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Abstract

This paper studies how non-rational risk shocks affect the macroeconomy. Using a novel identification design which exploits survey data on expectations of financial executives in the US, I identify non-rational risk shocks via distortions in beliefs. Belief distortions are measured through surprises in beliefs of credit spreads, defined as the difference between subjective and objective forecasts. They are then used as a proxy for exogenous variation in the risk premium. Belief distortions elicit due to overreaction of credit spreads, eventually leading to exaggerated beliefs on financial markets. Results indicate that the constructed shocks have statistically and economically meaningful effects. This has sizeable consequences for the U.S. economy: A positive non-rational risk shock moves credit spreads remarkably while real activity and the stock market decline.

Keywords: Business Cycles, Risk Shocks, Belief Distortions.

JEL Codes: C32, E32, E44, E71, G41.

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1. Introduction

Financial crises cause recessions and are costly. This insight was painfully acknowledged again after the last financial crisis elicited in the US and hit the world economy. This has renewed the interest in the long-standing question on how financial markets affect the macroeconomy. In comparison to garden-variety recessions, recessions caused by preceding financial crises are costlier (Jordà *et al.*, 2013). The exact causal underpinnings of financial crises are still at the forefront of the current state of debate. This paper provides an identification scheme lending support to the hypothesis of belief-driven, and thus non-rational, risk shocks leading to financial crises. From a policy perspective, non-rational risk shocks acting as a causal trigger of financial crises are of particular interest to make the economy more resilient against future financial instability.

Financial crises exhibit certain similarities in their emergence and phases they cycle through. Generally, we observe a pre-crisis, crisis, and after-crisis period. In the pre-crisis period there is a buildup of credit, leverage, a lowering of credit spreads, and an expansion of output. Optimism thrives, mounting in overoptimism. This leads to an undervaluation of the lower tail risk during the credit boom which translates into a neglection of crash risk. This credit boom lays the seeds for the subsequent collapse – the transition to the crisis is sudden. Bank runs, defaults, and losses to the financial sector follow. Risk premia rise and distress quickly spills over to the real sector leading to a contraction in credit and output. The aftermath of the crisis is a gradual recovery in credit, output, and a fall in credit spreads. These mechanisms at work has been shown by a large body of empirical literature, see inter alia Bordo *et al.* (2001), Borio and Lowe (2002), Schularick and Taylor (2012), Simsek (2013), Baron and Xiong (2017), López-Salido *et al.* (2017) and Krishnamurthy and Muir (2017).

Theoretical research on financial crises offers various channels capturing the interaction between the financial sector and the real economy. *First*, the financial accelerator framework (Kiyotaki and Moore, 1997, and Bernanke *et al.*, 1999) postulates that balance sheets are strengthened in booms and weakened in recessions, leading to an amplification of business cycle fluctuations. This does not only affect banks' balance sheets but can also affect non-financial firms or households. Hence, this amplification mechanism may also run through housing net worth (Mian and Sufi, 2014) or general household demand (Mian *et al.*, 2020). Furthermore, amplification effects can be highly nonlinear (Brunnermeier and Sannikov, 2014) or may be triggered by large, systemic shocks (He and Krishnamurthy, 2019). In addition, Christiano *et al.* (2014) enrich the framework to allow for time-varying risk premia characterized by the volatility of cross-sectional idiosyncratic uncertainty. *Second*, the channel focusing on liquidity mismatches (Diamond and Dybvig, 1983), i.e., the mismatch of short-term liabilities with illiquid long-term assets, allows for the possibility of bank runs. Bank runs lead to asset liquidation for ”fire sale” prices, again amplifying distress in financial and interbank markets due to the financial accelerator mechanism (Gertler and Kiyotaki, 2015, Gertler *et al.*, 2016, and Gertler *et al.*, 2020). *Third*, a stream of literature starting with Matsuyama *et al.* (2016) studies the endogeneity of credit cycles by introducing nonlinear dynamics. Here, different types of investment projects generate other dynamics. While the *Good* projects generate pecuniary externalities, the *Bad* projects redirect savings away from investment with demand spillovers.[1] *Fourth*, another stream of literature emphasizes the pivotal role of beliefs in the pre-crises periods. Starting with the ideas of Minsky (1977) and Kindleberger (1978), credit builds up over time due to exaggerated beliefs. A series of good-news shocks makes agents optimistic about the future path of the economy. On the contrary, bad news lead to a strong revision of agents' views on the economy, starting the transition to the crisis period. López-Salido *et al.* (2017) show that a mean-reversion in credit-market sentiments predicts a change in the composition of external finance. An inward shift in credit supply leads to a fall in net debt issuance and a contraction in economic activity. Similarly, Greenwood and Hanson (2013) show the deterioration of credit quality of corporate debt during credit booms.

In this paper, I study how non-rational risk shocks on credit markets affect the macroeconomy. Connecting to the literature on belief-driven shocks, I propose a novel approach for the identification of a shock to risk prevalent on credit and financial markets which constitutes one possible approach how a financial crisis is triggered. As a first step, I measure belief distortions to construct surprises in beliefs.[2] As a next step, I quantitatively analyze the macroeconomic consequences of this non-rational risk shock identified through surprises in beliefs. Here, I relate theoretically to the financial accelerator framework on how a risk shock propagates through the macroeconomy. A belief-driven shock refers back to the early ideas of behavioral forces driving the economy, as Keynes puts it in his *General Theory* that „our decisions to do something positive [...] can only be taken as the result of animal spirits —- a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities" (Keynes, 1936, pp. 161-162). Minsky (1977) applied the idea of animal spirits to financial markets, where traders driven by overoptimism begin to finance asset purchases by additional borrowing. This can lead to a collective Ponzi scheme in which investors' borrowing is merely based on the belief of an appreciation of asset values to keep the system afloat. If optimism ceases, instability follows.

I argue that belief surprises are exogenous and characterize how risk is driven by behavioral forces. Belief surprises are supposed to reflect exogenous variation in the risk premium according to investors' subjective notion of over- or undervaluation of risk. Credit spreads are a natural choice for

[1] Financial frictions are still assumed exogenous in the work by Matsuyama *et al.* (2016). An extension by Kubin *et al.* (2019) allows for a switching process in financial frictions according to aggregate sentiments in the economy, for which empirical support has been found by Böck and Zörner (2019).

[2] I will use the terms *belief distortions* and *belief surprises* interchangeably. While the former term is used as its theoretical concept, surprises refer to operationalization with actual data.

measuring risk premia. According to Elton *et al.* (2001) credit spreads differ across rating classes not only due to their risk premium, but also due to their expected default loss.[3] Additionally, a liquidity premium can arise in time of financial distress. In order to minimize the effect of the default premium, I use Moody's Aaa rated corporate bond rates.[4] There is also evidence that the liquidity component did not rise for Aaa rated corporate bonds (Dick-Nielsen *et al.*, 2012). Furthermore, I redo the analysis with Moody's Baa rated corporate bond rates to also gauge the effect of a higher default rate or liquidity component. From these bond rates a long-term government yield of similar maturity is deducted to construct credit spreads. Belief distortions in risk premia transmitted through credit spreads are then measured as the difference between subjective and objective expectations on risk. Hence, belief distortions are entirely forward looking and the stronger these distortions, the bigger the difference of the subjective valuation of risk compared to its objective valuation. For the subjective evaluations of the future, I rely on the Blue Chip (BC) Financial Indicators. In this survey, a panel of financial executives is asked on their subjective risk expectations and it thus offers a professionals' assessment of financial markets. Objective evaluations of the future are constructed in a model-consistent way, i.e., with the help of econometric models. Econometric models are not distorted by sentiments and act as a machine benchmark. This resembles performing predictions within the rational expectations framework. Hence, I estimate a series of flexible forecasting models, where out-of-sample performance is used to discriminate between them.

The proposed identification scheme rests on the assumption that agents make systematic errors in beliefs. Various explanations have been put forward, most noteworthy in this context is Bordalo *et al.* (2018) applying the expectation formation framework of *diagnostic expectations* to the Baa credit spread. Hence, before I construct surprises in beliefs, I analyze expectational reactions to new information in credit spreads. Similar to the results in Bordalo *et al.* (2020), I provide evidence that overreaction drives credit spreads. Therefore, evidence suggests to neglect the full information rational expectations (FIRE) hypothesis. The out-of-sample forecasting exercise reveals that credit spreads are best predicted by an autoregressive (AR) process with stochastic volatility (SV). This represents the construction of objective expectations. Furthermore, two additional insights are worth mentioning: Additional information on the macroeconomy features no predictive gains, pointing to the strong forward-looking component in credit spreads, and the inclusion of SV controls to some extent for excess volatility present in financial time series.

[3] The third component of credit spreads, the tax premium, arises because interest payments on corporate bonds are differently taxed than those on government bonds, but this is disregarded in the analysis. Although they are an important influence in explaining credit spreads, due to their inability to explain differences in credit spreads they are not of concern in this setting.

[4] An interesting alternative is the excess bond premium (Gilchrist and Zakrajšek, 2012), the residual of a micro-based approach to credit spreads freed from firm-specific information on default risk. Unfortunately, this is not suitable for the current framework due to unavailability of subjective expectations thereof.

After the construction of belief surprises, I analyze their macroeconomic effects. Using these belief surprises as an exogenous instrument in a vector autoregression (VAR), I am able to compute impulse response functions (IRFs) and perform a forecast error variance decomposition (FEVD) to the identified non-rational risk shock. I find that the shock has statistically and economically significant effects. Empirical estimates show that a non-rational risk shock elicits a jump in the risk premium, a drop in the stock market index, and a dip of real activity into recessionary tendencies. There is some subsample instability with respect to prices, but overall prices tend to decrease. Short-term interest rates indicate accomodative monetary policy with strong anticipation effects by the central bank. Effect sizes are stable across both spreads, indicating that the proposed proxy truly recovers exogenous movements in the risk premium and is not blurred by movements in the default premium. Additionally, the forecast error variance decomposition reveals that the non-rational risk shock explains the bulk of the variance of the credit spread for a horizon up to one year. Furthermore, a sizable share of the variance of the stock market variable while a notable share of real economic activity and short-term interest rates can be explained for a short-run horizon of 1-2 years.

The results further suggest that the responses of a wide range of macroeconomic variables to the identified non-rational risk shock have the expected signs and magnitudes. Studying various propagation channels, I examine how the risk shock affects real consumption and investment, credit market measures, the yield curve, the labor market, prices, and expectations. Interestingly, a shift in the composition of external funding is visible. In case of financial distress market participants shift their external funding from bond to bank finance valuing the higher flexibility. Risk shocks are also associated with a sudden drop in prices, a delayed adjustment on the labor market, and a sharp drop in expectations. Responses to expectations level out relatively quickly with a duration of about one to one and a half years. This also suggests that financial market disruptions endure only for a short time in subjective valuations.

To sum up, the contribution of this paper is threefold. First, I provide evidence on overreaction in credit spreads. Second, I provide a novel identification of non-rational risk shocks. Hereby, I use surprises in beliefs as an exogenous proxy to identify a VAR where belief surprises are defined as the difference between subjective and objective evaluations of the future. I use survey data to measure subjective evaluations of the future, while I resort to econometric models to construct objective evaluations. Third, I analyze the effects of non-rational risk shocks and how it affects macroeconomic quantitites.

Related empirical literature. This paper relates to several strands of literature. There is a large amount of literature neglecting the FIRE assumption giving rise to various forms of belief distortions. I also connect to the literature looking at how financial frictions affect uncertainty shocks and how to disentangle those shocks. Last, I connect to the literature explaining credit spreads.

First, the number of studies looking at belief distortions in macroeconomics and finance is growing fast. A large theoretical literature has emerged that tries to explain why economic agents make systematic errors embedded in beliefs. These reasons include the presence of information frictions (Coibion and Gorodnichenko, 2015), the use of extrapolative expectations (e.g., De Long *et al.*, 1990, Barberis *et al.*, 1998, Barberis *et al.*, 2015), the overweighting of personal experience (e.g., Malmendier and Nagel, 2011; 2016), the overreaction to incoming news (e.g., Bordalo *et al.*, 2018; Gennaioli and Shleifer, 2018; Bordalo *et al.*, 2020), the this-time-is-different thinking (Reinhart and Rogoff, 2009), or the use of simple heuristics to forecast (e.g., Anufriev and Hommes, 2012; Assenza *et al.*, 2019). However, they all have in common that the presence of new information is given too much or too little weight. This happens because agents only have limited attention (neglecting the full information assumption) or new information is processed in a non-rational or behavioral way (neglecting the rational expectation assumption). For a recent survey see also Manski (2018). Scholars are now also integrating those frameworks into macroeconomic models (Maxted, 2019) or look at the empirical consequences of belief distortions in inflation or GDP (Bianchi *et al.*, 2020). These observations reason the identification of financial risk shocks arising due to their non-rational nature. In particular, the literature concerned with financial market behavior tends to strongly neglect the rational expectations assumption.

Second, I also relate to the literature on the effects of economic uncertainty and its nexus to financial shocks. Economic uncertainty plays a veritable role in influencing the business cycle (Bloom, 2009) and scholars are increasingly interested in the exact causes and consequences of economic uncertainty, specifically financial uncertainty, and its interaction with financial shocks. A recent contribution by Ludvigson *et al.* (forthcoming) points out that macroeconomic uncertainty is just an endogenous reaction, while financial uncertainty is a truly exogenous impulse to the economy leading to a rapid drop in aggregate output. There is, however, a growing literature interested in the interaction between uncertainty shocks and financial shocks. Here, Alfaro *et al.* (2018) coin the term „finance-uncertainty multiplier“ (FUM) to indicate the role played by financial frictions in amplifying the effects of uncertainty shocks. There is ample empirical evidence in support of this hypothesis, e.g., Caldara *et al.* (2016), Furlanetto *et al.* (2019), Alessandri and Mumtaz (2019), Chatterjee *et al.* (2020), or Caggiano *et al.* (2021).

Third, I relate to the literature on explaining credit spreads. There is an ongoing discussion on the ”credit spread puzzle”, i.e., the claim that yield spreads on corporate bonds are larger than what can be explained by default risk (Elton *et al.*, 2001, Collin-Dufresn *et al.*, 2001, or Driessen, 2005). There are several studies on how liquidity affects asset prices and illiquidity has been put forward to explain the puzzle (Houweling *et al.*, 2005 or Dick-Nielsen *et al.*, 2012). Here, I add that behavioral forces are able to drive credit spreads.

The remainder of the paper proceeds as follows. In Section 2, I introduce the identification of non-rational risk shocks. For that, I propose how to construct belief suprises and provide evidence on overreaction in credit spreads. In the next section, Section 3, the methodology for constructing objective beliefs and for analyzing the macroeconomic effects to a non-rational risk shock is introduced. In Section 4, I present the results of the empirical analysis. It begins with finding the best model for constructing objective expectations, goes on with discussing the belief surprise series, and ends with analyzing the macroeconomic effects of non-rational risk shocks. For that, I rely on impulse response analysis, but also present alternative strategies for identification and computing impulse response. Furthermore, I discuss the quantitative importance of the shock with the help of a forecast error variance decomposition, before moving on to broader macroeconomic propagation channels. Section 5 provides a sensitivity analysis along several dimensions. Finally, Section 6 concludes.

2. Identification

The identification strategy of non-rational risk shocks in this paper builds upon the following observations. Financial markets do not seem to be efficient markets due to the presence of anomalies.[5] Anomalies happen for no fundamental reason but occur due to things such as *sunspots*, *animal spirits* or *mass psychology*.[6] Nevertheless, financial anomalies could also be present due to incomplete information about the structure of the economic environment. In particular, Brav and Heaton (2002) show that although both theories relax opposite assumptions of rational expectations, their predictive similarity make them hard to distinguish from each other. Irrespective of these alternatives, the outlined approach captures both aspects. After discussing the construction of belief surprises in detail, I provide evidence on overreaction in credit spreads. This evidence defends the assumption that surprises are indeed belief-driven in a non-rational manner.

[5] I 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."

[6] This led to the voluminous literature on behavioral finance, surveyed for instance in Shiller (2003, 2015) or Barberis and Thaler (2003). *Sunspots* refer to a change in expectations influencing the economy without a relation to economic fundamentals. *Animal spirits* as coined by Keynes refer to instincts, proclivities, and emotions influencing human behavior. *Mass psychology* is a branch of psychology engaged with studying how individual behavior changes and differs within a crowd.

Construction of Belief Surprises

Belief distortions on financial markets are measured as the difference between subjective and objective expectations of risk. Financial risk, in particular systematic risk, is strongly related to the risk premium. Variations in the risk premium reflect investors' subjective notion of over- or undervaluation of risk prevalent in the economy. Feedback across investors lead to waves of optimism or pessimism. Hence, I construct a series of belief surprises capturing belief distortions on financial markets that can be used to identify a structural non-rational risk shock. Here, I am following the framework in Bianchi *et al.* (2020) and define

$$\text{Surprise}_t[y_{t+h}] = \mathbb{F}_t[y_{t+h}] - \mathbb{E}_t[y_{t+h}], \tag{2.1}$$

where y_{t+h} refers to the h-step ahead ($h = 1, 2, 3, 4$) credit spread under consideration (either the Aaa or Baa credit spread), t indicates the time period. $\mathbb{F}_t[\cdot]$ refers to the subjective expectations operator, while $\mathbb{E}_t[\cdot]$ refers to the objective, or rational, expectations operator. The resulting difference is denoted as a surprise in beliefs at time t. This is the measure of exogenous belief distortions constructed in a completely forward-looking manner. Hence, the measure is also immune to the Lucas critique.

Overreaction in Credit Spread Expectations

For the proposed identification scheme to work, I assume a departure from rationality of credit spreads. This section defends this assumption and sheds light on the nature of belief distortions happening on financial markets. Besides providing evidence on the departure of the FIRE assumption, the data strongly point to overreaction in credit spreads. This can, for instance, be explained by the expectation formation framework of *diagnostic expectations* (Bordalo *et al.*, 2018). Testing the rational expectations hypothesis, Coibion and Gorodnichenko (2015) check whether forecast errors can be predicted using information already available at the time the forecast is made. Furthermore, understanding whether departures from rational expectations are due to over- or underreaction to information is important evidence for the proposed identification scheme.

Data comes from the BC survey which is conducted on a monthly basis, asking around 40 panelists from major financial institutions for their expectations with respect to several financial indicators.[7] The survey is conducted around the beginning of each month. Data is taken from the end-of-quarter month survey in March, June, September and December. Forecasts are available for the current quarter t and for quarters $t + 1$ through $t + 4$. In total, the survey consists of about 150

[7] The data were purchased and manually checked for errors before using the data in the analysis. Furthermore, one may worry that BC financial forecasts are distorted due to signaling reasons. However, forecasts for variables also entertained in the anonymous Philadelphia Fed Survey of Private Forecasters tend to be similar. The forecasts used in this study are only available in the Blue Chip professional forecasts.

Table 1: Error-on-Revision Regressions.

	Consensus			Individual					
	β_1^c	SE	Obs.	β_1^p	SE	Obs.	med(β_1^i)	med(Obs.)	I
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
h = 1									
Aaa spread	0.12	0.03	115	−0.13	0.01	4,096	−0.13	27.5	110
Baa spread	0.16	0.02	71	0.02	0.01	2,212	0.00	34.5	52
h = 2									
Aaa spread	0.08	0.10	114	−0.20	0.02	4,122	−0.21	27	111
Baa spread	0.28	0.05	70	0.03	0.02	2,214	0.02	34	53
h = 3									
Aaa spread	0.01	0.18	113	−0.26	0.02	4,105	−0.30	27	111
Baa spread	0.20	0.13	69	−0.06	0.03	2,206	−0.07	34	53
h = 4									
Aaa spread	0.14	0.21	112	−0.27	0.02	4,062	−0.30	27	111
Baa spread	0.05	0.43	68	−0.19	0.04	2,167	−0.22	34	51

Notes: This table shows coefficients from forecast error on forecast revision regression. Column 1 to 6 show the coefficients of consensus time series regressions and individual-level pooled panel regressions together with standard errors (SE) and number of observations (Obs.). Column 7-9 shows the median coefficients, median number of observations and number of forecasters (I) in forecaster-by-forecaster regressions. For consensus time series regressions and pooled panel regressions, standard errors are Newey-West with the automatic bandwidth selection procedure (Newey and West, 1994).

individual forecasters with varying sample lengths due to a change in the composition of forecasters in the survey. In particular, I use forecasts of the Aaa and Baa corporate bond yield and the 10-year Treasury yield. The spread is then computed as the difference between the particular corporate bond yield and the Treasury yield. Data on the Aaa spread covers the period 1988Q1 to 2020Q1, while the time series is considerably shorter for the Baa spread spanning from 1999Q1 to 2020Q1. Data sources of the actual credit spreads are listed in Appendix A.

I denote the h-step ahead consensus forecast made at time t for the future value of y_{t+h} of a credit spread with $\mathbb{F}_t[y_{t+h}]$. The consensus forecast is constructed with $\mathbb{F}_t[y_{t+h}] = (1/I)\sum_i \mathbb{F}_t^i[y_{t+h}]$, where $\mathbb{F}_t^i[y_{t+h}]$ is the forecast of individual i and $I > 1$ is the number of forecasters. Forecast revisions at time t of individual i are defined as $FR_{t,h}^i = (\mathbb{F}_t^i[y_{t+h}] - \mathbb{F}_{t-1}^i[y_{t+h}])$ and $FR_{t,h} = (1/I)\sum_i FR_t^i$ follows likewise. Predictability of forecast errors is measured by estimating the following consensus regression

$$y_{t+h} - \mathbb{F}_t[y_{t+h}] = \beta_0^c + \beta_1^c \mathrm{FR}_{t,h} + \eta_{t+h}, \quad \eta_{t+h} \sim \mathcal{N}(0, \sigma_{c,\eta}^2). \tag{2.2}$$

If forecast errors are not predictable from forecast revisions, I cannot reject the null hypothesis of FIRE. This essentially reduces to testing whether $\beta_1 = 0$. Otherwise, overreaction (underreaction) is implied by a negative (positive) coefficient β_1. For instance, a positive coefficient β_1 together with a positive forecast revision, $\mathrm{FR}_{t,h} > 0$, implies that the consensus forecast is not optimistic enough. Bordalo *et al.* (2020) extend this analysis by also analyzing forecast error predictability at the individual level. They propose estimating a pooled panel regression model,

$$y_{t+h} - \mathbb{F}_t^i[y_{t+h}] = \beta_0^p + \beta_1^p \mathrm{FR}_{t,h}^i + \eta_{t+h}^p, \quad \eta_{t+h}^p \sim \mathcal{N}(0, \sigma_{p,\eta}^2), \tag{2.3}$$

where the common coefficient β_1^p indicates whether the average forecaster under- or overreacts to their own information. Again, if $\beta_1^p = 0$ then FIRE cannot be rejected. Furthermore, they also suggest forecaster-by-forecaster regressions,

$$y_{t+h} - \mathbb{F}_t^i[y_{t+h}] = \beta_0^i + \beta_1^i \mathrm{FR}_{t,h}^i + \eta_{t+h}^i, \quad \eta_{t+h}^i \sim \mathcal{N}(0, \sigma_{i,\eta}^2), \quad i = 1, \ldots, I. \tag{2.4}$$

This yields a distribution of individual coefficients β_1^i ($i = 1, \ldots, I$), where I focus on the median coefficient. Since this can result in varying sample sizes for the estimation (due to the different lengths of different forecasters in the sample), I only keep forecasters with at least fifteen observations. Furthermore, I winsorize outliers.[8]

Results of the error-on-revision regressions are presented in Table 1. Looking at the coefficients from the consensus regression, $\beta_1^c > 0$ indicates underreaction with varying statistical power. On the contrary, coefficients from the pooled panel and individual-level regression are consistently and precisely estimated negative, pointing to overreaction. These findings are similar to the one presented in Bordalo *et al.* (2020). Their explanation is that individual forecasters overreact, but concurrently do not react to all the information received by their peers. This creates rigidity in the consensus forecast. In particular, this form of rigidity only holds for both credit spreads when looking at shorter horizons and vanishes at longer ones. This provides quite strong evidence of financial anomalies in credit spreads, e.g., excess volatility (Shiller, 1981) or herding behavior (Lux, 1995). These findings have also been documented in experimental studies explaining pricing on asset markets. Kocher *et al.* (2019) explain overpricing due to lack of traders' self-control transmitting into irrational exuberance in markets. Anufriev and Hommes (2012) argue in favor of evolutionary selection among heterogeneous expectation rules tending to outperform rational expectation benchmarks. To conclude this section, the FIRE assumption clearly does not hold for credit spreads while evidence points to overreaction as a response to new information.

3. Methodological Framework

As illustrated before, I have to set up a methodological framework for formulating objective expectations. Then, after the construction of surprises in beliefs, I illustrate the macroeconomic model

[8] I follow here the approach taken by Bordalo *et al.* (2020). They exclude forecasts which are five interquartile ranges away from the median. In case there is no variation in the interquartile range, I apply the interquartile range of the previous period. This ensures consistency of the forecasts.

identified with those surprises. In this section, I outline the methodological approach taken in this paper to tackle these issues.

Econometric Approach: Forecasting

For the construction of an objective forecast $\mathbb{E}_t[y_{t+h}]$ I need to specify a forecasting model. Let $\mathbb{E}_t[y_{t+h}]$ denote either a forecast of the Aaa or Baa credit spread at horizon $h \geq 1$ predicted at time t. In order to identify possible distortions in beliefs, it is imperative that the forecasting model be as rich in information as possible to reduce a possible omitted variable bias. Concurrently, the model has to be parsimonious to avoid spurious estimates. I tackle these issues with a two-pronged approach that combines the estimation of factor models with regularization techniques. The factor model allows for a parsimonious specification, where it reduces the information in more than 150 time series into a small number of factors. Regularization to the forecasting equation is introduced with the help of shrinkage priors that regularize coefficients of variables containing no predictive power towards zero. First, I take a high-dimensional dataset $\mathcal{X}_t$ of dimension $K = 159$ of economic information on the US economy. $\mathcal{X}_t$ is suitably transformed to induce stationarity of the series. Details on the exact dataset and the transformations can be found in Table A2 in the appendix. Let the high-dimensional dataset have a factor structure taking the form

$$\mathcal{X}_t = \mathbf{\Lambda} \boldsymbol{f}_t + \boldsymbol{\nu}_t, \quad \boldsymbol{\nu}_t \sim \mathcal{N}_K(\mathbf{0}, \mathbf{\Xi}). \tag{3.1}$$

$\mathbf{\Lambda}$ is a $K \times q$ factor loadings matrix, $\boldsymbol{f}_t$ a $q \times 1$ estimated factor with $q << K$ and $\boldsymbol{\nu}_t$ are i.i.d. standard normal errors. Common variation in the high-dimensional dataset $\mathcal{X}_t$ is thus captured by the vector of factors $\boldsymbol{f}_t$.[9] The idiosyncratic components in $\boldsymbol{\nu}_t$ are independent across series. Choosing the number of factors is a sensible issue (Bai and Ng, 2002). In order to find a trade-off between not adding too many regressors to the forecasting model, and using all of the factor information, I use $q = 3$ factors.[10] As results show, adding information to the model does not pay off in additional predictive power. Furthermore, let $\boldsymbol{x}_t$ $(l \times 1)$ being a subset of $\mathcal{X}_t$ containing additional non-factor information as controls in the forecasting model. Hence, in the most general form, I consider the following forecasting model for variable i

$$y_{t+h} = \alpha + \sum_{j=0}^{p-1} \phi_j y_{t-j} + \boldsymbol{\beta}_j^x \boldsymbol{x}_{t-j} + \boldsymbol{\beta}_j^f \boldsymbol{f}_{t-j} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, \delta_t^2), \quad h \geq 1. \tag{3.2}$$

Each forecasting equation contains an intercept α, autoregressive parameters ϕ_j, coefficients for the controls in $\boldsymbol{\beta}_j^x$ and coefficients for factors $\boldsymbol{\beta}_j^f$. Innovations $\eta_{i,t}$ follow a Gaussian distribution and its variances δ_t^2 are allowed to be time-varying. Furthermore, the prior distribution on all coefficients

[9] Factors are estimated with Principal Component Analysis.
[10] I re-estimate the model with $q = 7$ leading to no improvements in predictive power. See also Appendix F.

follows the Normal-Gamma (NG) shrinkage prior as laid out in Griffin and Brown (2010) and stochastic volatility is estimated with the framework provided by Kastner (2016).

This specification conveniently nests all models run in the forecasting exercise. In particular, it nests the random-walk (RW) by setting $\phi_0 = 1$ all else equal to zero. Furthermore, by setting $\boldsymbol{\beta}_j^x = \boldsymbol{\beta}_j^f = 0$ it nests a wide variety of autoregressive (AR) processes. Adding additional information in $\boldsymbol{x}_t$ which contains core economic variables[11], such as real gross domestic product (GDP), the price deflator of the gross domestic product, a short-term interest rate, and a stock market index together with factor information enriches the information content of the model thoroughly and results in an autoregressive distributed lag model (ARX). All specifications are run with time-variation in the second moment, denoted by stochastic volatility (SV).

In all cases, the forecast horizon $h = 1, 2, 3, 4$ is the same and predicted directly. Forecasts are computed for both credit spreads, the Aaa and Baa spread. The sample of both models starts in 1970Q1 and is estimated in a rolling window fashion to keep the amount of information constant across all models. The alternative of an extending window does not show qualitatively different results (see also Table F2 and F4 in the appendix). All estimations are based on 25.000 draws from the posterior distribution, where I discard the first 15.000 draws as burn-ins.

Econometric Approach: Shock Identification

Now I turn to the model description to analyze the macroeconomic effects of a non-rational risk shock. Let $\{\boldsymbol{y}_t\}_{t=1}^T$ denote an M-dimensional time series process. Consider the following reduced-form VAR(p) model

$$\boldsymbol{y}_t = \boldsymbol{c} + \boldsymbol{A}_1\boldsymbol{y}_{t-1} + \ldots + \boldsymbol{A}_p\boldsymbol{y}_{t-p} + \boldsymbol{u}_t, \quad \boldsymbol{u}_t \sim \mathcal{N}_M(\boldsymbol{0}, \boldsymbol{\Sigma}_t), \tag{3.3}$$

where p is the lag order, $\boldsymbol{c}$ is an $M \times 1$ vector of constants, $\boldsymbol{A}_1, \ldots, \boldsymbol{A}_p$ are $M \times M$ coefficient matrices and $\boldsymbol{u}_t$ denotes an $M \times 1$ vector of reduced-form Gaussian distributed innovations with possibly time-varying covariance matrix $\boldsymbol{\Sigma}_t$. In what follows I use stochastic volatility and a factorization of $\boldsymbol{\Sigma}_t$ to model the time-varying innovation covariance matrix

$$\boldsymbol{\Sigma}_t = \boldsymbol{H}^{-1}\boldsymbol{\Lambda}_t\boldsymbol{H}^{-1'}. \tag{3.4}$$

$\boldsymbol{\Lambda}_t$ is a diagonal matrix with generic jth element λ_{jt} and $\boldsymbol{H}^{-1}$ is a lower-triangular matrix with ones on its main diagonal (Carriero *et al.*, 2019). By taking logs the diagonal elements of $\boldsymbol{\Lambda}_t$, those elements follow a centered AR(1) process

$$\ln \lambda_{j,t} = \mu_j + \varphi_j(\ln \lambda_{j,t-1} - \mu_j) + \xi_{j,t}, \quad \xi_{j,t} \sim \mathcal{N}(0, \sigma_\xi^2), \quad j = 1, \ldots, M. \tag{3.5}$$

This constitutes the parameterized stochastic volatility model which intends to capture possible effects of heteroskedasticity present in the sample under consideration.

[11]Here I use the same set of variables later used in the VAR analysis.

Reduced-form innovations are related to the structural shocks via a linear mapping

$$\boldsymbol{u}_t = \boldsymbol{S}\boldsymbol{\varepsilon}_t, \tag{3.6}$$

where $\boldsymbol{S}$ is a non-singular $M \times M$ structural impact matrix and $\boldsymbol{\varepsilon}_t$ is an $M \times 1$ vector of structural shocks. By definition, structural shocks are mutually uncorrelated, i.e. $Var(\boldsymbol{\varepsilon}_t) = \boldsymbol{\Omega}$ being diagonal. From the linear mapping of the shocks the following holds

$$\boldsymbol{\Sigma}_t = \boldsymbol{S}\boldsymbol{\Omega}\boldsymbol{S}'. \tag{3.7}$$

In the following, I denote the non-rational risk shock without loss of generality as the first structural shock in the VAR, $\varepsilon_{1,t}$. Hence, the aim is to identify $\boldsymbol{s}_1$ corresponding to the first column of $\boldsymbol{S}$.

For the identification of the non-rational risk shock, I will use the series on belief surprises as an external instrument. The methodology on identification with external instruments has been introduced by Stock and Watson (2012), and is thoroughly discussed in Stock and Watson (2018) and Montiel-Olea *et al.* (2020). It alleviates possible concerns of measurement error in the belief surprise series. In general, an external instrument (or *proxy*) is a variable that is correlated with the shock of interest but not with other shocks and works as follows. Suppose Z_t denotes the external instrument, in particular belief surprises in the Aaa or Baa credit spread. To be a valid instrument, Z_t must be correlated with the non-rational risk shock $\varepsilon_{1,t}$ and orthogonal to all other shocks $\boldsymbol{\varepsilon}_{2:M,t}$, such that

$$\mathbb{E}[Z_t, \varepsilon_{1,t}] = \Phi, \tag{3.8}$$

$$\mathbb{E}[Z_t, \varepsilon_{2:M,t}] = \boldsymbol{0}. \tag{3.9}$$

Eq. (3.8) states the relevance assumption, while Eq. (3.9) is the exogeneity condition.[12] Under those assumption $\boldsymbol{s}_1$ is identified up to sign and scale. For the technical details, see Appendix B. The scale $s_{1,1}$ is then set by a normalization subject to $\boldsymbol{\Sigma}_t = \boldsymbol{S}_t\boldsymbol{\Omega}\boldsymbol{S}_t'$. In the analysis, I will set $\boldsymbol{\Omega} = \boldsymbol{I}_M$, which implies that a unit positive value of $\varepsilon_{1,t}$ has a one standard deviation positive effect on $y_{1,t}$. Having obtained the impact vector, all objects of interest such as IRFs, FEVDs or the structural shock series can be computed.

Following the work of Jarociński and Karadi (2020), I also use a second identification approach. Here, I directly append the belief surprise series as the first variable in the system and use the Cholesky decomposition for identification. Ordering the proxy first in a recursive identified VAR is also called *internal instrument* approach (see the discussion in Plagborg-Møller and Wolf, 2019). Implicitly, I assume the exogeneity of the belief surprise series to which all other variables in the system react contemporaneously. This approach has its own advantages and shortcomings. On a positive note, estimation is particularly simple and I do not have to rely on a two-step approach.

[12]Additionally, I have also to assume that the proxy is exogenous at all leads and lags to all structural shocks.

Furthermore, it is possible to look explicitly at the response of the credit spread as the measure of risk. A clear shortcoming is that possible measurement error can cause biases.

Additionally, structural VAR analysis is based on the invertability or fundamentalness assumption i.e., the VAR contains all relevant information to recover the structural shocks from past information. In case this assumption does not hold, it reduces essentially to an omitted variable bias problem.[13] Forni and Gambetti (2014) provide a testing procedure on whether a VAR contains sufficient information. In Section 5, I use this testing procedure and do not find evidence that the model is informationally insufficient.

Computing impulse responses using the VAR involves additional assumptions. For the validity of the responses, the VAR has to be an adequate representation of the dynamics. In particular, an impulse response of a VAR is a function of forecasts at increasingly distant horizons and misspecification errors are thus compounded with the forecast horizon. A useful alternative is to compute impulse responses to the identified non-rational risk shock using local projections (Jordà, 2005). Hence, I run the following set of regressions

$$y_{i,t+h} = \alpha_i + \tau_{i,h}\hat{\varepsilon}_{1,t} + \sum_{j=1}^{p} \boldsymbol{\delta}_{i,j,h}\boldsymbol{x}_{t-j} + \zeta_{i,t,h}, \quad \mathcal{N}(0, \sigma_{\zeta}^2), \tag{3.10}$$

where $y_{i,t+h}$ is the outcome variable of interest, $\hat{\varepsilon}_{1,t}$ is the estimated median non-rational risk shock identified from the external instruments VAR and $\boldsymbol{x}_{t-j}$ is a set of controls included up to lag $j = 1, \ldots, p$. The term $\tau_{i,h}$ can directly be interpreted as the impulse response of variable i at horizon h to the identified shock. In Section 4.4 I present the responses of the local projections approach which produce comparable results. There is also evidence that these two approaches should yield similar results (up to a scaling factor) as shown by Plagborg-Møller and Wolf (2019).

As the estimation procedure, I pursue a Bayesian approach to estimation. In particular, I follow the approach by Huber and Feldkircher (2019). Their VAR framework is quite flexible and allows for the introduction of adaptive shrinkage priors, particularly the Normal-Gamma prior (Griffin and Brown, 2010). Again, I introduce regularization methods in the estimation framework. The idea of shrinkage priors as a regularization technique is to push coefficients that are not adding any information to the model towards zero to enable a more efficient estimation. Furthermore, the triangularization in Eq. (3.4) easily allows for the introduction of stochastic volatility by Kastner and Frühwirth-Schnatter (2014) and is implemented with its associated software package (Kastner, 2016).

[13]This assumption has to be fulfilled for the mapping in Eq. (3.6) to work, i.e., that the shocks can be recovered from current and lagged values of observed data. However, identification in VARs with external instruments requires a weaker assumption (Miranda-Agrippino and Ricco, 2019). In particular, only the shock of interest has to be invertible since the identification scheme only leads to partial identification.

Empirical Specification

The baseline specification includes six variables: Surprises in beliefs, the credit spread under consideration, a stock market index, real GDP per capita, a price deflator of GDP, and a short-term interest rate. In particular, I use the S&P 500 as a proxy for the stock market and the 1-year Treasury constant maturity rate as the short-term interest rate depicting monetary policy actions. The choice towards an interest rate with maturity of one year has the following reason: Contrary to the effective federal funds rate or a Treasury bond with shorter maturity, the yield with one year maturity covers (at least partly) the monetary policy actions with respect to forward guidance. The other variables are standard in macroeconomic models. Nevertheless, the findings are robust to the choice of all these indicators. For details on robustness with different variables used, see also the sensitivity checks in Section 5.

The VAR is estimated in (log-)levels. A detailed overview on the data, the exact construction and its sources can be found in Appendix A. Responses can thus be interpreted as elasticities. The frequency of the data is quarterly, hence the lag order is set to $p = 4$. In terms of deterministics only a constant term is included. However, the results turn out to be robust with respect to all these choices, see again Section 5. All models considered are based on 25.000 draws from the posterior distribution, where I discard the first 15.000 draws as burn-ins. Furthermore, I discard ex post all non-stationary draws to ensure the stationarity of the VAR. In Appendix E I report convergence diagnostics and the share of retained draws in each of the considered models.

Surprises in beliefs are the proxy of non-rational risk shocks and only included when identified via the Cholesky decomposition. In the baseline model, it is used as an instrument to gauge exogenous variation in the credit spread variable. Sample size varies according to the credit spread under consideration: the sample including the Aaa spread spans from 1988Q1 to 2019Q4, while the one including the Baa spread spans from 1999Q1 to 2019Q4. The reason for using quarterly data is due to the nature of the survey forecasts for computing the belief surprises. By looking at both, a non-rational risk shock transmitted through the Aaa and Baa credit spread with different samples is done for two reasons. First, I can analyze the impact of possible higher default premiums present in the Baa spread. Second, effects may be imprecisely estimated using only a short sample for the Aaa spread. Nevertheless, similar effects across different identification procedures, sample spans, and credit spreads are reassuring that the proposed identification strategy for the non-rational risk shock is suitable.

4. Main Results

The presentation of the main results proceeds in six steps. First, I present results of the forecasting exercise. I discriminate among the forecasting models according to out-of-sample performance.

Table 2: Forecasting Evaluation.

	h=1		h=2		h=3		h=4	
	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread
RW	-101.99	-183.23	-65.78	-152.06	**-79.62**	-157.41	**-93.14**	-164.93
				Autoregressive Models				
AR(1)	-36.94	-114.43	-70.34	-142.71	-93.92	-153.86	-110.62	**-152.56**
AR(2)	-81.56	-168.57	-105.03	-185.68	-126.92	-176.36	-131.31	-157.78
AR(3)	-141.38	-232.3	-139.13	-219.37	-145.97	-180.55	-151.47	-171.01
AR(1)-SV	**-12.12**	**-54.54**	**-60.84**	**-96.15**	-80.4	-141.65	-109.93	-181.98
AR(2)-SV	-41.09	-87.88	-80.83	-119.23	-92.58	**-135.11**	-112.82	-170.07
AR(3)-SV	-92.91	-133.89	-101.19	-140.45	-104.99	-141.96	-122.22	-180.61
				Autoregressive Distributed Lag Models				
ARX(1)	-83.45	-173.27	-86.99	-174.12	-107.8	-181.34	-125.09	-182.44
ARX(2)	-132.86	-236.5	-115.06	-210.46	-131.95	-201.12	-162.38	-197.58
ARX(3)	-182.62	-315.82	-146.21	-238.14	-190.76	-215.42	-220.5	-209.72
ARX(1)-SV	-46.19	-90.4	-70.65	-112.35	-84.75	-145.49	-119.88	-202.15
ARX(2)-SV	-84.93	-133.17	-90.48	-142.36	-136.37	-161.35	-146.68	-221.77
ARX(3)-SV	-115.78	-181.21	-123.06	-170.33	-133.92	-177.08	-171.37	-227.81

Notes: Out-of-sample performance in terms of the sum of log predictive density scores (LPDS). Predictions are computed in a rolling window fashion. The bold figures indicate the best performing model for a given variable and time horizon. The following models nested in Eq. (3.2) are considered: RW - random walk, AR - autoregressive model, ARX - autoregressive distributed lag model. The number in the parentheses indicates the number of lags considered. SV refers to stochastic volatility.

Second, I construct and discuss belief surprises. Third, I turn to discussing the macroeconomic effects of a non-rational risk shock in the baseline model. Fourth, I discuss alternative strategies for identification and computation of impulse responses. Fifth, I examine the quantitative importance of the non-rational risk shock with a forecast error variance decomposition. Sixth, I look at wider macroeconomic effects of a non-rational risk shock not covered in the baseline model.

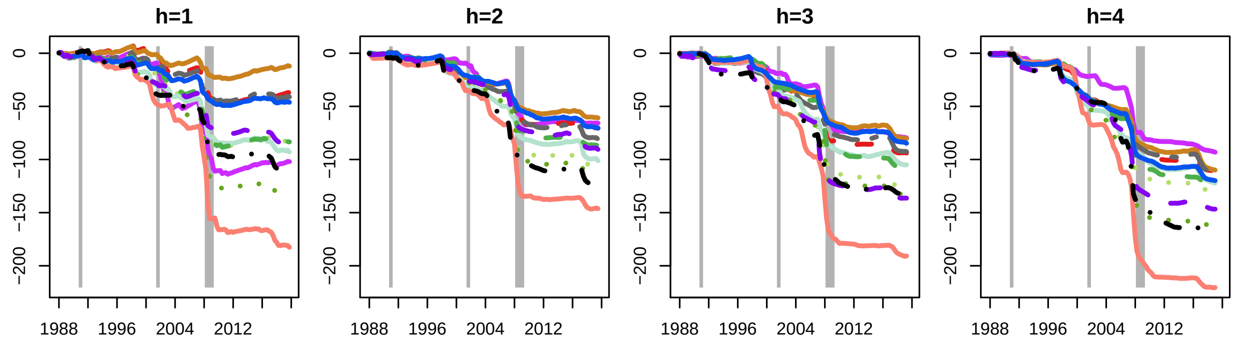
Objective Forecasts

In this section, I present the results of the objective forecasts constructed with the forecasting model. To construct the belief surprises, I have to compute objective forecasts beforehand. In particular, I assume that forecasts done with econometric models are model-consistent and use all available data at time point t for the out-of-sample prediction in $t + h$, ($h = 1, 2, 3, 4$). In order to support the hypothesis of objective forecasts, I run a series of forecasting models and use the best one to measure belief distortions.

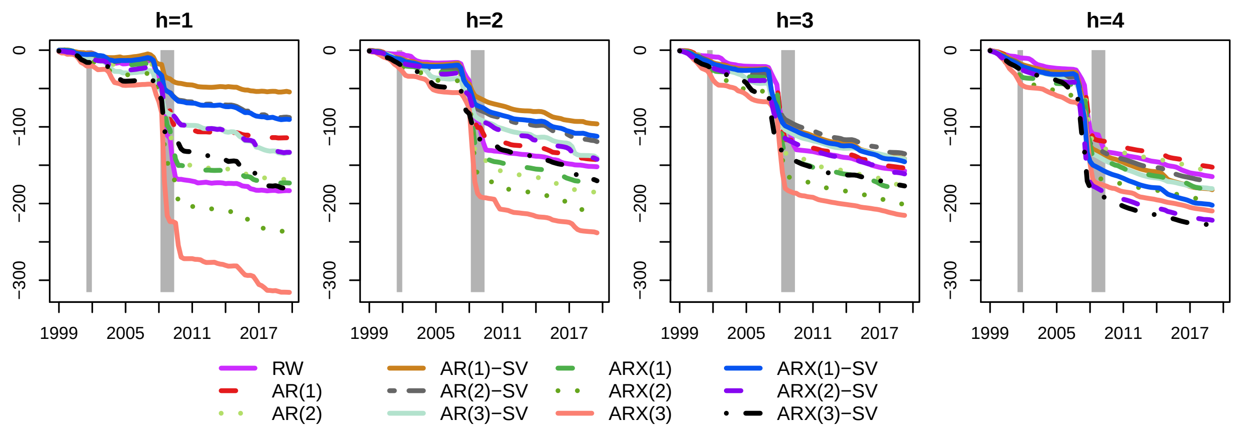
The results are presented in Table 2 and Figure 1. Generally, credit market spreads are extremely forward-looking variables and commonly used as recession indicators. Hence, it comes as no surprise that I do not find much predictive power through adding additional information and that the random walk is a strong competitor. Nevertheless, mean-reverting behavior is clearly present in

Figure 1: Forecasting Evaluation.

(a) Aaa spread.



(b) Baa spread.



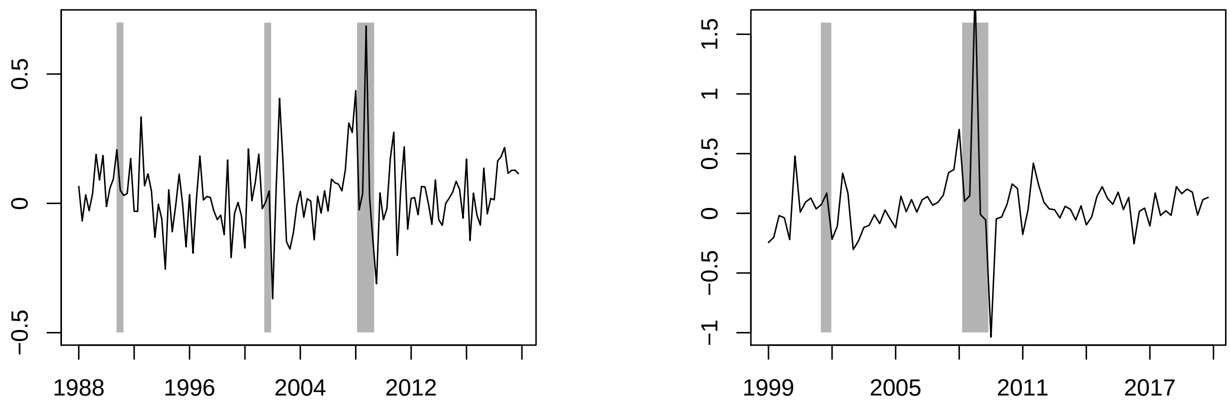
Notes: Cumulative log predictive density scores (LPDS) of out-of-sample forecasts of different models. Gray bars indicate the NBER recession dates.

credit spreads and thus AR models with a low number of lags show a better forecasting performance. Adding SV improves predictability further. Since both variables exhibit financial anomalies, such as excess volatility or herd behavior, stochastic volatility may account for this enhancing forecast performance. Looking more closely at the cumulative log predictive density scores (LPDS) in the presented figure reveals that the Great Financial Crisis led to substantial drop in predictive power. All recessions in both samples are indicated with gray bars corresponding to the NBER recession dates. For short forecasting horizons up to half a year, the AR model with one lag and driven by innovations with stochastic volatility is the best model. At longer horizons, the random walk outperforms all other models in case of the Aaa spread while the Baa spread is predicted best by other AR models.

On a more technical note, I perform predictions for both models with up to three lags, both with and without stochastic volatility leading to 13 competing models for each variable and forecasting horizon. Doing predictions including more lags, leads to a further deterioration in terms of LPDS and

Figure 2: Belief Surprises.

(a) Aaa surprises. **(b)** Baa surprises.



Notes: Belief surprises in the Aaa and Baa risk spreads. Gray bars indicate the NBER recession dates.

are not presented here.[14] As evaluation criterion, I use LPDS contrary to the commonly encountered mean absolute error (MAE) or root mean squared error (RMSE).[15] Bayesian estimation allows to inspect the whole predictive densitiy via LPDS which is considered to be superior to only inspecting the mean forecast. In particular, the LPDS is the logarithm of the likelihood of the unobserved predicted value. Hence, it also takes into account the uncertainty of the prediction.

Belief Surprises

After the construction of objective expectations, I can now construct a quarterly series of belief surprises as defined in Eq. (2.1). I do this for each horizon, but present and use for the main analysis the one-step ahead belief surprises. The series are shown in Figure 2. Narrative evidence for key historical episodes can be found. In particular, both series have a pronounced spike in the Great Financial Crisis. The spike is dated at 2008Q4 giving support to the presented hypothesis. After the Lehman Brothers bankruptcy on September 15, 2008 there was a huge positive surprise in beliefs. The intuition is as follows: Subjective forecasts substantially worsened after the bankruptcy leading to an increase in $\mathbb{F}_t[y_{i,t+1}]$ not yet accounted for in a rational manner (measured by $\mathbb{E}_t[y_{i,t+1}]$) since the Lehman bankruptcy *per se* did not lead to macroeconomic troubles). Furthermore, a strong negative belief surprise is visible in several instances after a positive deviation. The channel works also in the other direction, leading to a trend-reversal in subjective expectations.

Besides the narrative assessment, I also perform some simple diagnostic checks of the validity of the series for measuring belief distortions. Results can be found in Appendix C. As pointed

[14] The number of parameters in the forecasting model increase by three per additional lag. There is already a strong jump in LPDS from specifications with two to three lags depictable, which further exacerbates going up to four lags. Results are available upon request.

[15] Results are rather stable for RMSEs. This can be seen in Table F3 and F4.

out by Ramey (2016) structural shocks should not be autocorrelated or forecastable by other macroeconomic indicators. Another feature is the uncorrelatedness with other structural shocks. First, I inspect the series for autocorrelation where no evidence is found for its presence. Second, both shock series cannot be forecasted by other macroeconomic variables (I use those included in the VAR later on). A series of Granger-causality tests in Table C1 finds no evidence of any power in forecasting the two belief surprise series. Third, correlations to other structural shocks we know from the literature are low and presented in Figure C2. Therefore, the belief surprise series for both credit spreads are used as external instrument in the ongoing analysis in order to identify non-rational risk shocks.

Macroeconomic Effects of Non-Rational Risk Shocks

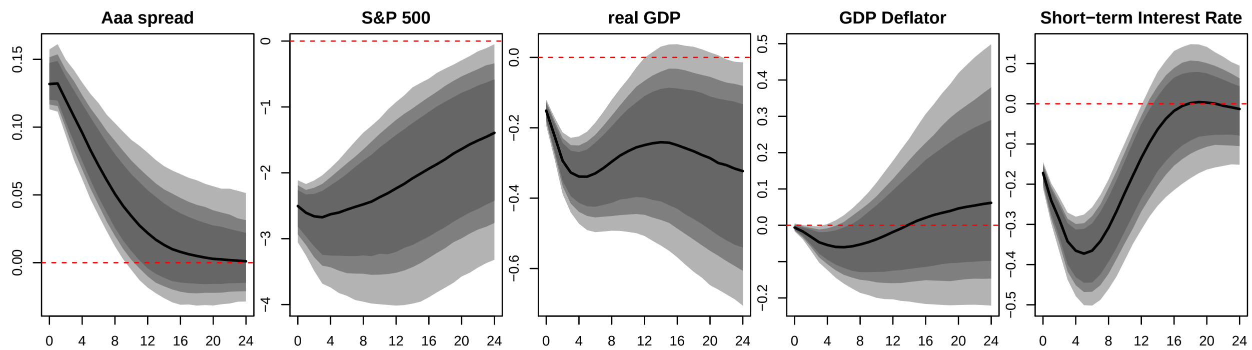
I present now the results from the baseline model, identified using the external instruments approach. Before discussing the effects on the macroeconomy, I also test for the strength of the instrument. Inference only produces reliables estimates when the instrument and the shock are strongly correlated. Hence, as a first step I test for the strength of the instrument. I follow the recommendation by Montiel-Olea *et al.* (2020) that a weak instrument problem is not present if the corresponding F-statistic of the first-stage regression is safely above 10. Evidence presented in Appendix D suggest that there is no weak instrument problem at hand.

Figure 3 presents the impulse responses to an identified non-rational risk shock, normalized to a one standard deviation shock to surprises in beliefs. The stock market index, real GDP per capita and the GDP deflator are in logs, responses can be interpreted as elasticities. The responses of credit spreads and the short-term interest rates are in percentage points. The solid black lines are the posterior median and the gray shaded areas are 68, 80 and 90 percent confidence bands. Impulse responses are computed for a horizon of 24 quarters.

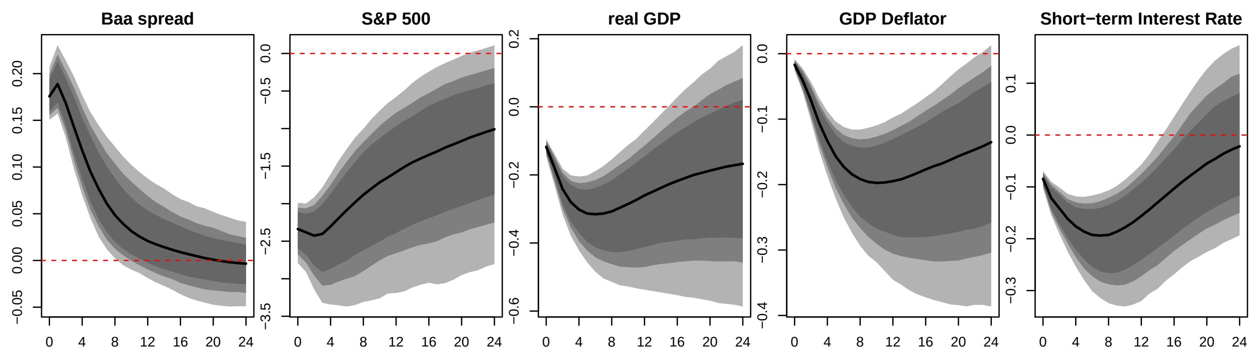
A one standard deviation increase in belief surprises causes a non-rational risk shock eliciting an immediate jump of credit spreads. The increase is slightly stronger for the Baa spread than for the Aaa spread. This causes a persistent and significant fall in both, the stock market and real activity. Responses to both risk shocks are remarkably similar in terms of their size, about -2.5% depreciation of asset prices and a loss of -0.2% in output as measured by GDP per capita. Prices, as measured by the GDP deflator, decline to both shocks. Although the response in the model identified with surprises in the Aaa credit spread does not seem to change significantly while it clearly does so in the model identified with belief surprises in the Baa spread. This is not a feature of one of the credit spreads but rather relates to a subsample stability problem. I re-estimate the model keeping the sample size constant (1999Q1-2019Q4) and report the results in Figure G1 in the appendix. Responses then show no qualitative differences across using different credit spreads. Last, short-term interest rate drops significantly on impact with a gradual return to the zero line.

Figure 3: Impulse Response Functions to a Non-Rational Risk Shock.

(a) Shock to Aaa belief surprise.



(b) Shock to Baa belief surprise.



Notes: Impulse response functions of the basline VAR. Identification via external instrument. Black line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals. The responses of stock market index, real activity, and prices are scaled in percent, while the spread and interest rate responses are scaled in percentage points.

This points to an accomodative expansionary monetary policy taken by the central banks. Since there are already counteractive measures visible on impact, this may point to the information set of the central bank being superior in anticipating financial market distress. Interestingly, responses are remarkably similar across the two models. While the Baa spread increases slightly stronger after a one standard deviation shock to the non-rational risk shock, effect sizes of outcome variables are robust to the choice of the credit spread. Hence, results do not seem to be driven by the presence of a higher default or liquidity premium in Baa credit spread. This indicates that the proposed identification scheme indeed recovers exogenous variation in the risk premium.

The macroeconomic effects are comparable to the ones in the literature. Gilchrist and Zakrajšek (2012) find that an increase in the excess bond premium of about 20 basis points leads to a reduction in the level of real GDP of about 0.5 percentage points. Similarly, Furlanetto *et al.* (2019) find a reaction of GDP of about 2-4% after a one-standard deviation financial shock identified with sign-restrictions. They use the spread between the Baa spread and the Federal Funds rate as a measure of the financial shock which exhibits a higher standard deviation than the Baa spread used here. Data in the sample used here imply a standard deviation of about 1.6 of the Baa to the Federal Funds rate spread, while both standard deviations of spreads used in this paper are between $0.5-0.7$. Also the work by López-Salido *et al.* (2017) finds a 2% change of real GDP per capita when a unit change in the Baa spread happens. Nevertheless, they do not state a causal statement but a mere predictive one.

Alternative Strategies

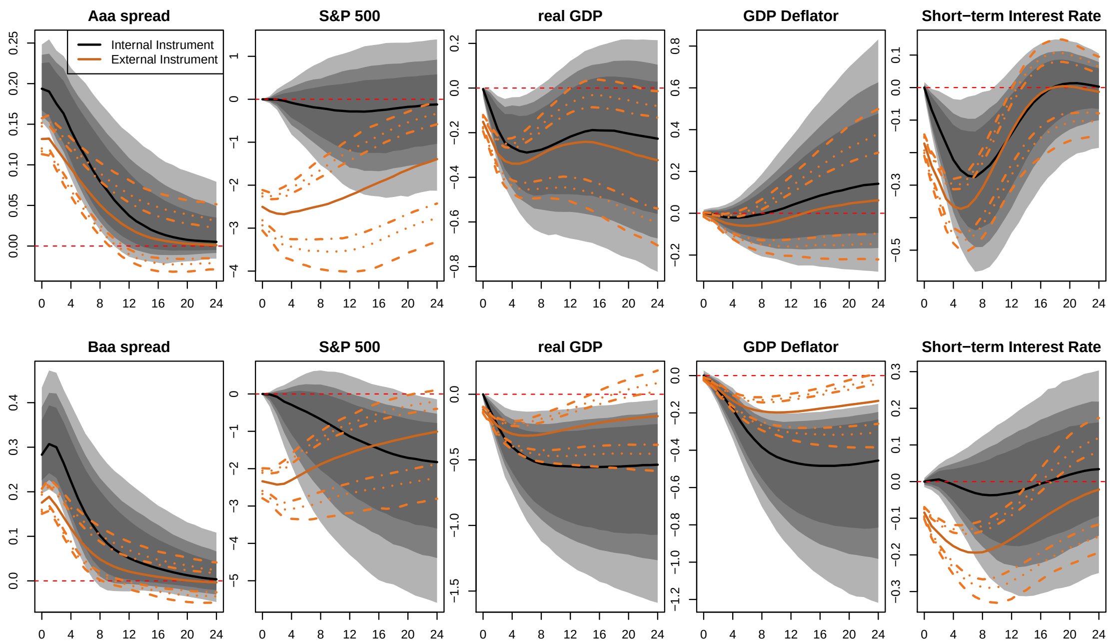
As discussed before, an alternative to using external instruments for identification is the internal identification approach. Furthermore, if the VAR is not an adequate representation of the dynamics in the data, an alternative is to compute impulses responses using local projections. Hence, I also present results using these approaches. Figure 4 shows in panel (a) impulse responses to the same shock by using the internal instrument approach. In panel (b) one finds the impulse responses computed with local projections.

The internal instruments approach is implemented by appending the proxy as the first variable in the VAR system and doing a simple Cholesky-type identification scheme. Hence, the underlying assumption is that all variables in the system can instantaneously react to the identified non-rational risk shock. First, effects are less precisely estimated which may be due to measurement error in the proxy. Second, impulse responses tend to be very similar qualitatively. Nevertheless, some differences are worth mentioning. Interestingly, most responses do not react on impact while their dynamic behavior is similar. This holds particularly for credit spreads, real GDP per capita, GDP deflator and partly for the short-term interest rate. Third, the strongest difference arises with respect to the stock market index. While there is a significant decline in the baseline model identified by external instruments, this is not depictable from the model identified by internal instruments. From economic theory we would expect that stock markets react to risk shocks, thus this may be a shortcoming of this approach.

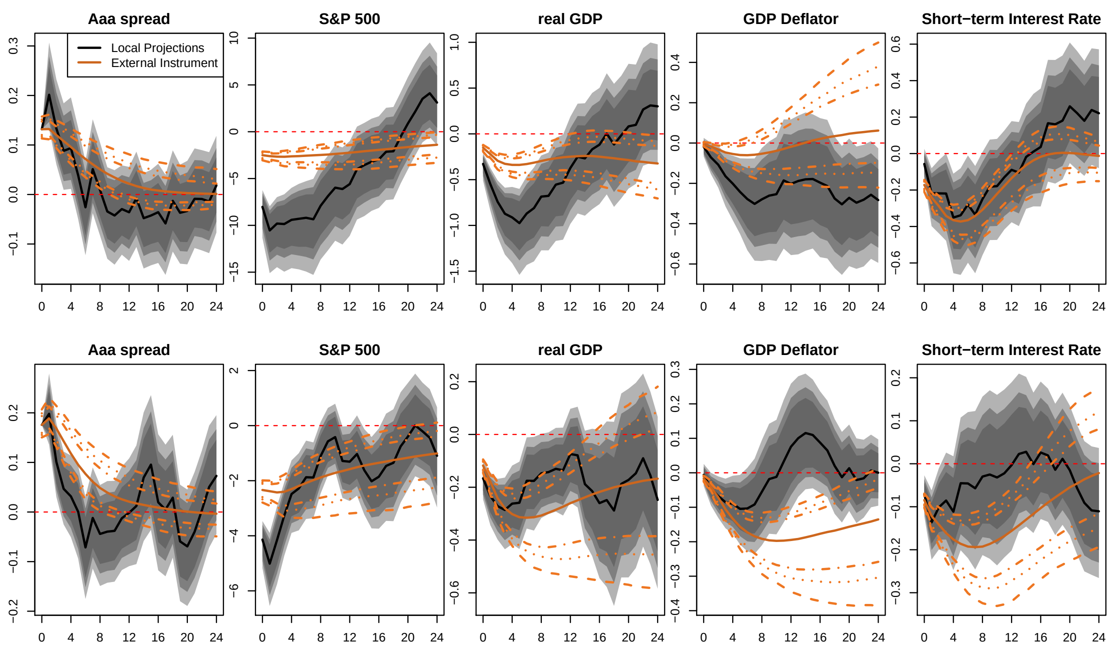
To analyze whether the impulse responses depend on the underlying VAR structure, I compute the responses to the identified non-rational risk shock using local projections. Generally, effects tend to be again very similar qualitatively, but less precisely estimated which is a known issue of local projections. Responses tend to smooth out faster in local projections than in the model identified by external instruments. This is clearly visible for the credit spreads, stock market index, real GDP per capita, and short-term interest rates. So, this may point to the fact that impulse responses of the VAR impose to much persistence on the responses and constitute an upper bound. Again, the most striking differences arise with respect to responses of the stock market index. Local projections point to a quite strong reaction of the stock market. This pattern is likewise visible for GDP per capita, while responses of prices and interest rates tend to be slightly smaller in magnitude.

Figure 4: Alternative Strategies.

(a) Identification with Internal Instrument.



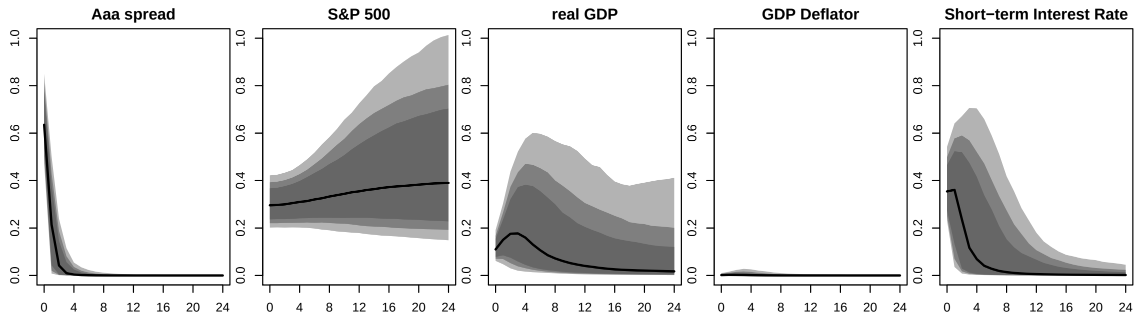
(b) Local Projections.



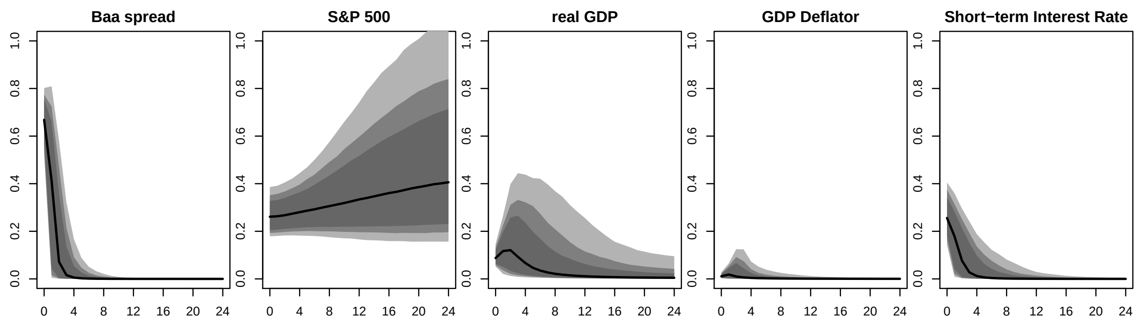
Notes: Impulse response functions to a non-rational risk shock. Upper panel is based on identification with internal instrument, lower panel shows local projections. Both are compared to impulse responses of the baseline VAR (orange). Bold lines denote median response while gray shaded areas / dashed lines denote the 68/80/90 percent confidence intervals. The responses of stock market index, real activity, and prices are scaled in percent, while the spread and interest rate responses are scaled in percentage points.

Figure 5: Forecast Error Variance Decomposition

(a) Shock to Aaa Belief Surprises.



(b) Shock to Baa Belief Surprises.



Notes: Forecast error variance decomposition of the variables in the system to the non-rational risk shock. Bold lines denote median response while gray shaded areas / dashed lines denote the 68/80/90 percent confidence intervals.

Summing up, alternative identification schemes and methods to compute impulse response do not show qualitatively different behavior despite minor differences. Non-rational risk shocks clearly have an impact on the stock market and the real sector while nominal adjustments happen. Behavioral forces can thus be seen as causal underpinnings of business cycle instabilities. The shock tends to be temporary and smooth out after 1-2 years.

Quantitative Importance

As a next step, I analyze the quantitative importance of non-rational risk shocks. This analysis reveals how much of the variation in the variables in the VAR system is explained by non-rational risk shocks. Figure 5 presents the results. Non-rational risk shocks explain initially a large share of the movements in credit spreads, which quickly declines pointing to the rather short longevity of the impact on spreads. However, the non-rational risk shock explains a sizable share in the forecast error variance of the S&P 500. Starting at a share of about one third, this increases further over the horizon. Furthermore, the quantitative impact on real activity as measured by real GDP per capita is visible. At maximum, 18 percent and 12 percent of the forecast error variance of real activity is explained in the respective model at rather short horizons. In the second year after the impact to the shock, the explained variance gradually declines towards zero. Similarly, the explained forecast error variance in short-term interest rates is only visible at short horizons before returning to the zero line. Almost none of the variance in prices is explained by non-rational risk shocks.

Together with the impulse response analysis, this provides further evidence of a strong, but short-lived temporary non-rational risk shock. Risk premia as measured by credit spreads are only temporarily pushed by non-rational forces while a strong impact to the stock market is presented. Belief distortions are able to have signifcant effects on the macroeconomy and contribute meaningfully to variations in real GDP per capita. Additionally, the findings are comparable to ones in the literature (Gilchrist and Zakrajšek, 2012; Furlanetto *et al.*, 2019).

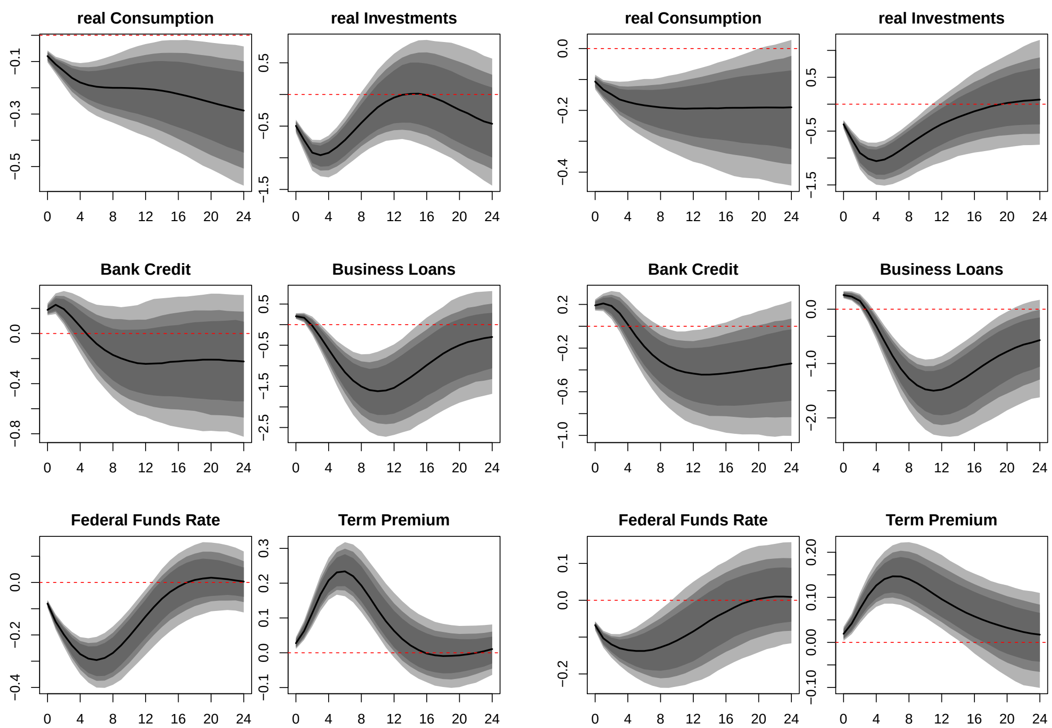
Wider Macroeconomic Effects

The baseline model is relatively small and leaves out core macroeconomic variables. In order to get a better understanding of how the risk shocks affect the macroeconomy, I estimate additional models extending the original baseline VAR by adding one variable at a time. This approach is quite flexible and allows me to look at various transmission channels of financial risk shocks. Sample size, lag specification and anything else related to the estimation is exactly as in the baseline model identified with external instruments. Again, I test for the strength of the instrument which is not an issue here where results are available in Appendix D. In the following, I will analyze the effects on various components of GDP, credit market measures, the yield curve, labor market indicators, prices, and expectations.

First, I look at subcomponents of real GDP per capita in Figure 6. To be comparable, I also transform real consumption and real investment into per capita terms. Responses are similar to a non-rational risk shock. Investment drops stronger than consumption and even stronger than GDP itself which relates to business cycle stylized facts. Turning to the responses to the shock of the credit market variables in Figure 6, i.e., bank credit, and commercial and industrial loans (labelled business loans), an initial positive reaction is visible for both variables. Afterwards responses turn negative eventually in the case of bank credit and quite significantly for business loans. Furthermore, the initial positive reaction is of shorter maturity for the latter. This constitutes a kind of credit puzzle for which I offer the following explanation: The initial positive reaction may point to a shift in the form of external financing. In particular, a portfolio redeployment effect can explain the short-term positive impact on credit-based measures indicating that agents start shifting from bond-based financing to bank-based financing on the financial markets. Crouzet (2018) investigates the transmission of financial shocks where corporate credit is intermediated via both bank and bond markets. He shows that firms trade-off greater flexibility of bank-based financing in case of financial distress against lower costs of bond issuance. Next, I turn to the respones of the yield curve and

Figure 6: GDP Components, Credit Market, and Yield Curve.

(a) Shock to Aaa belief surprises. **(b)** Shock to Baa belief surprises.



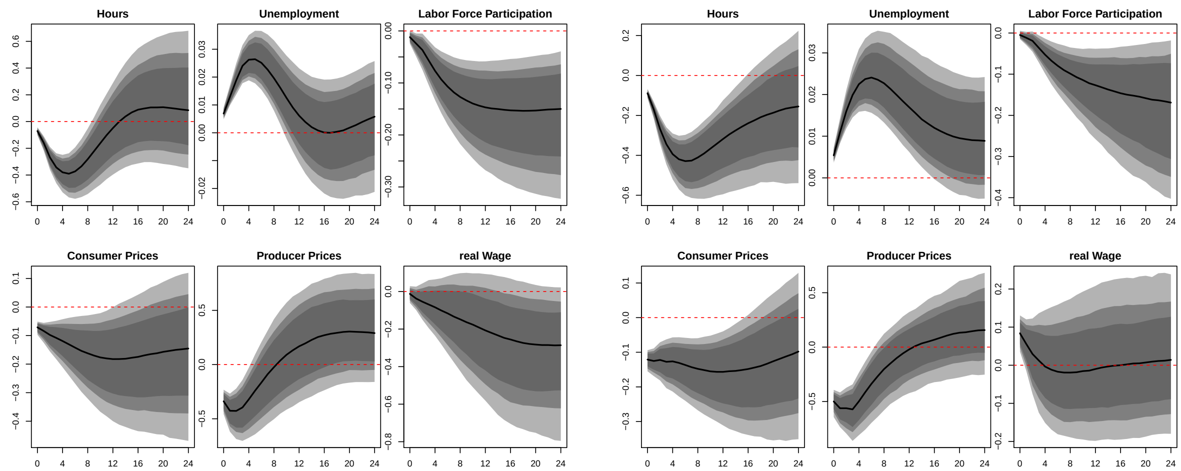
Notes: Responses to different components of GDP, the credit market and the yield curve. Identification via external instrument. Black line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals. Responses of GDP and credit market components are scaled in percent, while interest rate responses are scaled in percentage points.

the Federal Funds rate in Figure 6. The term premium is defined as the difference between 10-year and 1-year Treasury constant maturity rate. While the response of the former is almost identical to the responses of the short-term interest rate in Figure 3 showing that the exact measurement of monetary policy is only of minor importance. The term premium, or the slope of the yield curve, increases and reaches its maximum after two years. This indicates a flight to safe assets as measured by long-term yields in the case of the identified non-rational financial risk. In particular, after the Lehman collapse in 2008 safe assets contracted drastically. Since the sample period safely covers not only the period of the zero lower bound in the aftermath of the Great Financial Crisis, heightend demand for safe assets as an endogenous explanation for risk premia is not a pressing issue here (see inter alia Caballero *et al.*, 2017 or Caballero and Farhi, 2018).

Next, I turn to the discussion of labor market indicators and prices in Figure 7. The figure shows the impulse responses of labor market indicators, i.e., total hours worked, unemployment and labor force participation, and the reaction of various price measures, i.e., consumer prices, producer prices, and the real wage. The labor market is significantly and negatively affected, but with a short

Figure 7: Labor Market and Prices.

(a) Shock to Aaa belief surprises. **(b)** Shock to Baa belief surprises.



Notes: Responses to different indicators of the labor market and prices. Identification via external instrument. Black line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals. All responses are scaled in percent.

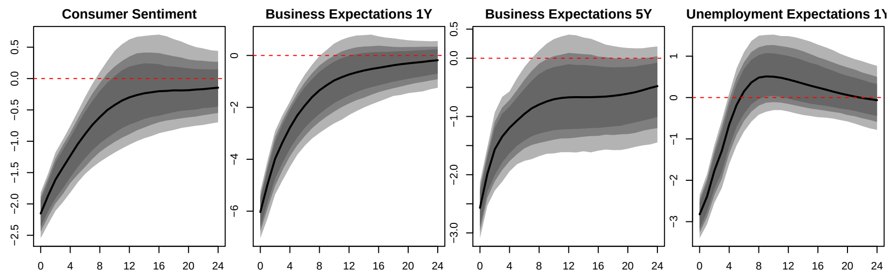
delay. Both the unemployment rate and total hours worked display a muted response on impact, reaching its maximum after about five quarters. Labor force participation also shows a significant decline. This is suggestive of the presence of frictions in the labor market, such as contractual obligations, which delays the adjustments. This is also in line with the findings of Chodorow-Reich (2014) showing that credit matters for employment decisions. Firms have a lower likelihood of obtaining a loan after a credit crunch resulting in adverse labor market outcomes. Concerning the price responses, wages decline in a sluggish fashion and are estimated with large uncertainty. Conversely, the contraction in consumer and producer prices is rather sudden.

Last, I also add four measures of expectations one at a time to the model. Responses are shown in Figure 8. All of them come from the University of Michigan Survey of Consumers and depict consumer sentiment, expected business conditions in the next and five years ahead, and unemployment expectations in the next year. They serve as proxies how economic agents perceive the current economic outlook and the future outlook, both tackling the consumers' view and the business' view. All of them show a sudden deterioration with a rather quick return to their old value. Depending on the exact measure and risk shock, adjustments to the old value are reached within two years. This is additional evidence for the transient nature of non-rational risk shocks and the interconnectedness of expectations. If agents experience unexpected surprises in beliefs, their outlook on other sectors of the economy is also affected.

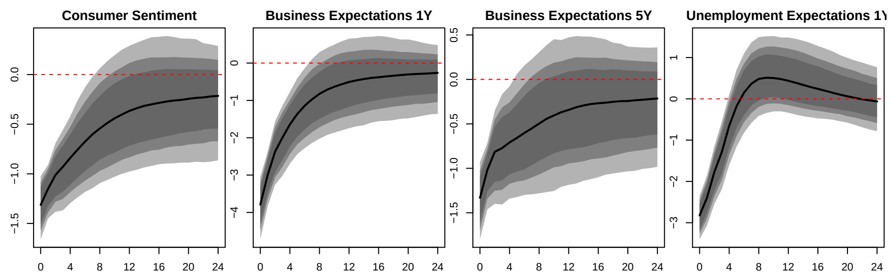
In this section, I only present the impulse response of the additional variable added to the model, but not the responses of the whole model to the non-rational risk shocks. Hence, Figure H6 in the

Figure 8: Measures of Expectations.

(a) Shock to Aaa belief suprises.



(b) Shock to Baa belief surprises.



Notes: Responses to different measures of expectations. Identification via external instrument. Black line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals. All responses are scaled in percent.

appendix presents the additional impulse responses of the baseline model together with the median responses of all models considered here. Responses of the other variables in the system do not change much when information is added to the model.

5. Sensitivity Analysis

In this section, I perform a comprehensive set of sensitivity checks. In particular, I present sensitivity checks with respect to the forecasting exercise, the identification of non-rational risk shocks and analyze the robustness of the macroeconomic model with respect to model specification and data choices. All corresponding tables and figures can be found in Appendices F to H.

Forecasting

Forecasts can be performed in various ways. To provide robustness to some of these choices, I conduct the following sensitivity checks which are presented in the Appendix F, i.e., Table F1 to F4. First, out-of-sample forecasts can either be done in an extended or rolling window fashion. While the former acknowledges all available information, the latter keeps the amount of information which is used constant. Switching to the extending window procedure, does not alter the forecasting performance much. In particular, the dominance of the AR(1)-SV as the best model is even more pronounced. Second, choosing the number of factors and additional controls is a sensible issue. To check the sensitivity of the results, I re-estimate the model using no controls in $\boldsymbol{x}_t$ and vary the number of factors with $q = 3$ and $q = 7$. Again, the best performing model only differs in on instance as compared to Table 2. Third, I discriminate among models with LPDS. Since I only use point estimates for constructing belief surprises, it is only fair to also base the evaluation criterion on the point forecast, e.g., using root mean squared errors (RMSEs). The dominance of the AR(1)-SV model is weaker and the RW wins the forecasting race quite often. This shows that the AR(1)-SV is picking up forecasts with lower uncertainty offering lower LPDS. Nevertheless, macroeconomic effects are stable with respect to switching to the random walk as objective forecasts.

Identification

Identification rests on the construction of surprises in beliefs to measure belief distortions on financial markets. Here, I provide sensitivity checks to three issues: choosing a different horizon for the expectations for the construction of the belief surprises, performing a placebo test in which I replace subjective survey forecasts with a simple RW, and checking whether the VAR is invertable. Results are available in Appendix G.

First, I check whether the specified horizon causes differences. For that, I examine the implied impulse responses when using the two-, three-, and four-step ahead belief surprise as well as the mean over the one- to four-step ahead belief surprises. Responses do change only little showing stability over these choices. In Figures G2 to G5, the results are presented.

Second, I perform a placebo exercise. Here, I replace subjective expectations with random-walk expectations. Hence, I check whether subjective forecasts have indeed information not present in objective evaluations of the future. As results in Figure G6 suggest, impulse responses vanish when checking with this placebo belief surprise series.

Third, I provide sensitivity with respect to invertability. A necessary condition for (partial) identification is that the VAR spans all relevant information. Forni and Gambetti (2014) provide a test procedure which works as follows. To verify that the structural shock with the baseline VAR specification can be truly recovered, I regress on the identified structural shock $\varepsilon_{1,t}$ macroeconomic factors. These factors $\boldsymbol{f}_t$ are the same as the one used in the forecasting exercise and represent the whole US macroeconomy. If all necessary information is already contained in the VAR, the structural shock – the non-rational risk shock – should be orthogonal to the lags of the factors $\boldsymbol{f}_{t-k}$, $k > 0$. Hence, this orthogonality condition is the necessary condition that the structural shock is free of measurement error. The null of fundamentalness is rejected if, and only if, orthogonality is rejected. Results can be found in Table G1 indicating that fundamentalness can be rejected overall.

Model Specification and Data Choices

The last set of sensitivity checks are concerned with the model specification and data choices. Choosing the appropriate lag length in VARs is a sensible issue, thus I re-estimate the baseline model with up to five lags. Nevertheless, this issue is of minor magnitude since I rely on regularization techniques. Moreover, macroeconomic concepts can be operationalized with various empirical available variables. For instance, industrial production is a widely used indicator for economic activity besides GDP. To provide robustness with respect to these choices, I re-estimate the baseline model exchanging one variable at a time. In particular, I use industrial production instead of GDP per capita as measure of economic activity, the NASDAQ composite index instead of the S&P 500 as a stock market index, and consumer prices instead of the GDP deflator as price measure. Finally, I also re-estimate the baseline model without stochastic volatility. Combining all these choice, results in 50 specifications which I provide in Figures H1 to H5 in Appendix H. I conclude that results are robust to all these choices.

6. Concluding Remarks

In this paper, I investigate how a non-rational risk shock affects the macroeconomy. For that purpose, I provide a novel identification scheme to identify non-rational risk shocks on financial markets. In particular, I use belief distortions to account for non-rational behavior on financial markets as documented by many scholars. For the identification, I define belief surprises as the difference between subjective and objective expectations. While the former are measured through survey forecasts on credit spreads from financial executives, the latter is constructed as an out-of-sample prediction of credit spreads estimated with the help of econometric models.

Evidence suggest that risk premia transmitted through credit spreads are overreacting to incoming news. This is a necessary condition for the identification to work. For the construction of objective forecasts, a set of econometric time series models are estimated where the AR(1)-SV has superior forecasting properties. For each horizon, the best – in terms of forecasting performance – model is chosen to construct surprises in beliefs.

The proxy identifies a non-rational risk shock in a VAR. A one-standard deviation surprise in beliefs leads to a jump in risk premia, a depression of output, and a decline in the stock market index. Furthermore, prices fall and monetary policy is accomodative. Interestingly, responses are stable across both credit spreads indicating that the non-rational component in belief surprises identifies movements in the risk premium and not in the default or liquidity premium. Furthermore, quantitative importance of the risk shock is shown by a forecast error variance decomposition. Last, the shock has the expected signs on a wide range of additional macroeconomic quantities and is robust to various choices.

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A. Data

All series were downloaded from the sources listed below including the FRED database, Blue Chip Financial Indicators, Robert Shiller's website and the Michigan Survey of Consumers (Dominitz and Manski, 2004). Data from the St. Louis' FRED database were downloaded using the R-package `fredr` (Boysel and Vaughan, 2019). All time series cover the time period 1970Q1 to 2019Q4 except the survey forecasts. All series are seasonally adjusted, either by downloading the already adjusted series from FRED or by applying a quarterly X11 filter based on an AR(4) model to the unadjusted series. Some series in the database are observed only on a monthly basis and quarterly values are computed by obtaining quarterly averages. Concerning the data series used for computing factors, all variables are transformed to be approximately stationary. In particular, the column *Tcode* shows the transformation I apply to a series: 1 – no transformation (levels); 2 – first difference; 4 – logarithms; 5 – first difference of logarithms; 6 – second difference in logarithms.

In Table A1 I define all variables used in the estimations. Table A2 provides a comprehensive overview of all variables and its exact definition. They are categorized in real activity measures, money, credit and finance measures, interest rates, prices, expectations, and additional. The latter is not used to construct the factors.

Table A1: Variable Definitions

Aaa spread	$\mathtt{AAA} - \mathtt{GS10}$
Baa spread	$\mathtt{BAA} - \mathtt{GS10}$
real GDP	$100 \times \ln\left(\frac{\mathtt{GDPC1}}{\mathtt{CNP16OV}}\right)$
S&P 500	$100 \times \ln(\mathtt{SP500})$
GDP Deflator	$100 \times \ln(\mathtt{GDPDEF})$
Short-term Interest Rate	$\mathtt{GS1}$
real Consumption	$100 \times \ln\left(\frac{\mathtt{PCEND+PCESV}}{\mathtt{CNP16OV} \times \mathtt{GDPDEF}}\right)$
real Investments	$100 \times \ln\left(\frac{\mathtt{GPDI+PCEDG}}{\mathtt{CNP16OV} \times \mathtt{GDPDEF}}\right)$
Bank Credit	$100 \times \ln(\mathtt{LOANINV})$
Business Loans	$100 \times \ln(\mathtt{BUSLOANS})$
Federal Funds Rate	$\mathtt{FEDFUNDS}$
Term Premium	$\mathtt{GS10} - \mathtt{GS1}$
Hours	$100 \times \ln\left(\frac{\mathtt{HOANBS}}{2080}\right)$
Unemployment	$\ln(\mathtt{UNRATE})$
Labor Force Participation	$100 \times \ln(\mathtt{CIVPART})$
Consumer Prices	$100 \times \ln(\mathtt{CPIAUCSL})$
Producer Prices	$100 \times \ln(\mathtt{PPIACO})$
real Wage	$100 \times \ln(\mathtt{COMPRNFB})$
Consumer Sentiment	$100 \times \ln(\mathtt{UMCSENT})$
Business Expectations 1Y	$100 \times \ln(\mathtt{BCE1Y})$
Business Expectations 5Y	$100 \times \ln(\mathtt{BCE5Y})$
Unemployment Expectations	$100 \times \ln(\mathtt{UE1Y})$
NASDAQ	$100 \times \ln(\mathtt{NASDAQCOM})$
Industrial Production	$100 \times \ln(\mathtt{INDPRO})$

Table A2: Raw Data

#	Mnemonic	Description	Tcode
Real Activity Measures			
1	GDPC1	Real Gross Domestic Product, 3 Decimal	5
2	GPDIC1	Real Gross Private Domestic Investment	5
3	TCU	Capacity Utilization: Total Index	1
4	CBI	Change in Private Inventories	1
5	FINSAL	Final Sales of Domestic Product	5
6	FSDP	Final Sales to Domestic Purchasers	5
7	FINSLC1	Real Final Sales of Domestic Product, 3 Decimal	5
8	GGSAVE	Gross Government Saving	1
9	TGDEF	Net Government Saving	1
10	GSAVE	Gross Saving	5
11	FPI	Fixed Private Investment	5
12	PRFI	Private Residential Fixed Investment	5
13	GFDEBTN	Federal Debt: Total Public Debt	5
14	W068RCQ027SBEA	Government total expenditures	5
15	W006RC1Q027SBEA	Federal government current tax receipts	5
16	SLINV	State and Local Government Gross Investment	5
17	SLEXPND	State and Local Government Current Expenditure	5
18	EXPGSC1	Real Exports of Goods and Services, 3 Decimal	5
19	IMPGSC1	Real Imports of Goods and Services, 3 Decimal	5
20	CIVA	Corporate Inventory Valuation Adjustement	1
21	CP	Corporate Profits After Tax	5
22	CNCF	Corporate Net Cash Flow	5
23	DIVIDEND	Net Corporate Dividends	5
24	PCE	Personal Consumption Expenditure	5
25	PCESV	Personal Consumption Expenditure: Services	5
26	PCEDG	Personal Consumption Expenditure: Durable Goods	5
27	PCEND	Personal Consumption Expenditure: Nondurable Goods	5
28	GPDI	Gross Private Domestic Investment	5
29	INDPRO	Industrial Production Index	5
30	HOABS	Business Sector: Hours of All Persons	5
31	HCOMPBS	Business Sector: Compensation per Hour	5
32	RCPHBS	Business Sector: Real Compensation per Hour	5
33	ULCBS	Business Sector: Unit Labor Cost	5
34	COMPNFB	Nonfarm Business Sector: Compensation per Hour	5
35	HOANBS	Nonfarm Business Sector: Hours of All Persons	5
36	COMPRNFB	Nonfarm Business Sector: Real Compensation per Hour	5
37	ULCNFB	Nonfarm Business Sector: Unit Labor Cost	5
38	UNRATE	Unemployment Rate	2
39	CIVPART	Labor Force Participation Rate	2
40	UEMPLT5	Civilians Unemployed for Less Than 5 Weeks	5
41	UEMP5TO14	Civilians Unemployed for 5-14 Weeks	5
42	UEMP15OV	Civilians Unemployed for Over 15 Weeks	5

Continued on next page

Table A2 – *Continued from previous page*

#	Mnemonic	Description	Tcode
43	UEMP15TO26	Civilians Unemployed for 15-26 Weeks	5
44	UEMP27OV	Civilians Unemployed for Over 27 Weeks	5
45	NDMANEMP	All Employees: Nondurable Goods	5
46	MANEMP	All Employees: Manufacturing	5
47	SRVPRD	All Employees: Service-Providing Industries	5
48	USTPU	All Employees: Trade, Transportation and Industries	5
49	USWTRADE	All Employees: Wholesale Trade	5
50	USTRADE	All Employees: Retail Trade	5
51	USFIRE	All Employees: Financial Activities	5
52	USEHS	All Employees: Education and Health Services	5
53	USPBS	All Employees: Professional and Business Services	5
54	USINFO	All Employees: Information Services	5
55	USSERV	All Employees: Other Services	5
56	USPRIV	All Employees: Total Private Industries	5
57	USGOVT	All Employees: Government	5
58	USLAH	All Employees: Leisure and Hospitality	5
59	AHECONS	Average Hourly Earnings: Construction	5
60	AHEMAN	Average Hourly Earnings: Manufacturing	5
61	AHETPI	Average Hourly Earnings: Total Private Industries	6
62	AWOTMAN	Average Weekly Hours: Overtime: Manufacturing	1
63	AWHMAN	Average Weekly Hours: Manufacturing	1
64	HOUST	Housing Starts: Total	5
65	HOUSTNE	Housing Starts: Northeast Census Region	5
66	HOUSTMW	Housing Starts: Midwest Census Region	5
67	HOUSTS	Housing Starts: South Census Region	5
68	HOUSTW	Housing Starts: West Census Region	5
69	HOUST1F	Housing Starts: 1-Unit Structures	5
70	PERMIT	New Private Housing Units Authorized by Building Permit	5
Money, Credit and Finance Measures			
71	NONREVSL	Total Nonrevolving Credit Outstanding, Billions of Dollars	5
72	USGSEC	US Government Securities at All Commercial Banks	5
73	OTHSEC	Other Securities at All Comercial Banks	5
74	TOTALSL	Total Consumer Credit Outstanding	5
75	CMDEBT	Household Sector: Liabilities: Household Credit Market Debt Outstanding	5
76	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks	5
77	CONSUMER	Consumer (Individual) Loans at All Commercial Banks	5
78	LOANS	Total Loans and Leases at Commercial Banks	6
79	LOANINV	Total Loans and Investments at All Commercial Banks	6
80	INVEST	Total Investments at All Commercial Banks	5
81	REALLN	Real Estate Loans at All Commercial Banks	6
82	AMBSL	Board of Governors Monetary Base, Adjusted for Changes in Reserve Requirements	5

Continued on next page

Table A2 – *Continued from previous page*

#	Mnemonic	Description	Tcode
83	REQRESNS	Required Reserves, Not Adjusted for Changes in Reserve Requirements	5
84	RESBALNS	Reserve Balances with Fed. Res. Banks, Not Adj. for Changes in Reserve Req.	5
85	BORROW	Total Borrowings of Depository Institutions from the Federal Reserve	5
86	M1SL	M1 Money Stock	6
87	CURRSL	Currency Component of M1	5
88	CURRDD	Currency Component of M1 Plus Demand Deposits	5
89	M2SL	M2 Money Stock	6
90	M2OWN	M2 Own Rate	6
91	M2MSL	M2 Minus Small Time Deposits	6
92	M2MOWN	M2 Minus Own Rate	6
93	MZMSL	MZM Money Stock	6
94	SVSTCBSL	Savings and Small Time Deposits at Commercial Banks	6
95	SVSTSL	Savings and Small Time Deposits - Total	6
96	SVGCBSL	Savings Deposits at Commercial Banks	6
97	SVGTI	Savings Deposits at Thrift Institutions	6
98	SAVINGSL	Savings Deposits - Total	6
99	STDCBSL	Small Time Deposits at Commercial Banks	6
100	STDTI	Small Time Deposits at Thrift Institutions	6
101	STDSL	Small Time Deposits - Total	6
102	USGVDDNS	US Government Demand Deposits and Note Balances - Total	5
103	USGDCB	US Government Demand Deposits at Commercial Banks	5
104	CURRCIR	Currency in Circulation	5
105	NASDAQCOM	NASDAQ Composite Index	5
Interest Rates			
106	MPRIME	Bank Prime Loan Rate	1
107	FEDFUNDS	Effective Federal Funds Rate	1
108	TB3MS	3-month Treasury Bill: Secondary Market Rate	1
109	TB6MS	6-month Treasury Bill: Secondary Market Rate	1
110	GS1	1-year Treasury Constant Maturity Rate	1
111	GS2	2-year Treasury Constant Maturity Rate	1
112	GS3	3-year Treasury Constant Maturity Rate	1
113	GS5	5-year Treasury Constant Maturity Rate	1
114	GS10	10-year Treasury Constant Maturity Rate	1
115	GS30	30-year Treasury Constant Maturity Rate	1
116	AAA	Moody's Seasoned Aaa Corporate Bond Yield	1
117	BAA	Moody's Seasoned Baa Corporate Bond Yield	1
Prices			
118	GDPDEF	Gross Domestic Product: Implicit Price Deflator	6

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Table A2 – *Continued from previous page*

#	Mnemonic	Description	Tcode
119	GDPCTPI	Gross Domestic Product: Chain-type Price Index	6
120	PCECTPI	Personal Consumption Expenditures: Chain-type Price Index	6
121	PPIACO	PPI: All Commodities	6
122	WPU0561	PPI by Commodity for Fuels and Related Products and Power: Crude Petroleum	6
123	WPUFD4111	PPI: Finished Consumer Foods	6
124	WPUFD49502	PPI: Finished Consumer Goods	6
125	WPSFD41311	PPI: Finished Consumer Goods Excluding Foods and Energy	6
126	WPSFD49207	PPI: Finished Goods	6
127	WPSFD41312	PPI: Finished Goods: Capital Equipment	6
128	PPIENG	PPI: Fuels and Related Products, Power	6
129	PPIIDC	PPI: Industrial Commodities	6
130	WPSID61	PPI by Commodity for Intermediate Demand by Commodity Type: Processed Goods for Intermediate Demand	6
131	CPIAUCSL	CPI for All Urban Consumers: All Items	6
132	CPIUFDSL	CPI for All Urban Consumers: Food	6
133	CPIENGSL	CPI for All Urban Consumers: Energy	6
134	CPILEGSL	CPI for All Urban Consumers: All Items Less Energy	6
135	CPIULFSL	CPI for All Urban Consumers: All Items Less Food	6
136	CPILFESL	CPI for All Urban Consumers: All Items Less Energy and Food	6
137	WTISPLC	Spot Oil Price: West Texas Intermediate	6
138	EXSZUS	Switzerland / US Foreign Exchange Rate	5
139	EXJPUS	Japan / US Foreign Exchange Rate	5
140	EXUSUK	US / UK Foreign Exchange Rate	5
141	EXCAUS	Canada / US Foreign Exchange Rate	5
Expectations			
142	sTB3MS	TB3MS - FEDFUNDS	1
143	sTB6MS	TB6MS - FEDFUNDS	1
144	sGS1	GS1 - FEDFUNDS	1
145	sGS3	GS3 - FEDFUNDS	1
146	sGS5	GS5 - FEDFUNDS	1
147	sGS10	GS10 - FEDFUNDS	1
148	sMPRIME	MPRIME - FEDFUNDS	1
149	sAAA	AAA - FEDFUNDS	1
150	sBAA	BBB - FEDFUNDS	1
151	MICH	University of Michigan: Inflation Expectation	1
152	BSCICP03USM665S	Business Tendency Surveys for Manufacturing: Confidence Indicators: Composite Indicators: OECD	1
153	CSINFT02USM460S	Consumer Opinion Surveys: Consumer Prices: Future Tendency of Inflation	1

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Table A2 – *Continued from previous page*

#	Mnemonic	Description	Tcode
154	AAA10Y	Moody's Seasoned Corporate Bond Yield Relative to Yield on 10-year Treasury Constant Maturity	1
155	BAA10Y	Moody's Seasoned Corporate Bond Yield Relative to Yield on 10-Yyear Treasury Constant Maturity	1
156	UMCSENT	University of Michigan: Index of Consumer Sentiment	1
157	BCE1Y	University of Michigan: Business Conditions Expected During the Next Year	1
158	BCE5Y	University of Michigan: Business Conditions Expected During the Next 5 Years	1
159	UE1Y	University of Michigan: Expected Change in Unemployment During the Next Year	1
Additional (not used for factor estimation)			
160	CNP16OV	Population Level (taken from FRED)	
161	SP500	Stock Market Index (taken from Robert Shiller's website; Link to website: http://www.econ.yale.edu/~shiller/)	
162	$\mathbb{F}_t[y_{Aaa,t+h}]$	Expectations on Aaa rated corporate bond yields (taken from Blue Chip Financial Indicators)	
163	$\mathbb{F}_t[y_{Baa,t+h}]$	Expectations on Baa rated corporate bond yields (taken from Blue Chip Financial Indicators)	
164	$\mathbb{F}_t[y_{GS10,t+h}]$	Expectation on 10-Year Treasury Constant Maturity Rate (taken from Blue Chip Financial Indicators)	

B. Identification based on External Instruments

The identification scheme on external instruments is introduced by Stock and Watson (2012) and Mertens and Ravn (2013). The approach used here resembles strongly the one pursued in Gertler and Karadi (2015) to identify monetary policy shocks. 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 $\boldsymbol{Z}_t$. I assume that the reduced-form innovation of the first variable in the system is the measurement of the structural shock. To proceed, I then regress the fitted values on the other reduced form residuals,

$$\boldsymbol{u}_{2:M,t} = \boldsymbol{\beta}\hat{u}_{1,t} + \zeta_t, \quad \zeta_t \sim N(0, \sigma_u^2). \tag{B.1}$$

Here, $\boldsymbol{u}_{2:M,t}$ are the reduced-form innovations of all other variables in the system, while $\hat{u}_{1,t}$ is the fitted value of the first-stage regression. Therefore,I get an estimate for the ratio $\boldsymbol{\beta}$, which is the structural effect of a unit shock on the other variables in the system. In order to use this, I have to restore the first column of $\boldsymbol{S}$ denoted by $\boldsymbol{s}_1$ to identify the non-rational structural risk shock. To do this, I partition the matrix of the structural coefficients, such that

$$\boldsymbol{S} = [\boldsymbol{s}_1 \quad \boldsymbol{s}_{2:M}] = \begin{bmatrix} s_{11} & \boldsymbol{s}_{12} \\ \boldsymbol{s}_{21} & \boldsymbol{s}_{22} \end{bmatrix}. \tag{B.2}$$

In the equation s_{11} is a scalar, $\boldsymbol{s}_{12}'$ and $\boldsymbol{s}_{21}$ are vectors of size $M-1\times 1$, and $\boldsymbol{s}_{22}$ is a matrix of size $M-1\times M-1$. Furthermore, we partition the reduced form covariance matrix $\boldsymbol{\Sigma}$ similarly,

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

Note that the baseline model is enriched with time-varying volatilities, thus the covariance matrix has an additional subindex t. In the following, I will use the median estimate of $\boldsymbol{\Sigma}_t$ for the computation of impulse responses. Then s_{11} is identified up to a sign convention and is obtained by the following closed form solution

$$(s_{11})^2 = \Sigma_{11} - \boldsymbol{s}_{12}\boldsymbol{s}_{12}', \tag{B.4}$$

where

$$\boldsymbol{s}_{12}\boldsymbol{s}_{12}' = (\boldsymbol{\Sigma}_{21} - \boldsymbol{\beta}\boldsymbol{\Sigma}_{11})'\boldsymbol{Q}^{-1}(\boldsymbol{\Sigma}_{21} - \boldsymbol{\beta}\boldsymbol{\Sigma}_{11}), \tag{B.5}$$

with

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

C. Diagnostics of the Belief Surprise Series

As discussed in the paper, I perform a number of validity checks on the surprise series. First, I investigate whether autocorrelation is present in the surprise series. Figure C1 depicts the autocorrelation function. For both series, there is no evidence that the series is serially autocorrelated. I also perform Granger causality tests. Table C1 shows that there is almost no predictive causality running from any of those variables to the constructed series of belief surprises. Only the stock market indices show modest amount of predictive density around the edges of conventional significance levels. Last, I compute correlations to other structural shocks we know from the literature. In particular, I compare the belief surprises in the Aaa and Baa credit spread to high-frequency monetary policy shocks in Jarociński and Karadi (2020) (labelled *HFI Monetary Policy*), the narrative fiscal policy shocks by Romer and Romer (2010) (labelled *RR Fiscal Policy*), the uncertainty indicators based on Jurado *et al.* (2015) (labelled *Financial Uncertainty*, *Macro Uncertainty* and *Real Uncertainty*), the economic policy uncertainty indicator by Baker *et al.* (2016) (labelled *Economic Policy Uncertainty*), the extended high-frequency monetary policy instrument by Miranda-Agrippino and Ricco (2020) (labelled *HFI Monetary Policy Ext1* and *HFI Monetary Policy Ext2*), the extended monetary policy measured constructed by Romer and Romer (2004) and extended by Breitenlechner (2018) (labelled *RR Monetary Policy 1* and *RR Monetary Policy 2*), high-frequency oil supply and supply news shocks by Känzig (2021) (labelled *HFI Oil Supply* and *HFI Oil News*), and the structural oil supply and demand as well as the aggregate demand shock by Kilian (2009) (labelled *Oil Supply*, *Aggregate Demand (Oil)*, and *Oil Demand*). Correlations are depicted in Figure C2 and are rather low to the proposed belief surprise series.

Table C1: Granger Causality Tests.

Variable	Aaa Belief Surprises	Baa Belief Surprises
FEDFUNDS	0.14	0.74
GS1	0.23	0.66
GDPC1	0.92	0.67
INDPRO	0.66	0.99
SP500	0.13	0.06
NADAQCOM	0.11	0.40
GDPDEF	0.45	0.37
CPIAUCSL	0.46	0.75

Notes: Table shows p-values of a series of Granger causality tests of the belief surprise series using a selection of macroeconomic and financial variables. Series are transformed to stationarity according to transformations provided in Table A2. The lag order is set to 1 and in terms of deterministics, only a constant term is included.

Figure C1: Autocorrelation Function of Belief Surprise Series.

(a) Aaa Belief Surprises. **(b)** Baa Belief Surprises.

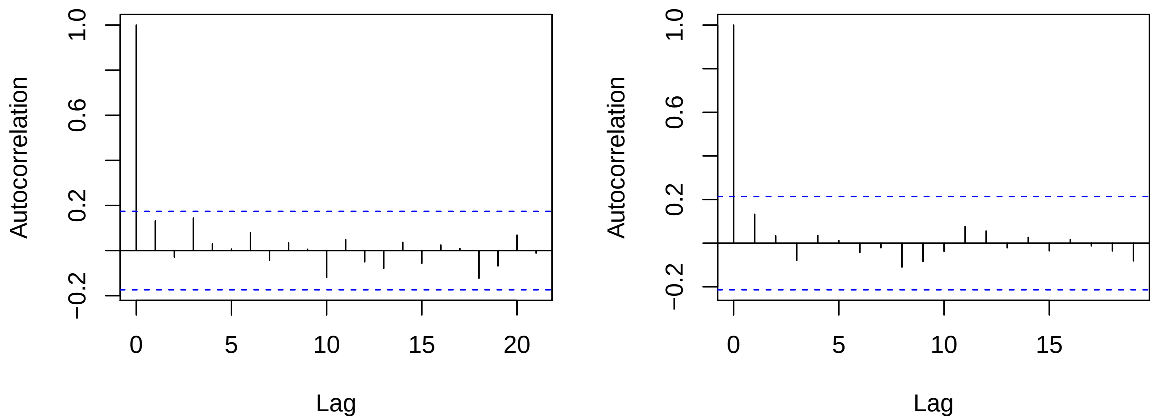
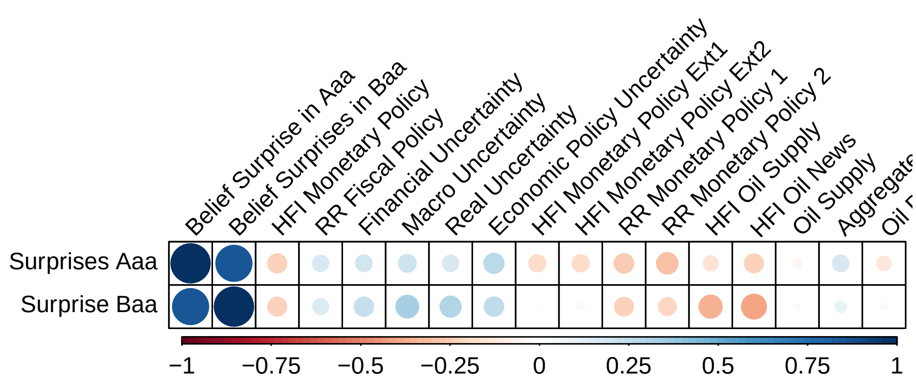


Figure C2: Correalation to Other Structural Shocks.



D. Weak Instrument Test

The main identifying assumption behind the external instruments approach is that the instrument is correlated with the shock of interest but uncorrelated with all other structural shocks. However, even if this holds, inference will not produce reliable results in case the instrument and the shock are only weakly correlated. Hence, it is important to test the strength of the instrument. Following Montiel-Olea *et al.* (2020), this can be done using an F-test in the first-stage regression of the credit spread residual from the VAR on the instrument. In order for the weak instrument problem not to be present, they recommend a threshold of 10 for the corresponding F-statistic.

Table D1 presents the results on this test for the models used in the analysis. I report the standard F-statistic and robust F-statistic allowing for heteroskedasticity. In addition, I test this by including lags of the proxies (the respective belief surprise series) where I choose the number of lags to be the same as in the VAR. The instruments turn out to be strong with F-statistics safely above the threshold of 10. In particular, for the baseline model the standard and robust F-statistics are above the threshold. Additionally, when looking at the model appending other variables, issues of weak instruments do not arise. Hence, overall evidence suggest that there is no weak instrument problem at hand.

Correlation of the belief surprises series is highest for the uncertainty indices which comes at no surprise. While this paper identifies a shock on its first-moment via distortions in beliefs, studies concentrating on uncertainty identify shocks with its second-moment. This also relates to the uncertainty literature as discussed earlier. Interestingly, the negative correlation to the high-frequency identified oil supply news shock series is not negligible although still small.

Table D1: Tests on Instrument Strength

Model	F-statistic	F-statistic (robust)	F-statistic + lags	F-statistic (robust) + lags
Baseline Model				
– Aaa	241.25	202.90	51.76	44.70
– Baa	335.11	57.30	80.24	18.06
Wider Model				
real Consumption:				
– Aaa	231.62	193.08	49.84	42.3
– Baa	290.89	24.77	72.11	9.45
real Investment:				
– Aaa	221.37	170.61	47.24	37.79
– Baa	286.38	30.4	72.2	14.40
Bank Credit:				
– Aaa	228.35	187.87	48.33	41.13
– Baa	331.56	37.28	77.94	14.05
Business Loans:				
– Aaa	227.08	202.28	50.32	45.08
– Baa	288.53	49.26	71.04	13.33
Federal Funds Rate:				
– Aaa	228.55	199.35	49.36	43.83
– Baa	300.18	55.66	75.28	17.63
Term Premium:				
– Aaa	210.66	170.27	45.82	39.04
– Baa	329.67	55.52	81.10	19.21

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Table D1 – *Continued from previous page*

Model	F-statistic	F-statistic (robust)	F-statistic + lags	F-statistic (robust) + lags
Hours:				
– Aaa	208.44	163.47	45.18	37.3
– Baa	323.59	38.06	75.91	12.87
Unemployment:				
– Aaa	221.95	151.75	48.22	35.09
– Baa	306.1	23.79	73.07	7.72
Labor Force Participation:				
– Aaa	223.64	179.66	48.10	39.46
– Baa	312.24	36.82	72.04	11.12
Consumer Prices:				
– Aaa	228.37	197.38	48.95	44.09
– Baa	300.12	49.9	69.80	14.91
Producer Prices:				
– Aaa	197.33	177.18	45.31	40.68
– Baa	282.16	52.16	62.37	10.91
Real Wage:				
– Aaa	241.68	195.79	50.83	41.20
– Baa	306.48	40.26	74.14	12.04
Consumer Sentiment:				
– Aaa	215.71	186.11	46.97	40.22
– Baa	282.69	44.96	70.38	16.89
Business Expectations 1Y:				
– Aaa	221.79	200.5	48.97	43.66
– Baa	259.42	69.74	67.49	22.34
Business Expectations 5Y:				
– Aaa	231.27	194.22	49.98	41.74
– Baa	300.05	50.42	72.58	14.3
Unemployment Expectations 1Y:				
– Aaa	218.93	139.62	46.75	32.43
– Baa	311.61	46.97	73.79	15.33

Notes: Table shows the results of the first-stage regressions of the credit spread residual $u_{1,t}$ on the belief surprises. Column 3 and 4 indicate with *lags* that lagged values are also included as controls. F-statistics above 10 indicate strong instruments. Robust F-statistic allow for heteroskedasticity.

E. Convergence Diagnostics

In this section, I evaluate convergence of the model presented in Section 3.2. For the MCMC algorithm I refer to Huber and Feldkircher (2019). To proceed, I look at three different convergence diagnostics. In an ideal setting, the sampler returns independent draws. The stronger the autocorrelation in the sampler, the more draws are needed. To evaluate the extent of autocorrelation in the MCMC chain, I use three different statistics. First, I compute inefficiency factors indicating how many draws are needed for drawing one identically and independently distributed draw. Second, I have a look at the Raftery and Lewis's diagnostic statistic (Raftery and Lewis, 1992). It is also a measure of autocorrelation and returns a dependence factor which should not exceed 5 in the ideal setting. Third, I examine Geweke's convergence diagnostic (Geweke *et al.*, 1991). This is a test of equality of the means of the first 10% and last 50% of the MCMC chain. Here, I report the share of Z-scores exceeding the critical value of 1.96.

For all models, convergence is safely achieved. While inefficiency factors are around 2-3, the dependence factors do not exceed 5 at a single time. Also, when looking at the share of Z-scores exceeding the critical value of 1.96 it does not seem to be an issue. In the last column of Table E1, I report the percentage of retained draws of stationary draws. This percentage share fluctuates more, but most of the time more than 10% of all draws are retained for posterior analysis.

Table E1: Convergence Statistics

Model	Inefficiency Factor	Dependence factor	Geweke's Z-scores	% draws retained
Baseline Model				
– Aaa	2.37	1.82	0.04	17.88
– Baa	3.00	2.47	0.02	29.29
Wider Model				
real Consumption:				
– Aaa	2.91	2.33	0.05	29.90
– Baa	2.65	2.43	0.02	23.81
real Investment:				
– Aaa	2.14	1.89	0.06	16.01
– Baa	2.52	2.19	0.03	17.53
Bank Credit:				
– Aaa	1.79	1.76	0.05	11.28
– Baa	3.21	2.67	0.03	27.70
Business Loans:				
– Aaa	2.25	1.95	0.02	18.05
– Baa	2.75	2.42	0.02	23.98
Federal Funds Rate:				
– Aaa	2.57	2.00	0.04	20.01
– Baa	3.01	2.66	0.03	27.49
Term Premium:				
– Aaa	2.31	2.01	0.06	19.38
– Baa	3.11	2.69	0.02	29.44
Hours:				
– Aaa	2.99	2.28	0.03	29.26
– Baa	2.44	2.20	0.05	17.36
Unemployment:				
– Aaa	2.41	2.00	0.03	19.21

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Table E1 – *Continued from previous page*

Model	Inefficiency Factor	Dependence factor	Geweke's Z-scores	% draws retained
– Baa	2.48	2.30	0.01	21.04
Labor Force Participation:				
– Aaa	3.25	2.65	0.02	39.65
– Baa	1.55	1.86	0.03	6.32
Consumer Prices:				
– Aaa	2.59	2.17	0.05	24.56
– Baa	2.46	2.25	0.06	20.03
Producer Prices:				
– Aaa	2.43	1.96	0.06	19.91
– Baa	1.59	1.91	0.03	7.62
Real Wage:				
– Aaa	1.85	1.81	0.10	11.22
– Baa	2.47	2.27	0.07	19.88
Consumer Sentiment:				
– Aaa	2.29	1.99	0.05	19.71
– Baa	2.64	2.41	0.03	22.97
Business Expectations 1Y:				
– Aaa	2.14	1.99	0.01	18.63
– Baa	2.93	2.69	0.02	26.15
Business Expectations 5Y:				
– Aaa	2.22	1.98	0.04	20.03
– Baa	2.58	2.30	0.04	19.97
Unemployment Expectations 1Y:				
– Aaa	2.04	1.92	0.05	15.33
– Baa	3.09	2.81	0.03	31.19

Notes: Table shows mean inefficiency factors and mean dependence factor for specific variable groups.

F. Robustness: Forecasting

In this section, I present additional results of the forecasting exercise. In the following, I extend Table 2 adding two additional models. First, in both models I exclude non-factor information in $\boldsymbol{x}_t$, indicated with $l = 0$, while I allow for either $q = 3$ factors like in the baseline specification, or up to $q = 7$ factors. Results show that there is a minor improvement in forecasting the Baa spread three quarters ahead. Apart from that, all results are robust to additional choices concerning the number of factors and including additional information.

Tables F2 to F4 present results from performing forecasts in an extending window fashion, and evaluating the forecasts with RMSEs. Interestingly, RMSEs point increasingly to the random-walk for forecasts at a more distant horizon. Nevertheless, the one-step ahead prediction is dominated by the AR(1)-SV model.

Table F1: Robustness: Forecasting Evaluation

	h=1		**h=2**		**h=3**		**h=4**	
	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread
RW	-101.99	-183.23	-65.78	-152.06	**-79.62**	-157.41	**-93.14**	-164.93
				Autoregressive Models				
AR(1)	-36.94	-114.43	-70.34	-142.71	-93.92	-153.86	-110.62	**-152.56**
AR(2)	-81.56	-168.57	-105.03	-185.68	-126.92	-176.36	-131.31	-157.78
AR(3)	-141.38	-232.3	-139.13	-219.37	-145.97	-180.55	-151.47	-171.01
AR(1)-SV	**-12.12**	**-54.54**	**-60.84**	**-96.15**	-80.4	-141.65	-109.93	-181.98
AR(2)-SV	-41.09	-87.88	-80.83	-119.23	-92.58	-135.11	-112.82	-170.07
AR(3)-SV	-92.91	-133.89	-101.19	-140.45	-104.99	-141.96	-122.22	-180.61
				Autoregressive Distributed Lag Models (q = 3, l = 4)				
ARX(1)	-83.45	-173.27	-86.99	-174.12	-107.8	-181.34	-125.09	-182.44
ARX(2)	-132.86	-236.5	-115.06	-210.46	-131.95	-201.12	-162.38	-197.58
ARX(3)	-182.62	-315.82	-146.21	-238.14	-190.76	-215.42	-220.5	-209.72
ARX(1)-SV	-46.19	-90.4	-70.65	-112.35	-84.75	-145.49	-119.88	-202.15
ARX(2)-SV	-84.93	-133.17	-90.48	-142.36	-136.37	-161.35	-146.68	-221.77
ARX(3)-SV	-115.78	-181.21	-123.06	-170.33	-133.92	-177.08	-171.37	-227.81
				Autoregressive Distributed Lag Models (q = 3, l = 0)				
ARX(1)	-71.54	-164.33	-84.78	-167.00	-105.11	-171.69	-118.58	-172.61
ARX(2)	-134.65	-233.27	-119.04	-206.89	-136.43	-197.82	-162.53	-192.32
ARX(3)	-180.53	-307.99	-152.24	-239.92	-187.32	-216.34	-222.08	-209.14
ARX(1)-SV	-39.56	-91.83	-65.13	-113.09	-83.45	**-130.83**	-116.76	-182.06
ARX(2)-SV	-87.46	-143.52	-90.99	-141.13	-119.5	-156.06	-136.71	-211.22
ARX(3)-SV	-116.65	-190.91	-128.49	-173.39	-123.35	-180.78	-166.06	-245.73
				Autoregressive Distributed Lag Models (q = 7, l = 0)				
ARX(1)	-67.55	-162.02	-80.83	-165.12	-108.16	-169.60	-131.37	-168.05
ARX(2)	-129.13	-236.46	-123.03	-206.45	-133.74	-196.02	-166.74	-190.68
ARX(3)	-177.28	-314.38	-152.98	-237.17	-191.82	-210.23	-220.61	-203.06
ARX(1)-SV	-36.61	-86.84	-64.81	-116.80	-88.53	-155.99	-124.39	-213.00
ARX(2)-SV	-79.88	-136.39	-94.51	-143.24	-112.86	-166.56	-139.28	-216.24
ARX(3)-SV	-110.63	-181.21	-116.48	-172.06	-131.08	-175.46	-153.38	-222.69

Notes: Out-of-sample performance in terms of the sum of log predictive density scores (LPDS). Predictions are computed in an rolling window fashion. The bold figures indicate the best performing model for a given variable and time horizon. The following models nested in Eq. (3.2) are considered: RW - random walk, AR - autoregressive model, ARX - autoregressive distributed lag model. The number in the parentheses indicates the number of lags considered. SV refers to stochastic volatility.

Table F2: Robustness: Forecast Evaluation (Extending Window).

	h=1		**h=2**		**h=3**		**h=4**	
	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread
RW	-80.60	-180.76	-62.62	-151.38	-80.45	-151.64	**-92.97**	-151.23
			Autoregressive Models					
AR(1)	-31.87	-116.11	-65.55	-138.82	-87.27	-148.42	-103.68	**-148.86**
AR(2)	-77.12	-169.69	-99.63	-183.57	-119.05	-174.37	-128.84	-154.39
AR(3)	-136.48	-237.15	-131.97	-213.73	-136.32	-172.61	-135.07	-160.56
AR(1)-SV	**-17.14**	**-57.77**	**-60.31**	**-97.17**	-82.44	-136.15	-108.84	-175.54
AR(2)-SV	-54.29	-87.92	-88.58	-120.17	-98.29	-140.65	-110.65	-177.05
AR(3)-SV	-109.68	-140.54	-107.61	-139.74	-109.19	-141.68	-102.16	-173.43
			Autoregressive Distributed Lag Models (q = 3, l = 4)					
ARX(1)	-73.25	-182.86	-77.7	-171.20	-89.43	-175.54	-102.42	-181.61
ARX(2)	-122.48	-250.79	-111.66	-209.13	-119.73	-200.29	-139.49	-200.12
ARX(3)	-176.65	-317.94	-141.22	-234.79	-140.55	-209.99	-148.95	-208.29
ARX(1)-SV	-52.69	-91.82	-71.72	-109.81	-90.81	-136.78	-119.66	-193.52
ARX(2)-SV	-101.40	-141.59	-99.54	-139.44	-124.31	-154.67	-165.96	-201.37
ARX(3)-SV	-142.02	-180.21	-123.79	-159.14	-131.14	-148.49	-146.54	-186.48
			Autoregressive Distributed Lag Models (q = 3, l = 0)					
ARX(1)	-67.95	-167.59	-78.66	-165.04	-92.68	-168.56	-106.80	-173.96
ARX(2)	-123.24	-236.47	-110.08	-204.03	-123.95	-192.15	-135.36	-193.13
ARX(3)	-173.98	-307.33	-141.30	-229.72	-143.76	-206.80	-143.28	-201.71
ARX(1)-SV	-50.54	-91.36	-70.90	-112.35	-86.35	-133.69	-103.89	-186.28
ARX(2)-SV	-102.79	-144.04	-99.77	-142.49	-109.91	-157.98	-118.52	-201.40
ARX(3)-SV	-146.71	-195.03	-125.56	-169.35	-117.09	-162.17	-118.44	-197.38
			Autoregressive Distributed Lag Models (q = 7, l = 0)					
ARX(1)	-62.53	-164.36	-72.82	-160.16	-85.00	-162.92	-94.71	-164.30
ARX(2)	-119.72	-238.05	-106.02	-201.34	-115.44	-189.83	-125.57	-187.17
ARX(3)	-167.24	-307.78	-134.73	-223.82	-137.61	-202.88	-135.86	-199.73
ARX(1)-SV	-45.15	-84.93	-65.52	-111.00	**-77.17**	**-128.20**	-100.32	-208.62
ARX(2)-SV	-96.55	-141.00	-96.08	-143.21	-103.56	-149.94	-126.34	-193.82
ARX(3)-SV	-134.66	-183.67	-117.82	-172.75	-121.33	-154.57	-124.92	-197.41

Notes: Out-of-sample performance in terms of the sum of log predictive density scores (LPDS). Predictions are computed in an extending window fashion. The bold figures indicate the best performing model for a given variable and time horizon. The following models nested in Eq. (3.2) are considered: RW - random walk, AR - autoregressive model, ARX - autoregressive distributed lag model. The number in the parentheses indicates the number of lags considered. SV refers to stochastic volatility.

Table F3: Robustness: Forecast Evaluation (RMSEs).

	h=1		**h=2**		**h=3**		**h=4**	
	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread
RW	27.95	33.88	**33.62**	**43.23**	**39.05**	**48.55**	**42.20**	53.22
			Autoregressive Models					
AR(1)	**27.03**	32.61	37.25	45.62	41.28	49.43	45.33	**51.57**
AR(2)	31.57	40.80	41.53	50.89	48.01	54.48	50.35	52.38
AR(3)	37.58	46.96	46.96	57.24	50.55	55.67	51.15	57.41
AR(1)-SV	27.23	**32.07**	38.89	46.72	43.58	51.81	47.82	55.36

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Table F3 – *Continued from previous page*

	h=1		h=2		h=3		h=4	
	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread
AR(2)-SV	31.94	41.05	41.87	51.88	48.34	55.95	52.20	53.62
AR(3)-SV	37.69	47.06	46.71	57.03	52.35	55.61	54.49	57.94
		Autoregressive Distributed Lag Models (q = 3, l = 4)						
ARX(1)	32.50	41.07	39.89	50.38	43.49	53.39	47.27	54.16
ARX(2)	37.47	46.93	43.26	55.99	46.05	56.40	48.06	54.03
ARX(3)	40.65	51.01	46.24	59.33	50.07	57.79	52.36	59.21
ARX(1)-SV	32.56	41.76	40.95	51.29	44.96	55.50	51.43	58
ARX(2)-SV	37.42	46.97	43.20	57.86	48.91	59.73	53.15	56.93
ARX(3)-SV	40.63	51.81	47.57	61.52	53.16	60.63	55.67	63.52
		Autoregressive Distributed Lag Models (q = 3, l = 0)						
ARX(1)	31.48	40.73	39.43	48.35	43.26	52.35	47.04	52.82
ARX(2)	37.95	47.04	44.29	55.96	47.35	55.72	49.80	53.73
ARX(3)	41.03	51.32	47.60	59.23	51.37	58.13	52.34	60.49
ARX(1)-SV	31.80	41.07	40.38	49.66	45.48	52.71	51.70	55.59
ARX(2)-SV	37.98	47.56	44.29	57.71	50.08	58.64	54.03	56.47
ARX(3)-SV	41.13	52.08	48.58	61.48	54.03	59.43	56.50	61.45
		Autoregressive Distributed Lag Models (q = 7, l = 0)						
ARX(1)	31.46	40.84	37.85	49.05	42.42	52.54	45.96	53.44
ARX(2)	37.55	47.65	44.04	56.02	46.37	56.81	49.26	56.55
ARX(3)	40.50	50.64	46.87	58.81	51.27	59.19	53.05	60.76
ARX(1)-SV	31.55	40.97	38.82	50.12	44.88	54.82	51.98	55.69
ARX(2)-SV	37.04	47.40	43.53	57.92	48.80	59.68	51.85	57.55
ARX(3)-SV	40.31	51.74	48.29	61.68	52.57	61.30	55.12	63.60

Notes: Out-of-sample performance in terms of the sum of root mean squared errors (RMSEs). Predictions are computed in an rolling window fashion. The bold figures indicate the best performing model for a given variable and time horizon. The following models nested in Eq. (3.2) are considered: RW - random walk, AR - autoregressive model, ARX - autoregressive distributed lag model. The number in the parentheses indicates the number of lags considered. SV refers to stochastic volatility.

Table F4: Robustness: Forecasting Evaluation (RMSEs + Extending Window).

	h=1		h=2		h=3		h=4	
	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread
RW	27.92	33.90	**33.59**	**43.20**	**39.09**	**48.54**	**42.21**	53.16
		Autoregressive Models						
AR(1)	27.03	32.29	37.39	45.11	41.72	48.97	45.66	**51.17**
AR(2)	31.94	40.45	41.61	50.25	48.39	54.8	51.81	51.64
AR(3)	37.66	46.49	47.03	57.05	52.08	54.84	54.6	56.41
AR(1)-SV	**26.98**	**31.81**	37.71	46.53	42.84	51.25	48.58	55.07
AR(2)-SV	32.02	40.93	41.75	51.55	48.51	56.81	52.82	54.45
AR(3)-SV	37.76	46.96	46.74	57.61	52.32	55.25	55.43	58.83
		Autoregressive Distributed Lag Models (q = 3, l = 4)						
ARX(1)	32.43	40.40	39.39	48.50	41.60	52.23	44.95	53.46
ARX(2)	37.55	46.47	44.33	54.64	47.65	55.40	50.59	54.98
ARX(3)	41.10	51.11	48.70	57.55	53.42	57.99	53.52	61.41
ARX(1)-SV	32.65	41.46	40.03	50.49	42.31	54.97	47.73	58.36

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Table F4 – *Continued from previous page*

	h=1		h=2		h=3		h=4	
	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread	Aaa spread	Baa spread
ARX(2)-SV	37.62	46.78	43.95	56.62	48.80	59.06	56.40	57.28
ARX(3)-SV	41.11	51.78	48.75	60.25	54.10	59.66	58.49	63.31
		Autoregressive Distributed Lag Models (q = 3, l = 0)						
ARX(1)	31.96	40.25	38.66	47.67	43.36	51.66	46.35	52.26
ARX(2)	37.59	46.23	44.37	54.23	49.46	54.77	53.30	54.28
ARX(3)	41.15	50.80	48.96	57.01	54.12	57.18	54.84	60.70
ARX(1)-SV	32.15	41.07	38.8	49.31	43.65	52.63	48.45	55.95
ARX(2)-SV	37.87	46.93	44.42	55.95	49.87	57.18	54.79	56.79
ARX(3)-SV	41.41	51.84	49.35	60.05	54.46	57.37	56.57	61.61
		Autoregressive Distributed Lag Models (q = 7, l = 0)						
ARX(1)	31.43	40.31	38.06	47.42	41.37	50.86	44.04	51.04
ARX(2)	37.33	46.71	43.85	54.89	47.13	54.65	51.16	54.47
ARX(3)	40.71	50.75	47.41	57.26	52.33	57.59	52.77	61.02
ARX(1)-SV	31.62	41.00	38.08	48.76	41.83	53.16	47.42	54.84
ARX(2)-SV	37.40	46.87	43.92	56.51	48.32	57.40	53.67	54.51
ARX(3)-SV	40.71	51.44	47.96	60.50	53.23	58.02	55.09	61.26

Notes: Out-of-sample performance in terms of the sum of root mean squared errors (RMSEs). Predictions are computed in an extending window fashion. The bold figures indicate the best performing model for a given variable and time horizon. The following models nested in Eq. (3.2) are considered: RW - random walk, AR - autoregressive model, ARX - autoregressive distributed lag model. The number in the parentheses indicates the number of lags considered. SV refers to stochastic volatility.

G. Robustness: Identification

Figure G1: Subsample Stability of Aaa Baseline Model.

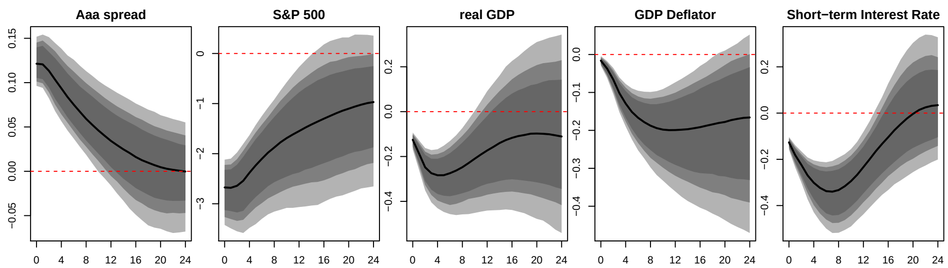
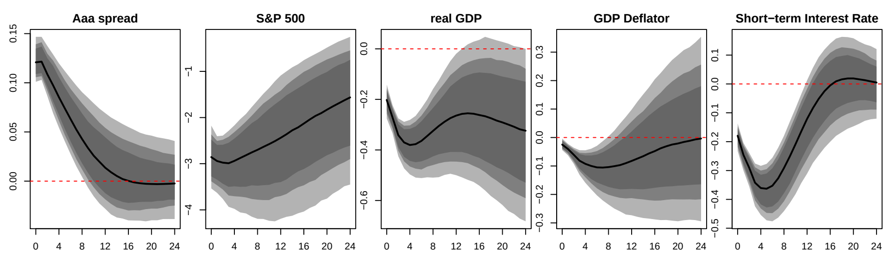
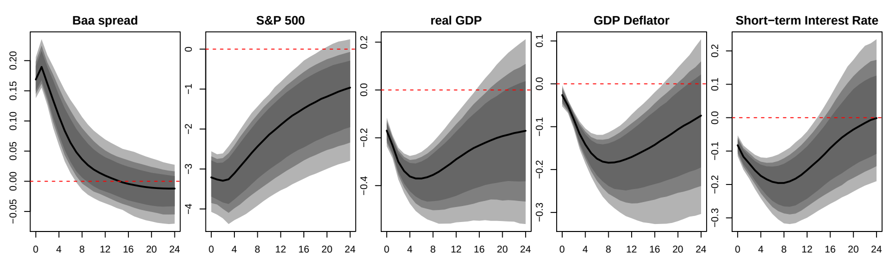


Figure G2: Belief Surprises with two-step ahead horizon.

(a) Shock to Aaa belief surprise.



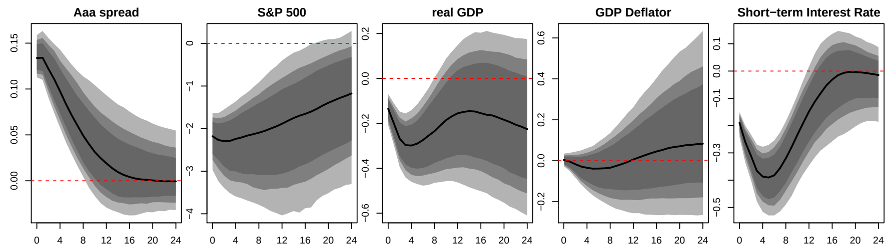
(b) Shock to Baa belief surprise.



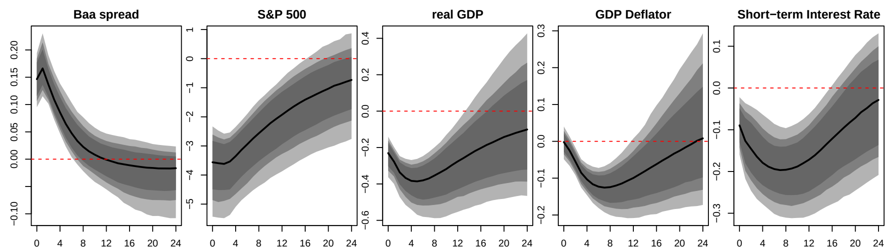
Notes: Impulse response functions of the baseline VAR with two-step ahead belief surprises. Identification via external instrument. Black line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals. The responses of stock market index, real activity, and prices are scaled in percent, while the spread and interest rate responses are scaled in percentage points.

Figure G3: Belief Surprises with three-step ahead horizon.

(a) Shock to Aaa belief surprise.



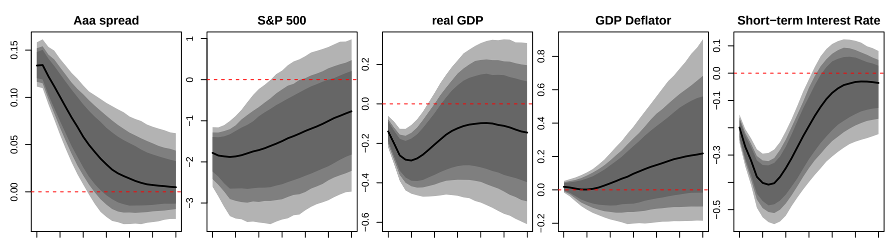
(b) Shock to Baa belief surprise.



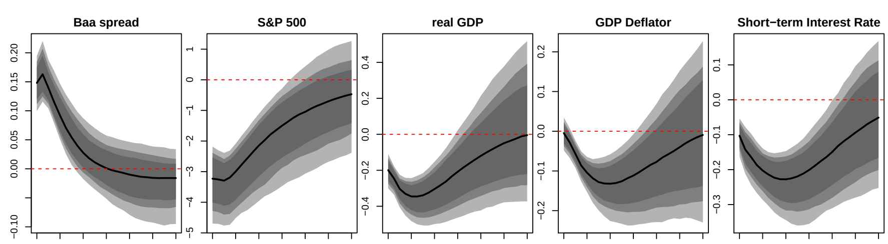
Notes: Impulse response functions of the baseline VAR with three-step ahead belief surprises. Identification via external instrument. Black line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals. The responses of stock market index, real activity, and prices are scaled in percent, while the spread and interest rate responses are scaled in percentage points.

Figure G4: Belief Surprises with four-step ahead horizon.

(a) Shock to Aaa belief surprise.



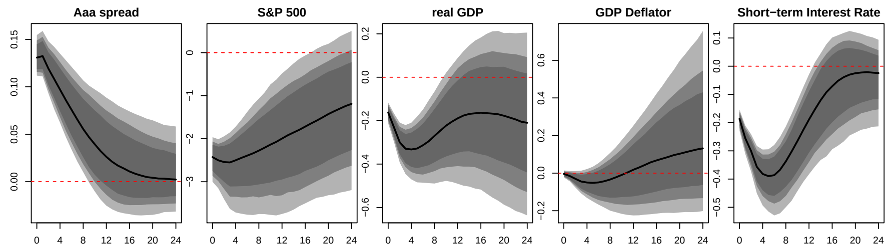
(b) Shock to Baa belief surprise.



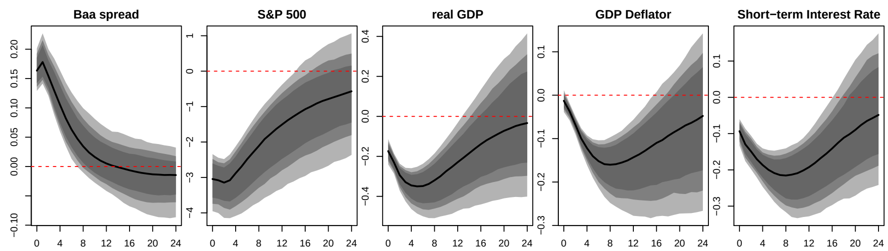
Notes: Impulse response functions of the baseline VAR with four-step ahead belief surprises. Identification via external instrument. Black line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals. The responses of stock market index, real activity, and prices are scaled in percent, while the spread and interest rate responses are scaled in percentage points.

Figure G5: Belief Surprises with mean of all horizons.

(a) Shock to Aaa belief surprise.



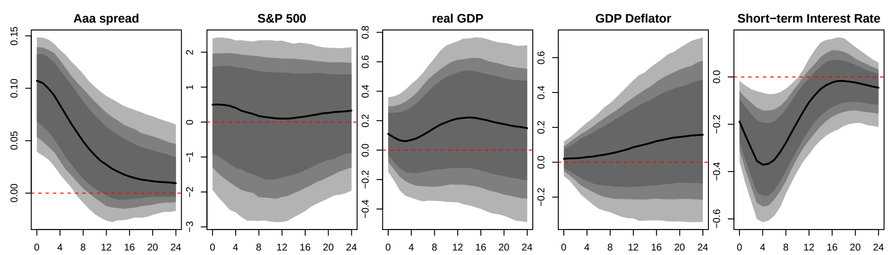
(b) Shock to Baa belief surprise.



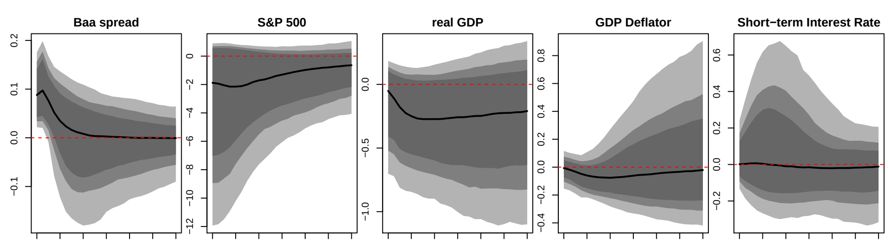
Notes: Impulse response functions of the baseline VAR with mean belief surprises over all horizons. Identification via external instrument. Black line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals. The responses of stock market index, real activity, and prices are scaled in percent, while the spread and interest rate responses are scaled in percentage points.

Figure G6: Placebo Identification.

(a) Shock to Aaa placebo surprise.



(b) Shock to Baa placebo surprise.



Notes: Impulse response functions of the baseline VAR with placebo belief surprises. Identification via external instrument. Black line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals. The responses of stock market index, real activity, and prices are scaled in percent, while the spread and interest rate responses are scaled in percentage points.

Table G1: Test for Fundamentalness.

Shock	Lags	Principal components (from 1 to k) 1	2	3	4	5	6	7	8	9	10
		Recursive Identification									
Aaa risk shock	1	0.76	0.91	0.98	0.39	0.10	0.06	0.09	0.10	0.15	0.17
Aaa risk shock	2	0.62	0.78	0.92	0.95	0.96	0.95	0.95	0.94	0.91	0.94
Aaa risk shock	3	0.73	0.84	0.19	0.31	0.44	0.52	0.28	0.21	0.27	0.21
Aaa risk shock	4	0.87	0.82	0.85	0.91	0.90	0.11	0.06	0.09	0.12	0.13
Baa risk shock	1	0.90	0.58	0.69	0.23	0.15	0.13	0.11	0.04	0.06	0.08
Baa risk shock	2	0.15	0.24	0.40	0.57	0.71	0.46	0.58	0.69	0.36	0.39
Baa risk shock	3	0.25	0.28	0.02	0.05	0.05	0.07	0.02	0.02	0.02	0.00
Baa risk shock	4	0.99	0.34	0.53	0.68	0.80	0.39	0.31	0.41	0.51	0.57
		External Instruments Identification									
Aaa risk shock	1	0.01	0.04	0.07	0.12	0.11	0.04	0.06	0.04	0.04	0.02
Aaa risk shock	2	0.56	0.84	0.44	0.50	0.64	0.75	0.76	0.75	0.63	0.71
Aaa risk shock	3	0.81	0.84	0.08	0.14	0.16	0.05	0.03	0.03	0.04	0.03
Aaa risk shock	4	0.43	0.44	0.23	0.36	0.39	0.15	0.08	0.11	0.16	0.09
Baa risk shock	1	0.03	0.10	0.12	0.11	0.08	0.03	0.05	0.02	0.02	0.00
Baa risk shock	2	0.82	0.77	0.34	0.32	0.44	0.53	0.54	0.64	0.62	0.70
Baa risk shock	3	0.83	0.45	0.07	0.14	0.16	0.10	0.09	0.08	0.11	0.07
Baa risk shock	4	0.69	0.30	0.35	0.51	0.66	0.32	0.12	0.17	0.23	0.12

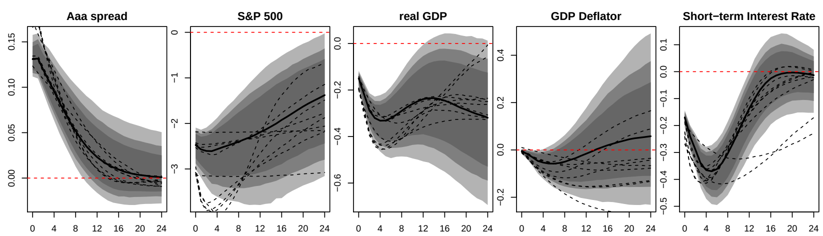
Notes: Results of the Fundamentalness Test. Each entry of the Table reports the p-value of the F-test in a regression of the non-rational risk shock estimated using the baseline specification on up to four lags of the first k principal components, $k = 1, \dots, 10$.

H. Model Specification and Data Choices

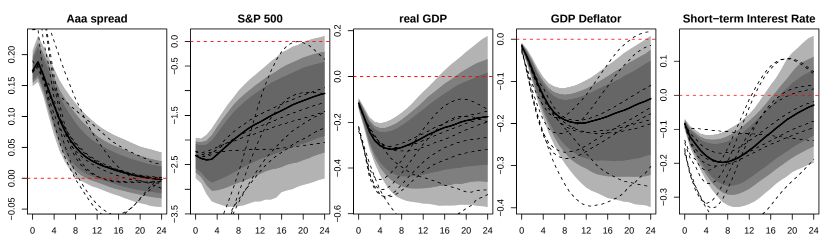
In this section, I present robustness with respect to model, lag, and data specification. The results are presented in the following format in Figures H1 to H5: In each figure, I provide the impulse responses of the baseline model presented in Section 4 of both identified risk shocks via recursive ordering or the external instruments approach. For the robustness analysis I draw additional ten lines covering all combinations of estimation with up to five lags and with or without stochastic volatility. While Figure H1 uses the baseline data specification, I exchange one variable at at time in Figures H2 to H5: NASDAQ instead of S&P 500, industrial production instead of GDP per capita, consumer prices instead of GDP deflator, and federal funds rate instead of 1-year Treasury constant maturity yield. Data definitions and transformations can be found in Appendix A.

Figure H1: Robustness: Baseline VAR.

(a) Shock to Aaa belief surprises.



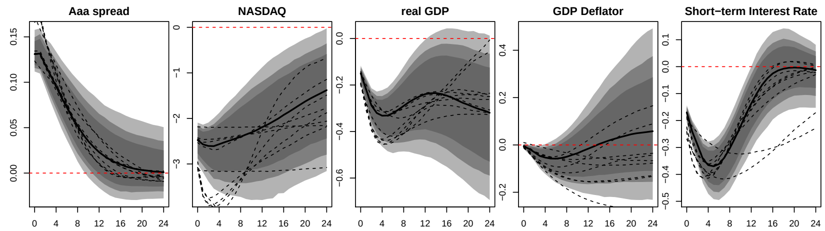
(b) Shock to Baa belief surprises.



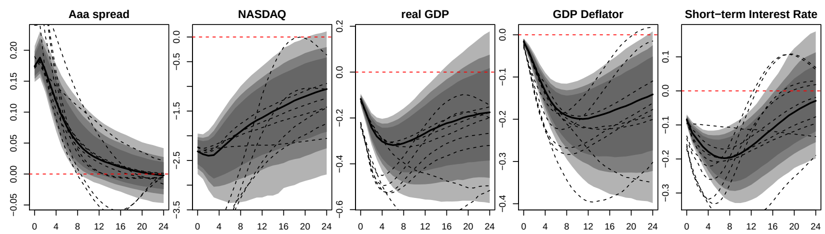
Notes: Impulse response functions of robust VARs of the baseline VAR. Identification via external instrument. Black solid line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals and refer to the baseline model. Black dashed lines refer to additional models. The responses of stock market index, real activity, and prices are scaled in percent, while the spread and interest rate responses are scaled in percentage points.

Figure H2: Robustness: NASDAQ.

(a) Shock to Aaa belief surprises.



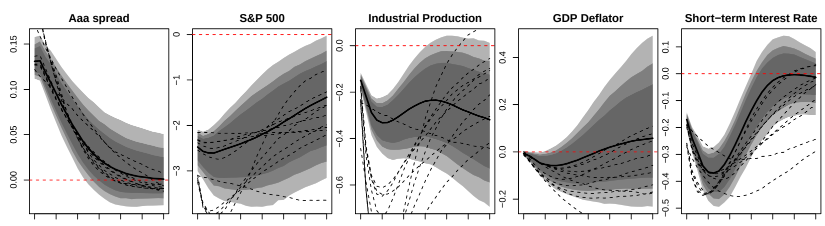
(b) Shock to Baa belief surprises.



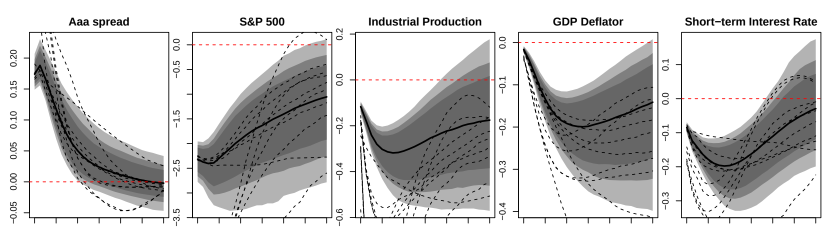
Notes: Impulse response functions of robust VARs estimated with NASDAQ. Identification via external instrument. Black solid line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals and refer to the baseline model. Black dashed lines refer to additional models. The responses of stock market index, real activity, and prices are scaled in percent, while the spread and interest rate responses are scaled in percentage points.

Figure H3: Robustness: Industrial Production.

(a) Shock to Aaa belief surprises.



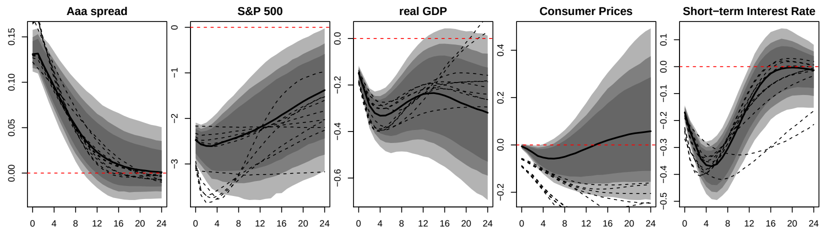
(b) Shock to Baa belief surprises.



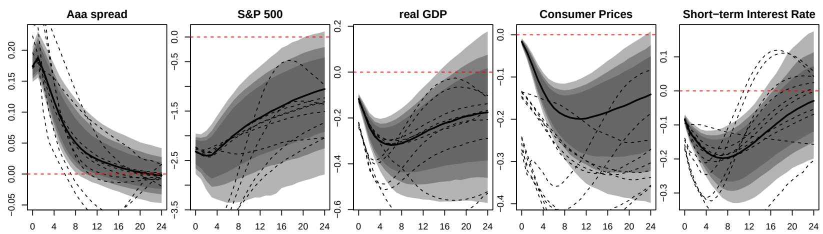
Notes: Impulse response functions of robust VARs estimated with industrial production. Identification via external instrument. Black solid line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals and refer to the baseline model. Black dashed lines refer to additional models. The responses of stock market index, real activity, and prices are scaled in percent, while the spread and interest rate responses are scaled in percentage points.

Figure H4: Robustness: Consumer Price Index.

(a) Shock to Aaa belief surprises.



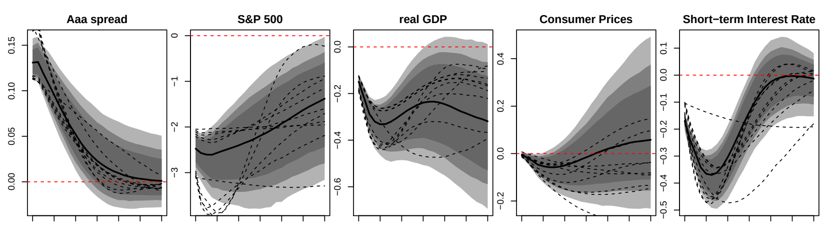
(b) Shock to Baa belief surprises.



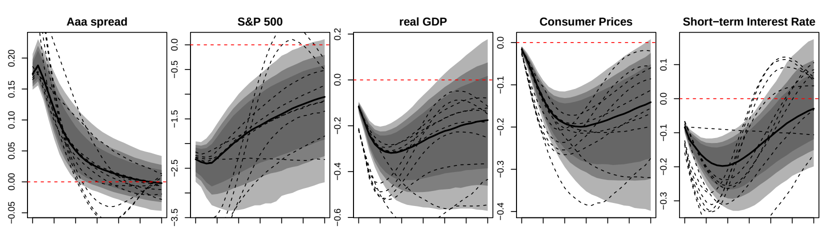
Notes: Impulse response functions of robust VARs estimated with the consumer price index. Identification via external instrument. Black solid line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals and refer to the baseline model. Black dashed lines refer to additional models. The responses of stock market index, real activity, and prices are scaled in percent, while the spread and interest rate responses are scaled in percentage points.

Figure H5: Robustness: Federal Funds Rate.

(a) Shock to Aaa belief surprises.



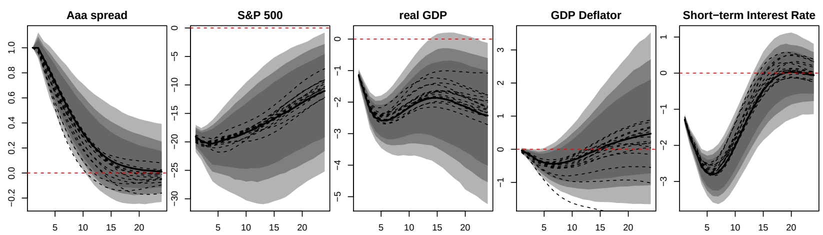
(b) Shock to Baa belief surprises.



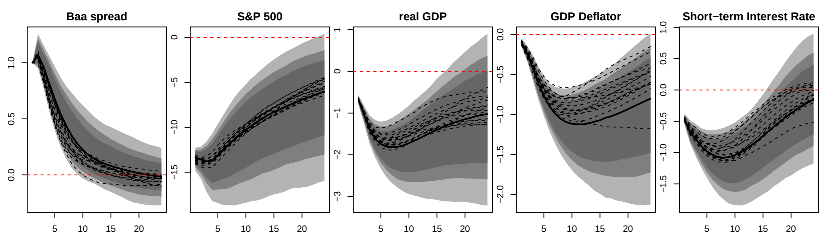
Notes: Impulse response functions of robust VARs estimated with the federal funds rate. Identification via external instrument. Black solid line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals and refer to the baseline model. Black dashed lines refer to additional models. The responses of stock market index, real activity, and prices are scaled in percent, while the spread and interest rate responses are scaled in percentage points.

Figure H6: Robustness: Wider Effects.

(a) Shock to Aaa belief surprises.



(b) Shock to Baa belief surprises.



Notes: Impulse response functions of the VAR with wider macroeconomic effects. Identification via external instrument. Identification via external instrument. Black solid line denotes median response while gray shaded areas denote the 68/80/90 percent confidence intervals of the baseline model. Black dashed line indicates models with additional macroeconomic variable. The responses of stock market index, real activity, and prices are scaled in percent, while the spread and interest rate responses are scaled in percentage points.