N, and Shleifer A (2018), "Diagnostic expectations and credit cycles," *The Journal of Finance* **73**(1), 199–227. [3, 4, 5, 7, 8, 12, 17]

Brav A, and Heaton JB (2002), "Competing theories of financial anomalies," *The Review of Financial Studies* **15**(2), 575–606. [5]

Brunnermeier M, Palia D, Sastry KA, and Sims CA (2017), "Feedbacks: financial markets and economic activity," Technical report, Princetion University. [4]

Caldara D, and Herbst E (2019), "Monetary policy, real activity, and credit spreads: Evidence from bayesian proxy svars," *American Economic Journal: Macroeconomics* **11**(1), 157–92. [4]

Carriero A, Clark TE, and Marcellino M (2015), "Large Vector Autoregressions with asymmetric priors and time varying volatilities," Working Paper 759, Queen Mary University of London. [21]

Carriero A, Galvao AB, Marcellino M, *et al.* (2018), "Credit Conditions and the Effects of Economic Shocks: Amplification and Asymmetries," Technical report, Economic Modelling and Forecasting Group. [4]

Chen CW, and Lee JC (1995), "Bayesian inference of threshold autoregressive models," *Journal of Time Series Analysis* **16**(5), 483–492. [23]

Cogley T, and Sargent TJ (2008), "Anticipated Utility And Rational Expectations As Approximations Of Bayesian Decision Making," *International Economic Review* **49**(1), 185–221. [5]

Eusepi S, and Preston B (2011), "Expectations, Learning, and Business Cycle Fluctuations," *American Economic Review* **101**(6), 2844–72. [5]

Evans GW, and Honkapohja S (1999), "Learning dynamics," *Handbook of Macroeconomics* **1**, 449–542. [3, 6]

Fama EF (1970), "Efficient Capital Markets: A Review of Theory and Empirical Work," *The Journal of Finance* **25**(2), 383–417. [5]

Gabaix X (2014), "A sparsity-based model of bounded rationality," *The Quarterly Journal of Economics* **129**(4), 1661–1710. [3, 6]

Gennaioli N, and Shleifer A (2018), *A Crisis of Beliefs: Investor Psychology and Financial Fragility*, Princeton University Press. [7, 23]

Gertler M, and Karadi P (2015), "Monetary policy surprises, credit costs, and economic activity," *American Economic Journal: Macroeconomics* **7**(1), 44–76. [3, 4, 11]

Gilchrist S, and Zakrajšek E (2012), "Credit spreads and business cycle fluctuations," *American Economic Review* **102**(4), 1692–1720. [2, 4, 21]

Greenwood R, and Hanson SG (2013), "Issuer quality and corporate bond returns," *The Review of Financial Studies* **26**(6), 1483–1525. [2, 5]

Haario H, Saksman E, Tamminen J, *et al.* (2001), "An adaptive Metropolis algorithm," *Bernoulli* **7**(2), 223–242. [11, 23]

Hommes C (2006), "Heterogeneous Agent Models in Economics and Finance," in L Tesfatsion, and KL Judd (eds.) "Handbook of Computational Economics," *Handbook of Computational Economics*, volume 2, chapter 23, 1109–1186, Elsevier. [7]

——— (2009), "Bounded Rationality and Learning in Complex Markets," in "Handbook of Research on Complexity," chapter 5, 87–123, Edward Elgar. [6, 7]

Hommes C, Makarewicz T, Massaro D, and Smits T (2017), "Genetic algorithm learning in a New Keynesian macroeconomic setup," *Journal of Evolutionary Economics* **27**(5), 1133–1155. [6]

Huber F, and Feldkircher M (2019), "Adaptive shrinkage in Bayesian vector autoregressive models," *Journal of Business & Economic Statistics* **37**(1), 27–39. [4, 10]

Jordà s, Schularick M, and Taylor AM (2016), "The great mortgaging: housing finance, crises and business cycles," *Economic Policy* **31**(85), 107–152. [2]

Kahneman D (2003), "Maps of Bounded Rationality: Psychology for Behavioral Economics," *American Economic Review* **93**(5), 1449–1475. [5]

Kahneman D, and Tversky A (1972), "Subjective probability: A judgment of representativeness," *Cognitive Psychology* **3**(3), 430–454. [3, 7]

Kastner G, and Früwirth-Schnatter S (2014), "Ancillarity-sufficiency interweaving strategy (ASIS) for boosting MCMC estimation of stochastic volatility models," *Computational Statistics Data Analysis* **76**, 408 – 423. [24]

Kindleberger CP (1978), *Manias, Panics and Crashes: A History of Financial Crisis*, New York: Basic Books. [2]

Kiyotaki N, and Moore J (1997), "Credit cycles," *Journal of Political Economy* **105**(2), 211–248. [2]

Krishnamurthy A, and Muir T (2017), "How Credit Cycles across a Financial Crisis," Working Paper 23850, National Bureau of Economic Research. [3]

Kubin I, Zörner TO, Gardini L, and Commendatore P (2019), "A credit cycle model with market sentiments," *Structural Change and Economic Dynamics* . [3, 5, 14, 17]

Leijonhufvud A (1973), "Effective Demand Failures," *The Swedish Journal of Economics* **75**(1), 27–48. [15]

López-Salido D, Stein JC, and Zakrajšek E (2017), "Credit-market sentiment and the business cycle," *The Quarterly Journal of Economics* **132**(3), 1373–1426. [2, 4, 5]

Malmendier U, and Nagel S (2016), "Learning from Inflation Experiences," *The Quarterly Journal of Economics* **131**(1), 53–87. [5]

Matsuyama K, Sushko I, and Gardini L (2016), "Revisiting the model of credit cycles with good and bad projects," *Journal of Economic Theory* **163**, 525–556. [3, 4]

McCracken MW, and Ng S (2016), "FRED-MD: A Monthly Database for Macroeconomic Research," *Journal of Business & Economic Statistics* **34**(4), 574–589. [9, 21]

Mertens K, and Ravn MO (2013), "The dynamic effects of personal and corporate income tax changes in the United States," *American Economic Review* **103**(4), 1212–47. [4, 11, 24]

Mian A, Sufi A, and Verner E (2017), "Household debt and business cycles worldwide," *The Quarterly Journal of Economics* **132**(4), 1755–1817. [2]

Minsky HP (1977), "The Financial Instability Hypothesis: An Interpretation of Keynes and an Alternative to "Standard" Theory," *Challenge* **20**(1), 20–27. [2, 3]

Nofsinger JR (2005), "Social mood and financial economics," *The Journal of Behavioral Finance* **6**(3), 144–160. [6]

Park T, and Casella G (2008), "The Bayesian Lasso," *Journal of the American Statistical Association* **103**(482), 681–686. [10]

Rajan RG (2006), "Has finance made the world riskier?" *European Financial Management* **12**(4), 499–533. [2, 15]

Sargent TJ (1993), *Bounded Rationality in Macroeconomics*, New York: Oxford University Press. [3, 6]

Schularick M, and Taylor AM (2012), "Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008," *American Economic Review* **102**(2), 1029–61. [2]

Simon HA (1955), "A Behavioral Model of Rational Choice," *The Quarterly Journal of Economics* **69**(1), 99–118. [5]

——— (1957), *Models of man; social and rational.*, New York: Wiley. [2]

Sims CA (1980), "Macroeconomics and reality," *Econometrica: Journal of the Econometric Society* 1–48. [9]

——— (2003), "Implications of rational inattention," *Journal of Monetary Economics* **50**(3), 665 – 690, swiss National Bank/Study Center Gerzensee Conference on Monetary Policy under Incomplete Information. [3, 6]

Stein JC (2014), "Incorporating Financial Stability Considerations into a Monetary Policy Framework : a speech at the International Research Forum on Monetary Policy, Washington, D.C., March 21, 2014," Speech 796, Board of Governors of the Federal Reserve System (U.S.). [2]

Tirole J (2010), *The Theory of Corporate Finance*, Princeton University Press. [3]

Tversky A, and Kahneman D (1974), "Judgment under Uncertainty: Heuristics and Biases," *Science* **185**(4157), 1124–30. [3]

Wagener FO (2014), "Expectations in Experiments," *Annual Review of Economics* **6**, 421–443. [6]

Wu JC, and Xia FD (2016), "Measuring the macroeconomic impact of monetary policy at the zero lower bound," *Journal of Money, Credit and Banking* **48**(2-3), 253–291. [9, 21]

A Data

Table 2: Data labels and sources

Database	Variable	Data set label	Source
FRED	Industrial Production	IP: Index	McCracken and Ng (2016)
	Loans	Commercial and Industrial Loans	McCracken and Ng (2016)
	Inflation	CPI: All Items	McCracken and Ng (2016)
	Baa	Moody's Seasoned Baa Corporate Bond Yield	McCracken and Ng (2016)
	GS10	10-Year Treasury Rate	McCracken and Ng (2016)
	FFR	Effective Federal Funds Rate	McCracken and Ng (2016)
Wu-Xia	SR	Wu-Xia shadow federal funds rate	Wu and Xia (2016)
Gilchrist-Zakrajšek	EBP	Excess bond premium	Gilchrist and Zakrajšek (2012)

B MCMC algorithm

Since the joint posterior density of the proposed model has no closed form solution, we apply Markov Chain Monte Carlo simulation techniques to draw from the joint posterior. Therefore, we employ a Gibbs sampler where we iterate over the conditional posterior densities to draw from the full posterior distribution. We discard the first 5.000 of 20.000 draws in order to ensure convergence of the MCMC algorithm. In the following we outline our sampling scheme:

I. Sample the VAR coefficients by employing the triangular algorithm of Carriero *et al.* (2015). Hereby, we transform the model such that we can estimate it *equation by equation* conditional on the state and the data. Hereby, we take the difference between the dependent variable and the estimated residuals of all $m-1$ ($m = 1, \ldots, M$) equations, such that

$$y^*_{m,S_t} = y_{m,S_t} - \sum_{l=1}^{m-1} h_{i,ml} d^{0.5}_{m-1} e_{m-1,S_t}, \tag{B.1}$$

where we use only the data y_{m,S_t} and innovations e_{m-1,S_t} which belong to the according regime. Thus, our system is then just a seemingly unrelated regression model, where we draw each row of the coefficient matrices $A_i = (c_i, A_{i1}, \ldots, A_{ip})$ with dimension $M \times K$ with $K = Mp + 1$. We define $X_t = (1^T, Y_{t-1}^T, \ldots, Y_{t-p}^T)^T$ and indicate the m-th row of A_i as $A_i^{\{m\}}$, such that the conditional posterior distribution reads

$$A_i^{\{m\}} \mid A_i^{\{1:m-1\}}, \Sigma_i, \gamma \sim \mathcal{N}(\overline{A}_i^{\{m\}}, \overline{V}_i^{\{m\}}), \tag{B.2}$$

with

$$\begin{aligned}
\overline{A}_i^{\{m\}} &= \overline{V}_i^{\{m\}} \left\{ \frac{X_{S_t} y^{*T}_{j,S_t}}{d_j} + \text{diag}\left(\frac{1}{\tau_{ij,m1}}, \ldots, \frac{1}{\tau_{ij,mK}}\right) \underline{a}_{i,kl} \right\}, \\
\overline{V}_i^{\{m\}} &= \left[\text{diag}\left(\frac{1}{\tau_{ij,m1}}, \ldots, \frac{1}{\tau_{ij,mK}}\right) + \frac{X_{S_t} X_{S_t}^T}{d_m} \right]^{-1}.
\end{aligned} \tag{B.3}$$

II. Sample the elements of H_i also *equation by equation* from normal distributions. We transform then the model to

$$e^*_{m,S_t} = y_{m,S_t} - X_{S_t} A_i^{\{m\}}. \tag{B.4}$$

Therefore, the conditional posterior distribution reads

$$h_{i,ml} \mid A_i^{\{m\}}, D, \gamma \sim \mathcal{N}(\overline{h}_{i,ml}, \overline{U}_{i,ml}) \tag{B.5}$$

with

$$
\begin{aligned}
\overline{h}_{i,j} &= \overline{V}_i^{\{m\}} \left\{ \frac{e_{S_t}^* y_{j,S_t}^T}{d_j} + \text{diag}\left(\frac{1}{\phi_{i,m1}}, \dots, \frac{1}{\phi_{i,mM}} \right) \underline{h}_{i,kl} \right\}, \\
\overline{U}_{i,j} &= \left[\text{diag}\left(\frac{1}{\phi_{i,m1}}, \dots, \frac{1}{\phi_{i,mM}} \right) + \frac{e_{S_t}^* e_{S_t}^{*T}}{d_m} \right]^{-1}.
\end{aligned}
\tag{B.6}
$$

III. Sample the regime-invariant variances of D from independent Inverse-Gamma distributions by rewriting the model, such that

$$\epsilon_m^* = y_m - \begin{pmatrix} X_{S_t=1} A_1^{\{m\}} \\ X_{S_t=2} A_2^{\{m\}} \end{pmatrix} - \begin{pmatrix} \sum_{l=1}^{m-1} h_{1,ml} d_{m-1}^{0.5} e_{m-1,S_t=1} \\ \sum_{l=1}^{m-1} h_{2,ml} d_{m-1}^{0.5} e_{m-1,S_t=2} \end{pmatrix}. \tag{B.7}$$

Then, after combining the prior $d_m \sim IG(a_0, b_0)$ where $a_0 = b_0 = 0.01$, with the likelihood, we get the conditional posterior density as follows

$$d_m \mid \epsilon_m^*, Y \sim IG(a_0 + 0.5T, b_0 + 0.5\epsilon_m^{*T}\epsilon_m^*). \tag{B.8}$$

IV. Sample the parameters needed for the Normal-Gamma prior of the matrices A_{ij}. The conditional posterior distribution of $\tau_{ij,kl}$ follows a generalized inverse Gaussian (GIG) distribution,

$$\tau_{ij,kl} \mid a_{ij,kl}, \vartheta_{\tau,j}, \lambda_{ij}^2 \sim GIG\left(\vartheta_{\tau,j} - \frac{1}{2}, \vartheta_{\tau,j}\lambda_{ij}^2, (a_{ij,kl} - \underline{a}_{ij,kl}) \right), \tag{B.9}$$

and the conditional posterior distribution of ζ_{ij} follows a Gamma distribution,

$$\zeta_{ij} \mid \tau_{ij}, \vartheta_{\tau,j} \sim G\left(c_0 + \vartheta_{\tau,j}M^2, d_0 + 0.5\vartheta_{\tau,j}\lambda_{ij-1}^2 \sum_{k,l \in A_{ij}} \tau_{ij,kl} \right). \tag{B.10}$$

The conditional posterior distribution of $\vartheta_{\tau,j}$ has no closed-form solution and thus a random-walk Metropolis-Hastings step is implemented, where a candidate draw is drawn from $\vartheta_{\tau,j}^* \sim \mathcal{N}\left(\ln(\vartheta_{\tau,j}^{(n-1)}), \kappa_{\tau,j} \right)$, with $\kappa_{\tau,j}$ being a tuning parameter. It reads

$$min\left[1, \frac{(\vartheta_{\tau,j}^* \lambda_{ij}^2/2)^{M^2\vartheta_{\tau,j}^*} \Gamma(\vartheta_{\tau,j}^*) q(\vartheta_{\tau,j}^*)}{(\vartheta_\tau^* \lambda_{ij}^2/2)^{M^2\vartheta_{\tau,j}^{(n-1)}} \Gamma(\vartheta_{\tau,j}^{(n-1)}) q(\vartheta_{\tau,j}^{(n-1)})} \right]. \tag{B.11}$$

V. Sample the parameters needed for the Normal-Gamma prior setup of the matrices H_i. The conditional posterior distribution of $\phi_{i,kl}$ follows again a GIG distribution,

$$\phi_{i,kl} \mid h_{i,kl}, \vartheta_\phi, \xi_i^2 \sim GIG\left(\vartheta_\phi - \frac{1}{2}, \vartheta_\phi\xi_i^2, (h_{i,kl} - \underline{h}_{i,kl}) \right), \tag{B.12}$$

and the conditional posterior distribution of ξ_i^2 follows a Gamma distribution,

$$\xi_i^2 \mid \phi_i, \vartheta_\phi \sim G(c_0 + \vartheta_\phi v, d_0 + 0.5\vartheta_\phi/2 \sum_{k=2}^{M} \sum_{l=1}^{M-1} \phi_{i,kl}), \tag{B.13}$$

where v denotes the number of free off-diagonal elements in H_i, $v = \frac{M(M-1)}{2}$. Again, the conditional posterior distribution of ϑ_ϕ has no closed-form solution and a random-walk MH step is applied, where a candidate draw is drawn from the following proposal distribution $\vartheta_\phi^* \sim \mathcal{N}(\ln(\vartheta_\phi^{(n-1)}), \kappa_\phi)$, with κ_ϕ being a tuning parameter. It reads

$$min \left[1, \frac{(\vartheta_\phi^* \xi_i^2/2)^{v\vartheta_\phi^*} \Gamma(\vartheta_\phi^*) q(\vartheta_\phi^*)}{(\vartheta_\phi^* \xi_i^2/2)^{v\vartheta_\phi^{(n-1)}} \Gamma(\vartheta_\phi^{(n-1)}) q(\vartheta_\phi^{(n-1)})} \right]. \tag{B.14}$$

VI. Sample the threshold parameter γ according to a adaptive random-walk Metropolis-Hastings step. Hereby, we follow Chen and Lee (1995) and propose a normally distributed candidate, $\gamma_c = \gamma^{(n-1)} + \mathcal{N}(0, C^{(n)})$, with $C^{(n)}$ being a tuning parameter and (n) denoting the n-th of N draws. The probability of accepting a candidate draw $\gamma_c^{(n)}$ depends on the ratio of the likelihood times the prior when evaluated with the candidate and existing draw, where we reject the candidate draw if

$$\min \left[1, \frac{p(\gamma_c \mid A_i, \Sigma_i) q(y_c)}{p(\gamma^{(t-1)} \mid A_i \Sigma_i) q(\gamma^{(t-1)})} \right], \tag{B.15}$$

and otherweise set $\gamma^{(n)} = \gamma_c$. We follow Haario *et al.* (2001) to adapt our tuning parameter $C^{(n)}$ by

$$C^{(n)} = \begin{cases} C_0 & \text{if } n \leq N_c, \\ s_d var(\gamma_1, \ldots, \gamma_{n-1}) + s_d \eta & \text{if } n > N_c, \end{cases} \tag{B.16}$$

thereby assuming a constant tuning parameter for the first $N_c = 50$ draws and afterwards using the empirical variance to tune the MH-step. We set η to a really small number and use s_d to fine tune the algorithm to achieve acceptance probabilities between 20% and 40%. Note that this algorithm is indeed non-Markovian, but Haario *et al.* (2001) show that this tuning algorithm has correct ergodicity properties.

C   Diagnostic Expectations

Diagnostic expectations are computed following the derivations from Gennaioli and Shleifer (2018), more precisely we refer to Proposition 5.1 and 6.1. We assume that the target distribution is the true distribution at time t if no news is received relative to time $t - 1$. They show in Proposition 5.1 that if the underlying process, $\hat{X}$ is normal with heteroscedastic errors assuming $\hat{X} \mid I_0 \sim \mathcal{N}(\mu_0, \sigma_0^2)$ and $\hat{X} \mid I_{-1} \sim \mathcal{N}(\mu_{-1}, \sigma_{-1}^2)$, where I_0 denotes the information set at time t and I_{-1} the information set one period before, that the mean μ_θ and variance σ_θ^2 is given by:

$$\mu_\theta = \mu_0 + \frac{\theta \sigma_0^2}{\sigma_{-1}^2 + \theta(\sigma_{-1}^2 - \sigma_0^2)}(\mu_0 - \mu_{-1}),$$
$$\sigma_\theta^2 = \sigma_0^2 \frac{\sigma_{-1}^2}{\sigma_{-1}^2 + \theta(\sigma_{-1}^2 - \sigma_0^2)}. \tag{C.1}$$

When applied to an AR(1) process with stochastic volatility,

$$\hat{X}_{t+1} \mid \rho, h_t \sim \mathcal{N}(\rho \hat{X}_t, \exp(h_{t+1})),$$
$$h_{t+1} \mid h_t, \mu, \phi, \sigma_h^2 \sim \mathcal{N}(\mu + \phi(h_t - \mu), \sigma_h^2), \tag{C.2}$$
$$h_0 \mid \mu, \phi, \sigma_h^2 \sim \mathcal{N}(\mu, \sigma_h^2/(1 - \phi^2)),$$

with $\sigma_t^2 = \exp(h_t)$. The estimation procedure of stochastic volatility models are described in Kastner and Früwirth-Schnatter (2014). Finally, we can compute the diagnostic expectations with

$$\mathbb{E}_t^\theta(\hat{X}_{t+1}) = \mathbb{E}_t(\hat{X}_{t+1}) + \theta[\mathbb{E}_t(\hat{X}_{t+1}) - \mathbb{E}_{t-1}(\hat{X}_{t+1})], \tag{C.3}$$

where $\mu_0 = \mathbb{E}_t(\hat{X}_{t+1}) = \rho\hat{X}_t$ with variance $\sigma_0^2 = \sigma_t^2$. Accordingly the comparison distribution has mean $\mu_{-1} = \mathbb{E}_{t-1}(\hat{X}_{t+1}) = \rho^2\hat{X}_{t-1}$ with variance $\sigma_{-1}^2 = \sigma_{t-1}^2$.

D   Identification based on External Instruments

The identification scheme on external instruments is introduced by Mertens and Ravn (2013). Generally, it is similar to a two stage least squares procedure, where the reduced form residuals of the structural shock are regressed on the instrument Z_{S_t}. Again, the subscript S_t denotes only those observations in regime $S_t = i$. The fitted values are then regressed on the other reduced form residuals,

$$\epsilon_{S_t}^q = \frac{\lambda_i^q}{\lambda_i^p}\hat{\epsilon}_{S_t}^p + \nu_{S_t} \qquad \text{if } S_t = i. \tag{D.1}$$

Therefore, we get an estimate for the ratio $\frac{\lambda_i^q}{\lambda_i^p}$ from which we can identify λ_i^q. We by partitioning the matrix of the structural coefficients, such that

$$\Lambda_i = [\lambda_i^p \quad \Lambda_i^q] = [\Lambda_{i,1} \quad \Lambda_{i,2}] = \begin{bmatrix} \lambda_{i,11} & \lambda_{i,12} \\ \lambda_{i,21} & \lambda_{i,22} \end{bmatrix}, \tag{D.2}$$

where $\lambda_{i,11}$ is a scalar, $\lambda_{i,12}^T$ and $\lambda_{i,21}$ are vectors of size $M - 1 \times 1$ and $\lambda_{i,22}$ is a matrix of size $M - 1 \times M - 1$. Furthermore, we partition the reduced form variance-covariance matrix with $\Sigma_{i,11}$ being a scalar and the others of the same size as the elements of Λ_i,

$$\Sigma_i = \begin{bmatrix} \Sigma_{i,11} & \Sigma_{i,12} \\ \Sigma_{i,21} & \Sigma_{i,22} \end{bmatrix}. \tag{D.3}$$

Then λ_i^p is identified up to a sign convention and is obtained by the following closed form solution

$$(\lambda_i^p)^2 = \lambda_{i,11}^2 = \Sigma_{i,11} - \lambda_{i,12}\lambda_{i,12}^T, \tag{D.4}$$

where

$$\lambda_{i,12}\lambda_{i,12}^T = (\Sigma_{i,21} - \frac{\lambda_{i,21}}{\lambda_{i,11}}\Sigma_{i,11})^T Q^{-1}(\Sigma_{i,21} - \frac{\lambda_{i,21}}{\lambda_{i,11}}\Sigma_{i,11}), \tag{D.5}$$

with

$$Q = \frac{\lambda_{i,21}}{\lambda_{i,11}}\Sigma_{i,11}\frac{\lambda_{i,21}^T}{\lambda_{i,11}} - (\Sigma_{i,21}\frac{\lambda_{i,21}^T}{\lambda_{i,11}} + \frac{\lambda_{i,21}}{\lambda_{i,11}}) + \Sigma_{i,22}. \tag{D.6}$$