The Impact of Credit Market Sentiment Shocks

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Abstract

This paper investigates the role of credit market sentiment and investor beliefs in credit cycle dynamics and their transmission to business cycle fluctuations. Using U.S. data from 1968 to 2014, we find that credit market sentiment is indeed able to detect asymmetries in a small-scale macroeconomic model. An unexpected credit market sentiment shock has different impacts in an optimistic and pessimistic credit market environment. While an unexpected movement in the optimistic regime leads to a rather muted impact on output and credit, we find a significant negative impact on these variables in the pessimistic regime. The findings highlight the relevance of expectation formation mechanisms as a source of macroeconomic instability.

Keywords: Credit Cycles, Expectation Formation, Structural Threshold VARs.

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

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1. Introduction

The Great Financial Crisis (GFC) of 2008-09 revived interest among economists and policymakers in the role of credit expansion, investor beliefs, and expectations in financial markets as a source of recurrent financial crises. In this paper, we propose an empirical macroeconomic model that links credit market dynamics with shocks to investors sentiment. The general idea is based on a promising strand of literature that finds a strong link between credit market sentiment in explaining different phases of economic activity. For instance, López-Salido, Stein and Zakrajšek (2017) show that low credit spreads used as a proxy for market sentiment predict both a rise in credit spreads and a decline in economic activity. The importance of investor sentiment raises the question of which measures or events might be influential in providing explanations for macroeconomic instability.

Hence, a growing body of literature, originating from Beaudry and Portier (2004, 2014), argues that sudden changes in expectations due to unexpected news are an independent and significant driver of macroeconomic fluctuations. The main idea of news-driven business cycles is that news about the future total factor productivity (TFP) exerts strong linkages to other macroeconomic fundamentals and is thus important in explaining fluctuations. Recently, Görtz, Tsoukalas and Zanetti (2022) present an analysis of how such TFP news shocks propagate in an environment with financial frictions. They report strong linkages between innovations due to news shocks as well as shocks explaining movements in risk indicators such as credit spreads. The role of news thus seems to be promising for explaining the origins of macroeconomic instability. However, these approaches focus on news about technological innovations and how these shocks shape agents' expectations concerning the stability properties of an economy. Instead, market sentiment in general tends to react rather quickly to unexpected news which are not necessarily based on fundamentals. As pointed out by Stein (2014), the relevance of risk measures and how agents form their expectations about future risks to monetary policy became apparent a few years after the crisis.

The rather strong assumption of rationality in the formation of expectations is criticized by many scholars originating from Simon (1957). In response, several branches of the literature relax this assumption and address the concept of *bounded rationality*. One strand of literature incorporates learning into the expectation formation process (Evans and Honkapohja, 1999; Sargent, 1993), another one deals with rational inattention (Gabaix, 2014; Mackowiak and Wiederholt, 2009; Sims, 2003), and finally the behavioral literature uses simple psychological heuristics (Tversky and Kahneman, 1974). Assenza et al. (2011) find several robust heuristics when agents forecast inflation dynamics in a learning-to-forecast experimental study. A more recent contribution by Bordalo, Gennaioli and Shleifer (2018) operationalizes the representativeness heuristic (Kahneman and Tversky, 1972) and presents a new belief formation mechanism – *diagnostic expectations* – to explain credit cycles.

Prominent models explaining credit cycle instability rely on some form of financial frictions. These models 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 constrained. Since agents are not fully aware of what their borrowing decisions trigger in the aggregate economy, they face externalities in their choice of leverage. The fragility of the system is then identified through leverage. This has initiated a plethora of empirical studies using balance sheet measures as predictors of recessions (Jordà, Schularick and Taylor, 2016; Mian, Sufi and Verner, 2017; Schularick and Taylor, 2012). In summary, according to this strand of the literature, the driving force behind fluctuations can be traced back to some sort of market imperfection.

On the contrary, behavioral theories highlight 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 behavioral finance literature, which emphasizes the time-varying component of credit conditions when the assumption of belief updating via rational expectations is relaxed. The literature introduces behavioral elements into 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 overheats and is thus a better predictor for recessions than rapid aggregate credit growth. Baron and Xiong (2017) highlight the undervaluation of crash risk in the face of credit expansions, while López-Salido, Stein and Zakrajšek (2017) provide evidence that sentiment on the credit market is a valid predictor of recessions. Using these concepts, Boeck (2023) examines the belief formation on financial markets in detail by investigating the responses of belief distortions to a financial risk shock.

While the financial frictions approach mostly assumes exogenous shocks and rational expectations in order to explain fluctuations, other models provide endogenous explanations without relying on the assumption of strict rationality. For example, Matsuyama, Sushko and Gardini (2016) propose a model of endogenous credit cycles in an overlapping generations setup without leaving the realm of rational expectations. They introduce financial frictions through the limited pledgability of collateral (Tirole, 2010). A recent contribution by Kubin et al. (2019) extends this model by endogenizing the pledgability parameter and allowing it to vary over time according to a simple heuristic rule: if the current state of the economy, proxied by net worth, is above or below some threshold, the agents' sentiment switches between an *optimistic* and a *pessimistic* credit market regime, reflecting the psychological state of the lenders. This translates into different degrees of what lenders are willing to accept as collateral and thus provides an endogenous behavioral explanation of how the general (or in particular the business) sentiment is anchored in perceptions of agency problems.

Taking this theoretical approach as a starting point, we propose an empirical macroeconomic model that incorporates both an endogenous explanation of credit cycles as well as switching dynamics resulting from periods of optimism and pessimism on the credit market. To this end, we test the conjecture that credit market sentiment can exert disruptive forces on the credit and business cycle. We distinguish between optimistic and pessimistic credit market conditions and expect more severe effects when the financial system is already in distress. Furthermore, we argue that when agents receive bad news about the state of the economy, sentiment towards the credit market deteriorates and credit spreads rise. This is then transmitted to real economy and we expect a decline in credit, investment, and eventually output. To investigate the proposed relationship, we employ a non-linear structural vector autoregression (VAR) with monthly data covering the period between January 1968 and December 2014 of the U.S. economy. This setup allows us to examine the impact of a credit market sentiment shock, which is equivalent to an unexpected news shock in the credit market. The identification is based on the different belief formation mechanisms that agents use to forecast risks in financial markets.

Our paper is also related to the literature on structural identification in threshold VARs (TVAR). While the structural VAR literature has made great advancements in identifying monetary policy shocks (Gertler and Karadi, 2015), the literature looking at financial market feedbacks 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, Stein and Zakrajšek, 2017) and reduced form multi-equation models (Gilchrist and Zakrajšek, 2012). A recent paper by Caldara and Herbst (2019) adds credit spread variables to a structurally identified multivariate framework but they restrict their analysis to monetary policy shocks. To the best of our knowledge, there are only two other papers that deal with the identification of a credit spread shock. Brunnermeier et al. (2021) use the identification via a heteroskedasticity based approach to identify a monetary policy shock and two "stress" shocks originating in the financial sector and propagating to the real economy. However, we use a proxy TVAR specification that is closer to Carriero, Galvao and Marcellino (2018). While they develop a variant of a smooth transition VAR model using a recursive ordering identification strategy, we rely on the forecast error based on the expectation formation mechanism of agents to identify a credit market sentiment shock.

To summarize, we provide several contributions to the literature. First, we use a non-linear specification to disentangle periods of optimism and pessimism in the credit market. It is a fairly well-established fact in the literature on credit activity that financial markets operate and react strongly in times of distress than in times of tranquility.[1] Second, we use a sophisticated shrinkage prior setup that exploits recent developments in the Bayesian literature on VARs (Huber and Feldkircher, 2019) for an efficient estimation of our model. Third, we propose a novel identification mechanism inspired by the literature on identification via external instruments (Gertler and Karadi, 2015; Mertens and

[1] For instance, Balke (2000) examines empirically whether credit plays a role as a non-linear propagator of shocks. Another example in the area of uncertainty shocks is Alessandri and Mumtaz (2019).

Ravn, 2013; Stock and Watson, 2012) based on diagnostic expectations as an expectation formation mechanism (Bordalo, Gennaioli and Shleifer, 2018) in a TVAR setting. Fourth, we discuss and compare our results with other expectation formation mechanisms, primarily rational expectations and a set of behaviorally and experimentally confirmed belief formation mechanisms discussed in Anufriev and Hommes (2012). This strategy allows us to identify a credit market sentiment shock, where unexpected news leads to different dynamics in regimes of optimism and pessimism.

Our results show that a credit market sentiment shock has two distinct features. First, there are strong asymmetries between different credit market regimes. When the credit market is calm, an unexpected news shock to the credit market sentiment has short-lived and small to muted effects on the credit and business cycles. On the contrary, in more turbulent times, when pessimistic sentiment is already prevalent in the economy, a shock to credit market sentiment induces severe negative effects on the business and the credit cycle. In addition, it also leads to a drop in prices. The economy starts to recover approximately after one to two years. Moreover, a comparison of different expectation formation mechanisms reveals heterogeneous reactions on impact on economic activity, prices, and short-term interest rates.

The remainder of the article is organized as follows. After introducing our credit market sentiment indicator and the issue of belief formation in macroeconomics in section 2, which presents the main identifying assumption in the model, we introduce our structural TVAR framework and the technical details of our identification strategy in section 3. Our main results and the comparison of using different expectation formation mechanisms as well as a sensitivity analysis are discussed in section 4 while section 5 concludes.

2. Expectation Formation in Macroeconomics

The causes of recurrent economic recessions and instabilities are subject to a variety of explanations. There exists a plethora of studies that identify the source of instability as an exogenous shock to the economy. Since our model relies on endogenous explanations supported by behavioral arguments, we focus on the role of expectation formation as the origin of instabilities. A prominent example of an endogenous explanation of credit market fluctuations has been provided by Matsuyama, Sushko and Gardini (2016). However, their model relies on the assumption of rational expectations as the belief formation mechanism.[2] The underlying idea is that financial frictions and heterogeneous investment projects cause and amplify instability and recurrent fluctuations in credit markets. In a recent extension, Kubin et al. (2019) incorporate empirical findings from the behavioral finance literature, which show that credit market sentiment does indeed play a role in driving aggregate fluctuations. Behavioral elements are introduced into the model to account for time-varying perceptions of risk.

[2] Note that we will use the terms *belief* and *expectation* interchangeably in our context.

Thus, beliefs about the state of the economy are directly incorporated, raising the question of how people perceive the state of the economy. While they model the perception-dependent friction parameter deterministically, we take a different approach here.

We introduce a credit market sentiment indicator denoted by $\{\omega_t\}_{t=1}^T$ and utilize it in a twofold fashion. First, we use the indicator to determine whether the economy is currently in an optimistic or pessimistic credit market regime. Second, we compute a forecast and use the resulting forecast error to characterize exogenous news from the credit market. Following López-Salido, Stein and Zakrajšek (2017), we operationalize this indicator by using the credit spread between yields on seasoned long-term Baa-rated corporate bonds and yields on long-term Treasury securities (henceforth the Baa spread). We assume that the Baa spread follows an autoregressive process of order one. However, to account for periods of financial turmoil, when uncertainty may be pronounced, we extend the specification to include stochastic volatility. Moreover, since a large number of events occur simultaneously in turbulent periods, agents may suffer from increased distortions resulting from specific memory effects. Taking this into account, we obtain the following specification

$$\omega_{t+1} = \rho\omega_t + \eta_t \tag{2.1}$$

with $\eta_t \sim \mathcal{N}(0, \exp(h_t/2))$, where the log-volatility, h_t, follows a centered AR(1) process and ρ denotes the persistence parameter. Furthermore, we define $\mathbb{E}_t[\cdot]$ as the expectation operator using all the information up to time point t. Hence, the forecast error is defined as the difference between the realization and the expectation of the credit spread

$$\mathrm{FE}_t[\omega_{t+1}] = \omega_{t+1} - \mathbb{E}_t[\omega_{t+1}]. \tag{2.2}$$

We now ask how agents form their expectations about the sentiment. If an agent forms a forecast based on rational expectations (RE), we obtain

$$\mathbb{E}_t^{RE}[\omega_{t+1}] = \rho\omega_t, \tag{2.3}$$

which implies that a resulting forecast error does not exhibit any observable pattern. However, the time series of the credit spread forecast exhibits financial anomalies that should not be present according to the assumption of rational expectations and efficient markets (Fama, 1970).[3] Using survey data, Bordalo, Gennaioli and Shleifer (2018) are able to show that forecast errors (and, interestingly, also forecast revisions) are predictable, which is inconsistent with the assumption of efficient markets and fully rational agents. In general, they find that a path of high returns triggers agents to overestimate the probability of high returns in the future (*excessive optimism*), while poor returns yield lower forecasts of future returns (*excessive pessimism*).

[3] Here, 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".

To cope with the aforementioned financial anomalies, Bordalo, Gennaioli and Shleifer (2018) introduce an expectation formation mechanism called *diagnostic expectations* based on the representativeness heuristic (Kahneman and Tversky, 1972). This heuristic states that agents judge a trait or attribute to be more common in a given population if the relative frequency of that attribute in a given population appears to be much higher than in a reference population. Therefore, people overestimate certain traits of a specific population, which are then *diagnostic* for that population.[4] Introducing this heuristic in a time series context, the reference group is based on the absence of information at time point t. Based on this consideration, Bordalo, Gennaioli and Shleifer (2018) formulate a distorted probability distribution of the sentiment, $p_t^{DE}(\omega_{t+1})$, which is inflated by a term denoting representativeness,

$$p_t^{DE}[\hat{\omega}_{t+1}] = p(\hat{\omega}_{t+1} \mid \omega_t = \hat{\omega}_t) \times \left[\frac{p(\hat{\omega}_{t+1} \mid \omega_t = \hat{\omega}_t)}{p(\hat{\omega}_{t+1} \mid \omega_t = \rho\hat{\omega}_{t-1})} \right]^{\theta} \frac{1}{Z}, \tag{2.4}$$

where the normalizing constant Z ensures that the probability distribution integrates to unity and $\theta \in [0, \infty)$ measures the severity of the judgement by representativeness. The first term on the right-hand side is the conditional distribution of rational expectations from current news $\hat{\omega}_t$ for predicting $\hat{\omega}_{t+1}$. The second term is the ratio of the predictions for $\hat{\omega}_{t+1}$ using current news and past news. This distortionary term represents memory limits, as beliefs inflate the probability of representative states and vice versa. Therefore, as long as $\theta > 0$, memory is limited while if $\theta = 0$, the distortionary term vanishes. In this situation, agents use all available information, which corresponds to the assumption of rational expectations. This can also be seen by taking expectations,

$$\mathbb{E}_t^{DE}[\omega_{t+1}] = \mathbb{E}_t^{RE}[\omega_{t+1}] + \theta \left[\mathbb{E}_t^{RE}[\omega_{t+1}] - \mathbb{E}_{t-1}^{RE}[\omega_{t+1}] \right], \tag{2.5}$$

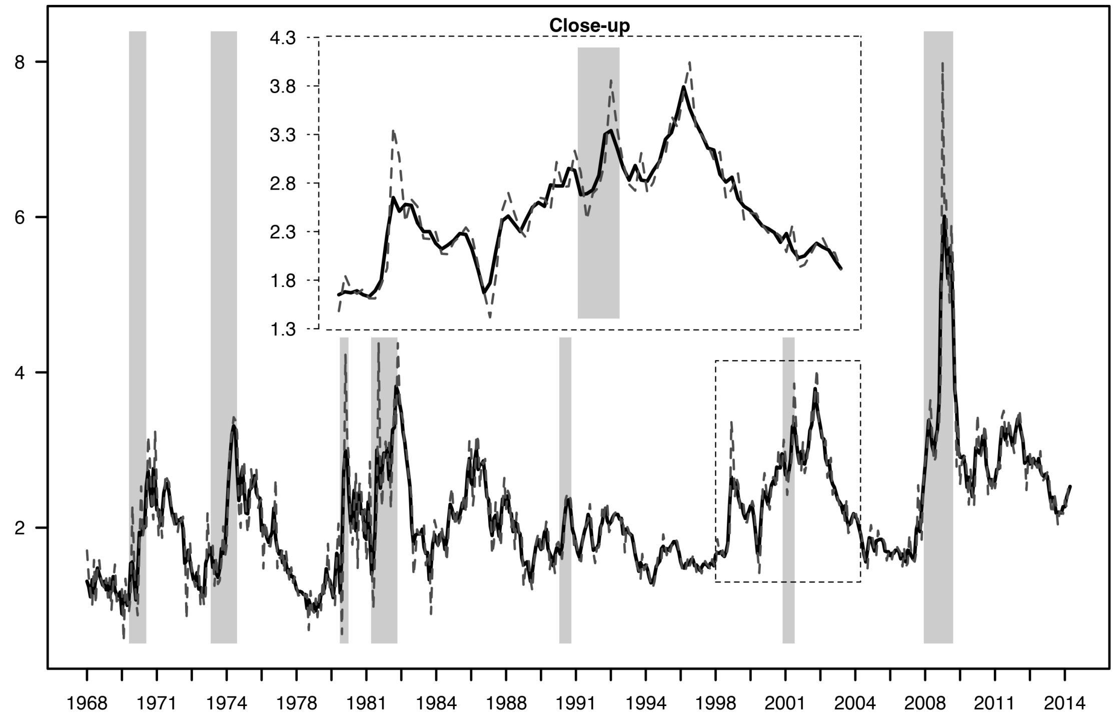
where rational expectations are inflated according to the diagnostic parameter θ times the forecast revisions between t and $t-1$.[5] Note that our analysis is based on the first moment of the diagnostic expectation. Concerning the parameter θ, Gennaioli and Shleifer (2018) refer to values between 0.7 and 1.0 while we stick to the value provided in Bordalo, Gennaioli and Shleifer (2018), $\theta = 0.91$. In the subsequent analysis, we use the forecast errors following Equation 2.2 which agents make when using the expectation heuristic in Equation 2.5 for the assessment of the Baa spread (i.e., the sentiment). The forecast error is then used to identify a credit market sentiment shock.

In Figure 1 we plot the Baa spread along with its diagnostic expectations. The black solid line denotes the credit spread, while the dashed gray line presents its diagnostic expectations, such that

[4] For clarification, we refer to the example given in Bordalo, Gennaioli and Shleifer (2018). Suppose you are trying to predict the proportion of Irish people with red hair. Most likely, you will overestimate the proportion of redheaded Irish because this trait is diagnostic for the Irish and occurs much more frequently than in your reference population. Of course, this does not apply if your reference population is the Irish population.

[5] Details and derivations are provided in Appendix C.

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 and the left axis denotes the height of credit spread in percent.

the difference between the two lines is the forecast error. The light gray shaded areas denote the NBER recession dates. For better readability, we provide an enlargement around the dot-com bubble between January 1998 and December 2004. We use credit market sentiment and credit spreads interchangeably, but with the opposite interpretation: High or optimistic credit market sentiment implies low credit spreads. Hence, we use credit market sentiment to refer to the expected return from bearing credit risk. From Figure 1 it is easy to see the high correlation between recessions and elevated credit spreads. A closer look at the plot reveals the effect of diagnostic expectations. After a few periods of rising or falling spreads, diagnostic expectations are close to the realized value. But after a reversal, diagnostic expectations overshoot in both directions due to the representativeness heuristic. Agents believe that positive or negative events from the previous period also have the highest probability of occurring in the current period (i.e., moving further up or down) and thus underestimate the tail risk of a reversal.

With this in mind, we also explore the possibility that agents rely on simple heuristics to form expectations. We then use these heuristics to compute the forecasting error that characterizes news from the credit market. To study agents' expectation formation routines, learning-to-forecast experiments in a laboratory setting provide further insights. Most interestingly, Hommes (2009) and

Hommes et al. (2017) show in such experiments that a few number of simple heuristics – combined with evolutionary switching between them – are sufficient to describe the expectation formation of economic agents.[6] Assenza et al. (2011) and Anufriev and Hommes (2012) provide valuable experimental insights into the heuristics agents use to forecast asset prices or macroeconomic quantities. A striking result of these experiments is that, in all sessions, participants managed to coordinate their forecasting behavior, which can be boiled down to four different forecasting heuristics: the adaptive heuristic (ADA), the weak and strong trend-following heuristic (WTR and STR), and the anchoring and adjustment heuristic with learning (LAA). When the price shows a slow convergence 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.[7] The second and the third heuristic use the last price observation and adjust it in the direction of the last price change. According to some extrapolation coefficient, a distinction can be made between weak and strong trend-followers. Compared to the weak trend-following case the parameter value exceeds unity for the strong variety. 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* value of the forecast quantity. For the heuristic with a learning anchor, we use the moving average of the last 24 months.

Table 1 provides an overview of all the expectation formation mechanisms considered. In the following analysis, we will use each of these mechanisms to construct forecast errors according to Equation 2.2 to create a proxy for credit market news. Due to the peculiarities of financial markets and the findings of the literature summarized above, our main specification relies on the diagnostic expectations framework (Bordalo, Gennaioli and Shleifer, 2018) and thus serves as a benchmark. This strategy allows us to quantify the differences in the reaction differences to a sentiment shock on impact of rational expectations as well as the remaining heuristics.

3. A VAR with Credit Market Regimes

In this paper, we rely on a structural vector autoregression (SVAR), one of the workhorse models for structural analysis in empirical macroeconomics (Sims, 1980). As pointed out by Balke (2000) and Atanasova (2003), the dynamics of the credit cycle dynamics tend to exhibit non-linearities and an asymmetric propagation of shocks. To take this empirical fact into account, we extend the linear specification with a threshold (TVAR) that allows us to differentiate between credit market regimes. Depending on the prevailing sentiment in the financial markets, agents may behave differently when

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

[7] Basically, the subjects use the random walk, $\mathbb{E}_t^{RW}(\omega_{t+1}) = \omega_t$, for predicting future values. Essentially, the best prediction of tomorrow is the realized value of today.

Table 1: Expectation Formation Mechanisms.

RE	rational expectations	$\mathbb{E}_t^{RE}[\omega_{t+1}] = \mathbb{E}_t(\omega_{t+1})$
DE	diagnostic expectations	$\mathbb{E}_t^{DE}[\omega_{t+1}] = \mathbb{E}_t^{RE}[\omega_{t+1}] + \theta[\mathbb{E}_t^{RE}[\omega_{t+1}] - \mathbb{E}_{t-1}^{RE}[\omega_{t+1}]]$
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	$\mathbb{E}_t^{LAA}[\omega_{t+1}] = 0.5(\omega_{t-1}^{av} + \omega_{t-1}) + (\omega_{t-1} - \omega_{t-2})$

Notes: While $\mathbb{E}[\cdot]^f$ denotes the credit market sentiment expectation with heuristic f, the sample average ω_{t-1}^{av} depends on the information set up to time point t, computed as the moving average of the last 24 months.

faced with positive or negative events.[8] Conditional on the threshold parameter, we can split our sample and estimate two linear SVAR models. We explain the external instruments identification strategy following Gertler and Karadi (2015) in more detail in a dedicated subsection.

The model wants to establish the link between five economic concepts, such that our vector of endogenous variables consists of

$$\boldsymbol{Y}_t = \{\omega_t, y_t, L_t, P_t, i_t\}, \tag{3.1}$$

where ω_t denotes the credit market sentiment, y_t measures economic activity, L_t is the credit volume, P_t indicates prices, and i_t denotes the short-term interest rate. Each of these concepts is proxied by a variable from the FRED database (McCracken and Ng, 2016) and covers the period from January 1968 to December 2014 for the U.S. economy. To proxy the credit market sentiment, we use the aforementioned credit spread, specifically the spread between yields on seasoned long-term Baa-rated corporate bonds and yields on long-term Treasury securities (10 year government bond yields). Thus, the sentiment is elevated when the expected return on credit risk is low and the spread is narrow. We use industrial production (log-differences) to characterize economic activity, commercial and industrial loans (log-differences) to proxy credit volume, the consumer price index (log-differences) for prices, and the federal funds rate for the short-term interest rate. Since we cover the zero lower bound period at the end of our sample, we also estimate specifications with the federal funds rate enriched with the shadow rate provided by Wu and Xia (2016). For more details on the data sources, see Appendix A. To provide a sensitivity analysis and check the fundamentalness of the shocks by augmenting the TVAR with a high-dimensional dataset in a consecutive subsection.

[8] The TVAR has proven advantageous in modeling non-linear processes and is therefore quite well supported in several empirical macroeconomic questions where the dynamics may be regime dependent. For example, Pizzinelli, Theodoridis and Zanetti (2020) show that labor market variables react differently to a variety of shocks in an expansionary and a recessionary regime, while Avdjiev and Zeng (2014) and Liu et al. (2019) put forward the question how monetary policy interacts in different credit condition and interest rate regimes, respectively.

3.1 Structure of the Model

In general, let $\boldsymbol{Y}_t$ be an M-dimensional vector of endogenous variables and $\boldsymbol{\varepsilon}_t$ a vector of structural white noise errors. Then the structural form of a K-regime threshold VAR (TVAR) is

$$\boldsymbol{B}_i \boldsymbol{Y}_t = \boldsymbol{c}_i + \sum_{j=1}^{p} \boldsymbol{C}_{ij} \boldsymbol{Y}_{t-j} + \boldsymbol{\varepsilon}_t, \quad \text{if } S_t = i, \tag{3.2}$$

where $i \in \{1, 2, \dots, K\}$ denotes the regime indicator, $\boldsymbol{B}_i$ $(M \times M)$ the identified impact matrix, $\boldsymbol{c}_i$ $(M \times 1)$ the unconditional mean, and $\boldsymbol{C}_{ij}$ $(M \times M)$ the structural coefficient matrix for each lag $j = 1, \dots, p$. After premultiplying each side of the equation with $\boldsymbol{B}_i^{-1}$, the reduced form representation is retrieved

$$\boldsymbol{Y}_t = \boldsymbol{a}_i + \sum_{j=1}^{p} \boldsymbol{A}_{ij} \boldsymbol{Y}_{t-j} + \boldsymbol{u}_t, \quad \text{if } S_t = i. \tag{3.3}$$

$\boldsymbol{a}_i$ is the regime-specific intercept, and $\boldsymbol{A}_{ij}$ are the regime-specific $M \times M$ coefficient matrices for each lag $j = 1, \dots, p$. The vector of the reduced-form shocks, $\boldsymbol{u}_t$, can be expressed as a function of the structural shocks

$$\boldsymbol{u}_t = \boldsymbol{B}_i^{-1} \boldsymbol{\varepsilon}_t, \quad \text{if } S_t = i, \tag{3.4}$$

and constitutes a mapping between the reduced form and the structural coefficients, i.e., $\boldsymbol{a}_i = \boldsymbol{B}_i^{-1} \boldsymbol{c}_i$, and $\boldsymbol{A}_{ij} = \boldsymbol{B}_i^{-1} \boldsymbol{C}_{ij}$. It is straightforward to compute the regime-dependent variance-covariance matrix of the reduced form model, which we denote by $\boldsymbol{\Sigma}_i$, as

$$\mathbb{E}[\boldsymbol{u}_t \boldsymbol{u}_t'] = \mathbb{E}[\boldsymbol{B}_i^{-1} \boldsymbol{B}_i^{-1'}] = \boldsymbol{\Sigma}_i \quad \forall i. \tag{3.5}$$

Our modeling framework thus allows for the occurrence of regime shifts with $K = 2$ regimes in the empirical specification. The regime-specific set of coefficients consists of the reduced-form VAR coefficients $\boldsymbol{\theta}_i = \{\boldsymbol{a}_i, \boldsymbol{A}_{i1}, \dots, \boldsymbol{A}_{ip}, \boldsymbol{\Sigma}_i\}$. Together these coefficients describe the dynamics depending on whether the economy is in an optimistic or pessimistic credit market regime. Therefore, the credit market sentiment indicator serves as a threshold variable,

$$\begin{aligned} S_t = 1 &\Longleftrightarrow \omega_{t-d} \leq \gamma, \\ S_t = 2 &\Longleftrightarrow \omega_{t-d} > \gamma, \end{aligned} \tag{3.6}$$

where both, the threshold parameter γ and the delay parameter d are treated as unknown parameters. Note that all remaining parameters are allowed to vary across regimes, and that the model also nests the linear case.

3.2 Prior Setup and Posterior Simulation

The estimation is based on a Bayesian framework using a Markov Chain Monte Carlo (MCMC) algorithm to sample from the joint posterior distribution. In the following, we discuss our prior choices and how to simulate from the joint posterior density. The latter is derived by multiplying the likelihood by the prior, but this does not result in a density from a known distribution. Therefore, we rely on a Gibbs sampler to iteratively draw from the conditional posterior densities. While we discuss our prior choices in more detail, we refer to Appendix B for the derivation of the joint posterior distribution.

The regime-specific coefficients are collected in $\boldsymbol{\theta} = \{\boldsymbol{\theta}_1, \dots, \boldsymbol{\theta}_K\}$ where we impose completely independent priors across the regimes. Thus, for the set of regime-specific coefficients $\boldsymbol{\theta}_i$ we start by assuming a Gaussian prior for each element corresponding to a coefficient of the conditional mean $[\boldsymbol{a}_i]_l \sim \mathcal{N}(0, 10)$, $l = 1, \dots, M$.[9] We proceed by specifying a prior distribution for the VAR coefficient matrices such that $\boldsymbol{\alpha}_{ij} = \text{vec}(\boldsymbol{A}_{ij})$ denotes an M^2-dimensional vector, where i is the regime indicator and j denotes the lag. On each of these coefficients, we impose a variant of the Normal-Gamma (NG) shrinkage prior (Huber and Feldkircher, 2019). This prior is from the class of global-local shrinkage priors (Griffin and Brown, 2010) and is centered around zero but features fat tails. Coefficients are shrunk towards zero if they do not entail information, which induces sparsity to the system. Shrinkage comes either from a local component, i.e., shrinkage of an individual coefficient, or from a global component, i.e., shrinking a group of coefficients – in this case, coefficients are grouped by belonging to a specific lag. For the lagwise NG prior, we define $\underline{\boldsymbol{V}_{ij}} = \text{diag}\left(\tau_{ij,1}, \dots, \tau_{ij,k}\right)$, where $k = M(Mp + 1)$ denotes the number of coefficients per lag.[10] Then the prior specification for the coefficients of regime i and lag j reads

$$\boldsymbol{\alpha}_{ij} \mid \boldsymbol{\tau}_{ij} \sim \mathcal{N}\left(\underline{\boldsymbol{\alpha}_{ij}}, 2\underline{\boldsymbol{V}_{ij}}/\lambda_{ij}^2\right), \quad \tau_{ij,l} \sim \mathcal{G}(\vartheta_{ij}, \vartheta_{ij}), \tag{3.7}$$

where $\tau_{ij,l}$ is the local shrinkage parameter ($l = 1, \dots, k$), and λ_{ij}^2 is the global-shrinkage parameter of all elements in $\boldsymbol{\alpha}_{ij}$. Thus, *global* refers to all coefficients associated with one particular lag of all equations. Additionally, we put a prior on $\vartheta_{ij} \sim Exp(1)$. This prior centers ϑ_{ij} a priori on unity, which translates into the Bayesian LASSO (Park and Casella, 2008), but allows for additional flexibility through the hyperprior. The peculiarity of the lagwise NG prior is that it features an own global shrinkage parameter per lag, which imposes more shrinkage for higher order lags (similar in spirit to the Minnesota prior setup of Doan, Litterman and Sims, 1984). Hence, the prior distribution

[9] In the following, $[\boldsymbol{v}]_l$ denotes the l-th element of the vector $\boldsymbol{v}$, while $[\boldsymbol{x}]_{ij}$ denotes the element in the i-th row and j-th column of the matrix $\boldsymbol{x}$.

[10] Note that we do not shrink constants involved but choose an uninformative Gaussian prior $\mathcal{N}(0, 10)$ on these coefficients.

on λ_{ij}^2 is a multiplicative Gamma prior

$$\lambda_{ij}^2 = \prod_{g=1}^{j} \zeta_{ig}, \tag{3.8}$$

with independent Gamma priors on each $\zeta_{ig} \sim \mathcal{G}(c_j, d_j)$. As long as the global shrinkage parameter λ_{ij}^2 exceeds unity, this prior shrinks coefficients associated with higher lags more toward zero. This implies that the coefficient matrix A_{ij} becomes increasingly sparse for higher lags.

Lastly, we have to specify a prior on the regime-dependent variance-covariance matrix $\boldsymbol{\Sigma}_i$, on which we elicit

$$\boldsymbol{\Sigma}_i \sim iW(\nu, \boldsymbol{S}), \tag{3.9}$$

where $\nu = M + 2$ denotes the degrees of freedom and $\boldsymbol{S} = \text{diag}(s_1^2, \ldots, s_M^2)$ denotes the scaling matrix. The diagonal elements of the scaling matrix s_i^2 denote the sample variance of the residuals from an AR(4) for the variable i, $i = 1, \ldots, M$ (Kadiyala and Karlsson, 1997). Conditional on the regime indicator, this prior setup is an independent Normal-inverse Wishart prior. This allows us to introduce asymmetric shrinkage priors across equations.

We are left with the coefficients governing the transition process, i.e., the threshold parameter γ and the delay parameter d, for which we specify a Gaussian prior and a discrete uniform distribution, respectively.

3.3 Identification of a Credit Market Sentiment Shock

In this section, we discuss the identification of a credit market sentiment shock. For that purpose, we need to restore the structural form of the model in Equation 3.2, which is done via the impact matrix $\boldsymbol{\Lambda}_i = \boldsymbol{B}_i^{-1}$ as pointed out in Equation 3.4. Opting for two different strategies, we discuss identification by recursive ordering and by external instruments. For the former, we introduce timing assumptions by exploiting the Cholesky decomposition. For the latter, we use forecast errors as external instruments. These errors come from agents that use different expectation formation mechanisms to forecast the sentiment. For this exercise, we take each of the belief formation hypotheses discussed in Table 1 and compute the forecast error according to Equation 2.2.

Identification by recursive ordering is achieved as follows. Credit spreads are ordered first in the system such that all other variables react contemporaneously to a credit market sentiment shock. This assumption is reasonable because financial market variables tend to be strongly forward-looking and economic aggregates are reacting rather fast to such movements. It also leads to another interesting observation. When the shock of interest originates from the first variable in the system, the reduced form errors associated with credit spreads are equal to the structural errors of the shock. These errors are model-consistent and we treat them as rational expectations. However, the results may be sensitive to the proposed ordering of the variables. As a robustness check, we order credit spreads last in the system, which implies that no variable reacts contemporaneously to a shock in credit spreads. A common argument concerns the relatively sluggish adjustment of economic aggregates, with a rather muted reaction within a month.

However, we provide the recursively identified results as mere robustness checks, as our argumentation relies on behavioral arguments within the external instruments approach. The methodology of using instruments to identify the dynamic causal effects of macroeconomic shocks dates back to Stock and Watson (2012), and is thoroughly discussed in Stock and Watson (2018) and Montiel-Olea, Stock and Watson (2020). For the identification of a credit market sentiment shock, we measure the exogenous movements in the credit market sentiment through an external instrument Z_t. Since this provides only a partial identification, we identify only one column of the impact matrix $\mathbf{\Lambda}_i$, which we denote as $\mathbf{\Lambda}_i^{\omega}$, associated with the credit market sentiment. The identification requires a valid instrument. To meet this requirement, the instrument Z_t has to be correlated with ε_t^{ω}, the structural shock associated with the credit market sentiment, and orthogonal to $\boldsymbol{\varepsilon}_t^{-\omega}$, all other structural shocks, such that

$$\mathbb{E}(Z_t \varepsilon_t^{\omega'}) = \mathbf{\Phi}, \tag{3.10}$$

$$\mathbb{E}(Z_t \boldsymbol{\varepsilon}_t^{-\omega'}) = \mathbf{0}. \tag{3.11}$$

To identify ε_t^{ω} up to sign and scale, both the relevance criterion in Equation 3.10 and the exogeneity criterion in Equation 3.11 must be satisfied. The approach is similar to a two-stage least squares procedure: First, we regress the reduced form error ϵ_t^{ω} on the instrument Z_t to isolate the variation in the reduced form residual associated with the sentiment corresponding to the news shock. The instrument is assumed to be correlated with the error term, which reflects the relevance or validity criterion in Equation 3.10. Similar to a two-stage least squares procedure, we form the fitted values $\hat{\epsilon}_t^{\omega}$ and regress them on the other reduced form residuals in the second stage regression

$$\boldsymbol{u}_t^{-\omega} = \boldsymbol{\beta}\hat{\epsilon}_t^{\omega} + \boldsymbol{\nu}_t, \quad \boldsymbol{\nu}_t \sim N(0, \mathbf{\Sigma}_{\boldsymbol{u}}), \tag{3.12}$$

where $\boldsymbol{\beta}$ captures the spillover effects of a unit increase in the sentiment. Moreover, the error term ν_t is assumed to be orthogonal to the instrument, i.e., the instrument is not correlated with structural shocks of macroeconomic fundamentals in our system (reflecting the exogeneity criterion in Equation 3.11). Note also that we do not allow for a structural break in $\boldsymbol{\beta}$, since we assume a constant influence of the external instrument, thus obtaining the average impact of the instrument.[11] Finally, using the variance-covariance matrix $\mathbf{\Sigma}_i$ an analytical solution can be derived to identify

[11] In principle, however, it would be possible to allow a structural break in $\boldsymbol{\beta}$. For instance, Mumtaz and Petrova (2018) discuss the case of a time-varying parameter proxy-VAR where they allow for changes in $\boldsymbol{\beta}$. Introducing a structural break according to the regime indicator S_t in the regression of our setting does not significantly change the results.

the elements of $\mathbf{\Lambda}_i^{\omega}$, which allows us to identify the responses to a structural shock in ε_t^{ω}. For the technical details, we refer to Appendix D.

As mentioned above and discussed in section 2, we use the forecast errors of the expectation heuristics of the credit market sentiment to its realized value as defined in Equation 2.2 as the instrument Z_t. Using the diagnostic expectations as a benchmark, Bordalo, Gennaioli and Shleifer (2018) highlight the convenient property that they are entirely forward-looking and thus immune to the Lucas critique. In our interpretation, the forecast errors are unexpected news or sentiment shocks emanating from financial markets. In principle, any expectation formation mechanism produces a forecast error, but not all capture different features of financial markets' behavior. Diagnostic expectations, however, provide a plausible explanation for reported financial anomalies. When agents use diagnostic expectations as a forecasting rule, they fail to detect sentiment (or mean-) reversals, which leads to the characteristic overshooting pattern after a reversal, as Figure 1 reveals. After periods of elevated credit spreads, agents would predict a further surge since their memory is constrained and therefore assess the probability of a further increase larger than it actually is. This does not only lead to a bad forecast, but also to a quite unexpected expectation correction, providing a valid and good instrument for our identification strategy.

Regarding the relevance criterion in Equation 3.10, we argue that unexpected movements in the credit spread have a strong correlation with the sentiment itself due to the empirical findings of Bordalo, Gennaioli and Shleifer (2018). Since it is possible to forecast prediction errors, the validity of this instrument is evident. According to this argument, a sentiment shock is strongly correlated with the structural innovation in the credit spread but decoupled from innovations stemming from macroeconomic fundamentals. As a consequence, the instrument is orthogonal to all the other structural innovations. Exogenous shocks to macroeconomic fundamentals, i.e., oil price shocks, monetary policy shocks, or technology shocks, are neither caused nor contemporaneously correlated with the forecast errors of economic agents in financial markets.

Lastly, the identification of an SVAR with an external instrument only works if the invertability assumption is satisfied. The invertability, or fundamentalness, assumption states that the VAR contains all relevant information to recover the structural shocks from past information. If this is not the case, the VAR essentially suffers from an omitted variable bias problem. While it is sufficient for the identification procedure with external instruments that only the shock of interest is invertible, as shown by Miranda-Agrippino and Ricco (2023), there is also another remedy. Plagborg-Møller and Wolf (2021) show that structural estimation can also be carried out by ordering the instrument first in a recursive VAR, even under nonfundamentalness. Hence, we also provide robustness by using the *internal instruments* approach as well.

4. Empirical Results

This section discusses the results. After presenting the findings from the linear baseline model, we turn to the discussion of the TVAR approach to check whether it is worthwhile to distinguish between optimistic and pessimistic credit market regimes. To check the differences with the other expectation formation heuristics listed in Table 1, we provide results based on forecast errors when using the alternative beliefs. In addition, we provide sensitivity results with a recursive identification scheme and under an extended information set.

We estimate all models using $p = 13$ lags due to the monthly frequency of the data and allow the delay parameter to take values $d \in \{1, 2, 3, 4\}$ in the non-linear model. Furthermore, we use 25,000 iterations of the algorithm to construct the Markov chain discarding the first 15,000 draws as burn-ins. To ensure the stationarity of the (T)VAR, we drop all non-stationary draws ex post. In Appendix E, the convergence diagnostics and the fraction of retained draws in each of the considered models can be found. All considered models converge to their posterior distribution.

4.1 The Impact of a Credit Market Sentiment Shock

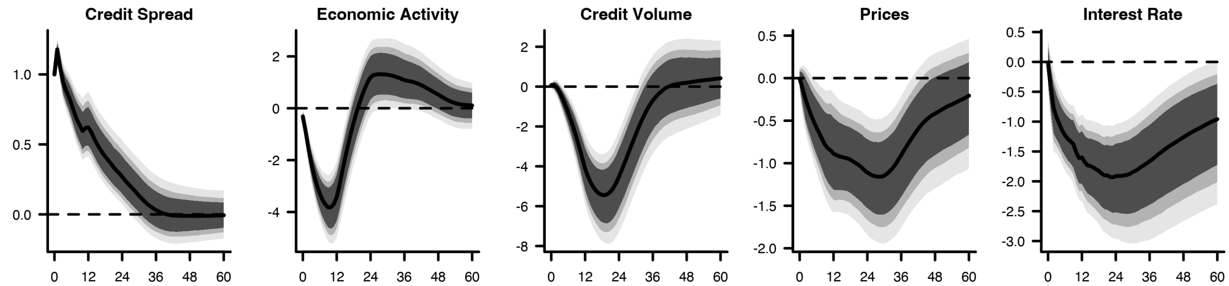
We now turn to the impact of an unexpected credit market sentiment shock through an impulse response analysis. As already pointed out and discussed in the previous section, we identify an exogenous shock to the credit market sentiment variable. We use the Baa spread as our credit market sentiment indicator where the identified credit market sentiment shock is normalized and moves the spread upwards by 100 basis points (bps). This increase in the Baa spread corresponds to a moderate deprivation in the sentiment. For comparison, during the last financial crisis 2007-08, the U.S. economy experienced a surge of the Baa spread of almost 400 bps. In all specifications, we report the impulse response functions over the horizon of 60 months (five years).

The baseline model assumes parameter linearity without distinguishing between regimes. In Figure 2 we show the structural impulse responses for two identification schemes. In the top panel, Figure 2a, the proposed proxy is used in order to identify a credit market sentiment shock. We argue that the unexpected movement in the credit market sentiment, predicted by agents with diagnostic expectations, is an exogenous proxy for the sentiment itself (identification via diagnostic expectations). However, in the bottom panel, Figure 2b, we report the results obtained using a conventional recursive identification scheme exploiting the Cholesky decomposition. We order the Baa spread first to capture the idea that all other variables in the system react contemporaneously to a credit sentiment shock. In the appendix, we provide robustness by using the internal instruments approach. As indicated in Figure F4, the results discussed below remain robust to this choice.

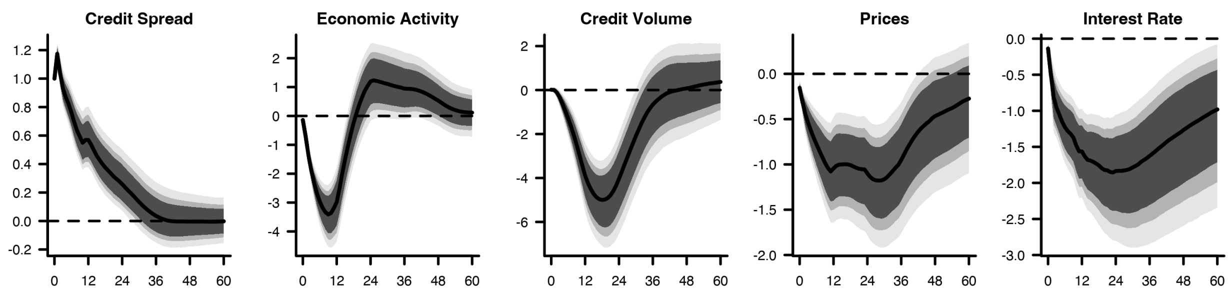
In general, the impulse response analysis shows that a shock to the credit market sentiment has a strong effect on all variables in our system. On impact, economic activity and credit volume barely

Figure 2: Impulse Responses to a Credit Market Sentiment Shock.

(a) Identification via Diagnostic Expectations.



(b) Identification via Recursive Ordering.



Notes: Impulse response functions to a credit market sentiment shock identified with diagnostic expectations and recursive ordering. The dashed black line is the median response, while the gray shaded areas depict the 95%, 90%, and 84% credible sets, respectively. The shock is normalized to a 100 bps shock to the credit spread and responses are scaled in growth rates of economic activity, credit volume, and prices, and in percentage points of credit spreads and interest rates.

reacts but deteriorates in the next periods. The maximum is reached after 12-18 months; we observe a decrease of 350 bps in the growth rate of industrial production, and an even more pronounced decrease in the growth rate of credit volume. After that, the effect fades out after about three years. A rebound effect is visible for economic activity. The interest rate does not react strongly on impact but quickly accommodates to the shock. Both identification schemes show qualitatively similar results, with a few differences. For example, interest rates or prices react more sluggishly on impact in the model identified with diagnostic expectations than when using the recursive identification scheme. This can be explained by the fact that the recursive ordering effectively resembles rational expectations and thus induces a faster nominal adjustment. However, the timing and the maximum decline are quite similar in both identification regimes, as is the rather persistent reaction of prices.

Thus, the impact of an unexpected sentiment shock is of substantial magnitude for the whole economy. However, following theoretical contributions (Kubin et al., 2019; Matsuyama, Sushko and Gardini, 2016) and well-established empirical facts (Alessandri and Mumtaz, 2019; Atanasova, 2003; Balke, 2000), the presence of non-linearities in credit market dynamics is prevalent. Therefore, the results from a linear specification have to be interpreted with caution due to potential misspecification. Hence, we proceed with the proposed TVAR specification to incorporate possible non-linear characteristics.

4.2 Asymmetries across Credit Market Sentiment Regimes

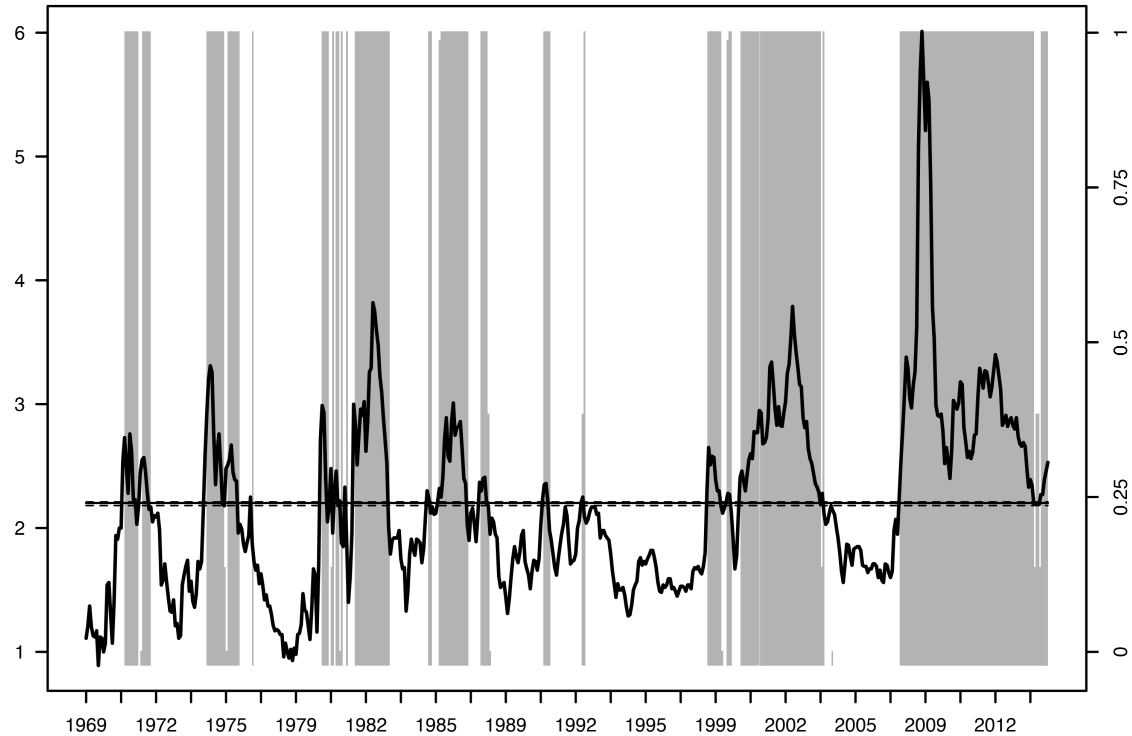
In Figure 3 we report the Baa spread along with the associated probabilities of being in one of the two regimes. The probabilities are calculated by looking at how often the threshold variable has exceeded the estimated threshold parameter γ, which is subject to a fairly precise estimation. The posterior median (along with its 95% credible set) of γ equals 2.20 $(2.18, 2.21)$. Concerning the delay parameter, almost all of the posterior mass is concentrated at $d = 1$, indicating that the credit market sentiment regime changes within a month of crossing the threshold. We refer to the two distinct regimes as either an optimistic (below the threshold) or a pessimistic (above the threshold) credit market sentiment regime.

Looking at the Figure 3, we notice that the pessimistic credit market sentiment regime roughly coincides with the NBER recession dates, but covers a much longer period of time, especially after the GFC. Thus, the credit market sentiment is still depressed after the last crisis, even though the economy is slowly recovering. This can be explained by the fact that *bad* experiences are still prevalent in the agents' memory, making them too cautious to switch to an optimistic sentiment. Apart from this observation, our regimes strongly resemble the business cycle dynamics of the U.S. economy.

Turning to the impulse response analysis, we define the shock analogously to the previous section normalized to a 100 bps increase in the Baa spread and computed for a 60-months horizon. The top (bottom) panel of Figure 4 reports the evolution and transmission of the shock for the optimistic (pessimistic) credit market regime. Here, we use the identification via diagnostic expectations while Figure 5 reports the results based on an identification via the Cholesky decomposition for a sensitivity check. In the appendix, we also provide robustness by using the internal instruments approach. As indicated in Figure F5, the results discussed below remain stable to this choice.

In both regimes the credit market sentiment quickly starts to mean-revert and returns to its equilibrium value after about two years. Interestingly, we observe a further improvement in the sentiment in the optimistic regime two years after the shock. While the credible sets of the impulse responses are rather narrow in the optimistic credit market sentiment regime, they are somewhat wider in the pessimistic regime reflecting the higher uncertainty associated with a pessimistic environment. However, in the optimistic regime, the responses for industrial production and credit volume react rather muted, but improve significantly after one to two years. In contrast, in the pessimistic regime both variables react strongly and negatively to the sentiment shock, reaching their respective maximum between 12 and 18 months after the shock has hit. Prices fall in both regimes, but the decline is more pronounced and more persistent in the optimistic regime over a

Figure 3: Credit Market Sentiment Regimes.

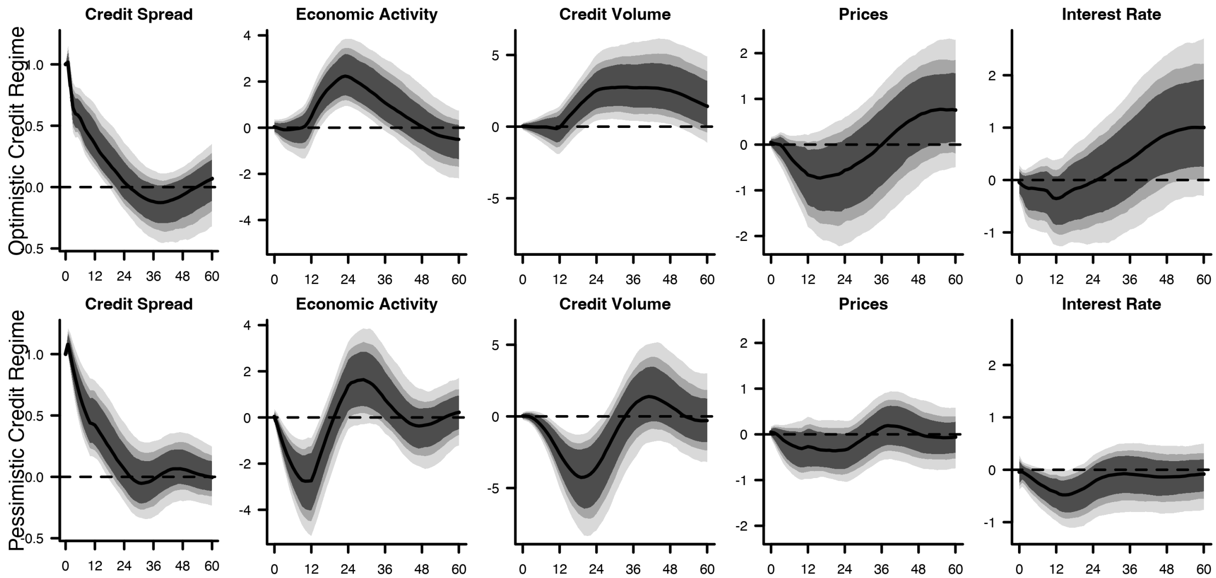


Notes: Gray shaded areas represent the periods when the U.S. economy is estimated to be in a pessimistic credit market regime, defined as a state where the Baa spread exceeds the critical threshold in the TVAR (the black line with its 95% credible set denoted by the dashed lines). The left axis denotes the credit spread in percent, while the right axis shows the probability of being in the pessimistic credit market regime.

horizon of two to three years. In the pessimistic regime, prices decrease only slightly and less significantly. For the short-term interest rate, we only observe a dip in the pessimistic regimes.

Overall, this is in line with our expectations and the predictions of the theoretical models. For instance, the model proposed by Kubin et al. (2019) also predict a rather small to negligible effect on the business and credit cycle in an optimistic regime, compared to a stronger response in the pessimistic regime. We also show that this is indeed the case in the pessimistic regime. The responses indicate adverse effects on economic activity and the credit volume with a pronounced magnitude: The contraction is relatively abrupt and the maximum decline in economic activity is about 350 bps after 12 months. Similarly, credit also contracts in the pessimistic regime, but more sharply, reaching its maximum after about 18 months. In the optimistic regime, on the other hand, credit starts to elevate after one year until five years after the shock. The price reaction is more pronounced in the optimistic regime. In the pessimistic regime, there is no reaction of prices. The short-term interest rate experiences a decline that peaks after one year in the pessimistic regime and then mean-reverts. Interestingly, if we compare the results to Figure 5, we find only minor differences on impact. The economic rationale that all variables react contemporaneously to a

Figure 4: Impulse Responses of a Credit Market Sentiment Shock (Diagnostic Expectations).

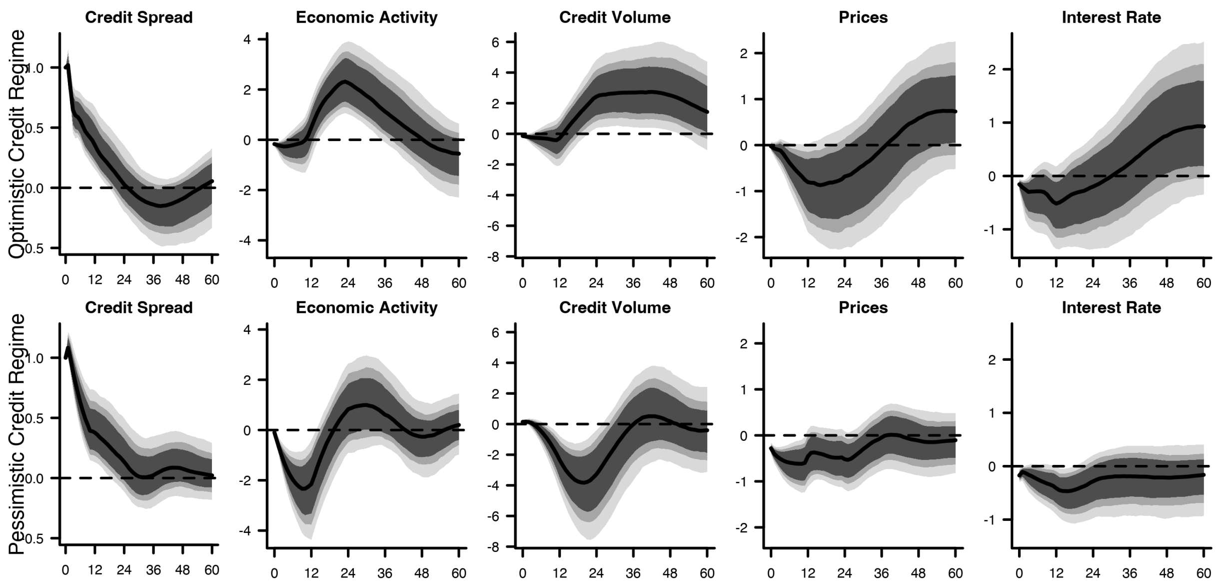


Notes: Impulse response functions to a credit market sentiment shock identified with diagnostic expectations. The black dashed line is the median response per regime, while the gray shaded areas depict the 95%, 90%, and 84% credible sets, respectively. The shock is normalized to a 100 bps shock to the credit spread and responses are scaled in growth rates of economic activity, credit volume, and prices, and in percentage points of credit spreads and interest rates.

credit sentiment shock can explain the rather small difference on impact. Again, in the model with diagnostic expectations, nominal variables react more sluggishly. It is reassuring, however, that our results employing diagnostic expectations are robust with respect to the recursive identification. Overall, our responses strongly resemble theoretical results except for the positive movement of credit volume in the optimistic regime after two years. Since the variable used for credit volume (commercial and industrial loans) represents only bank-based financing through the credit market, the positive impact may be due to an excess demand for credit. In the optimistic regime, the credit spread shows even a decline below its equilibrium value after about two years, pointing towards a further improvement in sentiment. This may induce agents to expand their investments further through additional external financing.

To summarize, we find a stronger impact on credit volume than on economic activity in the pessimistic regime, but both react quite strongly in response to a credit market sentiment shock. Furthermore, while industrial production tends to revert and eventually fades out after about 18 months, credit volume returns to its equilibrium value only after three years. Strong asymmetries between credit market regimes are observed. A moderate decline in the sentiment has different effects depending on the general prevailing mood in the economy. If the general mood is good, a decrease may initially cause some small disruptions. After the dust has settled, agents realize that the general mood is still good and return to the steady state, even increasing their demand for

Figure 5: Impulse Responses of a Credit Market Sentiment Shock (Recursive Ordering).



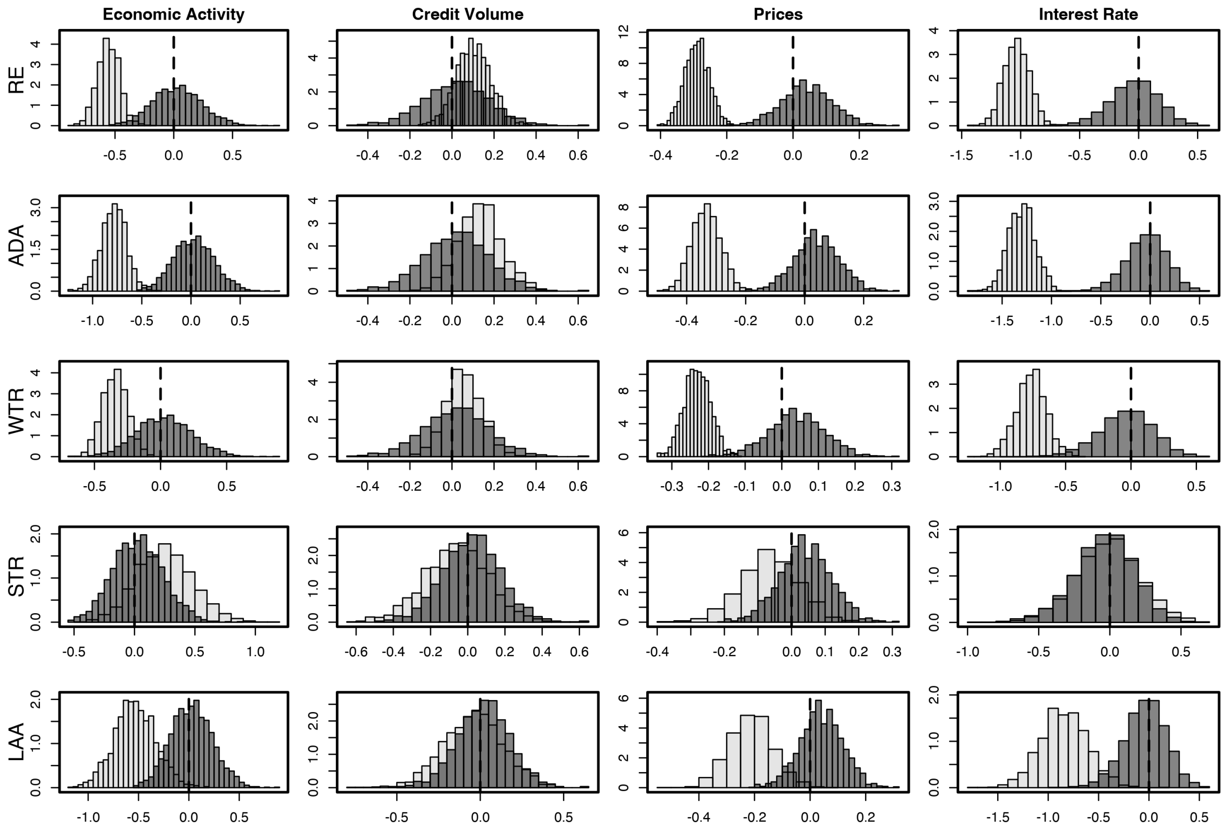
Notes: Impulse response functions to a credit market sentiment shock identified using the recursive ordering. The black dashed line is the median response per regime, while the gray shaded areas depict the 95%, 90%, and 84% credible sets, respectively. The shock is normalized to a 100 bps shock to the credit spread and responses are scaled in growth rates of economic activity, credit volume, and prices, and in percentage points of credit spreads and interest rates.

credit and thus boosting economic activity. On the contrary, if the general mood is already stale, a further decline in the sentiment exhibits detrimental and strong effects. This can be compared to the realization of the tail risks, which are completely neglected by a forecasting rule such as diagnostic expectations. Moreover, we can relate these features to the idea of *corridor stability*, originally introduced 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 to small shocks, while large disturbances have an irreversible and catastrophic effect on the economy. In our system, the degree of confidence can influence this corridor. In an optimistic regime, shocks hit a rather resilient economy, while in a pessimistic regime, this corridor is rather small, so that a shock has a severe impact on the whole economy.

4.3 Results across Different Expectation Formation Mechanisms

In this section we discuss additional results using the expectation formation mechanisms presented in Table 1. In the following, the identification via diagnostic expectations serves as a benchmark against the other heuristics. Again, we use the forecast error when using a specific expectation formation mechanism as an unexpected news shock on the credit market to identify the model. In Figure 6 we report and compare the distribution of each shock identified with a specific expectation mechanism

Figure 6: Distribution of Shock on Impact for Different Expectation Formation Mechanisms.



Notes: Identification via expectation formation mechanisms (light gray) listed in Table 1 compared to identification via diagnostic expectations (dark gray) and the resulting overlap (medium gray). The whole distribution on impact is depicted for the respective heuristic (row) and variable (column). The credit sentiment is excluded due to the employed normalization.

(light gray) on impact with the identification via diagnostic expectations (dark gray). The overlap of the respective distributions (medium gray) shows the similarities between the diagnostic belief formation and the heuristic of choice. Since we do not allow for a structural break in Equation 3.12, the resulting credit market sentiment shock on impact is the same across regimes.

Some interesting patterns emerge from Figure 6, suggesting the importance of different expectation formation mechanisms for macroeconomic outcomes. In terms of the impact on economic activity, we observe a much stronger negative effect for almost all other heuristics. In particular, the decline in economic activity is much more pronounced for rational expectations and the adaptive rule (ADA) heuristic. For credit volumes, the distributions are mostly qualitatively similar regardless of the expectation formation mechanism used, showing a rather muted reaction on impact compared to diagnostic expectations. For prices and short-term interest rates, the similarities vanish. Across the different expectation formation mechanisms, however, the strong trend-following rule (STR) is mostly in line with diagnostic expectations. Due to its specification (the extrapolation coefficient exceeds unity), overshooting occurs after a sentiment shock, which is also a feature of diagnostic expectations. Hence, the result is plausible. Both the weak trend-following rule (WTR) and the anchoring and adjustment rule with learning anchor (LAA) are unable to fully recover the current financial anomalies in our setting. However, rational expectations (RE) and the adaptive rule heuristic (ADA) do not feature such anomalies and do not exhibit overshooting behavior. These expectation formation mechanisms produce the strongest difference, especially for economic activity, prices, and interest rates.

In terms of prices, we argue that due to an expected credit market squeeze, fully rational firms should increase their available funds to avoid liquidity shortages. To overcome a potential liquidity squeeze, firms tend to liquidate their inventories to generate additional cash flows. Moreover, in the face of an impending recession, where a decline in consumption is typically expected, a kind of fire-sale behavior may set in. To achieve a rather quick inventory reduction, prices are forced to fall quickly. On the contrary, when agents use diagnostic expectations as a forecasting rule, they react rather sluggishly due to their memory constraints. Agents tend to expect the recent trend to continue and perceive the mean reversal with a delay. This results in a muted price reaction on impact compared to rational expectations.

In a similar vein, this comparison points to the fact that a fully rational central bank will cut interest rates on impact to fight recessionary tendencies triggered by the credit market sentiment shock. It thus raises the question about the ability of the central banks to detect a reversal in credit market sentiment and take the necessary policy action. In general, a central bank is probably best qualified to act in a fully rational manner to enact precautionary policy measures for macroeconomic stabilization. We conjecture that this explains the smaller effect size differential for interest rates compared to prices.

To conclude, our analysis reveals heterogeneous results for some variables in the distribution of impact impulses across different expectation formation heuristics. Hence, from a macroeconomic perspective the question of how agents form their expectations and how this translates into structural reactions to shocks is of paramount importance. In light of our overall results, policymakers should be aware of two implications. Rational expectations lead to optimal behavior in the face of financial and macroeconomic distress while diagnostic expectations (and perhaps the strong trend-following rule heuristic) show a more inert reaction. Hence, if agents use the latter approach to form forecasts policymakers should expect overshooting due to forecast errors. Ideally, they can take this behavior into account in their respective policy actions.

4.4 Enriching the Information Set

The conclusions reached in the previous sections are based on a five-variable macroeconomic model. The purpose of this section is to provide a sensitivity check by presenting results from an extended information set. A valid question concerns the recovery of the fundamental representation of the system. If the amount of information with a small number of variables is comparable to a large data set, we can claim that we have recovered the fundamental representation of the system. In order to show this, we replace the benchmark model with a factor-augmented TVAR (FA-TVAR). The introduction of a factor structure allows us to use a much richer set of information, correcting for any missing variable bias and accounting for the possibility of the nonfundamentalness of shocks (Forni and Gambetti, 2014). For the information-enriched model, we use a high-dimensional dataset $(K \times 1)$ $\boldsymbol{X}_t$ of the U.S. economy. These variables are assumed to contain relevant information on q underlying economic factors ($q << K$), which are not directly observable but are related to the information set by the following measurement equation

$$\boldsymbol{X}_t = \boldsymbol{\Gamma}^f \boldsymbol{f}_t + \boldsymbol{\Gamma}^y \boldsymbol{Y}_t + \boldsymbol{\eta}_t, \quad \boldsymbol{\eta}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Omega}), \tag{4.1}$$

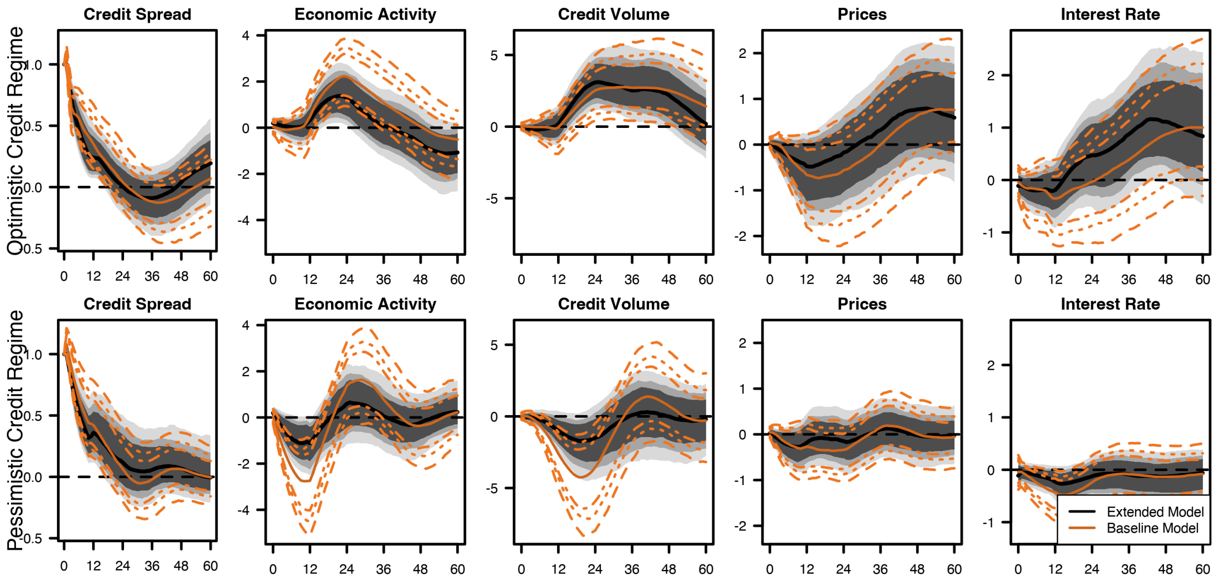
where $\boldsymbol{\Gamma}^f$ and $\boldsymbol{\Gamma}^y$ are factor loading matrices of dimension $N \times q$ and $N \times M$, respectively. The latent factors are denoted by the q-dimensional vector $\boldsymbol{f}_t$. The error term $\boldsymbol{\eta}_t$ is normally distributed with zero mean and variance matrix $\boldsymbol{\Omega} = \text{diag}(\omega_1, \dots, \omega_N)$. Then, we can write the dynamic state equation as

$$\begin{bmatrix} \boldsymbol{Y}_t \\ \boldsymbol{f}_t \end{bmatrix} = \tilde{\boldsymbol{a}}_i + \sum_{j=1}^{p} \tilde{\boldsymbol{A}}_{ij} \begin{bmatrix} \boldsymbol{Y}_{t-j} \\ \boldsymbol{f}_{t-j} \end{bmatrix} + \tilde{\boldsymbol{u}}_t, \quad \text{if } \tilde{S}_t = i, \tag{4.2}$$

where a tilde indicates a change in dimensionality, everything else being the same as in the baseline specification presented earlier. The information set in Equation 4.1 is a panel of $K = 128$ macroeconomic variables taken from McCracken and Ng (2016) and covers different aspects of the economy: output and income, the labor market, consumption and orders, orders and inventories, money and credit, interest rates and exchange rates, prices, and the stock market. In summary, this extended model incorporates additional information through factors $\boldsymbol{f}_t$ while keeping the set of macroeconomic indicators already used before. We fix $q = 3$ and use the same lag specification as in the benchmark case. For robustness checks, we re-estimate the model with $q = 7$ factors, with results available in Figure F3.

In Figure 7, we report the results of the factor-augmented TVAR together with the benchmark model. Similar to the benchmark model, we use forecast errors of credit market sentiment as an external instrument to identify a credit market sentiment shock in both regimes. This credit market sentiment shock elicits a jump in credit spreads in both regimes, fading out after about two years. The emerging pattern of reactions of the economic activity, credit volume, prices, and the interest rate does not differ qualitatively across the models. While the responses are rather muted in the optimistic credit market regime, we observe a negative change in the business and credit cycle variables. However, in a direct comparison with the benchmark model, the amplitude of the response of these variables is somewhat smaller. This pattern also holds for the price and interest

Figure 7: Comparison to an Factor-Augmented TVAR.



Notes: Comparison of impulse response functions of the baseline model to the factor-augmented TVAR. Credit market sentiment shock is identified with diagnostic expectations. The model with extended information is depicted by the black dashed line as its median response, while the gray shaded areas depict the 95%, 90%, and 84% credible sets, respectively. The baseline model is depicted by the orange solid line as its median response, while the dashed lines indicate the 95%, 90%, and 84% credible sets, respectively. The shock is normalized to a 100 bps shock to the credit spread and responses are scaled in growth rates of economic activity, credit volume, and prices, and in percentage points of credit spreads and interest rates.

rate response in the optimistic credit market regime. Thus, controlling for additional information makes the estimated quantitative effects more robust to any omitted variable bias.

5. Concluding Remarks

In this paper, we present a macroeconomic model of the U.S. economy that is capable of capturing asymmetries in the credit market. The identification strategy allows us to analyze an unexpected credit market sentiment shock in times of optimism or pessimism. Within this framework, we are able to empirically confirm the predictions of theoretical models that incorporate sentiment to explain cyclicality and sentiment-dependent behavior. Subsequently, drawing on recent developments in the behavioral finance literature, our model accounts for anomalies present in credit market sentiment data. Moreover, extending our analysis by using different expectation formation mechanisms indicates notable heterogeneous reactions to a sentiment shock, consistent with theoretical predictions.

We thus provide a framework for incorporating advances in the literature on expectation formation mechanisms into a macroeconometric analysis. By taking standard rational expectations, experimentally confirmed belief formation, and psychologically based behavioral expectation heuristics into account, we provide a comprehensive study of their importance in a macroeconomic setting. By using forecast errors when using such heuristics for identification of a sentiment shock, we gain interesting and novel insights into how different heuristics affect the shock absorption of the U.S. economy. We show that the transmission of a sentiment shock through the economy varies significantly, depending on the prevailing market sentiment (i.e., optimism or pessimism) and on the used belief formation heuristic. With respect to the policy dimension of our results, we conclude that the assumption of rationality in econometric models can lead to a different set of results that are not necessarily consistent with key empirical features of the data.

An interesting avenue for further research concerns the dynamics of expectation formation. Specifically, the experimental literature points to the empirical fact that belief formation exhibits switching behavior dependent on the current state of the economy. In addition, extending our analysis to other relevant macroeconomic issues where the importance of expectation formation is pronounced, such as forecasting inflation, unemployment, or other key macroeconomic variables, provides valuable insights. Finally, the presented belief formation mechanisms can be incorporated in more comprehensive general equilibrium models to further investigate the propagation and the transmission channels of the shocks. To conclude, the behavioral sphere of macroeconomic policy analysis seems to be promising in both academic and policymaking settings.

References

Alessandri P. and Mumtaz H. (2019) 'Financial Regimes and Uncertainty Shocks'. *Journal of Monetary Economics* Vol. 101, pp. 31–46.

Anufriev M. and Hommes C. (2012) 'Evolutionary Selection of Individual Expectations and Aggregate Outcomes in Asset Pricing Experiments'. *American Economic Journal: Microeconomics* Vol. 4(4), pp. 35–64.

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.

Atanasova C. (2003) 'Credit Market Imperfections and Business Cycle Dynamics: A Nonlinear Approach'. *Studies in Nonlinear Dynamics & Econometrics* Vol. 7(4).

Avdjiev S. and Zeng Z. (2014) 'Credit Growth, Monetary Policy and Economic Activity in a Three-Regime TVAR Model'. *Applied Economics* Vol. 46(24), pp. 2936–2951.

Balke N S. (2000) 'Credit and Economic Activity: Credit Regimes and Nonlinear Propagation of Shocks'. *Review of Economics and Statistics* Vol. 82(2), pp. 344–349.

Baron M. and Xiong W. (2017) 'Credit Expansion and Neglected Crash Risk'. *The Quarterly Journal of Economics* Vol. 132(2), pp. 713–764.

Beaudry P. and Portier F. (2004) 'An Exploration Into Pigou's Theory of Cycles'. *Journal of Monetary Economics* Vol. 51(6), pp. 1183 –1216.

Beaudry P. and Portier F. (2014) 'News-Driven Business Cycles: Insights and Challenges'. *Journal of Economic Literature* Vol. 52(4), pp. 993–1074.

Bernanke B S. and Gertler M. (1989) 'Agency Costs, Net Worth, and Business Fluctuations'. *American Economic Review* Vol. 79, pp. 14–31.

Boeck M. (2023) *Belief Distortions and Risk Premia*. Working Paper 314. WU Vienna University of Economics and Business.

Bordalo P., Gennaioli N. and Shleifer A. (2018) 'Diagnostic Expectations and Credit Cycles'. *The Journal of Finance* Vol. 73(1), pp. 199–227.

Brav A. and Heaton J B. (2002) 'Competing Theories of Financial Anomalies'. *The Review of Financial Studies* Vol. 15(2), pp. 575–606.

Brunnermeier M., Palia D., Sastry K A. and Sims C A. (2021) 'Feedbacks: Financial Markets and Economic Activity'. *American Economic Review* Vol. 111(6), pp. 1845–79.

Caldara D. and Herbst E. (2019) ‘Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs’. *American Economic Journal: Macroeconomics* Vol. 11(1), pp. 157–92.

Carriero A., Galvao A B. and Marcellino M. (2018) *Credit Conditions and the Effects of Economic Shocks: Amplification and Asymmetries*. Tech. rep. Economic Modelling and Forecasting Group.

Chen C W. and Lee J C. (1995) ‘Bayesian Inference of Threshold Autoregressive Models’. *Journal of Time Series Analysis* Vol. 16(5), pp. 483–492.

Doan T., Litterman R. and Sims C. (1984) ‘Forecasting and Conditional Projection using Realistic Prior Distributions’. *Econometric reviews* Vol. 3(1), pp. 1–100.

Evans G W. and Honkapohja S. (1999) ‘Learning Dynamics’. *Handbook of Macroeconomics* Vol. 1, pp. 449–542.

Fama E F. (1970) ‘Efficient Capital Markets: A Review of Theory and Empirical Work’. *The Journal of Finance* Vol. 25(2), pp. 383–417.

Forni M. and Gambetti L. (2014) ‘Sufficient Information in Structural VARs’. *Journal of Monetary Economics* Vol. 66, pp. 124–136.

Gabaix X. (2014) ‘A Sparsity-Based Model of Bounded Rationality’. *The Quarterly Journal of Economics* Vol. 129(4), pp. 1661–1710.

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

Gertler M. and Karadi P. (2015) ‘Monetary Policy Surprises, Credit Costs, and Economic Activity’. *American Economic Journal: Macroeconomics* Vol. 7(1), pp. 44–76.

Geweke J. et al. (1991) *Evaluating the Accuracy of Sampling-Based Approaches to the Calculation of Posterior Moments*. Vol. 196. Federal Reserve Bank of Minneapolis, Research Department Minneapolis, MN.

Gilchrist S. and Zakrajšek E. (2012) ‘Credit Spreads and Business Cycle Fluctuations’. *American Economic Review* Vol. 102(4), pp. 1692–1720.

Görtz C., Tsoukalas J D. and Zanetti F. (2022) ‘News shocks under financial frictions’. *American Economic Journal: Macroeconomics* Vol. 14(4), pp. 210–43.

Greenwood R. and Hanson S G. (2013) ‘Issuer Quality and Corporate Bond Returns’. *The Review of Financial Studies* Vol. 26(6), pp. 1483–1525.

Griffin J. and Brown P. (2010) ‘Inference with Normal-Gamma Prior Distributions in Regression Problems’. *Bayesian Analysis* Vol. 5(1), pp. 171–188.

Haario H., Saksman E., Tamminen J. et al. (2001) ‘An Adaptive Metropolis Algorithm’. *Bernoulli* Vol. 7(2), pp. 223–242.

Hommes C. (2006) ‘Heterogeneous Agent Models in Economics and Finance’. *Handbook of Computational Economics*. Ed. by L Tesfatsion and K L Judd. Vol. 2. Handbook of Computational Economics. Elsevier. Chap. 23, pp. 1109–1186.

Hommes C. (2009) ‘Bounded Rationality and Learning in Complex Markets’. *Handbook of Research on Complexity*. Edward Elgar. Chap. 5, pp. 87–123.

Hommes C., Makarewicz T., Massaro D. and Smits T. (2017) ‘Genetic Algorithm Learning in a New Keynesian Macroeconomic Setup’. *Journal of Evolutionary Economics* Vol. 27(5), pp. 1133–1155.

Huber F. and Feldkircher M. (2019) ‘Adaptive Shrinkage in Bayesian Vector Autoregressive Models’. *Journal of Business & Economic Statistics* Vol. 37(1), pp. 27–39.

Jordà O., Schularick M. and Taylor A M. (Jan. 2016) ‘The Great Mortgaging: Housing Finance, Crises and Business Cycles’. *Economic Policy* Vol. 31(85), pp. 107–152.

Kadiyala K R. and Karlsson S. (1997) ‘Numerical Methods for Estimation and Inference in Bayesian VAR-Models’. *Journal of Applied Econometrics* Vol. 12(2), pp. 99–132.

Kahneman D. and Tversky A. (1972) ‘Subjective Probability: A Judgment of Representativeness’. *Cognitive Psychology* Vol. 3(3), pp. 430–454.

Kastner G. and Früwirth-Schnatter S. (2014) ‘Ancillarity-Sufficiency Interweaving Strategy (ASIS) for Boosting MCMC Estimation of Stochastic Volatility Models’. *Computational Statistics & Data Analysis* Vol. 76, pp. 408 –423.

Kindleberger C P. (1978) *Manias, Panics and Crashes: A History of Financial Crisis*. New York: Basic Books.

Kiyotaki N. and Moore J. (1997) ‘Credit Cycles’. *Journal of Political Economy* Vol. 105(2), pp. 211–248.

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

Kubin I., Zörner T O., Gardini L. and Commendatore P. (2019) ‘A Credit Cycle Model with Market Sentiments’. *Structural Change and Economic Dynamics*.

Leijonhufvud A. (1973) ‘Effective Demand Failures’. *The Swedish Journal of Economics* Vol. 75(1), pp. 27–48.

Liu P., Theodoridis K., Mumtaz H. and Zanetti F. (2019) ‘Changing Macroeconomic Dynamics at the Zero Lower Bound’. *Journal of Business & Economic Statistics* Vol. 37(3), pp. 391–404.

López-Salido D., Stein J C. and Zakrajšek E. (2017) ‘Credit-Market Sentiment and the Business Cycle’. *The Quarterly Journal of Economics* Vol. 132(3), pp. 1373–1426.

Mackowiak B. and Wiederholt M. (2009) ‘Optimal Sticky Prices under Rational Inattention’. *American Economic Review* Vol. 99(3), pp. 769–803.

Matsuyama K., Sushko I. and Gardini L. (2016) ‘Revisiting the Model of Credit Cycles with Good and Bad Projects’. *Journal of Economic Theory* Vol. 163, pp. 525–556.

McCracken M W. and Ng S. (2016) ‘FRED-MD: A Monthly Database for Macroeconomic Research’. *Journal of Business & Economic Statistics* Vol. 34(4), pp. 574–589.

Mertens K. and Ravn M O. (2013) ‘The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States’. *American Economic Review* Vol. 103(4), pp. 1212–47.

Mian A., Sufi A. and Verner E. (2017) ‘Household Debt and Business Cycles Worldwide’. *The Quarterly Journal of Economics* Vol. 132(4), pp. 1755–1817.

Minsky H P. (1977) ‘The Financial Instability Hypothesis: An Interpretation of Keynes and an Alternative to "Standard" Theory’. *Challenge* Vol. 20(1), pp. 20–27.

Miranda-Agrippino S. and Ricco G. (2023) ‘Identification with External Instruments in Structural VARs under Partial Invertibility’. *Journal of Monetary Economics* Vol. 135, pp. 1–19.

Montiel-Olea J L., Stock J H. and Watson M W. (2020) ‘Inference in Structural Vector Autoregressions Identified with an External Instrument’. *Journal of Econometrics*.

Mumtaz H. and Petrova K. (2018) *Changing Impact of Shocks: a Time-Varying Proxy SVAR Approach*. Working Paper 875. Queen Mary University.

Park T. and Casella G. (2008) ‘The Bayesian Lasso’. *Journal of the American Statistical Association* Vol. 103(482), pp. 681–686.

Pizzinelli C., Theodoridis K. and Zanetti F. (2020) ‘State Dependence in Labor Market Fluctuations’. *International Economic Review* Vol. 61(3), pp. 1027–1072.

Plagborg-Møller M. and Wolf C K. (2021) ‘Local Projections and VARs Estimate the Same Impulse Responses’. *Econometrica* Vol. 89(2), pp. 955–980.

Raftery A E. and Lewis S M. (1992) '[Practical Markov Chain Monte Carlo]: Comment: One Long Run with Diagnostics: Implementation Strategies for Markov Chain Monte Carlo'. *Statistical Science* Vol. 7(4), pp. 493–497.

Rajan R G. (2006) 'Has Finance Made the World Riskier?' *European Financial Management* Vol. 12(4), pp. 499–533.

Sargent T J. (1993) *Bounded Rationality in Macroeconomics*. New York: Oxford University Press.

Schularick M. and Taylor A M. (2012) 'Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008'. *American Economic Review* Vol. 102(2), pp. 1029–61.

Simon H A. (1957) *Models of Man*. New York: Wiley.

Sims C A. (1980) 'Macroeconomics and Reality'. *Econometrica* Vol. 48(1), pp. 1–48.

Sims C A. (2003) 'Implications of Rational Inattention'. *Journal of Monetary Economics* Vol. 50(3), pp. 665 –690.

Stein J C. (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.)

Stock J H. and Watson M W. (2012) *Disentangling the Channels of the 2007-2009 Recession*. Tech. rep. National Bureau of Economic Research.

Stock J H. and Watson M W. (2018) 'Identification and Estimation of Dynamic Causal Effects in Macroeconomics using External Instruments'. *The Economic Journal* Vol. 128(610), pp. 917–948.

Tirole J. (2010) *The Theory of Corporate Finance*. Princeton University Press.

Tversky A. and Kahneman D. (1974) 'Judgment under Uncertainty: Heuristics and Biases'. *Science* Vol. 185(4157), pp. 1124–30.

Wu J C. and Xia F D. (2016) 'Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound'. *Journal of Money, Credit and Banking* Vol. 48(2-3), pp. 253–291.

A. Data

Table A1: Data Labels and Sources.

Database	Variable	Data Set Label	Transformation
FRED	Industrial Production	IP: Index	$100 \times \ln x_t / x_{t-1}$
	Loans	Commercial and Industrial Loans	$100 \times \ln x_t / x_{t-1}$
	Inflation	CPI: All Items	$100 \times \ln x_t / x_{t-1}$
	Baa spread	Moody's Seasoned Baa Corporate Bond Yield	
	GS10	10-Year Treasury Rate	
	FFR	Effective Federal Funds Rate	
Wu and Xia (2016)	SR	Shadow Federal Funds Rate	

B. MCMC Algorithm

We obtain the joint posterior density by multiplying the likelihood with the prior. First, we define $\boldsymbol{Y}$ and $\boldsymbol{S}$ as the full history of $\boldsymbol{Y}_t$ and S_t $(t = 1, \dots, T)$. By the use of Bayes theorem we obtain

$$\begin{aligned} p(\boldsymbol{\theta}, \gamma, d \mid \boldsymbol{Y}) &\propto p(\boldsymbol{Y} \mid \boldsymbol{\theta}, \gamma, d) p(\boldsymbol{\theta}, \gamma, d) \\ &\propto \prod_{i=1}^{K} p(\boldsymbol{Y} \mid \boldsymbol{\theta}_i) p(\boldsymbol{\theta}_i \mid \boldsymbol{S}) p(\boldsymbol{S} \mid \gamma, d) p(\gamma, d). \end{aligned} \tag{B.1}$$

As we rely on data augmentation, we iterate between the following two steps. First, we classify the observations into one of the regimes, and second, we draw the parameters of the model conditional on the classification. For the classification step, we sample the group indicator $\boldsymbol{S}$ according to

$$p(\boldsymbol{S} \mid \boldsymbol{Y}, \boldsymbol{\theta}, \gamma, d) \propto p(\boldsymbol{Y} \mid \boldsymbol{S}, \boldsymbol{\theta}, \gamma, d) p(\boldsymbol{S} \mid \gamma, d). \tag{B.2}$$

The regime-dependent coefficients in $\boldsymbol{\theta}$ are assumed to be fixed and the indicator depends on the threshold parameter γ and delay parameter d. The posterior density of those parameters is given by

$$p(\gamma, d \mid \boldsymbol{Y}, \boldsymbol{\theta}) \propto p(\boldsymbol{Y} \mid \boldsymbol{\theta}, \gamma, d) p(\gamma) p(d). \tag{B.3}$$

Conditional on the regime indicator $\boldsymbol{S}$, sampling the regime-specific parameters $\boldsymbol{\theta}_i$ is particularly easy because we can rely on well-known conditional posterior densities of linear time series models. This results in applying Bayes theorem

$$p(\boldsymbol{\theta}_i \mid \boldsymbol{Y}, \boldsymbol{S}) \propto p(\boldsymbol{Y} \mid \boldsymbol{S}, \boldsymbol{\theta}_i) p(\boldsymbol{\theta}_i \mid \boldsymbol{S}), \quad i = 1, \dots, K, \tag{B.4}$$

and retrieving the posterior distribution of the regime-specific coefficients $\boldsymbol{\theta}_i$.

We employ a Gibbs sampler to draw iteratively from the joint posterior density. The resulting Markov chain is then used to inspect and analyze the posterior quantities. In the following, we will outline the individual Gibbs steps and how to draw from the conditional posterior distributions.

(i) Conditional on the regime indicator S_i, we start by sampling the regime-specific coefficients. These consist of three group of coefficients: the VAR coefficients, the associated shrinkage prior coefficients, and the variance covariance matrix. First, we gather all variables in $\boldsymbol{X}_t = (1, \boldsymbol{y}'_{t-1}, \dots, \boldsymbol{y}'_{t-p})'$ and stack them into matrix form $\boldsymbol{X} = (\boldsymbol{X}_1, \dots, \boldsymbol{X}_T)'$. Similarly, we stack $\boldsymbol{y} = (\boldsymbol{y}_1, \dots, \boldsymbol{y}_T)'$ and $\boldsymbol{\varepsilon} = (\boldsymbol{\varepsilon}_1, \dots, \boldsymbol{\varepsilon}_T)'$. Then, it is convenient to define $\tilde{\boldsymbol{X}}_i = \boldsymbol{D}_i \boldsymbol{X}$, $\tilde{\boldsymbol{Y}}_i = \boldsymbol{D}_i \boldsymbol{Y}$, and $\tilde{\boldsymbol{\varepsilon}}_i = \boldsymbol{D}_i \boldsymbol{\varepsilon}$. $\boldsymbol{D}_i$ is a selection matrix of size $T_i \times T$ and T_i denotes the number of observations per regime i. Hence, $\tilde{\boldsymbol{X}}_i$, $\tilde{\boldsymbol{y}}_i$, and $\tilde{\boldsymbol{m}}_i$ denote all observations in the respective regime i. The VAR in matrix notation thus reads

$$\tilde{\boldsymbol{Y}}_i = \tilde{\boldsymbol{X}}_i \boldsymbol{A}_i + \tilde{\boldsymbol{\varepsilon}}_i, \tag{B.5}$$

where $\boldsymbol{A}_i = \left(\boldsymbol{c}_i, \boldsymbol{A}_{i1}, \ldots, \boldsymbol{A}_{ip}\right)'$ gathers all coefficients, which have to be estimated in the VAR equation. As a last step, we denote with $\boldsymbol{\alpha}_i = \text{vec}(\boldsymbol{A}_i)$ the vectorized version of $\boldsymbol{A}_i$.

(a) We sample the VAR coefficients as follows. First, we construct a $k \times k$ prior covariance matrix $\underline{\boldsymbol{V}_i} = \text{diag}(\tau_1^{-1}, \ldots, \tau_k^{-1})$. This yields the following conditional posterior distribution

$$\boldsymbol{\alpha}_i \mid \Sigma_i \sim \mathcal{N}\left(\overline{\boldsymbol{\alpha}}_i, \overline{\boldsymbol{V}}_i\right), \tag{B.6}$$

with $\overline{\boldsymbol{\alpha}_i} = \overline{\boldsymbol{V}_i}\left(\underline{\boldsymbol{V}_i^{-1}}\underline{\boldsymbol{\alpha}}_i + \boldsymbol{\Sigma}_i^{-1} \otimes \tilde{\boldsymbol{X}}_i'\tilde{\boldsymbol{X}}_i\hat{\boldsymbol{\alpha}}_i\right)$ and $\overline{\boldsymbol{V}_i} = \left(\underline{\boldsymbol{V}_i^{-1}} + \boldsymbol{\Sigma}_i^{-1} \otimes \tilde{\boldsymbol{X}}_i'\tilde{\boldsymbol{X}}_i\right)$, where $\hat{\boldsymbol{\alpha}}_i = \left(\tilde{\boldsymbol{X}}_i'\tilde{\boldsymbol{X}}_i\right)^{-1} \tilde{\boldsymbol{X}}_i'\tilde{\boldsymbol{Y}}_i$ denotes the OLS estimates of the VAR coefficients.

(b) Now we proceed to sample the parameters of the Normal-Gamma prior of the elements in $\boldsymbol{\alpha}_{ij}$. The conditional posterior distribution of $\tau_{ij,l}$ follows a generalized inverse Gaussian (GIG) distribution,

$$\tau_{ij,l} \mid \boldsymbol{\alpha}_{ij,l}, \vartheta_{ij}, \lambda_{ij}^2 \sim GIG\left(\vartheta_{ij} - 0.5, \vartheta_{ij}\lambda_{ij}^2, \boldsymbol{\alpha}_{ij,l}^2\right), \tag{B.7}$$

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

$$\zeta_{ij} \mid \tau_{ij}, \vartheta_{ij} \sim G\left(c_j + \vartheta_{ij}M^2, d_j + 0.5\vartheta_{ij}\lambda_{ij-1}^2 \sum_l \tau_{ij,l}\right). \tag{B.8}$$

As the conditional posterior distribution of ϑ_{ij} is not of a well-known form, we implement a random-walk Metropolis-Hastings step, where a candidate draw is drawn from $\vartheta_{ij}^* \sim \mathcal{N}\left(\ln(\vartheta_{ij}^{(n-1)}), \kappa_{\tau,ij}\right)$. κ_{ij} is a tuning parameter and (n) indicates the n-th iteration of the algorithm, yielding

$$min\left[1, \frac{\left(\vartheta_{ij}^*\lambda_{ij}^2/2\right)^{M^2\vartheta_{ij}^*}\Gamma(\vartheta_{ij}^*)q(\vartheta_{ij}^*)}{\left(\vartheta_{ij}^{(n-1)}\lambda_{ij}^2/2\right)^{M^2\vartheta_{ij}^{(n-1)}}\Gamma\left(\vartheta_{ij}^{(n-1)}\right)q\left(\vartheta_{ij}^{(n-1)}\right)}\right]. \tag{B.9}$$

(c) Draw $\boldsymbol{\Sigma}_i$ from its conditional distribution

$$\boldsymbol{\Sigma}_i \mid \boldsymbol{\alpha}_i \sim iW\left(\overline{\nu}_i, \overline{\boldsymbol{S}}_i\right), \tag{B.10}$$

where $\overline{\nu}_i = \nu + T_i$ and $\overline{\boldsymbol{S}}_i = \boldsymbol{S} + \left(\tilde{\boldsymbol{Y}}_i - \tilde{\boldsymbol{X}}_i\boldsymbol{\alpha}_i\right)'\left(\tilde{\boldsymbol{Y}}_i - \tilde{\boldsymbol{X}}_i\boldsymbol{\alpha}_i\right)$.

(ii) We proceed by sampling the threshold parameter γ according to an adaptive random-walk Metropolis-Hastings step. Hereby, we follow Chen and Lee (1995) and propose a normally distributed candidate which we draw from a Gaussian, i.e., $\gamma^* \sim \mathcal{N}(\gamma^{(n-1)}, C^{(n-1)})$. $C^{(n-1)}$ is a tuning parameter and (n) denotes the n-th of N draws. The probability of accepting a candidate draw γ^* 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

$$\min\left[1, \frac{p(\gamma^* \mid \boldsymbol{Y}, \boldsymbol{\theta}, d)q(\gamma^*)}{p(\gamma^{(n-1)} \mid \boldsymbol{Y}, \boldsymbol{\theta}, d)q(\gamma^{(n-1)})}\right], \tag{B.11}$$

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

$$C^{(n)} = \begin{cases} C_0 \quad \text{if } n \leq N_c, \\ s_d \text{Var}\left(\gamma^{(1)}, \ldots, \gamma^{(n-1)}\right) + s_d \eta \quad \text{if } n > N_c, \end{cases} \tag{B.12}$$

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, Saksman, Tamminen et al. (2001) show that this tuning algorithm has correct ergodicity properties.

(iii) Finally, we sample the delay parameter d from its conditional posterior distribution, which is a multinomial distribution with probability

$$p(d \mid \boldsymbol{Y}, \boldsymbol{\theta}, \gamma) = \frac{p(\boldsymbol{\theta}, \gamma, d \mid \boldsymbol{Y})}{\sum_{d_l=1}^{d_n} p(\boldsymbol{\theta}, \gamma, d \mid \boldsymbol{Y})}, \tag{B.13}$$

where $d_n = 4$ denotes the maximum delay.

C. Diagnostic Expectations

Diagnostic expectations are computed according to Proposition 5.1 and 6.1 of the derivations from Gennaioli and Shleifer (2018). 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 heteroskedastic 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 are given by

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

Applied to an AR(1) process with stochastic volatility this yields

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

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 based on external instruments is introduced in Stock and Watson (2012) and Mertens and Ravn (2013), and thoroughly discussed in Stock and Watson (2018). 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_t. The fitted values are then regressed on the other reduced form residuals,

$$\boldsymbol{\epsilon}_t^{-\omega} = \boldsymbol{\beta}\hat{\epsilon}_t^{\omega} + \boldsymbol{\nu}_t, \quad \boldsymbol{\nu}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma}_u). \tag{D.1}$$

Therefore, we get an estimate for the ratio $\boldsymbol{\beta}$, which is the structural effect of a unit shock on the credit market sentiment on the other variables in the system. In order to use this, we have to restore the column of $\boldsymbol{\Lambda}_i$ with the structural shock, which we denote as $\boldsymbol{\Lambda}_i^{\omega}$. We partition the matrix of the structural coefficients, such that

$$\boldsymbol{\Lambda}_i = [\boldsymbol{\Lambda}_i^{\omega} \quad \boldsymbol{\Lambda}_i^{-\omega}] = \begin{bmatrix} \lambda_{i,11} & \boldsymbol{\lambda}_{i,12} \\ \boldsymbol{\lambda}_{i,21} & \boldsymbol{\lambda}_{i,22} \end{bmatrix}, \tag{D.2}$$

where the credit market sentiment is assumed to be the first variable in the system. Nevertheless, this holds in general for any ordering. Furthermore, $\lambda_{i,11}$ is a scalar, $\boldsymbol{\lambda}'_{i,12}$ and $\boldsymbol{\lambda}_{i,21}$ are vectors of size $M-1 \times 1$ and $\boldsymbol{\lambda}_{i,22}$ is a matrix of size $M-1 \times M-1$. Furthermore, we partition the reduced form variance-covariance matrix according to $\boldsymbol{\Lambda}_i$,

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

Then $\lambda_{i,11}$ is identified up to a sign and scale convention and is obtained by the following closed form solution

$$(\lambda_i^{\omega})^2 = \lambda_{i,11}^2 = \Sigma_{i,11} - \boldsymbol{\lambda}_{i,12}\boldsymbol{\lambda}'_{i,12}, \tag{D.4}$$

where

$$\boldsymbol{\lambda}_{i,12}\boldsymbol{\lambda}'_{i,12} = (\boldsymbol{\Sigma}_{i,21} - \boldsymbol{\beta}\boldsymbol{\Sigma}_{i,11})'\boldsymbol{Q}_i^{-1}(\boldsymbol{\Sigma}_{i,21} - \boldsymbol{\beta}\boldsymbol{\Sigma}_{i,11}), \tag{D.5}$$

with

$$\boldsymbol{Q}_i = \boldsymbol{\beta}\boldsymbol{\Sigma}_{i,11}\boldsymbol{\beta}' - (\boldsymbol{\Sigma}_{i,21}\boldsymbol{\beta}' + \boldsymbol{\beta}\boldsymbol{\Sigma}'_{i,21}) + \boldsymbol{\Sigma}_{i,22}. \tag{D.6}$$

E. Convergence Diagnostics

Here, we evaluate the convergence of the models presented in section 3. For the MCMC algorithm we refer to Appendix B. In an ideal setting, the sampler returns independent draws, while the stronger the autocorrelation in the sampler is, the more draws are needed. To evaluate the extent of autocorrelation in the MCMC chain, we use three different convergence diagnostics. First, we compute inefficiency factors indicating how many draws are needed for drawing one identically and independently distributed draw. Second, we take a look at the Raftery and Lewis (1992) diagnostic statistic, which also serves as a measure of autocorrelation and returns a dependence factor that should not exceed 5 in an ideal setting. Third, we examine the Geweke et al. (1991) convergence diagnostic, which is a test of equality of the means of the first 10% and last 50% of the MCMC chain. Here, we report the share of Z-scores exceeding the critical value of 1.96.

For both models, convergence is safely achieved as depicted in Table E1. While the linear model shows an inefficiency factor of up to 5, we observe lower factors for the threshold model. Factors below 1 indicate the presence of negative autocorrelation. The dependence factor does not exceed 3 at all and also the share of the Z-scores exceeding the critical value of 1.96 does not seem to be an issue. In the last column, we report the percentage of retained draws of stationary draws. While more than 80% of the draws are retained for the linear model, we only keep around 10% of the draws in the threshold model. Nevertheless, we kept a sufficiently high amount of 1.200 posterior draws to conduct the posterior analysis. This renders our choice in a relatively high number of saved posterior draws of 10.000.

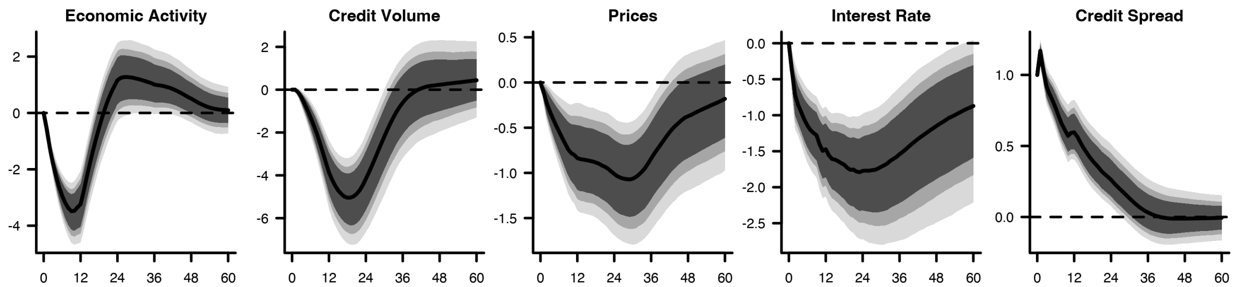
Table E1: Convergence Statistics.

Model	Inefficiency Factor	Dependence Factor	Geweke's Z-scores	% draws retained
Linear Model				
– Baseline	4.633	2.975	0.150	0.865
– Ext. Inf.	5.022	2.820	0.269	0.858
Threshold Model				
– Regime 1	2.522	3.228	0.119	0.181
– Regime 2	2.359	3.110	0.154	0.181
– Ext. Inf. Regime 1	0.408	2.822	0.165	0.069
– Ext. Inf. Regime 2	0.454	3.024	0.133	0.069

Notes: Mean inefficiency factors and mean dependence factor for the baseline variable set and the model with the extended information set.

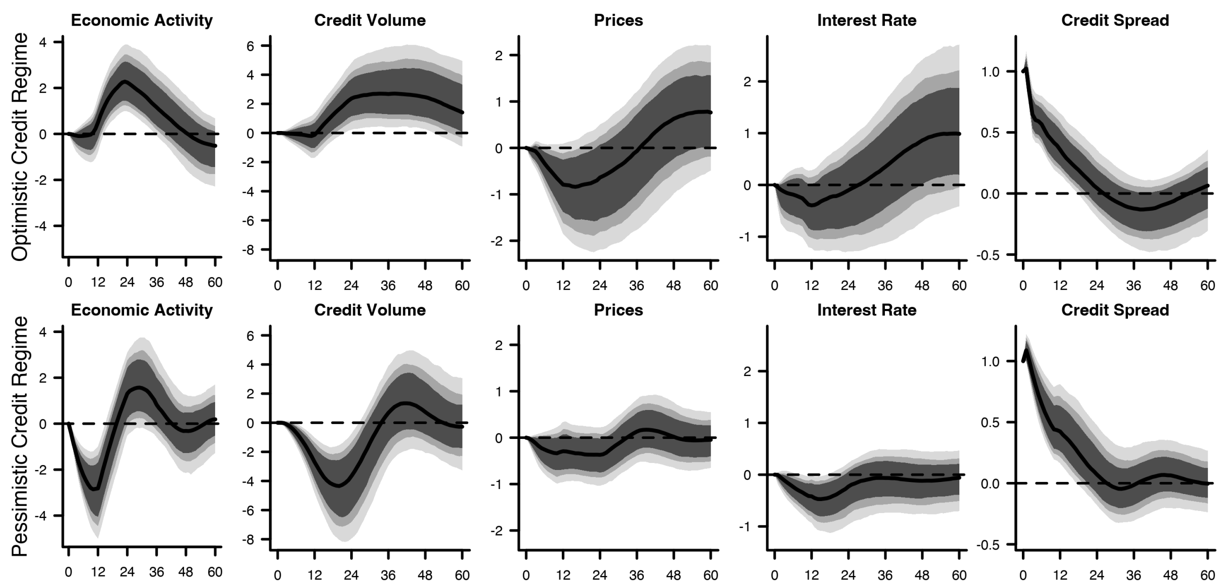
F. Additional Results

Figure F1: Alternative Ordering of VAR – Linear Model.



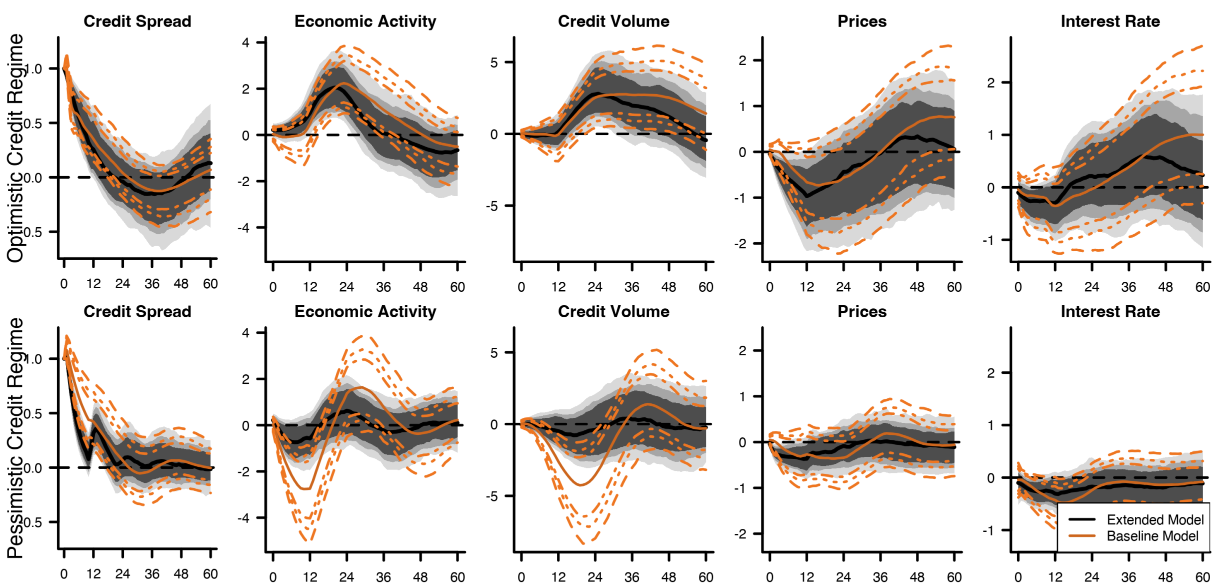
Notes: Impulse response functions to a credit market sentiment shock identified with recursive ordering using an alternative ordering. The black dashed line is the median response, while the gray shaded areas depict the 95%, 90%, and 84% credible sets, respectively. The shock is normalized to a 100 bps shock to the credit spread and responses are scaled in growth rates of economic activity, credit volume, and prices, and in percentage points of credit spreads and interest rates.

Figure F2: Alternative Ordering of VAR – Threshold Model.



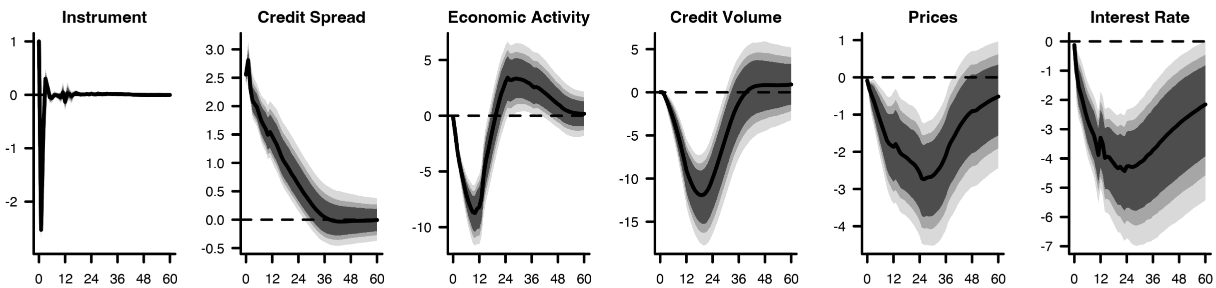
Notes: Impulse response functions to a credit market sentiment shock identified with recursive ordering using an alternative ordering. The black dashed line is the median response, while the gray shaded areas depict the 95%, 90%, and 84% credible sets, respectively. The shock is normalized to a 100 bps shock to the credit spread and responses are scaled in growth rates of economic activity, credit volume, and prices, and in percentage points of credit spreads and interest rates.

Figure F3: Enriching the Information Set with Seven Factors.



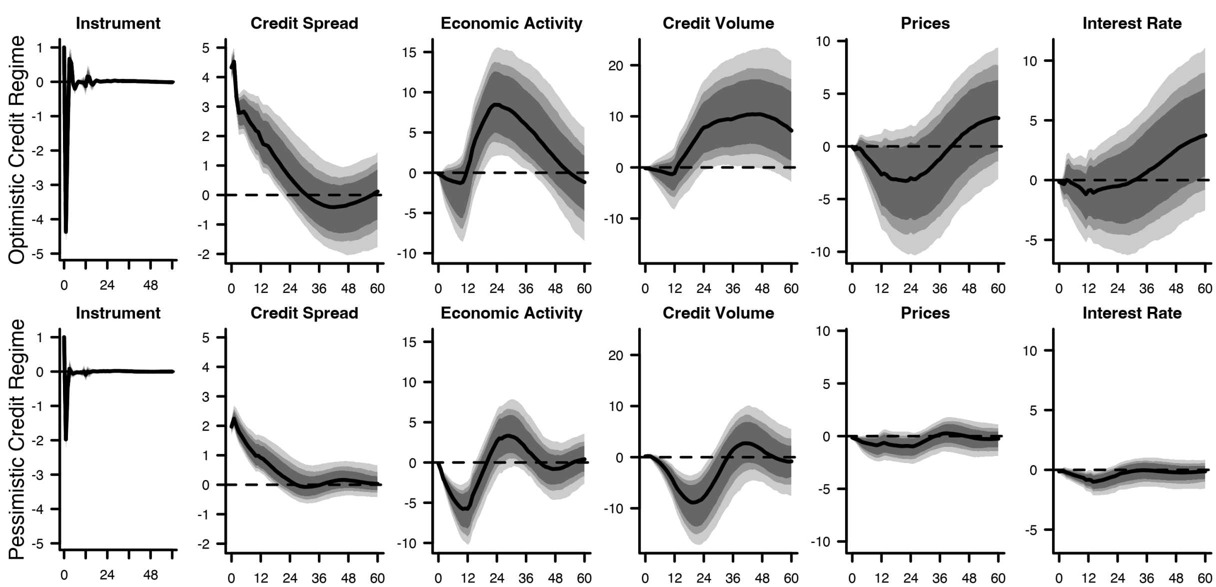
Notes: Comparison of impulse response functions to a credit market sentiment shock to the factor-augmented TVAR using $q = 7$ factors. The credit market sentiment shock is identified with diagnostic expectations. The model with extended information is depicted by the black dashed line as its median response, while the gray shaded areas depict the 95%, 90%, and 84% credible sets, respectively. The baseline model is depicted by the orange solid line as its median response, while the dashed lines indicate the 95%, 90%, and 84% credible sets, respectively. The shock is normalized to a 100 bps shock to the credit spread and responses are scaled in growth rates of economic activity, credit volume, and prices, and in percentage points of credit spreads and interest rates.

Figure F4: Internal Instruments Approach – Linear Model.



Notes: Impulse response functions to a credit market sentiment shock identified with the internal instruments approach. The black dashed line is the median response, while the gray shaded areas depict the 95%, 90%, and 84% credible sets, respectively. The shock is normalized to a 100 bps shock to the credit spread and computed impulse responses over a horizon 60 months. Responses are scaled in growth rates of economic activity, credit volume, and prices, and in percentage points of credit spreads and interest rates.

Figure F5: Internal Instruments Approach – Threshold Model.



Notes: Impulse response functions to a credit market sentiment shock identified with the internal instruments approach. The black dashed line is the median response, while the gray shaded areas depict the 95%, 90%, and 84% credible sets, respectively. The shock is normalized to a 100 bps shock to the credit spread and computed impulse responses over a horizon 60 months. Responses are scaled in growth rates of economic activity, credit volume, and prices, and in percentage points of credit spreads and interest rates.