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The Impact of Uncertainty and Financial Shocks in Recessions and Booms

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Abstract

The literature has widely discussed the role of financial and economic uncertainty shocks for the macroeconomy. However, it has turned out to be difficult to isolate these shocks from financial market indicators and uncertainty proxies because any identifying restriction on their response profile requires strong assumptions. To obtain more robust results, I model financial and uncertainty shocks jointly in a state-dependent FAVAR setup for the U.S. and provide agnostic identification bounds on their effects. I document that (i) uncertainty shocks are of limited relevance for real activity and asset prices in boom periods but have significantly contractionary effects in recessions. (ii) By comparison, adverse financial shocks are contractionary both in recessions and boom periods. (iii) Identifying assumptions play a significant role in the effect magnitudes, especially for uncertainty shocks and in recessions. (iv) Financial conditions are generally a key transmission channel of uncertainty shocks. (v) Uncertainty transmits financial shocks to a noticeable degree in recessions.

Keywords: Macroeconomic tail events, nonlinear FAVARs, uncertainty shocks, financial shocks

JEL classification: E32, E37, E44

1. Introduction

The unprecedented disruptions of the Great Recession, its depth and duration have led to the question of whether traditional sources of business cycle fluctuations are sufficient in times of economic stress. Therefore, more recently theorists and empiricists have increasingly focused on the role of financial tightness and uncertainty and, in particular, the interplay between both (Bachmann et al. (2013), Bloom

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(2009), Curdia and Woodford (2010), Ajello (2016)). There is strong evidence that periods of elevated financial stress are associated with higher volatility in economic indicators, and jointly both factors have significant and sizeable real effects. Caldara et al. (2016), for instance, find that the Great Recession was likely an acute manifestation of the toxic interaction between uncertainty and financial shocks. Alessandri and Mumtaz (2018) moreover document that the impact of exogenous increases in uncertainty is six times larger during times of financial stress.

The connection between financial indicators and uncertainty suggests that it is essential to model them jointly to separate autonomous changes from endogenous reactions. Indeed, parts of the literature question uncertainty as an exogenous driver of the business cycle but instead emphasize its endogeneity to financial and other shocks. For example, Ludvigson et al. (2015) find that sharply higher macroeconomic uncertainty in recessions is often an endogenous response to output shocks, while shocks that originate in the financial market are a likely source of output fluctuations. As a result, exogenous disturbances in macroeconomic uncertainty play a minor role once financial shocks are controlled for (Popescu and Smets (2010)).

However, the empirical isolation of uncertainty shocks from financial shocks is difficult, as Stock and Watson (2012) show in their analysis of the channels of the Great Recession. Under the nonexistence of valid instruments we need identifying restrictions on the shocks' response profile, and these are typically strong. To give an example, financial and uncertainty indicators are assumed to react to each other on impact, which precludes plausible contemporaneous zero restrictions in an SVAR setup. Popescu and Smets (2010) accordingly document that the coexistence of financial and uncertainty indicators raises identification issues if a recursive ordering is used.

In this paper, I use an agnostic identification scheme based on the penalty function approach (Uhlig (2005) and Caldara et al. (2016)) to estimate the impact of financial and uncertainty shocks on real economic activity and asset prices in the United States. I apply the identification to a state-dependent FAVAR framework in which I include a large panel of macroeconomic and financial indicators. To measure uncertainty, I use a set of proxies capturing different categories, namely macroeconomic, financial and economic policy uncertainty. As an indicator of financial stress I use the excess bond premium from Gilchrist and Zakrajšek (2012).

I contribute in several ways to the literature. First, the penalty function approach yields identification bounds on the effects of uncertainty and financial shocks that reflect views stressing the role of uncertainty shocks as a source of business cycle

fluctuations (e.g. Bachmann et al. (2013), Bloom (2009)) as well as conservative views (e.g. Popescu and Smets (2010) and Ludvigson et al. (2015)). The bounds are constructed by defining a “large” and a “small” version of the uncertainty and the financial shock. The large uncertainty shock is defined as the shock that induces the maximal increase in an uncertainty proxy. By the same token, the large financial shock is characterized as the shock which yields the largest increase in the excess bond premium. The small uncertainty shock is the empirical residual of the uncertainty indicator that is not explained by the large financial shock. The analogous definition is applied to the small financial shock. As it will turn out, the large versions of both shocks yield the strongest contraction in real activity and thus the lower bound. The small versions consequently generate the upper bound.

Second, the identification bounds indicate how financial and uncertainty shocks are transferred to the business cycle. Following the view of Bloom (2009) uncertainty shocks have real effects since investment projects are partially irreversible. As a consequence, entrepreneurs respond to adverse uncertainty shocks by deferring real capital expenditures or recruiting until prospects become clearer, a behavior that is commonly referred to as “wait-and-see business cycles” (Bachmann et al. (2013)). This mechanism serves for both versions of the uncertainty shock since each of them induces an increase in uncertainty proxies. However, since the large uncertainty shock is inflated by the excess bond premium it also takes up the financial view on uncertainty shocks that was shaped by Gilchrist et al. (2014), Christiano et al. (2014) and Alessandri and Mumtaz (2018). The narrative here is that uncertainty shocks are contractionary because they induce a rise in risk premia on external finance and thus in marginal costs of production.

Third, I distinguish between recessions and boom regimes in the FAVAR dynamics and hence provide further evidence on the state-dependence of uncertainty and financial shocks. Besides, I account for the empirical evidence that uncertainty and financial shocks were a major driving force of the Great Recession (e.g., Stock and Watson (2012) and Caldara et al. (2016)). To my knowledge, there are no other contributions that address the role of both shocks in a joint setup and distinguish between recessions and boom periods at the same time.

My findings can be summarized as follows: The effects of uncertainty shocks are highly state-dependent. Whereas adverse uncertainty shocks are of limited relevance in boom periods, they have contractionary and noticeable effects in recessions. By contrast, adverse financial shocks lower real activity and asset prices in both regimes. In general, identifying assumptions play a non-negligible role in the effects of uncer-

tainty shocks. Their identification bounds are sizeable, especially in the recession regime and in terms of the impact on asset prices. Financial shocks, by contrast, exhibit relatively tight limits, which confirms their role as sources of macroeconomic fluctuations. As a result, while financial conditions are generally important transmitters of uncertainty shocks, uncertainty transmits financial shocks only in recessions.

The paper is organized as follows. Sections 2 and 3 describe the model setup and the estimation approach. Section 4 presents the data and their transformations. In section 5, I discuss impulse responses and forecast error variance decompositions of asset prices and real activity indicators in response to financial and uncertainty shocks. Section 6 concludes.

2. Empirical setup

To identify financial and uncertainty shocks, I employ a state-dependent version of the factor-augmented vector autoregressive (FAVAR) framework for the United States. I augment a VAR of a financial indicator and an uncertainty proxy by a limited number of latent but estimable factors. This augmentation has two advantages: it circumvents the curse of dimensionality when a large panel of economic variables is of interest by reducing the panel to a small set of common factors. Hence, I do not need to restrict the variables entering the analysis to a few key measures. Besides, since the common factors concentrate a broad set of real, financial and price indicators they are informative enough to serve as business cycle controls (Bernanke et al. (2005) and Forni and Gambetti (2010)). To account for state-dependence in the FAVAR, I distinguish between a recessionary and a non-recessionary state (which I henceforth refer to as boom state). The states are identified by the recession chronology of the National Bureau of Economic Research (NBER).

2.1. State-dependent FAVAR

The starting point of the state-dependent FAVAR is a recession indicator R_t , defined as

$$R_t = \begin{cases} 1 & \text{if period } t \text{ is an NBER recession} \\ 2 & \text{otherwise.} \end{cases}$$

R_t assigns an $n \times 1$ -dimensional vector X_t of $n = 101$ U.S. macroeconomic variables either a recession or a boom subsample. Both subsamples are assumed to follow a factor structure, so each $X_{i,t}$ is driven by a common and an idiosyncratic component. The state-specific observation equation of the FAVAR is accordingly given by

$$X_t = \Lambda_R Y_t + \xi_t \tag{1}$$

where $\Lambda_R Y_t$ denotes the common component and ξ_t the idiosyncratic component with diagonal covariance matrix $\text{Var}(\xi_t) = \Omega_R = \text{diag}(\omega_{1,R}^2 \dots \omega_{n,R}^2)$. $\omega_{i,R}^2$ is the variance of the idiosyncratic component of $X_{i,t}$. $Y_t = [F_t', EBP_t, UN_t]'$ is $k \times 1$ and contains a set of m latent but estimable factors $F_t = [F_{1,t}, \dots, F_{m,t}]'$ and a finance-uncertainty bloc consisting of two observable variables, the excess bond premium EBP_t , and a proxy for economic uncertainty UN_t ¹. In section 4, I describe further details on the indicators in the finance-uncertainty bloc and the series in X_t .

The identification of the latent factors follows the scheme suggested by Bernanke et al. (2005): in case of m latent factors the first m variables in X_t have identity as loading matrix. In addition, I set their loadings on the finance-uncertainty bloc to zero. Since the latent factors only serve as control variables in my analysis, I refrain from using any rotations on top of the just-identification. However, I impose further zero restrictions on the loadings of slow-moving variables in X_t on the finance-uncertainty bloc. Here I assume that variables such as industrial production do not instantaneously react to financial or uncertainty shocks but adjust with a delay of at least one month through the latent factors F_t . Accordingly, the loadings of fast-moving variables such as stock prices are left unrestricted and thus react to the finance-uncertainty bloc on impact.

The dynamic relationship between the finance-uncertainty bloc and F_t follows a structural VAR, which forms the transition equation of the FAVAR:

$$Y_t = \sum_{j=1}^p B_{R,j} Y_{t-j} + u_t \quad (2)$$

$$u_t = P_R \epsilon_t \quad (3)$$

where p denotes the lag order. $u_t \sim N(0, \Sigma_{Rt})$ represents the vector of reduced-form residuals and $\epsilon_t \sim N(0, I_m)$ the structural shocks of the FAVAR. The matrix P_R describes the contemporaneous relationship between the reduced-form residuals and the structural shocks of interest, namely the uncertainty shock and the financial shock.

P_R is subject to identifying restrictions that are discussed in the following. To isolate the finance-uncertainty bloc as a whole from the latent variables F_t , I initially assume a recursive chain. Hence, the EBP can react to the latent factors on impact but not vice versa, a scheme that mimics Bernanke et al. (2005) and Forni and Gam-

¹The indicators in the finance-uncertainty bloc are mean adjusted for the purpose of estimation. The series in X_t are additionally standardized.

betti (2010). By setting uncertainty below the latent factors I follow Popescu and Smets (2010) and Jurado et al. (2015), relying on the assumption that uncertainty shocks should not affect the business cycle on impact because of various information or decision lags.

2.2. The penalty function approach

The isolation of financial shocks *from* uncertainty shocks is a key issue of my contribution and therefore deserves special attention. I refrain from using contemporaneous zero restrictions since the EBP and the uncertainty proxy are assumed to react to each other on impact. I instead employ the penalty function approach (PFA) proposed by Uhlig (2005) and Caldara et al. (2016), which leaves the mutual impact responses of the EBP and the uncertainty proxy unrestricted. In brief, the PFA selects a structural (FA)VAR shock that maximizes a criterion function subject to inequality constraints. Uhlig (2005), for example, isolates a monetary policy shock by maximizing the shock’s contribution to the forecast error variance of the federal funds rate².

In this paper, the criterion function consists of the sum of impulse response functions (IRFs) of selected variables from horizon 0 to horizon h , while the inequality constraints correspond to sign restrictions on these IRFs³. Using this design of the PFA, I choose two different identification schemes. The “EBP-max” scheme defines the financial shock as the one which maximizes the cumulative IRF of the EBP. I call it the “large” financial shock because it has a maximal effect on the EBP. The “UN-max” scheme defines the uncertainty shock as the one which maximizes the cumulative IRF of the uncertainty proxy. I call it the “large” uncertainty shock.

Apart from the large versions, the PFA also defines “small” editions of both shocks. They arise from the fact that after controlling for the factors in the FAVAR, the uncertainty proxy and the EBP are still positively correlated. Hence, in the EBP-max scheme the (large) financial shock is associated with a rise in the uncertainty proxy. The uncertainty shock, in turn, is the residual component of uncertainty that

²My version of the PFA and that of Caldara et al. (2016) slightly differs from that of Uhlig (2005). Instead of maximizing the forecast error variance of a target variable in response to a specific structural shock, I maximize the cumulative IRF. This approach has the advantage that it prevents the target variable from switching signs over the forecast horizon.

³This design of the PFA is a generalization of the Cholesky identification since it collapses to Cholesky if the IRF horizon is zero. Moreover, the PFA implies that depending on the chosen IRF horizon, contractionary financial and uncertainty shocks induce a prolonged period of elevated financial stress and uncertainty, respectively. I follow Caldara et al. (2016) in choosing $h = 6$ months. However, the robustness checks in Appendix A show that other horizons yield similar results.

is not explained by the EBP under this identification. As a result, it turns out small in size. The analogous definition applies to the UN-max scheme: since the large uncertainty shock is inflated with financial components, the financial shock arises from the residual part of the EBP that is not explained by the uncertainty proxy, and is thus small.

I implement the PFA by means of a two-dimensional Given's rotation matrix Q for which holds $Q'Q = Q^{-1}Q = I$. First, I compute the Cholesky decomposition of the estimated residual covariance matrix $\hat{\Sigma}$. Using the definition

$$P_R = \text{chol}(\Sigma_R) \begin{pmatrix} I_m & \mathbf{0}_{m \times 2} \\ \mathbf{0}_{2 \times m} & Q \end{pmatrix},$$

I then rotate the lower-right 2×2 submatrix of the Cholesky factor such that it maximizes the h -step cumulative IRF of either the uncertainty proxy or the EBP in response to their own shock, which gives P_R .

2.3. Identification bounds

The PFA provides identification bounds on the effects of financial and uncertainty shocks on macroeconomic variables. Since the large versions of both shocks induce a more substantial reduction in real activity and asset prices than the small versions, they will always yield the lower bound in the IRFs. The small shocks accordingly generate the upper bound. Hence, the PFA proposes a corridor for the possible effects of financial and uncertainty shocks. This corridor is interesting from an agnostic point of view since it reflects different perspectives of the literature. On the one hand, theories and findings emphasizing uncertainty shocks as driving forces of the business cycle and financial conditions (Alessandri and Mumtaz (2018), Bloom (2009), Christiano et al. (2014)) are mirrored by the UN-max scheme, hence the lower bound of uncertainty shocks and the upper bound of financial shocks. On the other hand, views emphasizing the endogeneity of uncertainty to other shocks rather than its exogeneity (Ludvigson et al. (2015), Popescu and Smets (2010) and Carriero et al. (2018)) are echoed by the EBP-max scheme, hence the upper bound of uncertainty shocks and the lower bound of financial shocks.

A further feature of the identification bounds is that they indicate transmission channels of uncertainty and financial shocks. Uncertainty shocks, for instance, act through the presence of real frictions on the labor and investment market (Bloom (2009) and Bachmann and Bayer (2013)). More specifically, when investment decisions are irreversible, entrepreneurs respond to an adverse uncertainty shock by deferring real capital expenditures or recruiting and wait until prospects become

clearer. This narrative applies to both identification schemes since each version of the uncertainty shock by definition induces an increase in uncertainty. However, an uncertainty shock arising from the UN-max scheme possibly also produces a rise in the EBP that is explained by uncertainty. It thus raises the risk premia in external finance, resulting in a further decline in spending. This mechanism underlies the financial view of uncertainty shocks discussed by Alessandri and Mumtaz (2018) and Christiano et al. (2014).

Financial shocks can be considered analogously. In general, they increase the EBP and thus the cost of external financing, leading to a contraction in real activity and a decline in asset prices. In the EBP-max scheme, however, they possibly also induce a rise in uncertainty and therefore intensify the overall effects, approximated by the lower bound. Firms might be uncertain about how severely financial shocks spill over to real activity, and by which degree monetary and fiscal authorities act to mitigate adverse effects. Baker et al. (2016), for example, document that economic policy uncertainty increases during times of financial turmoil and that economic policy uncertainty, in turn, has notable real effects. As a result, firms withhold their activities until the conditions are better predictable, leading to a further contraction in real activity⁴.

3. Estimation

The estimation of the (reduced-form) FAVAR (equations (1) and (2)) is Bayesian, and I implement it using a Gibbs sampling routine⁵. Since I measure uncertainty by three different proxies, I also estimate the FAVAR three times. Each time the FAVAR incorporates the EBP and one of the three uncertainty proxies as observable variables. The estimation settings are otherwise identical. I describe the uncertainty proxies in section 4.

Before I start the estimation, I split the observations into a recession and a boom subsample according to the chronology of the NBER. The sequence of regimes is presented in Figure C.6. Since I carry out the Gibbs sampling steps for each regime separately using only its specific observations, I omit the regime subindex R in the following.

⁴The evidence on this issue is still scant since the relevant evidence does not distinguish between regime-specific dynamics. Caldara et al. (2016) admittedly find that the transmission is negligible, but they base their conclusions on constant-parameter VARs.

⁵In the baseline estimation setup, the number of lags in the VAR part and the number of latent factors are set to $p = 6$ months and $m = 4$, respectively. As the robustness checks in Appendix A show, however, other choices of p and m do not affect my conclusions.

The sampling of the observation equation coefficients Λ_i and ω_i^2 is conducted for each $X_{i,t}$ separately, i.e., equation-wise. The priors are (independent) Normal and inverse-Gamma, respectively. The prior of the VAR parameters B and Σ is normal inverse-Wishart. Further details on the priors and hyperparameters can be found in Appendix D.

Given the two subsamples and the priors, the Gibbs sampling steps are the following:

1. I sample from the conditional posterior distributions of the coefficients Λ_i and ω_i^2 of the observation equation (1). The sampling distributions are given by

$$\Lambda_i|X_i, \omega_i^2 \sim N(\bar{\Lambda}_i, \bar{\Sigma}_{\Lambda_i}), \quad \omega_i^2|X_i, \Lambda_i \sim IG(\bar{\theta}_i, \bar{\phi})$$

2. I sample from the conditional posterior distributions of the coefficients B and Σ of the transition equation (2), i.e., the VAR part. They are given by

$$\text{vec}(B)|Y, \Sigma \sim N(\text{vec}(\bar{B}), \bar{\Sigma}_B), \quad \Sigma|Y, B \sim IW(\bar{S}, \bar{\alpha})$$

3. I run the Kalman filter and then the Carter-Kohn algorithm to find the factors F_t . The filtering is conditional on the regime-specific estimates of Λ , Ω , B and Σ . Hence, it switches from the recession regime to the boom regime and back.

To ensure convergence, I repeat these steps 10,000 times from which I discard the first 5,000 repetitions. Details on the derivation of conditional posteriors of the observation and transition equation can be found in Appendix D.

4. Data

The vector X_t contains 101 key macroeconomic and financial variables for the United States at monthly frequency and over the period 1975:m1-2016:m8. This time window contains $T = 500$ observations from which 61 are NBER recessions. The selection of series is orientated at the dataset by Forni and Gambetti (2010) and a list of them is presented in Table C.6.

As financial indicator I take the excess bond premium (EBP) introduced by Gilchrist and Zakrajšek (2012). The authors construct a credit spread index based on a comprehensive data set of prices of corporate bonds trading in the secondary market. Then they decompose the index into a component explained by the available firm-specific information on expected defaults and a residual, which is the excess bond premium (EBP). The EBP approximates the *pricing* of default risk and thus

the investors’ sentiment or risk appetite in the corporate bond market. The authors show that an increase in the EBP reflects a lower capacity or willingness to bear risk in the financial sector and, consequently, a reduction in the supply of credit.

Since uncertainty is a wide concept and hard to measure, I use three different indicators as proxies. I rely on the uncertainty measure proposed by Jurado et al. (2015) to measure macroeconomic uncertainty, and I call it the “JLN” measure in the following. It is based on the unpredictable component of a broad set of macroeconomic and financial variables⁶.

To highlight the role of financial uncertainty, I use the VXO index from Bloom (2009), which I call the “Bloom” measure hereafter. For the period from January 1986 onward, this index corresponds to the implied volatility of S&P100 options 30 days to expiration. For the Pre-1986 period I follow Bloom (2009) in using realized stock return volatility⁷, measured by monthly standard deviations of the S&P500.

As a proxy for economic policy uncertainty I use the newspaper-based economic policy uncertainty index by Baker et al. (2016), which I call the “BBD” measure in the following. This index rests upon the frequency of newspaper references to policy-related economic uncertainty.

The transformations of the series in X_t are broken down for each series in Table C.6. To prevent the data from being driven by large outliers, I trim those observations which are further than five times the interquartile range away from their median to the respective threshold. Since I extract factors, I standardize them to obtain a zero mean and a variance of one. Series which exhibit a seasonal pattern are seasonally adjusted. All series are taken from the webpage of the Federal Reserve Bank of St. Louis.

5. Results

I base my conclusions on state-dependent impulse responses of real activity indicators and asset prices to uncertainty and financial shocks and forecast error variance decompositions. I rely on three estimated versions of the FAVAR, each of which includes one of the three uncertainty proxies. Moreover, I present the results from the

⁶The proxy is constructed by aggregating the conditional volatility of the unpredictable component of a h -step ahead realization of each macroeconomic time series. I choose $h = 1$ (month) in my analysis, but since the horizons $h = 3$ and $h = 12$ yield similar results this choice is not relevant.

⁷For the pre-1986 period the VXO index is unavailable, so Bloom (2009) takes the monthly standard deviation of the daily S&P500 index normalized to the same mean and variance as the VXO index when they overlap from 1986 onward.

EBP-max and the UN-max identification of the PFA jointly in one figure or table, hence the differences can be interpreted as identification bounds.

5.1. Cross-effects of uncertainty and financial shocks

Figure 1 shows the IRFs of the EBP and the uncertainty proxies to a financial and an uncertainty shock. The solid graphs result from the EBP-max scheme and thus depict the effects of the large financial and the small uncertainty shock. The dashed graphs result from the UN-max scheme and accordingly represent the effects of the large uncertainty shock and the small financial shock.

I adjust the magnitude of both shocks to obtain a predetermined response of the uncertainty proxies and the EBP. In particular, I scale the large uncertainty shock such that the corresponding uncertainty proxy jumps on impact by one regime-specific standard deviation. I adjust the size of the small uncertainty shock proportionally. I repeat this procedure for the financial shock: its large version raises the EBP by one regime-specific standard deviation, and the size of the small version adapts proportionally.

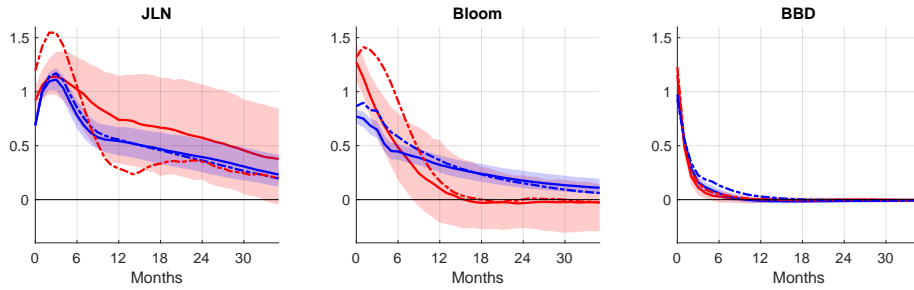
As the panels a) and c) show, financial and uncertainty shocks induce a persistent rise in their respective indicators, as defined by the identifying assumptions in the PFA. Moreover, except for the hump-shaped reaction of the JLN measure all effects peak on impact. The differences between the small and large shock versions are generally significant but slightly larger in terms of the uncertainty shocks.

The panels b) and d) show the cross-effects, i.e., the reactions of the uncertainty proxies to the financial shock and that of the EBP to the uncertainty shock. We see that in general, the cross-effects are larger in recessions and have slightly wider identification bounds than in boom periods. Moreover, they are considerably smaller when the shocks result as a residual component from the PFA. In the UN-max scheme, the EBP jumps on impact by up to 2.5 standard deviations in response to an uncertainty shock, a result which confirms the transmitting role of credit conditions (e.g., Christiano et al. (2014) and Alessandri and Mumtaz (2018)). In the EBP-max scheme, however, only shocks to the JLN measure have a positive and significant impact on the EBP. Financial shocks exhibit cross-effects that are slightly different from those of uncertainty shocks. They increase all three uncertainty measures, at least in the EBP-max scheme. However, the effect magnitudes are smaller than those of uncertainty shocks on the EBP, and the identification bounds are slightly tighter.

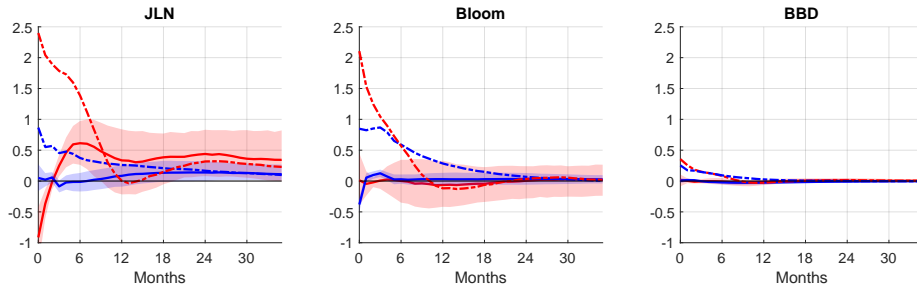
These findings imply three conclusions: first, the optimization setup in the PFA and thus identifying assumptions play a pivotal role for uncertainty shocks. By comparison, financial shocks exhibit a slightly better identifiability. Second, large

Figure 1: Cross-effects of uncertainty and financial shocks

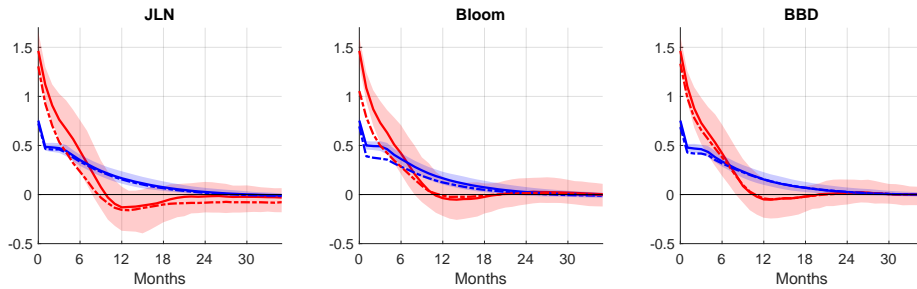
(a) Response of uncertainty to an uncertainty shock



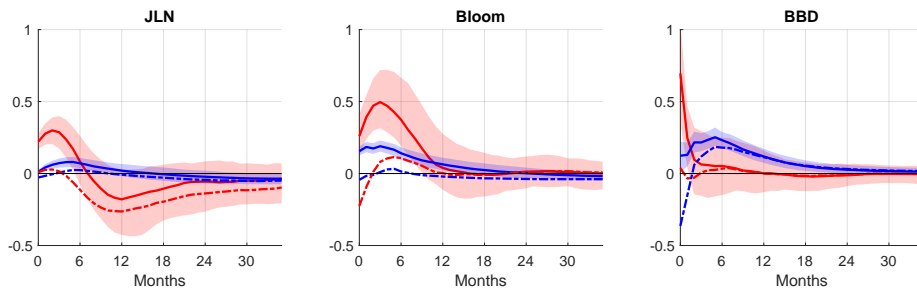
(b) Response of the EBP to an uncertainty shock



(c) Response of the EBP to a financial shock



(d) Response of uncertainty to a financial shock



Notes: The panels show regime-specific impulse response functions (IRFs) of the uncertainty proxies and the EBP to a contractionary uncertainty shock and a financial shock. The units on the y-axis are standard deviations of the responding variables. The red graphs depict the IRFs in the recession regime and the blue graphs those in the boom regime. The solid and dashed graphs are median IRFs resulting from the EBP-max and the UN-max identification, respectively. The shaded areas are 68 percent confidence intervals on the IRFs of the EBP-max identification. The shock magnitudes are adjusted such that the large uncertainty (financial) shock induces a rise in the corresponding uncertainty proxy (EBP) by one regime-specific standard deviation.

uncertainty shocks are associated with a considerable tightening in credit conditions, while large financial shocks only induce a moderate increase in the uncertainty indicators. The small versions of both shocks generally have limited cross-effects. Third, the choice of the identification scheme plays a greater role in the recession regime.

5.2. Macroeconomic implications of uncertainty shocks

Figure 2 shows the IRFs of the percentage 3-month growth rates of industrial production, employment, stock prices, and house prices to an adverse uncertainty shock.

The IRFs confirm the contractionary character of uncertainty shocks and are comparable in size to what the related literature has found⁸. The impact on the economic indicators are larger in recessions than in boom periods and hence state-dependent, albeit depending on the chosen uncertainty measures to a different degree. Shocks to the JLN measure reduce industrial production growth by up to 1.5 percent in recessions but have insignificant effects in boom periods⁹. In contrast, the effects of BBD shocks exhibit a considerably milder state-dependence. Interestingly, house prices fall during recessions but tend to increase in booms, a result that might arise from a flight-to-safety mechanism (Brogaard and Detzel (2015)).

The IRFs of all uncertainty proxies exhibit sizeable identification bounds, especially in recessions and in terms of the effects on asset prices. Whereas a shock to the Bloom measure reduces stock returns by up to 15 percent in the UN-max scheme, it has insignificant effects in the EBP-max scheme. Hence, the identification entirely accounts for the state-dependence in this case. The bounds on the real activity indicators tend to be tighter than those on asset prices. If we consider shocks to the JLN measure, the EBP-max identification yields real effects that amount to about 50 percent of those in the UN-max scheme, which implies that small uncertainty shocks are likewise contractionary. Taking this result together with the limited impact of small uncertainty shocks on credit conditions discussed in section 5.2, I conclude that financial conditions play an essential role in transmitting uncertainty shocks, but real option effects are also at work.

⁸The effects of uncertainty and financial shocks on industrial production and stock prices are comparable to those of Caldara et al. (2016) and Gilchrist and Zakrajšek (2012).

⁹This finding draws a picture of the role of uncertainty which is more differentiated than what other empirical works have found so far. Jurado et al. (2015), for example, show in a constant-parameter VAR that uncertainty has an adverse and considerable impact on real activity. My findings, however, indicate that the observations in the recession regime are primarily relevant in this proposition.

To account for the relative importance of uncertainty shocks for the considered indicators, I compute variance decompositions after 24 months¹⁰, displayed in Table 1. The variance decompositions confirm the findings from the impulse response analysis. In general, uncertainty shocks are of limited importance in boom periods but account for significant variance shares in recessions. We also observe that the higher relevance of uncertainty shocks in recessions comes along with broader identification bounds. The limits often include variance shares close to zero, only the JLN measure also exhibits positive shares in the EBP-max specification.

The variance shares differ most between the identification schemes if we consider shocks to the Bloom measure. On the one hand, this result could reflect spillover effects from financial volatility shocks to the EBP, which then translate into reactions of real indicators and asset prices. On the other hand, it may also reflect the difficulty of distinguishing between first and second-moment financial shocks. Accordingly, Stock and Watson (2012) find in their analysis of the channels of the Great Recession that credit spreads and proxies for financial uncertainty do not identify distinct shocks.

Another striking result is the limited relevance of shocks to the BBD measure, to which only stock returns react. This result contrasts that of Baker et al. (2016), who find in a classical VAR that an adverse economic policy uncertainty shock reduces industrial production and employment to a moderate but significant degree. There are multiple reasons for this difference, but one is presumably due to the conditioning of the uncertainty shock on the EBP¹¹.

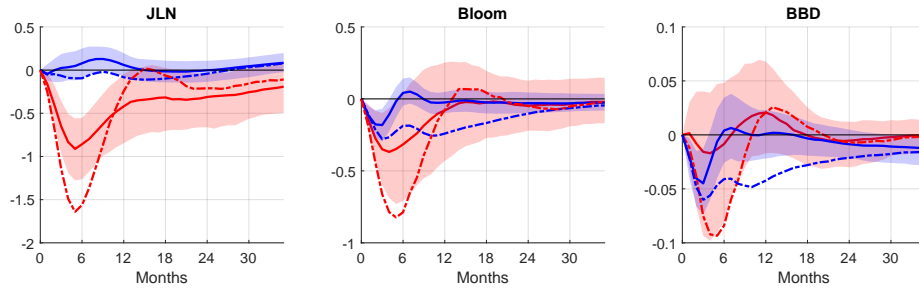
As a result, I rely on the JLN measure of macroeconomic uncertainty for the remainder of this paper. I base this choice not only on the identification issues of the Bloom index and the limited relevance of the BBD measure but also on the result by Caldara et al. (2016) that the JLN measure gives economic uncertainty the maximum role in explaining business cycle fluctuations out of a set of uncertainty

¹⁰I omitted variance decompositions at different horizons to save space and since different horizon choices do not change my conclusions.

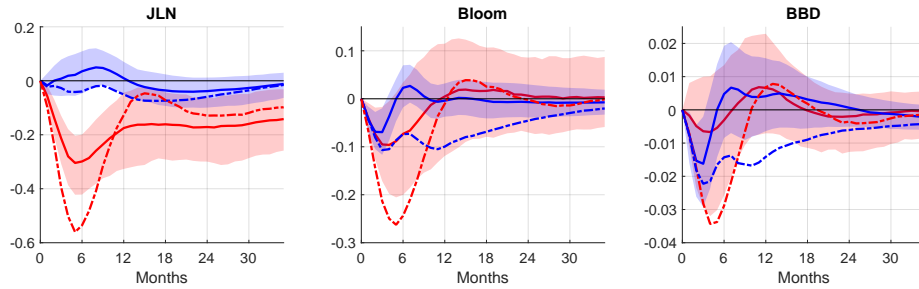
¹¹Baker et al. (2016) find that a shock of two standard deviations in the BBD index lowers industrial production by 1.1 percent and employment by about 0.35 percent nine months after the shock. Under the UN-max setup, I find slightly smaller corresponding effects, namely between 0.27 percent (recessions) and 0.31 percent (boom periods) on industrial production and between 0.1 percent (recessions) and 0.12 percent (boom periods) on employment. Apart from the conditioning on financial stress, the Bayesian approach estimation setup might also play a role for the different results since the mean parameters are shrunk towards zero. Moreover, Baker et al. (2016) order uncertainty first in a Cholesky identification, implying that uncertainty shocks potentially contain business cycle dynamics.

Figure 2: Macroeconomic effects of an uncertainty shock

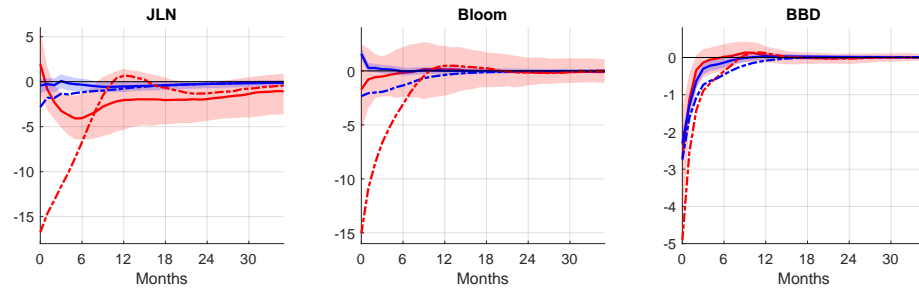
(a) Industrial production growth



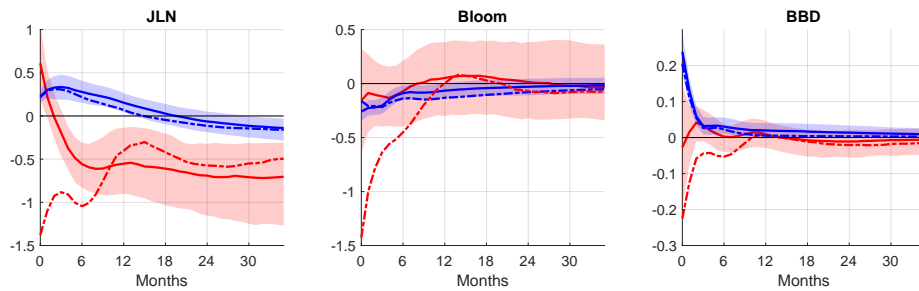
(b) Employment growth



(c) Stock returns



(d) House price inflation



Notes: The panels show regime-specific impulse response functions (IRFs) of the percentage 3-month growth rates of industrial production, employment, stock prices and house prices to a contractionary shock to uncertainty. The red graphs depict the IRFs in the recession regime and the blue graphs those in the boom regime. The solid and dashed graphs are median IRFs resulting from the EBP-max and the UN-max identification, respectively. The shaded areas are 68 percent confidence intervals on the IRFs of the EBP-max identification. The shock magnitudes are adjusted such that the large uncertainty shock induces a rise in the corresponding uncertainty proxy by one regime-specific standard deviation.

Table 1: Forecast error variance decomposition - Uncertainty shock

Variable \ Identification +Regime	Recessions		Booms	
	EBP-max	UN-max	EBP-max	UN-max
Uncertainty measure: JLN				
Industrial production growth	5.3	10.8	0.2	0.7
Employment growth	7.7	14.1	0.8	1.9
Stock returns	1.1	11.4	0.2	1.0
House price inflation	3.8	7.8	0.8	0.7
Uncertainty measure: Bloom				
Industrial production growth	1.5	5.1	0.1	1.6
Employment growth	1.6	6.2	0.2	2.0
Stock returns	4.8	20.4	2.8	8.4
House price inflation	0.3	4.9	0.2	0.1
Uncertainty measure: BBD				
Industrial production growth	0.2	1.1	0.3	1.4
Employment growth	0.2	1.5	0.5	1.3
Stock returns	2.9	10.8	7.7	13.4
House price inflation	0.1	1.6	2.7	1.9

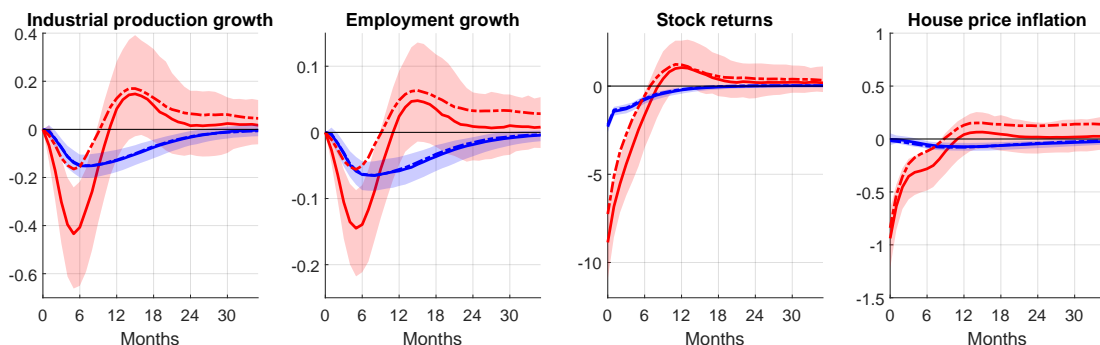
Notes: The table shows the percentage shares of the forecast error variance of key macroeconomic variables accounted for by an uncertainty shock. The forecast horizon is set to 24 months.

measures, including those I use¹².

5.3. Macroeconomic implications of financial shocks

Figure 3 displays the IRFs of the real activity and asset price indicators to an adverse financial shock using the JLN measure of uncertainty in the FAVAR. As in the case of uncertainty shocks, financial shocks are contractionary and state-dependent. The effects are more significant in recessions than in boom periods, especially if we consider asset returns. Stock returns, for example, fall by up to nine percent on

Figure 3: Macroeconomic effects of a financial shock



Notes: The panels show regime-specific impulse response functions (IRFs) of the percentage 3-month growth rates of industrial production, employment, stock prices and house prices to a contractionary financial shock and using the JLN measure of uncertainty. The red graphs depict the IRFs in the recession regime and the blue graphs those in the boom regime. The solid and dashed graphs are median IRFs resulting from the EBP-max and the UN-max identification, respectively. The shaded areas are 68 percent confidence intervals on the IRFs of the EBP-max identification. The shock magnitudes are adjusted such that the large financial shock induces a rise in the EBP by one regime-specific standard deviation.

impact during recessions but only by two percent in boom periods. The real activity measures moreover exhibit state-specific dynamic patterns. Whereas industrial production growth falls by 0.2 percent after six months and remains negative in boom periods, it falls by up to 0.4 percent in recessions, recovers within ten months and overshoots. The overshoot, however, is not statistically significant.

The IRFs are more robust to the identification than those in response to uncertainty shocks. The dashed and solid graphs significantly differ only in the recession state and for the real activity indicators. In this case, however, the difference is sizeable since the real effect in the EBP-max scheme amounts to about twice the effect in the UN-max scheme¹³.

¹²For the sake of completeness and to review the robustness of the baseline results, I show the IRFs and variance shares of the financial shock using the other two uncertainty measures in Figure B.5 and Table B.5.

¹³This finding hinges on the chosen uncertainty measure. As Figure B.5 and Table B.5 show, if I choose the BBD measure the identification bounds are barely distinguishable even in recessions. Hence, the transmission of financial shocks by economic policy uncertainty is negligible.

Table 2: Forecast error variance decomposition - Financial shock

Variable \ Identification + Regime	Recessions		Booms	
	EBP-max	UN-max	EBP-max	UN-max
Industrial production growth	9.7	4.1	8.0	7.5
Employment growth	12.3	5.9	13.2	11.9
Stock returns	26.1	15.5	9.0	8.2
House price inflation	16.6	12.3	1.1	1.2

Notes: The table shows the percentage shares in the forecast error variance of key macroeconomic variables accounted for by the financial shock and using the JLN measure of uncertainty. The forecast horizon is set to 24 months.

The forecast error variance shares of the financial shock are reported in Table 2. We can see that they are significant in both states of the economy, a finding which contrasts Table 1 on uncertainty shocks. The identification bounds are again of considerable width in recessions. In booms, however, the limits are barely distinguishable, a result that reflects the limited impact of financial shocks on economic uncertainty discussed in section 5.2. Hence, whereas financial shocks only act through a purely financial transmission channel in boom periods, uncertainty noticeably transmits them in recessions. Interestingly, if we consider the UN-max scheme and the real activity indicators, the share of the financial shock is slightly smaller in recessions than in boom periods. At the same time, the shares in the EBP-max scheme are almost identical in both regimes. I conclude from this finding that compared to the boom regime, the financial channel shrinks in favor of the uncertainty channel in recessions.

To the best of my knowledge, this result reveals a property of financial shocks that the existing evidence still lacks. Most contributions in this field rely on constant-parameter models and consequently do not allow for different regimes of economic stress, for example Caldara et al. (2013) or Popescu and Smets (2010). Since the number of stressful periods is usually small compared to the total number of observations (61 recession periods vs. 439 boom periods in this paper), their conclusions are congruent with mine during boom periods, which is that uncertainty plays a negligible role in transmitting financial shocks.

5.4. Impacts on sectoral employment

To further exploit the cross-sectional dimension of the FAVAR framework, I analyze the relevance of uncertainty and financial shocks for several real activity dis-

aggregates. Table 3 shows the shares of both shocks in the forecast error variance of sectoral employment growth. In general, the considered employment indicators

Table 3: Forecast error variance decomposition - Sectoral employment growth

Sector	Identification +Regime	Recessions		Booms	
		EBP-max	UN-max	EBP-max	UN-max
Uncertainty shocks					
Total		7.7	14.1	0.8	1.9
Manufacturing		5.5	11.7	0.1	0.7
Construction		6.7	6.8	0.7	1.3
Total Private Industries		8.6	15.6	0.5	1.6
Government		0.1	0.1	0.3	0.4
Retail Trade		6.2	10.2	0.2	0.7
Wholesale Trade		7.3	13.1	0.3	1.0
Financial Activities		12.4	13.7	0.4	0.7
Mining and Logging		0.4	0.8	0.1	0.1
Durable Goods		5.4	10.8	0.2	0.7
Nondurable goods		4.0	9.5	0.0	0.2
Goods-Producing Industries		7.7	13.0	0.4	1.2
Service-Providing Industries		7.8	13.7	0.7	1.6
Trade, Transportation and Utilities		8.1	14.7	0.4	1.2
Financial shocks					
Total		12.3	5.9	13.2	11.9
Manufacturing		10.9	4.6	10.0	9.4
Construction		4.2	4.0	4.7	4.1
Total Private Industries		13.5	6.4	11.2	10.1
Government		0.3	0.2	0.2	0.1
Retail Trade		7.7	3.7	5.0	4.5
Wholesale Trade		10.8	4.9	7.8	7.0
Financial Activities		6.8	5.4	1.7	1.4
Mining and Logging		0.7	0.3	1.1	1.1
Durable Goods		9.8	4.4	9.5	8.8
Nondurable goods		9.0	3.5	4.3	4.2
Goods-Producing Industries		10.9	5.5	10.6	9.8
Service-Providing Industries		11.5	5.6	7.0	6.1
Trade, Transportation and Utilities		12.0	5.4	8.0	7.2

Notes: The table shows the percentage shares of the forecast error variance of sectoral employment growth accounted for by a JLN uncertainty shock and a financial shock. The forecast horizon is set to 24 months.

confirm the conclusions of the sections 5.2 and 5.3. Whereas uncertainty shocks account for significant variance shares mainly in recessions, financial shocks are relevant in both regimes. Moreover, financial shocks identified by the UN-max scheme are slightly more important in booms than in recessions.

However, the relevance of both shocks differs across sectors. Uncertainty shocks are relatively important for the employment fluctuations in the private sector, especially financial activities, trade, manufacturing, the goods producing sector, and the service sector. The shares in the EBP-max scheme amount to about 50 percent the shares in the UN-max in most sectors, which again reflects a lack of identification robustness of uncertainty shocks. Interestingly, employment in the financial industries exhibit very tight bounds and are thus significantly affected.

The picture is similar if we look at financial shocks. Again, the private sector is generally affected, but especially trade, manufacturing, the goods producing sector, and the service sector. Compared to uncertainty shocks, financial industries take a lower position in the ranking. Overall, the government and mining sector is entirely unaffected by both shocks.

The low weight of the financial shocks in the fluctuations of financial activities is puzzling at first sight but results from the fact that the EBP only contains bond prices of non-financial firms. Moreover, Prassas (2011) shows that historically, employment in financial activities has been affected little by economic downturns, thus times in which the EBP is typically high. The only exception was the period around the Great Recession of 2008/09 when housing-related financial industries lost 348,000 jobs.

6. Conclusions

I analyze the effects of uncertainty and financial shocks based on a state-dependent FAVAR and U.S. data from 1975 to 2016. The FAVAR allows for a recession and a boom regime and includes a comprehensive set of macroeconomic and financial variables, different proxies for uncertainty, and a financial stress indicator. To identify financial and uncertainty shocks I employ the penalty function approach proposed by Uhlig (2005), which enables the construction of identification bounds. The bounds consider both shocks jointly and provide a corridor for their effects on macroeconomic indicators. They are agnostic since they unite different views on financial and uncertainty shocks in one framework and thus also refer to different implicit transmission mechanisms.

The empirical results document that uncertainty shocks have highly state-dependent effects on real activity and asset prices. Whereas adverse uncertainty shocks are generally of limited relevance in boom periods, they have a contractionary and noticeable impact in recessions. By contrast, adverse financial shocks significantly lower real activity and asset prices in both regimes.

However, identifying assumptions play a crucial role. In general, the identification bounds are wider in recessions than in boom periods and tighter after financial shocks than after uncertainty shocks. The degree of identifiability differs most between both shocks when we consider the impact on asset prices. In this case, the bounds play a subordinate role in the impact of financial shocks. Those of uncertainty shocks, however, include considerable as well as negligible effects. Finally, the results emphasize the key role of financial conditions for understanding uncertainty shocks and show that the transmission of financial shocks through uncertainty is limited to recessions.

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Appendix A. Robustness checks

As customary in empirical papers, I perform several sensitivity checks to strengthen the credibility of my results. I re-estimate the FAVAR using a range of alternative settings in which I depart from a single property of the baseline setup while leaving all others unchanged. Figure A.4 and Table A.4 show the resulting IRFs and variance decompositions of industrial production growth after a shock to the JLN measure of uncertainty and a financial shock alongside the baseline results.

First, I check if the lag order in the FAVAR drives my results. In the baseline setup of the FAVAR, I use six months since this choice has been considered as optimal in various business cycle VARs, e.g., Eickmeier (2010). However, to account for potential serial correlation in the disturbance term U_t and since other applications such as Bachmann et al. (2013) consider a lag order of 12 months as optimal, I re-estimate the FAVAR with 12 lags. As Table A.4 shows, this alternative specification yields similar results as the baseline, which is why I keep the more parsimonious one with six lags.

I also test if a higher number of factors plays a role in my conclusions. In the baseline setup, I set it to four in order to capture 78 percent of the variance in X_t . Since a fifth factor accounts for another six percent, I check its relevance in a further estimation that allows for five latent factors. This alternative setting admittedly yields slightly smaller shares of financial shocks in boom periods. However, the remaining results are relatively robust, and since my main conclusions are not affected I keep the baseline setup with four factors.

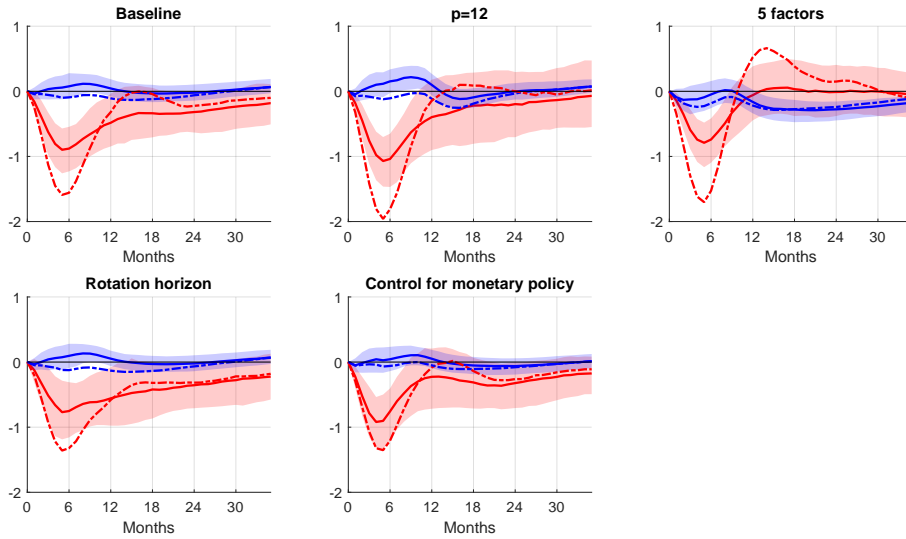
The IRF horizon in the PFA is an ingredient of my shock identification and thus another potential determinant of my results. In the baseline setup, I follow Caldara et al. (2016) in choosing six months since the authors find this horizon optimal for identifying uncertainty and financial shocks in a constant-parameter VAR. To check if this choice drives my results, I re-run the PFA using twelve months as identification horizon. It turns out, however, that the IRF horizon does not play a significant role in my conclusions.

Finally, I include the federal funds rate (FFR) as observable variable into the finance-uncertainty bloc of the FAVAR to control for the stance of monetary policy¹⁴. I place the FFR at the bottom of the FAVAR, so I treat it as the most fast-moving

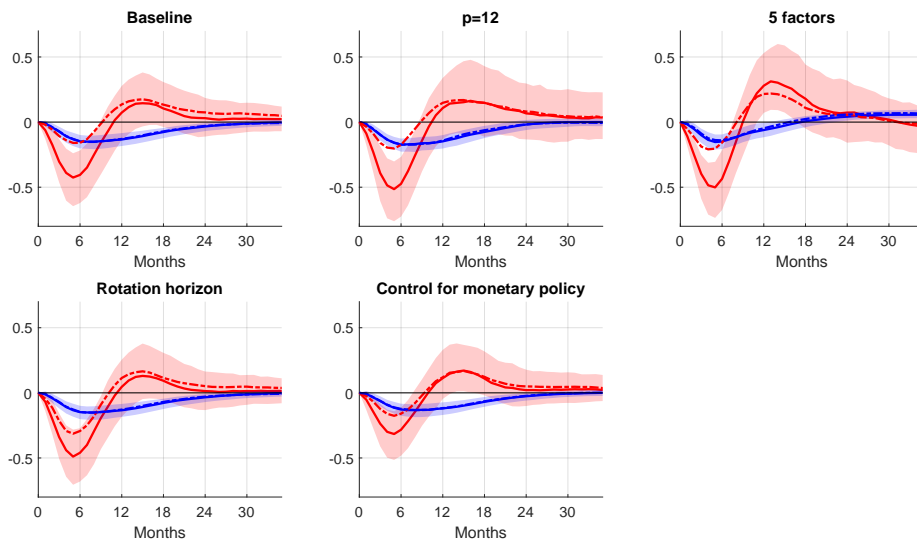
¹⁴Since the FFR fell to its zero lower bound during and after the Great Recession, namely from december 2008 until november 2015, I replace this period by the shadow short rates proposed by Krippner (2015).

Figure A.4: Robustness checks

(a) Uncertainty shock



(b) Financial shock



Notes: The panels show regime-specific impulse response functions (IRFs) of the percentage 3-month growth rates of industrial production, employment, stock prices and house prices to a contractionary financial shock. The red graphs depict the IRFs in the recession regime and the blue graphs those in the boom regime. The solid and dashed graphs are median IRFs resulting from the EBP-max and the UN-max identification, respectively. The shaded areas are 68 percent confidence intervals on the IRFs of the EBP-max identification. The shock magnitudes are adjusted such that the large uncertainty (financial) shock induces a rise in the corresponding uncertainty measure (EBP) by one regime-specific standard deviation.

variable in the finance-uncertainty bloc (see, e.g. Prieto et al. (2016)). Again, this alternative setup does not significantly alter my results, and my conclusions remain valid.

Table A.4: Robustness checks

Variable	Identification +Regime	Recessions		Booms	
		EBP-max	UN-max	EBP-max	UN-max
Uncertainty shocks					
Baseline		5.3	10.8	0.2	0.7
12 lags		3.8	10.5	0.3	0.6
Number of factors		2.4	11.6	0.7	0.8
Rotation horizon		4.3	8.2	0.6	2.3
Control for monetary policy		4.2	7.0	0.1	0.1
Financial shocks					
Baseline		9.7	4.1	8.0	7.5
12 lags		10.4	3.4	6.9	6.6
Number of factors		14.7	5.4	3.0	2.9
Rotation horizon		11.0	6.3	9.4	7.8
Control for monetary policy		8.5	5.4	5.4	5.3

Notes: The table shows the percentage shares of the forecast error variance of industrial production growth accounted for by a JLN uncertainty shock and a financial shock. The forecast horizon is set to 24 months.

Appendix B. Further results

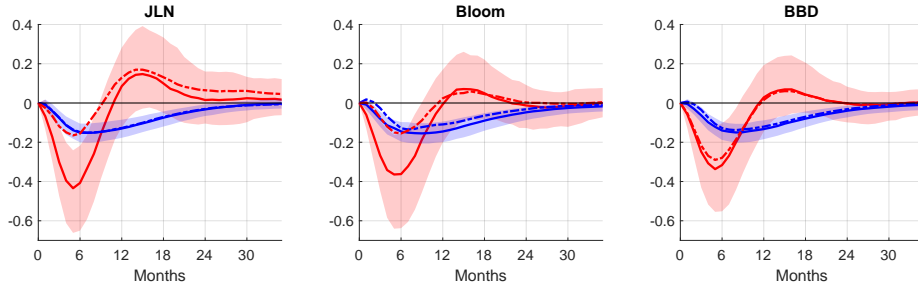
Table B.5: Forecast error variance decomposition - Financial shock

Variable \ Identification +Regime	Recessions		Booms	
	EBP-max	UN-max	EBP-max	UN-max
Uncertainty measure: JLN				
Industrial production growth	9.7	4.1	8.0	7.5
Employment growth	12.3	5.9	13.2	11.9
Stock returns	26.1	15.5	9.0	8.2
House price inflation	16.6	12.3	1.1	1.2
Uncertainty measure: Bloom				
Industrial production growth	6.1	2.3	7.2	5.8
Employment growth	8.2	3.4	13.3	11.6
Stock returns	27.8	11.6	9.9	4.5
House price inflation	17.2	12.2	1.0	1.1
Uncertainty measure: BBD				
Industrial production growth	6.3	5.1	4.8	5.3
Employment growth	8.1	6.6	7.4	9.4
Stock returns	28.8	20.5	5.5	5.6
House price inflation	15.8	14.0	0.8	0.9

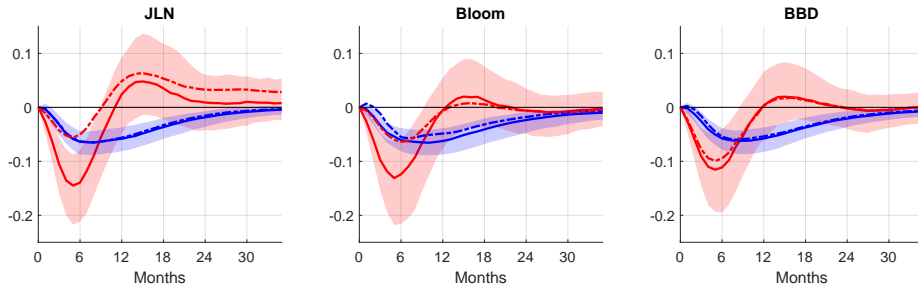
Notes: The table shows the percentage share of the forecast error variance of key macroeconomic variables accounted for by a financial shock. The forecast horizon is set to 24 months.

Figure B.5: Macroeconomic effects of a financial shock

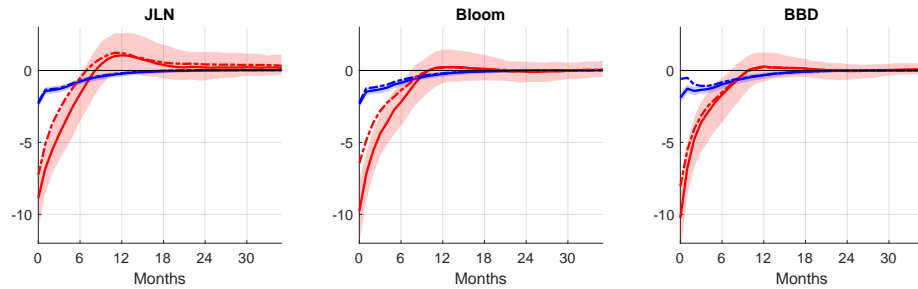
(a) Industrial production growth



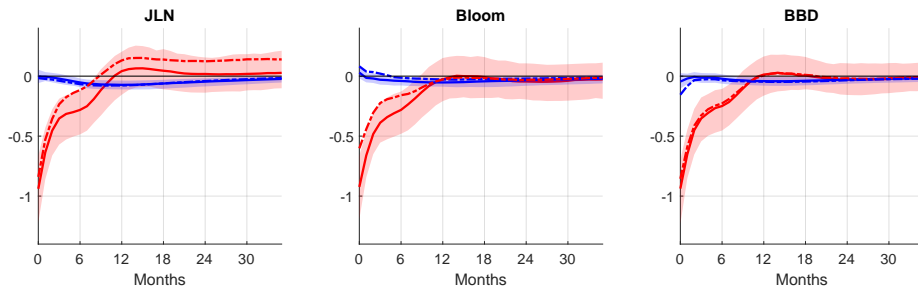
(b) Employment growth



(c) Stock returns



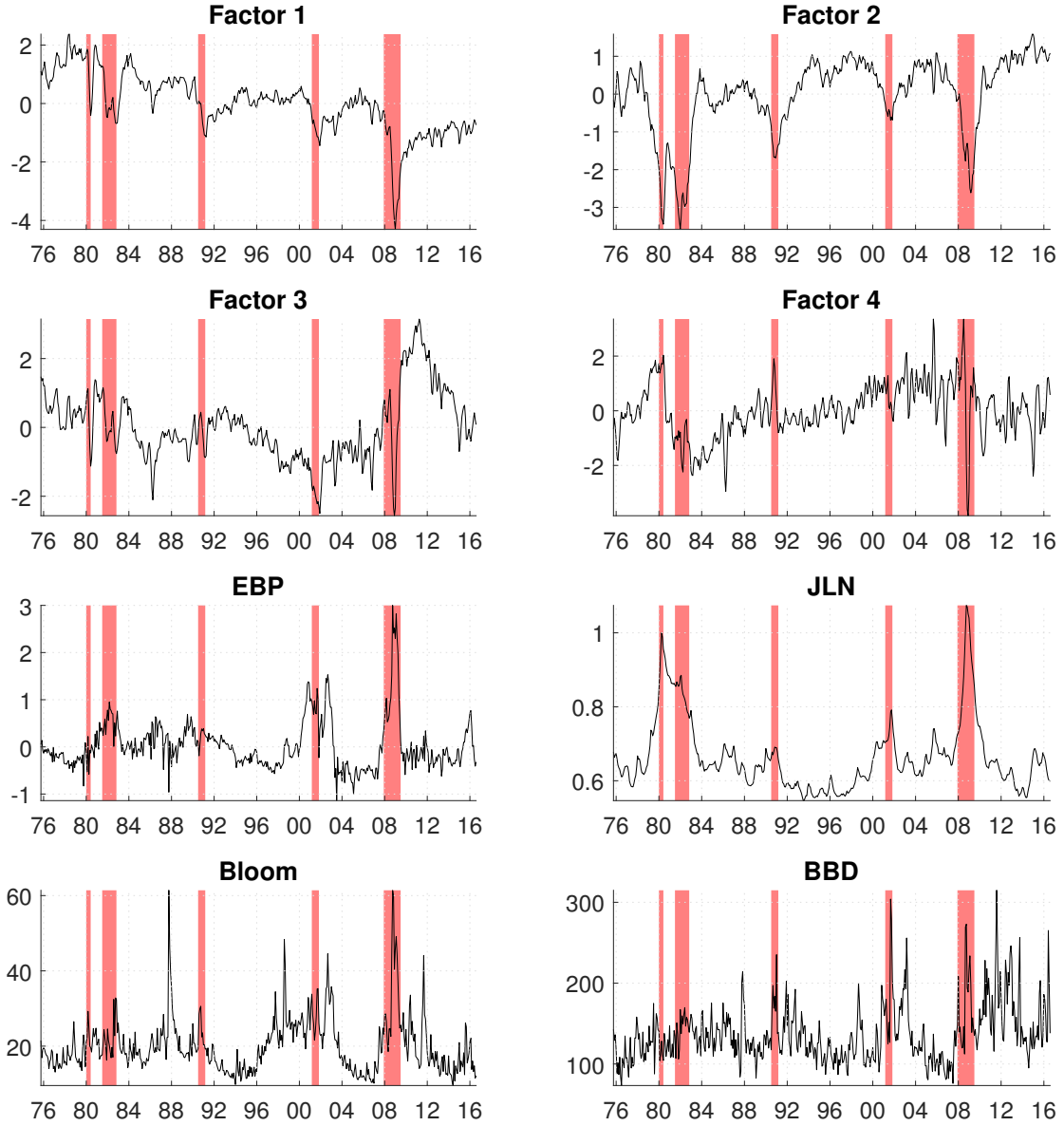
(d) House price inflation



Notes: The panels show regime-specific impulse response functions (IRFs) of the percentage 3-month growth rates of industrial production, employment, stock prices and house prices to a contractionary financial shock. The red graphs depict the IRFs in the recession regime and the blue graphs those in the boom regime. The solid and dashed graphs are median IRFs resulting from the EBP-max and the UN-max identification, respectively. The shaded areas are 68 percent confidence intervals on the IRFs of the EBP-max identification. The shock magnitudes are adjusted such that the large financial shock induces a rise in the EBP by one regime-specific standard deviation.

Appendix C. Data

Figure C.6: Series in Y_t



Notes: The panels show the series in the vector Y_t of the baseline FAVAR, i.e., the estimated factors, the excess bond premium and the JLN uncertainty index. In addition, it shows the Bloom and the BBD uncertainty proxy. The shaded areas depict the NBER recessions. Details of the series are outlined in section 4.

Table C.6: Series in X_t

Variable	Transf.
Real Disposable Personal Income	1
Personal Income	1
Real Personal Consumption Expenditures	1
Industrial Production Index	1
Industrial Production: Consumer Goods	1
Industrial Production: Durable Consumer Goods	1
Industrial Production: Nondurable Consumer Goods	1
Industrial Production: Business Equipment	1
Industrial Production: Final products	1
Industrial Production: Fuels	1
Industrial Production: Residential utilities	1
Industrial Production: Materials	1
Industrial Production: Durable goods materials	1
Industrial Production: Nondurable goods materials	1
Industrial Production: Manufacturing (SIC)	1
Capacity Utilization: Manufacturing (NAICS), Percent of Capacity	0
Civilian Employment Level	1
All Employees: Total Nonfarm Payrolls	1
Number of Civilians Unemployed for 5 to 14 Weeks	1
Number of Civilians Unemployed for 15 Weeks and Over	1
Number of Civilians Unemployed for 15 to 26 Weeks	1
Number of Civilians Unemployed for 27 Weeks and Over	1
Number of Civilians Unemployed for Less Than 5 Weeks	1
Civilian Unemployment Rate	0
All Employees: Manufacturing	1
All Employees: Construction	1
All Employees: Total Private Industries	1
All Employees: Retail Trade	1
All Employees: Government	1
All Employees: Wholesale Trade	1
All Employees: Financial Activities	1
All Employees: Mining and Logging: Mining	1
All Employees: Durable Goods	1
All Employees: Nondurable goods	1
All Employees: Goods-Producing Industries	1
All Employees: Service-Providing Industries	1
All Employees: Trade, Transportation and Utilities	1
Average Weekly Hours of Production and Nonsupervisory Employees: Total private	2
Average Weekly Hours of Production and Nonsupervisory Employees: Goods-Producing	2
Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing	2
Average Weekly Overtime Hours of Production and Nonsupervisory Employees: Manufacturing	2
New Private Housing Units Authorized by Building Permits in the Midwest Census Region	2
New Private Housing Units Authorized by Building Permits in the Northeast Census Region	2
New Private Housing Units Authorized by Building Permits, Thousands of Units	2
New Private Housing Units Authorized by Building Permits in the South Census Region	2
New Private Housing Units Authorized by Building Permits in the West Census Region	2
Housing Starts: Total: New Privately Owned Housing Units Started, Thousands of Units	2
Housing Starts in Midwest Census Region, Thousands of Units	2
Housing Starts in Northeast Census Region, Thousands of Units	2
Housing Starts in South Census Region, Thousands of Units	2
Housing Starts in West Census Region, Thousands of Units	2
Real Manufacturing and Trade Inventories	1
M1 Money Stock	1
M2 Money Stock	1
Monetary Base	1

Notes: The table shows the series which enter the vector X_t of the FAVAR. The transformation codes have the following meaning: 0 = no transformation; 1 = 3-month log differences; 2 = logs.

Table C.6: Series in X_t ctd.

Variable	Transf.
Reserves of Depository Institutions, Nonborrowed	1
Total Reserves of Depository Institutions	1
Commercial and Industrial Loans	1
Total Consumer Credit Owned and Securitized, Outstanding	1
SP500	1
Effective Federal Funds Rate	0
3-Month Treasury Bill: Secondary Market Rate	0
6-Month Treasury Bill: Secondary Market Rate	0
10-Year Treasury Constant Maturity Rate	0
5-Year Treasury Constant Maturity Rate	0
1-Year Treasury Constant Maturity Rate	0
Moody's Seasoned Aaa Corporate Bond Yield	0
Moody's Seasoned Baa Corporate Bond Yield	0
Narrow Effective Exchange Rate for United States	1
Canada / U.S. Foreign Exchange Rate, Canadian Dollars to One U.S. Dollar	1
Japan / U.S. Foreign Exchange Rate, Japanese Yen to One U.S. Dollar	1
Switzerland / U.S. Foreign Exchange Rate, Swiss Francs to One U.S. Dollar	1
U.S. / U.K. Foreign Exchange Rate, U.S. Dollars to One British Pound	1
Producer Price Index by Commodity for Final Demand: Personal Consumption Goods (Finished Consumer Goods)	1
Producer Price Index by Commodity for Final Demand: Finished Goods	1
Producer Price Index for All Commodities, Index 1982=100	1
Producer Prices Index: Total Intermediate Goods for the United States	1
Consumer Price Index for All Urban Consumers: All Items	1
Consumer Price Index for All Urban Consumers: Apparel	1
Consumer Price Index for All Urban Consumers: Transportation	1
Consumer Price Index for All Urban Consumers: Medical Care	1
Consumer Price Index for All Urban Consumers: Commodities	1
Consumer Price Index for All Urban Consumers: Durables	1
Consumer Price Index for All Urban Consumers: Services	1
Consumer Price Index for All Urban Consumers: All Items Less Food	1
Consumer Price Index for All Urban Consumers: All items less medical care	1
Consumer Price Index for All Urban Consumers: All items less shelter	1
Average Hourly Earnings of Production and Nonsupervisory Employees: Construction	1
Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing	1
Average Hourly Earnings of Production and Nonsupervisory Employees: Goods-Producing	1
Real Narrow Effective Exchange Rate for Switzerland	2
Real Narrow Effective Exchange Rate for Japan	2
Real Narrow Effective Exchange Rate for United Kingdom	2
Real Narrow Effective Exchange Rate for Canada	2
Long-Term Government Bond Yields: 10-year: Main (Including Benchmark) for the United Kingdom	0
Long-Term Government Bond Yields: 10-year: Main (Including Benchmark) for Canada	0
CPI less food and energy	1
CPI less energy	1
Crude oil spot price WTI	1
Case-Shiller House price index	1

Notes: The table shows the series which enter the vector X_t of the FAVAR. The transformation codes have the following meaning: 0 = no transformation; 1 = 3-month log differences; 2 = logs.

Appendix D. Priors and posteriors

Transition equation

I impose normal inverse Wishart (natural conjugate) priors along the lines of Bańbura et al. (2010), Sims and Zha (1998) and Kadiyala and Karlsson (1997) for each regimes of the regime-switching. For better readability, I omit the regime subindices in the matrices here.

The coefficients B_1, \dots, B_p are assumed to be a priorily independent and normally distributed with moments

$$E[(B_l)_{ij}] = \begin{cases} \delta_i, & j = i, l = 1 \\ 0, & \text{otherwise} \end{cases}, \quad \text{Var}[(B_l)_{ij}] = \begin{cases} \frac{\lambda^2}{l^2}, & j = i \\ \frac{\lambda^2 \sigma_i^2}{l^2 \sigma_j^2}, & \text{otherwise} \end{cases} \quad (\text{D.1})$$

where the hyperparameter λ governs the degree of shrinkage. To implement the priors, I write the VAR in matrix form as

$$Y = XB + U$$

where $Y = (Y_1, \dots, Y_T)'$, $X = (X_1, \dots, X_T)'$ with $X_t = (Y'_{t-1}, \dots, Y'_{t-p})$, $U = (u_1, \dots, u_T)'$, and $B = (B_1, \dots, B_p)'$.

The Normal inverse-Wishart prior is given by

$$\text{vec}(B)|\Sigma \sim N(\text{vec}(\underline{B}), \Sigma \otimes \underline{\Psi}) \quad \text{and} \quad \Sigma \sim IW(\underline{S}, \underline{\alpha})$$

where the prior parameters \underline{B} , \underline{S} , $\underline{\Psi}$ and $\underline{\alpha}$ are set so that they are consistent with equations (D.1). The expectation of Σ is equal to a diagonal matrix with diagonal elements σ_i^2 . The conditional posterior distribution of the VAR parameters is given by

$$\text{vec}(B)|\Sigma, Y \sim N(\text{vec}(\overline{B}), \Sigma \otimes \overline{\Psi}) \quad \text{and} \quad \Sigma|Y \sim IW(\overline{S}, \overline{\alpha})$$

I compute the posterior parameters \overline{B} , \overline{S} , $\overline{\Psi}$ and $\overline{\alpha}$ using dummy observations as proposed by Bańbura et al. (2010). I also follow Bańbura et al. (2010) in choosing σ_i^2 as the residual variance of a univariate autoregression of $Y_{i,t}$ with lag length $p = 6$. The parameter δ_i is set to the estimate of a univariate autoregression of $Y_{i,t}$ with lag length 1. By setting the overall tightness parameter λ to 0.1 I follow Chiu and Hacıoglu Hoke (2016), Carriero et al. (2015), Canova (2011) and Blake et al. (2012).

Measurement equation

For each measurement equation

$$X_{i,t} = \Lambda_i Y_t + \xi_{i,t}$$

I assume an (independent) normal-inverse Gamma prior for Λ_i and $\omega_i^2 = \text{Var}(\xi_{i,t})$:

$$\Lambda_i \sim N(\underline{\Lambda}, \underline{\Sigma}_\Lambda) \quad \omega_i^2 \sim IG(\underline{\theta}, \underline{\phi})$$

where $\underline{\Lambda}$ and $\underline{\Sigma}_\Lambda$ are the prior moments for Λ_i and $\underline{\phi}$ and $\underline{\theta}$ are the prior degrees of freedom and scaling parameters of ω_i^2 , respectively. I follow Bernanke et al. (2005) in setting the loose priors $\underline{\Lambda} = \mathbf{0}$, $\underline{\Sigma}_\Lambda = I_k$, $\underline{\phi} = 0$ and $\underline{\theta} = 3$.

The conditional posterior distributions are derived in Koop (2003), p. 61:

$$\Lambda_i | X_i, \omega_i^2 \sim N(\bar{\Lambda}_i, \bar{\Sigma}_{\Lambda_i}), \quad \omega_i^2 | X_i, \Lambda_i \sim IG(\bar{\theta}_i, \bar{\phi})$$

with the posterior parameters

$$\begin{aligned} \bar{\Lambda}_i &= \left(\underline{\Sigma}_{\Lambda_i}^{-1} + \frac{1}{\omega_i^2} Y Y' \right)^{-1} \left(\underline{\Sigma}_{\Lambda_i}^{-1} \underline{\Lambda}' + \frac{1}{\omega_i^2} Y X_i' \right), & \bar{\Sigma}_{\Lambda_i} &= \left(\underline{\Sigma}_{\Lambda_i}^{-1} + \frac{1}{\omega_i^2} Y Y' \right)^{-1} \\ \bar{\theta}_i &= (X_i - \Lambda_i Y)(X_i - \Lambda_i Y)' + \underline{\theta}, & \bar{\phi} &= T + \underline{\phi}. \end{aligned}$$