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Alex Parker, Enzo Weber

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Measuring Labor Market Uncertainty

Alex Parker (University of Regensburg, Germany)

Enzo Weber (IAB, University of Regensburg, Germany)

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Abstract

We develop a measure of labor market uncertainty at the aggregate level. We build a search and matching model with factor stochastic volatility, where the common component of the conditional volatilities is defined as labor market uncertainty. Using rich administrative data from Germany, we show that labor market uncertainty is countercyclical and captures salient historical narratives in the German labor market. Including the measure in a VAR, we find that labor market uncertainty shocks persistently increase unemployment and primarily operate through the hiring margin. Our findings suggest that, in contrast to macro uncertainty, labor market uncertainty is more likely to cause a decline in the search intensity in the job finding rate than in the reduction of vacancy postings.

Zusammenfassung

Wir entwickeln ein Maß für die Unsicherheit am Arbeitsmarkt auf gesamtwirtschaftlicher Ebene. Hierzu verwenden wir ein Such- und Matching-Modell mit faktorbasierter stochastischer Volatilität. Die gemeinsame Komponente der bedingten Volatilitäten definieren wir als Arbeitsmarktunsicherheit. Auf Basis umfangreicher administrativer Daten für Deutschland zeigen wir, dass die Arbeitsmarktunsicherheit antizyklisch verläuft und sich in ihr wichtige historische Entwicklungen des deutschen Arbeitsmarkts widerspiegeln. In einem VAR-Modell untersuchen wir anschließend die Auswirkungen von Schocks der Arbeitsmarktunsicherheit. Diese Schocks führen über längere Zeit zu höherer Arbeitslosigkeit und wirken dabei vor allem über die Einstellungsseite. Die Ergebnisse zeigen, dass Arbeitsmarktunsicherheit im Vergleich zu makroökonomischer Unsicherheit eher zu Verfestigung von Arbeitslosigkeit führt als bestehende Beschäftigung zu bedrohen.

JEL classification

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Keywords

Factor Stochastic Volatility Models, Labor Markets, Uncertainty

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1 Introduction

Since the onset of multiple economic crises, uncertainty has become a central topic in macroeconomic research. Following the seminal work of (Bloom, 2009), numerous studies on different types of uncertainty have been developed to explain the countercyclical fluctuations found in the data. To quantify uncertainty shocks, the literature has employed or built measures of uncertainty to explore a wide range of macroeconomic questions.

A common question that is asked is the response of unemployment to uncertainty shocks; see, e.g., (Bloom, 2009; Bloom/Floetotto/Jaimovich et al., 2018; Jurado/Ludvigson/Ng, 2015), among others. Unemployment can be decomposed into differences between workers transitioning into unemployment and those flowing out of unemployment. These transitions capture only part of the broader dynamics of the labor market, as they are ultimately driven by job creation and job separations conditions as well as the ability for workers and firms to form matches. Shocks to these three processes induce fluctuations in their respective volatility that lead to changes in the uncertainty of the labor market processes, which can then propagate throughout the labor market. The common latent volatility of the three processes we define as labor market uncertainty. We find that this measure of uncertainty is a fundamental feature of labor market dynamics, distinct from broader macroeconomic uncertainty. To the best of our knowledge, no measure of labor market uncertainty has been constructed that jointly combines the job finding, job creation, and job separation conditions. Our paper establishes that labor market uncertainty is more than the labor market's exposure to uncertainty generated by macroeconomic shocks. We develop a dynamic labor market model with factor stochastic volatility, adhering to the basic tenets of the standard search and matching model of (Mortensen/Pissarides, 1994). We construct a latent factor that spans the space of the volatilities for job finding, job creation, and job separation. We identify this latent factor as labor market uncertainty. Using Bayesian methods, we show that a small, parsimonious model can extract an explanatory and representative measure of labor market uncertainty. We find several large episodes of uncertainty in the 1990s that macroeconomic uncertainty does not capture. In addition, we observe that labor market uncertainty did not rise to the same levels as macroeconomic uncertainty did during the 2008 global financial crisis. Both empirical facts underscore the value of modeling labor market volatility separately from general macroeconomic uncertainty.

Furthermore, in contrast to financial-market proxies such as the widely used VIX (see, for instance, (Bloom, 2009)), we rely on stochastic volatility. This allows us to capture latent uncertainty dynamics, which translate into persistent responses to uncertainty shocks within structural frameworks. Consistent with the findings in (Jurado/Ludvigson/Ng, 2015), we show that labor market uncertainty shocks generate persistent and statistically significant responses. Lastly, we use a Markov-switching heteroskedastic structural vector autoregression (MSH-SVAR) to juxtapose the effects of labor market uncertainty and macroeconomic uncertainty shocks. Shocks to both types of uncertainty increase the real-option value to wait. According to our results, labor market uncertainty shocks reduce search intensity along the hiring margin, while macroeconomic uncertainty shocks operate primarily along the firing margin. We show that the decline in the job finding rate cannot be fully explained by the decline in job vacancies. Therefore, labor market uncertainty lowers search and hiring intensity, i.e., the efforts invested in

filling vacancies and finding jobs.

The remainder of the paper goes as follows. We describe the connection with the literature in Section (2). Section (3) discusses the empirical model. Section (4) outlines the data and the Bayesian algorithm. Section (5) explores the implications of labor market uncertainty. Section (6) proposes an MSH–SVAR to contrast labor market uncertainty shocks and macroeconomic uncertainty shocks. In Section (7), we include a series of robustness checks. The final section, Section (8), concludes the paper.

2 Literature

Our paper contributes to three strands of literature. First, we contribute to recent developments in volatility-based uncertainty measures; see e.g., (Carriero/Clark/Marcellino, 2018; Creal/Wu, 2017; Jurado/Ludvigson/Ng, 2015). These authors develop large vector autoregressions with stochastic volatility to measure uncertainty. We avoid working with high-dimensional models such as VARs and instead choose parsimony. We link the theory of labor market dynamics using a search and matching model and extend it with factor stochastic volatility to construct our uncertainty measure.

Second, our paper extends the literature on uncertainty shocks in search and matching models. Specific labor-related uncertainty shocks have been investigated in the literature, e.g. ((Bachmann/Bayer/Merkl et al., 2021; Haan/Freund/Rendahl, 2021; Riegler, 2019; Schaal, 2017)). In (Haan/Freund/Rendahl, 2021; Riegler, 2019; Schaal, 2017), uncertainty shocks are identified through the job creation channel by second-moment productivity shocks. In (Bachmann/Bayer/Merkl et al., 2021), uncertainty is identified through job separations. We differ in two ways. First, the uncertainty shocks identified in these papers focus on one specific channel; uncertainty in our paper is driven by a common volatility factor between job finding, job creation, and job separation volatility. Second, our search and matching approach is adapted for an empirical time series application.

Lastly, we contribute to the discussion on the dynamic effects of our uncertainty shocks in a structural vector autoregression; see, e.g., (Bloom, 2009; Caggiano/Castelnuovo/Groshehny, 2014; Jurado/Ludvigson/Ng, 2015; Ludvigson/Ma/Ng, 2021; Oh/Picco, 2025). In particular, (Oh/Picco, 2025) studies the effects of macroeconomic uncertainty on job separation and job finding. In our approach, we contrast the effects of macroeconomic uncertainty and labor market uncertainty. In addition, we identify both uncertainty shocks through heteroskedasticity, while (Oh/Picco, 2025) uses short-run restrictions obtained via the Cholesky decomposition.

3 Measuring Labor Market Uncertainty

Our empirical framework belongs to a broader class of search and matching models that allow for time-varying volatility. In what follows, we sketch out the core elements required to estimate labor market uncertainty.

We assume that there are three blocks to capturing labor market dynamics. The first block is the standard matching function, expressed in the familiar Cobb–Douglas form,

$$M_t = \mu v_t^\alpha u_t^{1-\alpha} \quad (1)$$

where M_t is the rate of matching, μ denotes matching efficiency, and v_t and u_t are the stocks of vacancies and unemployed workers, respectively. The matching function describes the investment that workers and firms employ to search for one another. The simple framework captures the heterogeneity observed in the labor market without modeling it explicitly. The second and third blocks represent job creation and job separation, respectively. Which can be written in mirror form

$$k_t = J(a_t, w_t, E_t \pi_{t+1}) \quad (2)$$

the left-hand side denotes the stock of vacancies or the separation rate, $k_t \in \{v_t, s_t\}$. The right-hand side expresses J as a function of labor productivity, wages, and expectations of future revenues from the match. The choice of assuming that the two conditions are similarly specified is based on search-and-matching theory. It is well established that the job creation equation is a decreasing function of labor market tightness, whereas the job separation condition is an increasing function of labor market tightness (Pissarides, 2000, 2).

The job creation and job separation conditions correspond to hiring and firing, respectively.¹ Under partial irreversibility, firms face labor adjustment costs that take time to resolve, increasing the value of waiting. For job creation, firms expect that the hired worker's productivity will be at least as high as their reservation productivity, even though this is not known ex-ante. A similar logic applies to separation decisions: firms are fully informed about the productivity of an employed worker, and even if it falls below a profitable threshold, they may still find it optimal to retain the worker if the option value of waiting is sufficiently large to compensate for current losses.

The matching function and the job creation and job separation conditions represent three building blocks of the labor market. Each fundamental process is subject to shocks, which can lead to a rise in their conditional volatility. The volatility of generated shocks represents the degree of uncertainty about future developments in the labor market. The common volatility component shared across these labor market blocks is defined as labor market uncertainty. Labor market uncertainty characterizes the cross-sectional dependence between the conditional volatility process of the structural errors.

To model labor market uncertainty, we extend the search and matching model with factor stochastic volatility. To identify the latent volatility factor as representing uncertainty in the labor market, we build a stochastic model by log-linearizing Eqs. (1) and (2).

The first building block is the stochastic matching function, as in Eq. (1)

$$m_t = \alpha_0 + \alpha_1 v_{t-1} + \alpha_2 u_{t-1} + \xi_1 Z_{1t} + e_t^m; \quad (3)$$

where m_t is the job finding rate, $m_t = M_t/u_{t-1}$, α_0 denotes the matching efficiency, u_t , and v_t denote the stock of unemployed workers and vacancies. For the data matrix Z_{1t} , we include

¹ Note that, for simplicity, we assume that the job separation condition and the job destruction condition are a joint event. Since they are assumed to be the same action, in the remainder of the paper, they correspond to the same event, and we use the terms interchangeably.

three Hartz reform dummies for the first quarter of each year of implementation, a COVID dummy, and a time trend to capture permanent movements in the job finding rate. The job creation and job separation conditions (Eq. 2) are linearized into the following form:

$$v_t = \varphi_0 + \dot{\varphi}_1 J(E_t \pi_{t+1}, w_{t-1}, a_{t-1}, M_{t-1}) + \xi_2 Z_{2t} + e_t^v \quad (4)$$

$$s_t = \psi_0 + \dot{\psi}_1 J(E_t \pi_{t+1}, w_{t-1}, a_{t-1}) + \xi_3 Z_{3t} + e_t^s \quad (5)$$

where v_t represents vacancies and s_t denotes the job separation rate, defined as $(s_t = S_t/E_{t-1})$.² J is a function of the expected profits associated with a filled position, w_t stands for real wages, and a_t indicates labor productivity. The intercepts are given by φ_0 and ψ_0 . In line with (Gehrke/Weber, 2018), we assume that the matching rate in period M_{t-1} is exogenous with respect to the current job creation conditions. The control matrix Z_{2t} and Z_{3t} for the job creation and job separation equations includes a time trend and time dummies that account for Hartz reforms and recessions in both series.

To enrich the dynamics of Eqs. (3)–(5), the variances of the equations are subject to time-varying volatility. To allow for this, the Eqs. (3)–(5) are stacked on top of each other into a system of seemingly unrelated regressions (Zellner, 1962). First, note that,

$$X_{1t} = [1, u_{t-1}, v_{t-1}, Z_{1t}] \quad (1 \times m_1) \quad (6)$$

$$X_{2t} = [1, J(E_t \pi_{t+1}, w_{t-1}, a_{t-1}, M_{t-1}), Z_{2t}] \quad (1 \times m_2) \quad (7)$$

$$X_{3t} = [1, J(E_t \pi_{t+1}, w_{t-1}, a_{t-1}), Z_{3t}] \quad (1 \times m_3) \quad (8)$$

Where X_{1t} is of size $1 \times m_1$, X_{2t} is of size $1 \times m_2$, and X_{3t} is of size $1 \times m_3$. Let $m = m_1 + m_2 + m_3$ denote the total number of regression coefficients to be estimated. The regression coefficients for each equation are held in the $m \times 1$ vector B . In stacked form, the system of equations is expressed as

$$\begin{bmatrix} m_t \\ v_t \\ s_t \end{bmatrix} = \begin{bmatrix} X_{1t} & 0 & 0 \\ 0 & X_{2t} & 0 \\ 0 & 0 & X_{3t} \end{bmatrix} \begin{bmatrix} B_1 \\ B_2 \\ B_3 \end{bmatrix} + \begin{bmatrix} e_t^m \\ e_t^v \\ e_t^s \end{bmatrix} \quad (9)$$

and in vector form

$$Y_t = X_t B + e_t \quad (10)$$

$$e_t = \Lambda_t^{0.5} \vartheta_t; \quad \vartheta_t \sim \mathcal{N}(0, I_n) \quad (11)$$

where Y_t is defined as a $n \times 1$ vectorized matrix of the n endogenous variables ($\text{vec}(m_t, v_t, s_t)$). The matrix X_t is a $n \times m$ block-diagonal matrix. The off-diagonal zeroes are designed to ensure that each equation only depends on its own regressors in B .

To capture common shocks from the volatility processes, the covariance matrix (Λ_t) is decomposed using Constant Conditional Correlation (CCC); see (Bollerslev, 1990).

$$\Lambda_t = H_t^{0.5} R H_t^{0.5'} \quad (12)$$

² Both the job finding rate and the job separation rate are measured on the 15th of each month, with contemporaneous coefficients evaluated at $t - 1$. Furthermore, E_{t-1} denotes the stock of employed workers in the preceding period.

$$H_t = \begin{bmatrix} \sqrt{f_t^\beta h_{1t}} & 0 & \dots & 0 \\ 0 & \sqrt{f_t^\beta h_{2t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \sqrt{f_t^\beta h_{nt}} \end{bmatrix} \quad R = \begin{bmatrix} 1 & \rho_{12} & \dots & \rho_{mj} \\ \rho_{12} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \rho_{mn} \\ \rho_{mj} & \dots & \rho_{mn} & 1 \end{bmatrix} \quad (13)$$

Let H_t and R be $n \times n$ matrices, where H_t is a diagonal matrix with a multiplicative factor volatility process and R is a time-invariant correlation matrix, respectively. The vector β denotes the $n \times 1$ factor loading vector. The $n \times 1$ idiosyncratic volatilities are denoted by h_{jt} . The latent common factor is denoted as f_t .

We identify the latent common factor as labor market uncertainty index; $f_t \equiv \mathcal{L}_t^u$. Our measure of uncertainty spans the idiosyncratic volatilities rather than being embedded as a single stochastic volatility process. Since each idiosyncratic volatility captures uncertainty dynamics related to each structural innovation, e_t , the shared cross-sectional dependence between the idiosyncratic volatility series represents the joint volatility dynamics of the labor market.

Our model treats the communality of the variances as being modeled multiplicatively. Instead of assuming that the FSV follows an additive process, where the factor only contributes an additive component to each series, the multiplicative factor model specifies that the latent common factor and the idiosyncratic volatilities interact proportionally series:

$$\lambda_t = f_t^\beta h_{jt}; \quad j = 1, \dots, n \quad (14)$$

From Eq. (14) we see that the total variance is product of factor and idiosyncratic. Through the multiplicative structure the common factor scales the idiosyncratic volatilities, strengthening the shared dependence driven by the common factor. This strategy enables us to capture volatility clustering in a simple way and uncover periods of heightened uncertainty.

Prior to proceeding to next section, we briefly explain main differences between our approach and the existing literature. First, the search and matching literature introduces uncertainty through a single exogenous process. Uncertainty shocks are commonly embedded as stochastic volatility processes in productivity; see, e.g., (Bernstein/Plante/Richter et al., 2024; Haan/Freund/Rendahl, 2021). We expand on this framework by introducing factor stochastic volatility to the search and matching model. Moreover, we do not introduce stochastic volatility to the productivity process; instead, we use the uncertainty from the matching function and the job creation and job separation conditions to extract a common latent factor. Second, our approach closely resembles the modeling strategy in (Carriero/Clark/Marcellino, 2018). However, (Carriero/Clark/Marcellino, 2018) estimates a large VAR with factor stochastic volatility that captures two distinct forms of uncertainty: (1) macroeconomic and (2) financial uncertainty. Our main departure from (Carriero/Clark/Marcellino, 2018) is rooted in the integration of economic theory with data. Drawing on insights from the standard macro-labor model and leveraging detailed administrative data, we show that the idiosyncratic volatility embeds substantial information about the latent factor.

4 Data and Bayesian Inference

4.1 Data

We study the evolution of labor market uncertainty in Germany from January 1992 to December 2022. Methodologically, we leverage rich administrative data that offers a high degree of precision in capturing the fundamental dynamics of the German labor market. We employ the Integrated Employment Biographies (IEB), a two percent sample of all workers who have ever experienced a spell of unemployment and have applied for social security. Thus, capturing the transitions in and out of unemployment for an individual worker can be done accurately.³ To define matching (flow into employment) and job separation (flow into unemployment), we follow (Gartner/Rothe/Weber, 2023; Gehrke/Weber, 2018; Hutter/Carbonero/Klinger et al., 2022) and track the status of an individual from the fifteenth day of each month.⁴ To measure if a worker has transitioned into employment, we record the moment they have de-registered from social security. For a worker to be classified as unemployed, we count the month in which they have registered for social security. Both series capture the gross flows of workers entering or exiting unemployment. We transform the gross flows into transition probabilities in the regression section.

We construct an index of hourly real wages using two datasets. First, we obtain gross wages and salaries per employee hour from the German Federal Statistical Office (Destatis), measured at a quarterly frequency (deflated by the GDP deflator). To disaggregate the monthly data, we impute the quarterly wages with granular mean monthly hourly full-time wages from the IEB sample. For labor productivity, we use output per hour, which is retrieved from Destatis at a quarterly frequency. The series is then imputed using worker output per hour from the manufacturing sector to obtain a monthly frequency.⁵

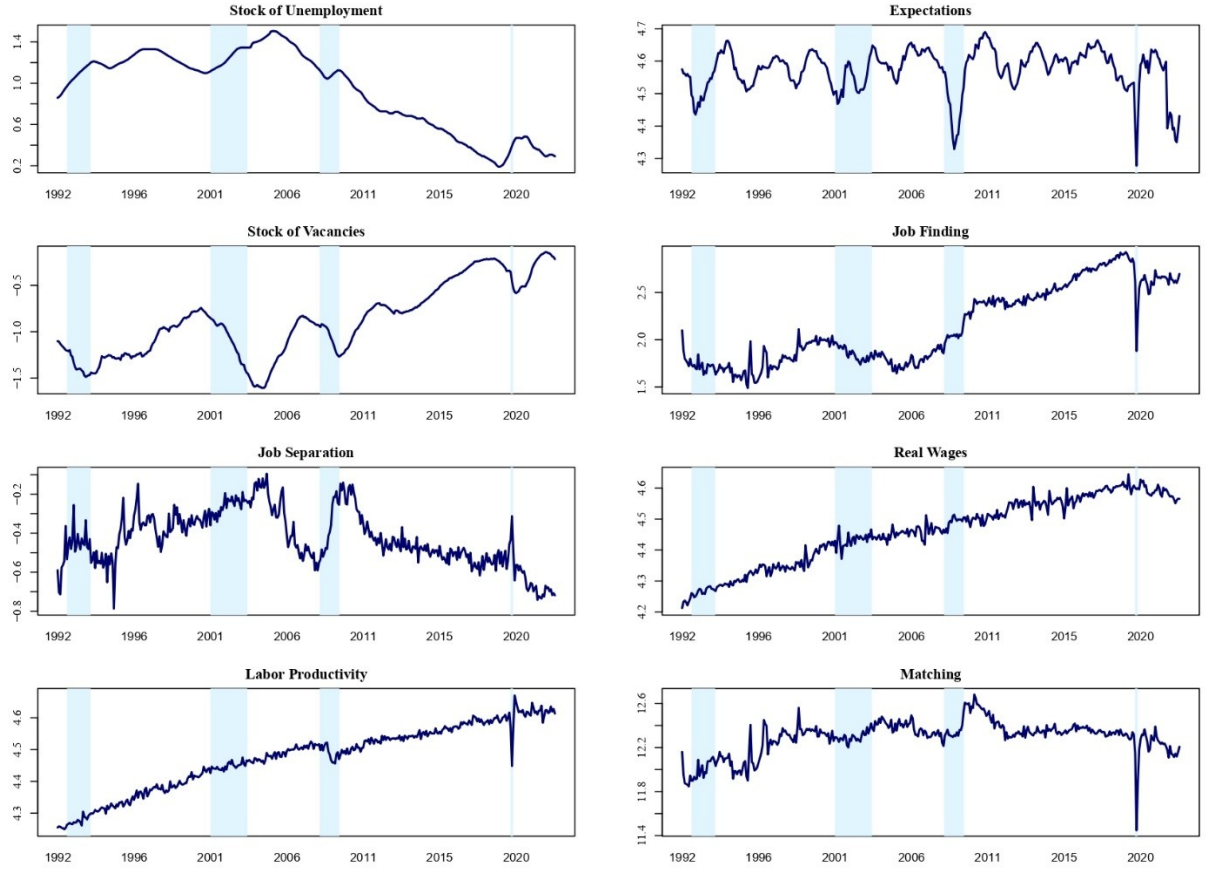
The stock of unemployed persons is obtained from the German Statistical Office (based on the definition of the European labor force survey), and the number of vacancies is retrieved from the Federal Employment Agency (FEA). Note that we scale both series by one million.

³ We thank Ben Lochner and Hermann Gartner for providing us with codes to construct the job flows and wages and Christian Hutter, who provided us with an older dataset that helped facilitate the early development of the paper.

⁴ Worker flows are only tracked for persons between the ages of 15 and 65 years old.

⁵ We also use shift dummies when necessary

Figure 1: Time Series Data



Notes: All data is transformed into logs. The blue rectangular shading represents recessions determined by German Council of Economic Council (GCEE).

Source: Author's own computation. Data used as explained in the text

⁶ Lastly, to proxy expected discounted revenue for a matched worker, we use the business expectations series constructed by the Ifo Institute. All data are seasonally adjusted by an ARIMA-X13 to remove seasonal patterns if necessary. ⁷ Time series are plotted in Figure (1).

4.2 State Space Form

In this section, we show how we can cast Eq. (11) into a linear state-space model, which will be useful when we discuss the estimation approach later. We square and take logs of Eq. (11); it can be re-expressed in the following linear state space model,

$$\ln(\tilde{e}_{jt} + \hat{c})^2 = \beta_j \ln f_t + \ln h_{jt} + \ln \tilde{\vartheta}_t^2; \quad \hat{c} = 1e^{-4} \quad (15)$$

$$\ln f_t = \zeta \ln f_{t-1} + u_t \quad (16)$$

$$\ln h_{jt} = \gamma_{j0} + \gamma_{j1} \ln h_{jt-1} + \epsilon_{jt}; \quad (17)$$

⁶ Special thanks again to Christian Hutter, who provided the vacancy time series from 1992M1 to 2017M12.

⁷ If there were compositional changes in reporting by the BA for both gross flows and wages, we employ shift dummies to remove outliers.

$$u_t, \epsilon_{jt} \sim \mathcal{N}(0, Q) \quad (18)$$

$$|\{\zeta, \gamma_{j1}, \dots, \gamma_{n1}\}| < 1 \quad (19)$$

Eq. (15) refers to the observation equation, and Eqs. (16) and (17) are the state equations for the factor and idiosyncratic volatility series, respectively. For the identification of the factor, we normalize the first loading β_1 to be equal to one and the unconditional mean of the state equation for f_t to be equal to zero. The errors of the state equations are assumed to be uncorrelated, such that $Q = \text{diag}(\sigma_1^2, \dots, \sigma_{n+1}^2)$

Table 1: Prior Distribution

Parameters	Description	Density	Distribution	Notes
<i>Job Finding Equation</i>				
α_1^m	Stock of vacancies $v_{t-1} \dots v_{t-z}$	Normal	$\mathcal{N}(\mu_{v_{z \times 1}}, 25^2)$	$\mu_{v_{z \times 1}} = \{0.40, 0, \dots, 0\}$
α_2^m	Stock of unemployed workers $u_{t-1} \dots u_{t-z}$	Normal	$\mathcal{N}(\mu_{u_{z \times 1}}, 25^2)$	$\mu_{u_{z \times 1}} = \{-0.40, 0, \dots, 0\}$
A_0^m	Intercept	Normal	$\mathcal{N}(0, 1000^2)$	
A_p^m	Lags of $m_{t-1} \dots m_{t-p}$	Normal	$\mathcal{N}(\mu_{m_{p \times 1}}, \sigma_m^2/\lambda)$	$\mu_{m_{p \times 1}} = \{1, 0, \dots, 0\}, \lambda = 0.001$
Z_{1t}	Controls	Normal	$\mathcal{N}(0, 1000^2)$	
<i>Job Creation Equation</i>				
α_1^v	Business expectation $E_t \pi_{t+1-1}, \dots, E_t \pi_{t+1-0}$	Normal	$\mathcal{N}(0, 25^2)$	
α_2^v	Wages $w_{t-1} \dots w_{t-h}$	Normal	$\mathcal{N}(0, 25^2)$	
α_3^v	Productivity $a_{t-1} \dots a_{t-q}$	Normal	$\mathcal{N}(0, 25^2)$	
A_0^v	Intercept	Normal	$\mathcal{N}(0, 1000^2)$	
A_p^v	Lags of v_t	Normal	$\mathcal{N}(\mu_{v_{p \times 1}}, \sigma_v^2/\lambda)$	$\mu_{v_{p \times 1}} = \{1, 0, \dots, 0\}, \lambda = 0.001$
Z_{2t}	Controls	Normal	$\mathcal{N}(0, 1000^2)$	
<i>Job Destruction Equation</i>				
α_1^s	Business expectation $E_t \pi_{t+1-1}, \dots, E_t \pi_{t+1-0}$	Normal	$\mathcal{N}(0, 25^2)$	
α_2^s	Wages $w_{t-1} \dots w_{t-h}$	Normal	$\mathcal{N}(0, 25^2)$	
α_3^s	Productivity $a_{t-1} \dots a_{t-q}$	Normal	$\mathcal{N}(0, 25^2)$	
A_0^s	Intercept	Normal	$\mathcal{N}(0, 25^2)$	
A_p^s	Lags of $s_{t-1} \dots s_{t-p}$	Normal	$\mathcal{N}(\mu_{s_{p \times 1}}, \sigma_s^2/\lambda)$	$\mu_{s_{p \times 1}} = \{1, 0, \dots, 0\}, \lambda = 0.001$
Z_{3t}	Controls	Normal	$\mathcal{N}(0, 1000^2)$	
<i>Stochastic Factor Volatility</i>				
β	Loading vector	Normal	$\mathcal{N}(1, 0.5^2)$	
ζ	AR(1) for latent factor	Normal	$\mathcal{N}(0.95, 0.15^2)$	
γ_{1j}	AR(1) for latent idiosyncratic series	Normal	$\mathcal{N}(0, 0.20^2)$	
γ_{0j}	Unconditional variances for the latent idiosyncratic series	Normal	$\mathcal{N}(\log(\hat{\eta}_{jt}), 0.50^2)$	
f_0, h_{j0}	Initial States	Normal	$\mathcal{N}(\{0, \log(\hat{\eta}_j^2)\}, \mathbf{1})$	
σ_f, σ_{hj}	State Innovations	Inverse-Gamma	$\mathcal{IG}(a, b)$	$a = \{5, 5, 5, 5\}, b = \{0.01, 0.05, 0.05, 0.05\}$
ρ	Constant Conditional Correlation	Modified Beta	$\nu = 3$	

Notes: σ_m^2 is the variance of each endogenous series, where $\sigma_j^2 \in \{\text{var}(m_t), \text{var}(v_t), \text{var}(s_t)\}$. $\hat{\eta}_{jt}$ denotes the residual variance from an OLS regression for each equation.

Source: Author's own computation

4.3 Priors

We estimate the model using Bayesian methods that impose prior distributions on each parameter to be estimated. We choose to use conjugate priors, thereby facilitating fast and efficient sampling from the posterior distribution.

We employ independent Gaussian priors on the regressors, $B_i \sim \mathcal{N}(\mu_i, \omega^2)$. For the autoregressive lags in each equation, we adopt a standard shrinkage scheme similar to the Minnesota prior of (Litterman, 1986). Specifically, the first own lag in each equation is assigned a prior mean of $\mu_{m_{ji}} = 1$ for $j = i$, which corresponds to the usual random walk assumption. The prior variance is specified as $\text{var}(Y_{jt})/\lambda$ ($Y_{jt} \in \{m_t, v_t, s_t\}$). The hyperparameter λ governs the tightness of the prior variance, which is set to 0.001.

The exogenous regressors are given diffuse priors, in line with (Gehrke/Weber, 2018), with prior means set to zero and a standard deviation equal to 25. In addition, we impose prior means on the first covariates of u_t and v_t equal to -0.4 and 0.4 , respectively.⁸

For the loading vector (β_j), we use the conventional priors from stochastic factor volatility models, specifying a prior mean of one, $\beta_j \sim \mathcal{N}(1, 0.5^2)$. The priors on the autoregressive coefficients for each state equation align with previous results in the uncertainty literature that are closest to our research, e.g., (Bernstein/Plante/Richter et al., 2024; Carriero/Clark/Marcellino, 2018; Jurado/Ludvigson/Ng, 2015), and our knowledge with respect to fundamental labor market conditions. For the factor series, the prior takes the form $\zeta \sim \mathcal{N}(0.95, 0.15^2)$. The idiosyncratic autoregressive parameters (γ_{jt}) follow in the spirit of (Carriero/Clark/Marcellino, 2018), $\mathcal{N}(0, 0.20^2)$. The latent intercepts are prescribed a prior distribution $\gamma_{j0} \sim \mathcal{N}(\log(\eta_j^2), 0.5^2)$. Where η_j is the unconditional residual variance of each equation obtained by OLS. This

⁸ The choice of these prior means is in line with empirical evidence of the matching function; see, e.g., (Gartner/Rothe/Weber, 2023).

follows the initial history priors $f_0, h_0 \sim N(\{0, \log(\eta_j^2)\}, \mathbf{1}_{(n+1) \times 1})$.

Table 2: DIC for Different Model Specifications

p	q	l	h	z	o	DIC
6	5	4	3	2	2	-7422.2309
6	5	4	3	2	3	-7418.6676
6	5	3	3	2	2	-7418.4867
6	5	3	3	2	3	-7417.3406
6	4	4	3	2	2	-7417.2906
6	4	5	3	2	2	-7416.6223
6	5	5	3	2	2	-7416.2412
6	4	3	3	2	2	-7415.7273
6	4	3	3	2	3	-7415.4693
6	5	5	3	2	3	-7415.4602

Notes: The table shows the ten best model fits based on 5,000 retained draws. The DIC = $-2L_M + 2p_{DIC}$, where $p_{DIC} = 2(L_M - E_{post}L_M)$ and L_M is the log-likelihood at the posterior medians. Lag orders are denoted as follows: p autoregressive parameters, q labor productivity, h wages, z unemployment and vacancies, and o expectations.

Source: Author's own computation

The state innovations, σ_f^2 and $\sigma_{h_{jt}}^2$, follow an inverse-gamma prior $\mathcal{IG}(a, b)$, where a denotes the shape parameter and b is the scale parameter. The hyperparameters a and b are in the spirit of (Carriero/Clark/Marcellino, 2018; Carriero/Mumtaz/Theodoridis et al., 2015). We are slightly more informative to account for the fact that our sample starts in a volatile period. The shape parameter a is fixed to 5 across all latent states. The scale b is given as 0.01 for the latent factor equation and 0.05 for the latent idiosyncratic equations.

For the time-invariant correlation matrix R , some care is needed. This is due to the positive-definite condition. We follow (Barnard/McCulloch/Meng, 2000) using a separation strategy on the covariance matrix Λ_t . Using this approach, the prior on the time-varying covariance $p(\Lambda_t)$ can be factorized in terms of the standard deviations $H_t^{0.5}$ and the correlation matrix R ; $p(\Lambda_t) = p(H_t)p(R|H_t)$. This is well suited for our framework because we already decompose the Λ_t through constant conditional correlation. We use the marginally uniform prior on each element ρ_{kj} ($k \neq j$), which is a modified Beta distribution on $[-1, 1]$. As shown by (Barnard/McCulloch/Meng, 2000), the marginal uniform prior for $n = 3$ implies,

$$p(\rho_{12}, \rho_{13}, \rho_{23} | \nu) \propto \frac{(1 - \rho_{12}^2 - \rho_{13}^2 - \rho_{23}^2 + 2\rho_{12}\rho_{13}\rho_{23})^{\nu-n+1}}{[(1 - \rho_{12}^2)(1 - \rho_{13}^2)(1 - \rho_{23}^2)]^{\frac{\nu-n+1}{3}}} \quad (20)$$

$$s. t. \quad 1 - \rho_{12}^2 - \rho_{13}^2 - \rho_{23}^2 + 2\rho_{12}\rho_{13}\rho_{23} \geq 0 \quad (21)$$

The tuning parameter ν controls the tail behavior of the prior distribution on ρ_{kj} . We set $\nu = n$. A full summary of the priors on the parameters can be found in Table (1).

Table 3: MCMC Convergence Diagnostics

Parameter	No. of Parameters	Mean IF	Median IF	Min IF	Max IF	Convergence Diagnostics Rejection Rate
B	64	6.95	6.12	1.57	16.76	0.13
β	2	1.00	1.00	1.00	1.00	0.00
ζ, γ_{j1}	4	1.00	1.00	1.00	1.00	0.00
γ_{j0}	3	1.02	1.00	1.00	1.05	0.00
σ_j^2	4	4.62	1.79	1.33	13.56	0.00
ρ_{mn}	3	2.83	2.99	2.46	3.05	0.00

Notes: Based on 5,000 retained draws. Inefficiency factors are computed by the equation N/ESS_m , where N is the number of retained draws and ESS_m is the effective sample for parameter m . To confirm good mixing, we follow the rule $IF < 20$, proposed by (Primiceri, 2005). The final column denotes the (Geweke, 1992) convergence diagnostic test for the Markov chain. The test compares for equality means from the first 10% and the last 50% of the retained draws of the Markov chain based on the 5% rejection rate.

Source: Author's own computation

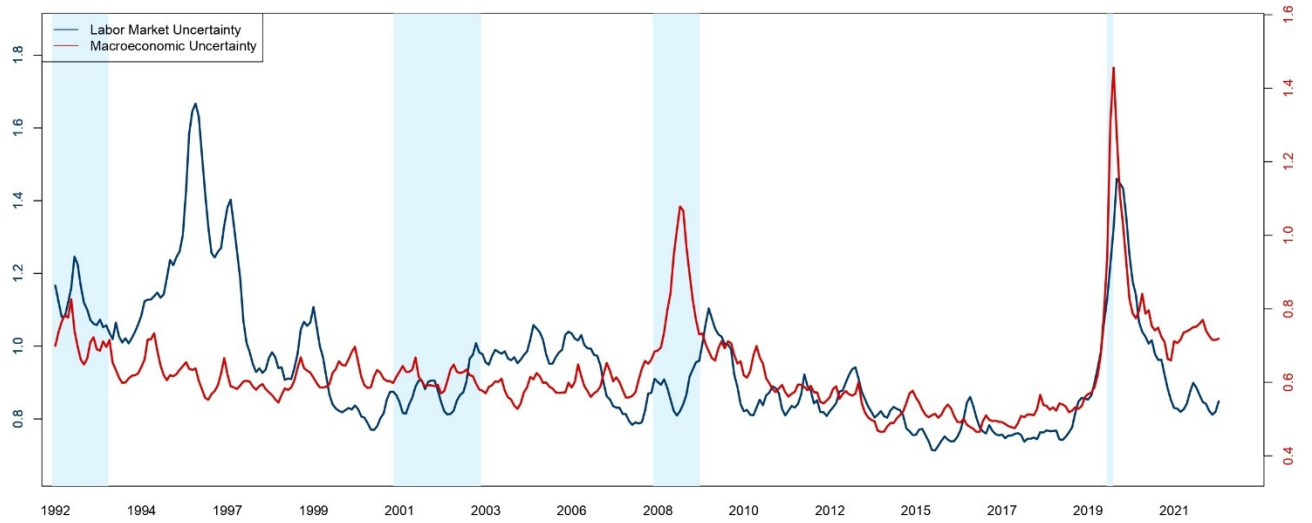
4.4 MCMC Algorithm

Our model is estimated using the Gibbs sampler, as outlined in (Del Negro/Primiceri, 2015). As the authors noted, the inclusion of stochastic volatility using the (Kim/Shephard/Chib, 1998) sampler requires employing a two-block sampling strategy to draw from the correct posterior distribution. The two blocks are defined as (1) the volatility histories $\varphi \equiv \{f_t, h_{jt}\}$ and (2) the second block, (θ, s^T) , which includes the set of parameters $\theta \equiv \{B, \rho, \beta, \Gamma_t, Q\}$ and mixture indicators (s^T) . The mixture indicators (s^T) are used to approximate a Gaussian distribution from the non-Gaussian $\ln \tilde{\vartheta}_t^2 \sim \chi^2(1)$; see (Kim/Shephard/Chib, 1998). This approximation allows us to use the forward filtering (Kalman Filter) and backward smoothing algorithm of (Carter/Kohn, 1994) to draw the latent volatility states. Finally, the data block is denoted as $z_t = \{Y_t, X_t\}$

The Gibbs sampler can be summarized as follows:

1. Draw $p(\varphi|\theta, s^T, z_t)$.
2. Draw $p(\theta, s^T|\varphi, z_t)$.
 - a. Draw $p(B|\varphi, \rho, z_t)$
 - b. Draw $p(\Gamma_t|\varphi, B, Q, z_t)$
 - c. Draw $p(\beta|\varphi, \Gamma_t, B, Q, z_t)$
 - d. Draw $p(\sigma_t^2|\varphi, \Gamma_t, B, \beta, z_t)$

Figure 2: Labor Market Uncertainty and Macroeconomic Uncertainty



Notes: The MCMC is based on 5,000 retained draws. The solid blue line represents the posterior median of the factor volatility index f_t . The solid red line shows a macroeconomic uncertainty index for Germany developed by (Grimme/Stöckli, 2018), based on the model of (Jurado/Ludvigson/Ng, 2015). Blue shaded areas indicate recessions as determined by the German Council of Economic Experts (GCEE).

Source: Author's own computation

e. Draw $p(\boldsymbol{\rho}|\boldsymbol{\varphi}, \Gamma_t, B, \boldsymbol{\beta}, z_t)$ ⁹

f. Draw $p(s^T|\boldsymbol{\varphi}, \boldsymbol{\theta}, z_t)$ ¹⁰

Given the proliferation in the number of parameters, lags on endogenous and exogenous variables, we compare a large number of competing models using the Deviance Information Criterion (DIC) (Spiegelhalter/Best/Carlin et al., 2002). Table (2) displays the ten best-fitting models in descending order, with the baseline model in bold.

We draw 300,000 times from the posterior distribution, discarding the first 50,000 as burn-in.¹¹. From the remaining 250,000 draws, we retain every 50th draw, leaving us with 5,000 draws for inference. The diagnostics for the MCMC algorithm are reported in Table (3). Overall, the diagnostics indicate satisfactory mixing in the chain and convergence of the Markov chain.

5 Exploring Labor Market Uncertainty

Now that we have laid the foundational design of our empirical model, we move on to the estimated results. Figure (2) shows the measure of labor market uncertainty ($\mathcal{L}_t^u$), contrasted

⁹ Drawing from the correlations posterior distribution is not straightforward. We utilize the Griddy Gibbs sampler (Ritter/Tanner, 1992), using 300 equidistant grid points for each pairwise correlation.

¹⁰ We use the ten-state mixture approximation of (Omori/Chib/Shephard et al., 2007) instead of the seven-state mixture of (Kim/Shephard/Chib, 1998)

¹¹ The computational expense of estimation at this scale is non-trivial; we implement the entire MCMC algorithm in C++ using RcppArmadillo (Eddelbuettel/Francois, 2011; Eddelbuettel/Sanderson, 2014).

with macroeconomic uncertainty ($\mathcal{M}_t^u$).¹² Doing so provides a better understanding of how labor market uncertainty fits into the historical narrative of general macroeconomic uncertainty. First, we find a sudden sharp rise in $\mathcal{L}_t^u$ in the first quarter of 1996. This sharp rise, interestingly, occurs around the same time as the collapse in the convergence between East and West Germany, as noted in the growth literature; see, e.g., (Burda/Severgnini, 2018; Sinn, 2002). The large number of swings in labor market uncertainty during the mid-1990s also corresponds to general findings surrounding the German labor market; see, e.g., (Gehrke/Weber, 2018). Following the dot-com crash, there was a shift upward during the implementation of the Hartz reform. An interesting result comes from the fact that there is no appreciable rise in labor market uncertainty during the 2008 Great Recession. The increase in labor market uncertainty is mild compared to macroeconomic uncertainty. There was a rise during the Great Recession, peaking after the recession. Compared to other increases in labor market uncertainty, it was only marginally important. The marginal rise in labor market uncertainty could be related to the policy change to short-time work (Gehrke/Weber, 2018), and the use of labor hoarding by firms (Weber, 2015) played a role in stabilizing the labor market. Both series rose significantly during the initial stages of the COVID-19 lockdown. Where macroeconomic uncertainty experienced a level shift; conversely, labor market uncertainty returns to its pre-lockdown level. The non-trivial rise in volatility in labor market uncertainty during the 1990s likely points to the unprecedented economic transition that occurred following the reunification of East and West Germany. Through this, there is a large difference between both regions labor markets; for example, the difference in productivity levels between East and West German workers. We do not see this pattern in the macroeconomic uncertainty of (Grimme/Stöckli, 2018) and other German-based uncertainty measures, e.g., (Bachmann/Elstner/Sims, 2013). Guided by theoretical considerations, our approach suggests that periods of elevated uncertainty do not necessarily coincide with established recessions.

¹² The macroeconomic uncertainty index is a German version based on the methodology of (Jurado/Ludvigson/Ng, 2015), developed by (Grimme/Stöckli, 2018). Note that the (Grimme/Stöckli, 2018) series is only available until 2021 and had to be imputed to the year 2022 using the U.S. series of (Jurado/Ludvigson/Ng, 2015).

Table 4: Pairwise Correlation

$h \pm$	u_t	m_t	s_t	v_t	a_t	$\mathcal{M}_t^u$
-12	0.2322***	-0.3931***	-0.0138	-0.3835***	-0.4743***	0.2905***
-6	0.3101***	-0.4727***	0.09**	-0.4791***	-0.5278***	0.3822***
-3	0.3558***	-0.5118***	0.1633***	-0.5209***	-0.5451***	0.4596***
0	0.3976***	-0.5337***	0.1944***	-0.5524***	-0.5564***	0.439***
3	0.4213***	-0.5308***	0.164***	-0.548***	-0.5266***	0.3528***
6	0.4365***	-0.5288***	0.1446***	-0.5264***	-0.5077***	0.2865***
12	0.4496***	-0.5082***	0.0781	-0.4392***	-0.4783***	0.1618***

Notes: The entries denote cross-correlations for leads and lags ($h = \pm 12$). $\tau_h = \text{corr}(x_t, \log(\mathcal{L}_{t+h}^u))$. The test statistics are computed using heteroskedasticity-robust cross-correlation tests; see (Dalla/Giraitis/Phillips, 2022). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: Author's own computation

In addition, consistent with the findings in the uncertainty literature, e.g., (Jurado/Ludvigson/Ng, 2015), labor market uncertainty departs from Gaussianity, exhibiting skewness of 1.51 and kurtosis of 5.73.

Finally, Table (4) shows the pairwise correlation for the different data. The dynamic pairwise correlations confirm that labor market uncertainty is countercyclical. Furthermore, a majority of the data strongly correlated at $h = 0$. Interestingly, all measures of unemployment exhibit their strongest correlation at $h > 0$, which suggests that spikes in labor market uncertainty could be an earlier sign of increases in unemployment.

6 Dynamic Analysis of Labor Market Uncertainty

Having outlined the labor market uncertainty measure in the previous section, we now turn to investigating the dynamic effects of labor market uncertainty. We focus on both structural and dynamic variation within the labor market. We include macroeconomic uncertainty shocks to ensure that effects are not incorrectly attributed to labor market uncertainty shocks and conversely.

6.1 Structural VAR

The structural VAR can be written in the form

$$B_0 z_t = c_0 + \sum_{i=1}^p A_p z_{t-p} + Q d_t + \epsilon_t; \quad \epsilon_t \sim \mathcal{N}(0, \Sigma) \quad (22)$$

where z_t is a $K \times 1$ vector of endogenous variables, $z_t = (\log(\mathcal{M}_t^u), \log(\mathcal{L}_t^u), u_t, a_t, v_t, s_t, m_t)$. The $K \times 1$ vector c_0 contains the intercepts, $A_{1 \leq p}$ are $K \times K$ matrices of the slope coefficients, and d_t is an $E \times 1$ vector of exogenous variables, which includes a linear and quadratic trend and

a dummy variable for the COVID recession. The vector of white noise errors, denoted by ϵ_t , is independent and identically distributed. The $K \times K$ impact multiplier matrix is denoted by B_0 . The impact multiplier matrix B_0 follows a recursive ordering. The placement of the uncertainty measures follows the established positions in the literature; see, e.g., (Bachmann/Elstner/Sims, 2013; Bloom, 2009; Jurado/Ludvigson/Ng, 2015). Namely, macroeconomic uncertainty is placed first, and labor market uncertainty is placed second. The key identifying assumption is that macroeconomic uncertainty shocks have a contemporaneous effect on labor market uncertainty, while labor market uncertainty shocks can only affect macroeconomic uncertainty with lags. This is motivated by the fact that labor market uncertainty is localized to the labor market and cannot propagate throughout the entire economy immediately. Later, we test the validity of these restrictions using identification through heteroskedasticity; see Section (6.1.4).

The VAR is estimated by OLS with 5 lags, as per the recommendation of the Akaike Information Criterion (AIC). However, testing for homoskedasticity, we find significant evidence against it; see Table (5). Building on these findings, we demonstrate in the next section how the existence of heteroskedasticity can be used to identify uncertainty shocks.

Table 5: Breusch-Pagan Test for Heteroskedasticity

	$e_t^{M^u}$	$e_t^{L^u}$	e_t^u	e_t^a	e_t^s	e_t^m	e_t^v
LM	177.16 ***	51.90*	51.35*	214.61 ***	92.49***	234.51***	60.87**

Notes: The test statistics, Lagrange-Multiplier (LM), from the Breusch-Pagan is based formulate $TR^2 \xrightarrow{p} \chi_q^2$. Where the R^2 is obtained from auxiliary regression $\epsilon_{it}^2 = c + \gamma Z_{t-p} + \eta_{it}$. $q = Kp + E + 1$. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$, denotes the 10—, 5—, 1— percent level.

Source: Author's own computation

6.1.1 Heteroskedasticity

In the previous section, we found strong evidence for the VAR in Eq. (22) exhibiting heteroskedasticity. We take this fact into account by extending the VAR to allow for endogenous switching. This approach allows us to capture shifts in the variance without imposing a strong assumption about the timing of structural breaks.¹³ The VAR in Eq. (22) can be extended into a Markov-switching heteroskedastic SVAR (MSH-SVAR), by conditioning the errors on a discrete latent Markov process s_t ($t = 0, 1, \dots, T$)

$$\epsilon_t | s_t \sim \mathcal{N}(0, \Sigma_{s_t}) \quad (23)$$

The covariance matrix Σ_{s_t} is now time-varying and indexed by the latent regime s_t ; $s_t \in \{1, \dots, M\}$. Let $\mathbf{P}$ be the $M \times M$ transition probability matrix capturing the transition between the M states.

¹³ In practice, structural exogenous regime shifts can be difficult to assign. In a system of structural shocks, the variance of each series may shift at different times.

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{21} & \dots & p_{M1} \\ p_{21} & p_{22} & \dots & p_{M2} \\ \vdots & \vdots & \ddots & \vdots \\ p_{1M} & p_{2M} & \dots & p_{MM} \end{bmatrix} \quad (24)$$

The transition probability $\mathbf{P}$ is determined by the Markov Chain, $p_{ij} = \Pr(s_t = j | s_{t-1} = i)$ for $i, j = 1, \dots, M$ and $\sum_{j=1}^M p_{ij} = 1$. The reduced-form covariance matrix is expressed according to the following decomposition

$$\Sigma_{s_t} = B_0^{-1} \Lambda_{s_t} B_0'^{-1} \quad (25)$$

where Λ_{s_t} is a $K \times K$ diagonal matrix of strictly positive eigenvalues; $\text{diag}(\lambda_{1,s_t}, \dots, \lambda_{K,s_t})$. The matrix Λ_{s_t} implies that the cross-regime variances of the structural shocks are different. Fundamental shifts in the relative variances within each regime yield additional identifying information related to the structural shocks in the data. This identification strategy is better known as *identification through heteroskedasticity*; see, e.g., (Brunnermeier/Palia/Sastry et al., 2021; Lanne/Lütkepohl/Maciejowska, 2010; Lütkepohl/Netšunajev, 2014; Lütkepohl/Shang/Uzeda et al., 2025; Lütkepohl/Woźniak, 2020; Rigobon, 2003; Weber, 2009; Woźniak/Droumaguet, 2015). Under the condition that there is sufficient variation in the structural equations, we can uniquely identify all K^2 elements in B_0 up to a sign change of the columns; see (Lanne/Lütkepohl/Maciejowska, 2010) for details. Lastly, following (Brunnermeier/Palia/Sastry et al., 2021), we impose the following restriction on the regime-specific variances

$$\frac{1}{M} \sum_{s_t=1}^M \lambda_{s_t,k} = 1 \quad \forall k \in \{1, \dots, K\} \quad (26)$$

The decision to impose this normalization will become clearer in the next section.

6.1.2 Prior for MSH-VAR

As we did when we estimated the search and matching model, we use Bayesian methods to estimate the MSH-VAR. And as before, we specify a set of priors for the parameters. First, the reduced-form slope coefficients $A_{1:p}$ follow a conditional Gaussian prior:

$$p(A_{1:p}) | \delta_{A,k} \sim \mathcal{N}(V_A, \delta_{A,k} \Xi) \quad (27)$$

Where V_A is a $K \times (Kp + l)$ matrix of zeros, except for the i^{th} variable in the i^{th} row, we then follow the standard Minnesota assumption of a highly persistent AR(1) process with the mean equal to one. The prior covariance matrix (Ξ) is a $(Kp + l) \times (Kp + l)$ matrix of zeros, where the diagonal contains the vector $(h^{-2} \otimes I_K)$ and is a h sequence of integers from 1 to p . The exogenous variables are set with uninformative priors $c_0 \sim \mathcal{N}(0, 10^3)$ and $Q \sim \mathcal{N}(0, 10^5)$. The equation-specific hyperparameter $\delta_{A,k}$ is subject to a three-level global-local hierarchical prior (Giannone/Lenza/Primiceri, 2015):

$$\begin{aligned} \delta_{A,k} | r_{A,k} &\sim \mathcal{IG}2(r_{A,k}, \underline{\omega}_A) \\ r_{A,k} | s_{A,k} &\sim \mathcal{G}(s_{A,k}, \underline{q}_A) \\ s_A &\sim \mathcal{IG}(\underline{s}_{sA}, \underline{q}_{sA}) \end{aligned} \quad (28)$$

We fix $\underline{\omega}_A = \underline{q}_A = \underline{s}_{sA} = \underline{q}_{sA} = 10$ and r_A , s_A , and δ_A are random variables. Each random variable is drawn from either Inverse-Gamma 2 ($\mathcal{IG}2$), Gamma ($\mathcal{G}$), or Inverse-Gamma ($\mathcal{IG}$) distribution. To draw the elements in the structural impact matrix B_0 , we follow (Waggoner/Zha, 2003) and impose the zero restriction row-by-row through the decomposition of the structural impact matrix $B_{0,k}$,

$$B_{0,k} = b_k V_k \quad (29)$$

where b_k is an $1 \times r_k$ vector of the elements to be estimated, and V_k is an $r_k \times K$ selection matrix that maps the elements into the correct order for $B_{0,k}$.

The structural impact matrix B_0 employs a normal-generalized-normal distribution (see, e.g., (Arias/Rubio-Ramírez/Waggoner, 2018; Waggoner/Zha, 2003)),

$$p(B_0) | \delta_{B,1}, \dots, \delta_{B,K} \sim |\det(B_0)|^{\nu_B - K} \exp \left(-\frac{1}{2} \delta_{B,k}^{-1} \text{vec}(B_0)' \Xi_{B,k}^{-1} \text{vec}(B_0) \right) \quad (30)$$

where ν_B is the scalar shape parameter equal to K , and Ξ_B is a $r_k \times r_k$ scale matrix set to $10 \mathbf{I}_{r_k}$. Analogous to the slope parameters, the hyperparameters $\delta_{B,k}$ are assigned a three level global-local hierarchical prior as before:

$$\begin{aligned} \delta_{B,k} | r_{B,k} &\sim \mathcal{IG}2(r_{B,k}, \underline{\omega}_B) \\ r_{B,k} | s_B &\sim \mathcal{G}(s_B, \underline{q}_B) \\ s_B &\sim \mathcal{IG}2(\underline{s}_{sB}, \underline{q}_{sB}) \end{aligned} \quad (31)$$

In which δ_B , r_B , and s_B are to be estimated. We set $\nu_B = K$, $\underline{\omega}_B = 10$, $\underline{q}_B = 10$, $\underline{s}_{sB} = 1$, and $\underline{q}_{sB} = 100$.

For the variance and Markov process, we specify the priors for the regime switching on the conditional variance matrix Λ_{s_t} . The Markov process evolves according to an $M \times M$ transition matrix $\mathbf{P}$, where each entry p_{ij} denotes the probability of transitioning from state i to state j . The initial probabilities are contained in an $M \times 1$ vector $\mathbf{x}_0$.

For the elements in Λ_{s_t} follow a M -dimensional Dirichlet distribution of the form as in (Brunnermeier/Palia/Sastry et al., 2021).

$$\lambda_{1,s_t}/M, \dots, \lambda_{K,s_t}/M \sim \mathcal{D}_M(\varsigma_\lambda, \dots, \varsigma_\lambda) \quad (32)$$

where $\varsigma_\lambda = 1$. As noted in (Brunnermeier/Palia/Sastry et al., 2021), this restricts the relative variances to the interval $[0, M]$. The prior is centered to equal variances, and the normalization ensures that for each structural shock, the relative variance averages to 1 across regimes. The transition probability matrix $\mathbf{P}_{s_t}$ and the initial states also have Dirichlet priors imposed on them

$$\begin{aligned} \mathbf{P}_{s_t} &\sim \mathcal{D}_M(\varsigma_0, \dots, \varsigma_0) \\ \mathbf{x}_0 &\sim \mathcal{D}_M(\varsigma_1, \dots, \varsigma_1) \end{aligned} \quad (33)$$

The hyperparameters are fixed to one: $\varsigma_0 = \varsigma_1 = 1$.

6.1.3 Estimation

The estimation of the nonlinear VAR model by an MCMC algorithm is described in (Lütkepohl/Woźniak, 2020; Wozniak/Droumaguet, 2015).¹⁴ We draw 300,000 times from the posterior distribution, using the first 100,000 as burn-in and keeping every 40th draw to reduce autocorrelation. The same lag length is used as above, while the number of regimes will be determined in the next section.

Table 6: Savage-Dickey Density Ratio for Assessing Heteroskedasticity

	$e_t^{M^u}$	$e_t^{L^u}$	e_t^u	e_t^a	e_t^s	e_t^m	e_t^v
MSH(2)	−46.06	−2.52	−2.6	−54.08	−24.6	−97.58	−27.72
(Recursive)	(4.36)	(0.29)	(2.27)	(5.01)	(1.92)	(5.88)	(7.03)
MSH(2) (Non-Recursive)	−3.56	−3.66	−3.62	−2.58	−3.08	−4.13	−4.94
	(3.19)	(5.29)	(9.43)	(1.4)	(0.72)	(12.4)	(5.68)
MSH(3)	−83.45	−7.99	−30.58	−158.52	−72.31	−290.77	−146.08
(Recursive)	(8.22)	(4.41)	(14.69)	(11.76)	(11.15)	(16.02)	(15.6)
MSH(3) (Non-Recursive)	−12.9	−18.00	−9.52	−11.01	−4.38	−15.79	−11.23
	(146.14)	(86.3)	(41.06)	(38.31)	(26.74)	(185.12)	(50.84)

Notes: The table reports the log Savage-Dickey Density Ratio (SDDR). The SDDRs are constructed based on 5,000 retained draws. The numerical standard errors (in brackets) are constructed through 30 sub-samples of the log-ordinates of the marginal posterior and prior distribution; see, (Lütkepohl/Woźniak, 2020).

Source: Author's own computation

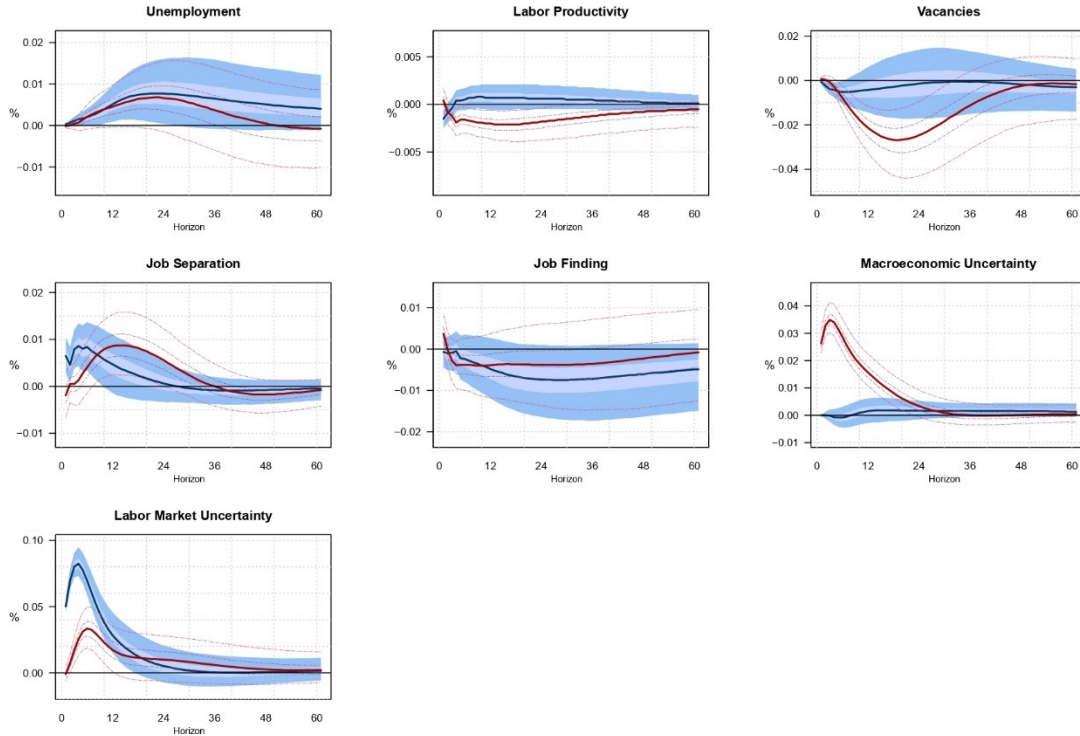
6.1.4 Testing for Identification

Before proceeding to empirical analysis, we test to see if the identification restrictions are supported by the data. Indeed, the number of regimes M plays an important role in the identification of the elements in B_0 . In principle, as the number of regimes grows, the model is able to capture additional shifts in the relative variances. These shifts are relevant for the identification of B_0 . Whether this is supported by the data is a matter that requires further examination. For identification to be satisfied, at least $K - 1$ structural shocks must exhibit heteroskedasticity. We employ a Bayes Factor test using the Savage-Dickey Density Ratio (SDDR); see (Lütkepohl/Shang/Uzeda et al., 2025; Lütkepohl/Woźniak, 2020). If $|\log(\text{SDDR})| \geq 5$, it suggests very strong evidence against homoskedastic shocks.

We focus on four specifications with MSH-VAR using $M = 2, 3$ and B_0 , following the recursive specification discussed above and a non-recursive specification. In the non-recursive specification of B_0 , we assume that shocks have contemporaneous effects on both uncertainty measures.

¹⁴ We use the R package *bsvars* developed by (Woźniak, 2024) for estimation

Figure 3: Impulse Response Functions for Uncertainty Shocks

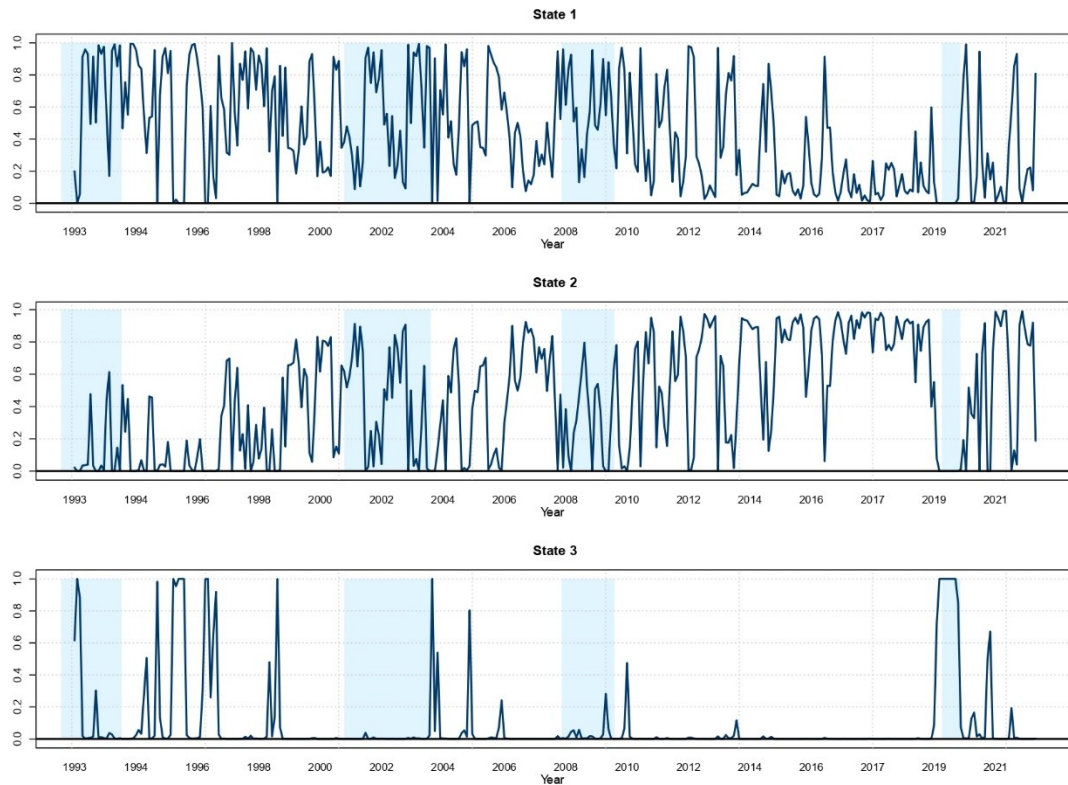


Notes: The figure is based on 5,000 retained draws from the posterior distribution. Solid red line: Posterior median for $\mathcal{M}_t^u$. Solid blue line: Posterior median for $\mathcal{L}_t^u$. Shaded blue regions and dashed red lines represent the 90% and 68% posterior credible bands.

Source: Author's own computation

Table (6) shows the SDDR for the non-recursive and recursive orderings of B_0 in the MSH(2) and MSH(3) specifications. For both MSH(2) specifications, we do not find strong evidence for the alternative. Since more than two $|\log(\text{SDDR})|$ are below 5. In the MSH(3) specification, both identification schemes indicate strong evidence against the null. However, under the non-recursive specification, there is a nontrivial degree of simulation uncertainty surrounding the $\log(\text{SDDR})$, as their numerical standard errors are large, in some cases exceeding the $\log(\text{SDDR})$ by a factor of five. Therefore, we cannot reliably conclude that the identification holds for the non-recursive form. As a result, we proceed with MSH(3) using the recursive specification for B_0 .

Figure 4: Smoothed State Probabilities



Notes: The figure based on 5,000 retained draws from the posterior distribution. Solid Blue Line: Posterior median for smoothed regime probabilities. Shaded blue regions denotes. The blue rectangular shading indicates recessions determined by German Council of Economic Experts (GCEE).

Source: Author's own computation

6.2 Impulse Response Functions

We plot the impulse responses to $\mathcal{L}_t^u$ and $\mathcal{M}_t^u$ shocks in Figure (3). Following a shock to $\mathcal{L}_t^u$, we observe a rise in the stock of unemployment and the job separation rate, as well as a decline in the job finding rate. The latter shows a pronounced, persistent decline over the entire horizon, while for the stock of vacancies, there is only a slight reaction. There is a small negative effect on labor productivity, but it is short-lived.

The impulse responses show that macroeconomic uncertainty shocks have significant effects on unemployment, labor productivity, and the stock of vacancies. These results are consistent with (Oh/Picco, 2025), who found that uncertainty shocks cause a decline in the job finding rate and a rise in unemployment and job separation with U.S. data. Importantly, the IRFs show that the response of unemployment to macroeconomic uncertainty shocks exhibits the *volatility overshoot* discussed in (Bloom, 2009).

We observe that labor market uncertainty shocks affect labor market dynamics more through changes in the job finding margin than in the job separation margin. However, the decline in the job finding rate following a labor market uncertainty shock cannot be explained by the decline in vacancies. According to a standard matching function, the typical elasticity lies somewhere between 0.2 and 0.3 (see, e.g., (Nordmeier, 2016)), implying that the decline in vacancies would

still be unable to account for the fall in the job finding rate. This result is not observed following a macroeconomic uncertainty shock, as the fall in vacancies and the job finding rate is consistent with the matching function elasticity.

The responses of the job finding rate and the stock of vacancies to labor market uncertainty shocks are consistent with the theory of procyclical search intensity, e.g., (Hartl/Hutter/Weber, 2026).¹⁵ In view of higher uncertainty, firms become more hesitant to fill open positions.

Concurrently, workers become less optimistic about finding a job that meets or exceeds their reservation wage. This leads to a decline in matching efficiency and ultimately a lower job finding rate. This suggests the real-option value of waiting for both workers and firms. Delaying a hiring decision or the acceptance of a job offer grows in value as long as the uncertainty shock persists, increasing the real option value of waiting; see, e.g., (Bernanke, 1983). As a consequence, search intensity falls on both sides of the market, generating sustained unemployment relative to its pre-shock level.

Our results illustrate why it is important to identify different types of uncertainty shocks. As discussed in the introduction, unemployment can be decomposed into flows of workers entering and exiting employment, and uncertainty can be generated through different mechanisms. As the literature shows, general uncertainty shocks have a significant effect on unemployment over time, e.g., (Jurado/Ludvigson/Ng, 2015). However, when uncertainty is decomposed into its underlying sources, aggregate uncertainty shocks fade out. By contrast, labor market uncertainty shocks have persistent scarring effects on long-run unemployment.

¹⁵ Search intensity is defined as the effort exerted by both parties to fill an open position.

Table 7: Forecast Error Variance Decomposition

Variable	Shock/State	$h = 1$	$h = 12$	$h = 24$	$h = 36$	$h = 48$	$h = 60$
u_t	$\mathcal{M}_{t,\Lambda_1}^u$	0.20 (0.08, 0.46)	1.57 (0.73, 2.89)	2.55 (1.22, 4.66)	2.77 (1.38, 5.13)	2.92 (1.62, 5.30)	3.20 (1.78, 5.60)
	$\mathcal{M}_{t,\Lambda_2}^u$	0.13 (0.05, 0.29)	1.86 (0.87, 3.36)	3.67 (1.71, 6.71)	4.24 (2.12, 7.90)	4.70 (2.53, 8.23)	5.09 (2.83, 8.56)
	$\mathcal{L}_{t,\Lambda_1}^u$	0.69 (0.27, 1.49)	3.05 (1.46, 5.29)	6.50 (3.38, 10.57)	7.66 (3.81, 12.75)	8.02 (4.07, 13.47)	8.07 (4.12, 13.54)
	$\mathcal{L}_{t,\Lambda_2}^u$	0.24 (0.10, 0.49)	2.02 (0.97, 3.54)	5.25 (2.74, 8.63)	6.44 (3.36, 10.84)	6.87 (3.58, 11.70)	7.04 (3.71, 11.91)
	$\mathcal{M}_{t,\Lambda_1}^u$	0.19 (0.07, 0.41)	1.31 (0.72, 2.38)	1.80 (0.90, 3.27)	1.99 (1.03, 3.86)	2.22 (1.13, 4.27)	2.42 (1.22, 4.58)
	$\mathcal{M}_{t,\Lambda_2}^u$	0.37 (0.14, 0.83)	2.16 (1.18, 3.98)	2.77 (1.43, 5.22)	3.22 (1.69, 6.09)	3.63 (1.87, 6.74)	3.86 (2.02, 7.27)
f_t	$\mathcal{L}_{t,\Lambda_1}^u$	0.17 (0.06, 0.36)	1.78 (0.92, 3.35)	4.00 (2.01, 7.75)	5.45 (2.63, 9.99)	6.11 (2.98, 11.04)	6.42 (3.12, 11.49)
	$\mathcal{L}_{t,\Lambda_2}^u$	0.20 (0.07, 0.41)	1.67 (0.89, 3.11)	3.73 (1.83, 6.81)	4.98 (2.48, 8.90)	5.58 (2.76, 9.95)	5.92 (2.94, 10.50)
	$\mathcal{M}_{t,\Lambda_1}^u$	0.12 (0.04, 0.27)	1.85 (1.07, 3.11)	3.97 (2.27, 6.53)	4.42 (2.57, 7.20)	4.59 (2.72, 7.29)	4.72 (2.85, 7.38)
	$\mathcal{M}_{t,\Lambda_2}^u$	0.23 (0.08, 0.52)	3.59 (2.07, 6.12)	7.82 (4.49, 12.59)	8.68 (5.06, 13.69)	8.98 (5.49, 13.98)	9.25 (5.70, 14.13)
	$\mathcal{L}_{t,\Lambda_1}^u$	1.63 (1.00, 2.43)	6.40 (4.14, 9.50)	7.01 (4.55, 10.40)	7.18 (4.69, 10.51)	7.21 (4.81, 10.65)	7.32 (4.92, 10.68)
	$\mathcal{L}_{t,\Lambda_2}^u$	1.81 (1.08, 2.73)	7.06 (4.56, 10.37)	7.58 (5.00, 11.28)	7.69 (5.14, 11.43)	7.77 (5.20, 11.39)	7.85 (5.29, 11.44)

Notes: The figure is based on 5,000 retained draws from the posterior distribution. Table reports the posterior medians and 68% posterior intervals are in brackets.

Source: Author's own computation

6.3 Forecast Error Variance Decomposition

In this section, we explore the contribution of each uncertainty shock to the variance of the data. A valuable feature of our identification approach is that, while the impulse responses are constant through B_0 , the variance is not. (Lütkepohl/Netšunajev, 2014) shows that one can split the forecast error variance decomposition (FEVD) by regime, weighted by the variance-specific regimes (Λ_{s_t}). Therefore, we can explore the dynamics of the regime-dependent effects. Figure (4) shows the state regime probabilities for the estimated models. State 1 and State 3 capture high and low volatility states, respectively. State 1 corresponds to the special events in the labor market. State 3 is set aside, while State 1 and State 2 will be the main focus.

Table 8: Alternative Model Forms

<i>Alternative Lag Order (1)</i>				
$p = 6, q = 5, l = 4, h = 3, z = 2, o = 3$				
<i>Alternative Lag Order (1)</i>				
$p = 6, q = 4, l = 5, h = 3, z = 2, o = 2$				
<i>Alternative FSV Prior Form (1)</i>				
β	Loading vector	Normal	$\mathcal{N}(1,1)$	
ζ	AR(1) for the latent factor	Normal	$\mathcal{N}(0.95, 0.15^2)$	
γ_{1j}	AR(1) for the latent idiosyncratic series	Normal	$\mathcal{N}(0, 0.20^2)$	
γ_{0j}	Unconditional variances for latent idiosyncratic series	Normal	$\mathcal{N}(\hat{\eta}_{jt_{n \times 1}}, 1^2)$	
f_0, h_{j0}	Initial states	Normal	$(\{0, \log(\eta_j^2)\}, 2^2_{(n+1) \times 1})$	
σ_f, σ_{hj}	State Innovations	Inverse-Gamma	$\mathcal{IG}(a, b)$	$a = \{10, 10, 10, 10\}; b = \{0.01, 0.05, 0.05, 0.05\}$
ρ	Constant Conditional Correlation	Modified Beta	$\nu = 10$	
<i>Alternative FSV Prior Form (2)</i>				
β	Loading vector	Normal	$\mathcal{N}(1, 0.2^2)$	
ζ	AR(1) for latent factor	Normal	$\mathcal{N}(0.95, 0.15^2)$	
γ_{1j}	AR(1) for latent idiosyncratic series	Normal	$\mathcal{N}(0, 0.20^2)$	
γ_{0j}	Unconditional variances for latent idiosyncratic series	Normal	$\mathcal{N}(\hat{\eta}_{jt_{n \times 1}}, 0.20^2)$	
f_0, h_{j0}	Initial states	Normal	$(\{0, \log(\eta_j^2)\}, 0.5^2_{n+1 \times 1})$	
σ_f, σ_{hj}	State Innovations	Inverse-Gamma	$\mathcal{IG}(a, b)$	$a = \{2.5, 2.5, 2.5, 2.5\}; b = \{0.01, 0.05, 0.05, 0.05\}$
ρ	Constant Conditional Correlation	Modified Beta	$\nu = 4$	

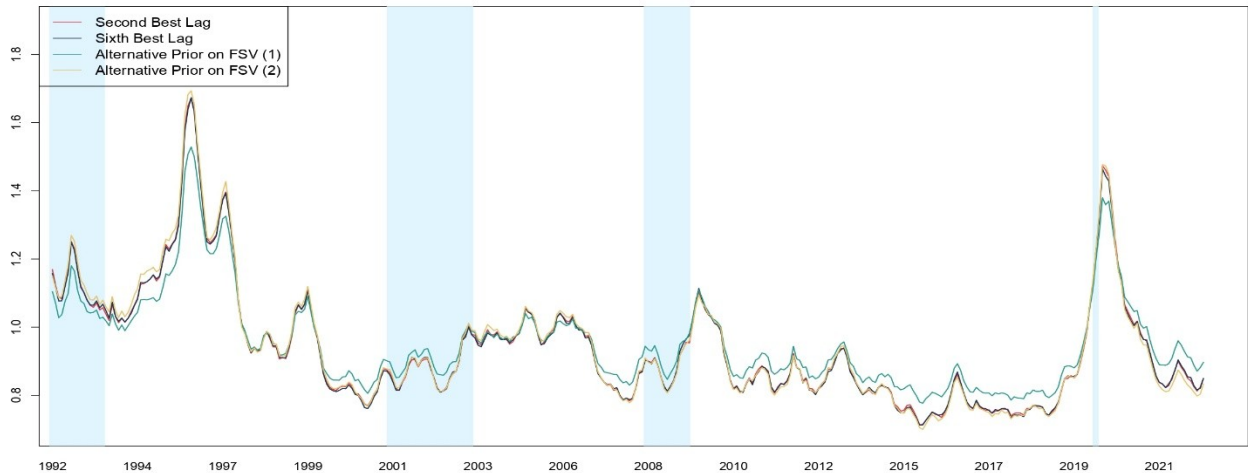
Notes: $\hat{\eta}_{jt}$ denotes the residual variance from an OLS regression for each equation.

Source: Author's own computation

Table (7) shows the contributions of both uncertainty shocks to the job finding rate, job separation rate, and unemployment. The contributions of both uncertainty shocks are qualitatively similar, accounting for around 5 percent of the total variance of unemployment over the five years. The contributions to the variance of the two labor market transition rates reinforce the evidence from the impulse responses. Macroeconomic uncertainty shocks operate through the firing margin, as they contribute more strongly to the job separation rate. By contrast, labor

market uncertainty shocks mainly come through the hiring margin, contributing most significantly to the job finding rate.

Figure 5: Labor Market Uncertainty under Different Specifications



Notes: The MCMC is based on 5,000 retained draws. The solid lines represent the posterior median of the factor volatility index f_t using different model specifications. Blue shaded areas indicate recessions as determined by the German Council of Economic Experts (GCEE).

Source: Author's own computation

Table 9: Pairwise Correlations with Baseline

	Second Best Lag	Sixth Best Lag	Alternative Prior on FSV (1)	Alternative Prior on FSV (2)
Baseline	0.9998	0.9996	0.9948	0.9989

Source: Author's own computation

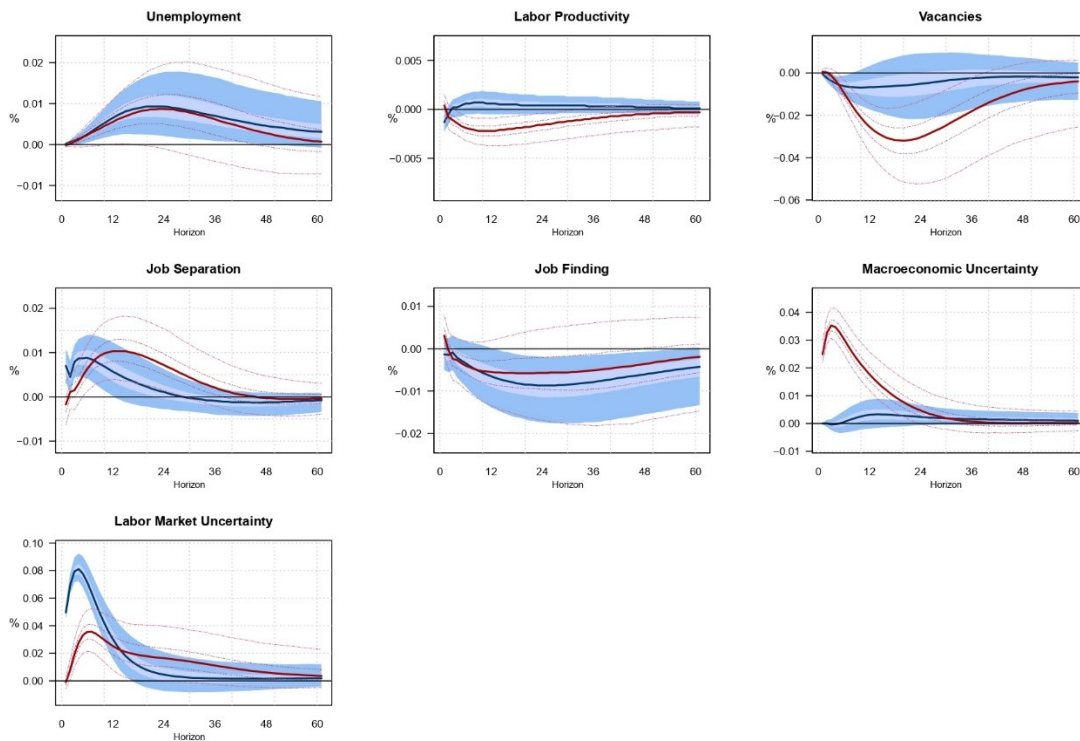
7 Robustness Checks

To verify the robustness of our findings, we estimate four alternative specifications of the search-and-matching model with FSV. For SM-FSV, we re-estimate the model using the second- and sixth-best DIC reported in Table (2). We also consider two additional specifications that vary the informativeness of the priors on the FSV parameters; see Table (8). Each model is estimated using the same number of draws as the baseline specification. The resulting uncertainty measures,

plotted in Fig. (5), are highly similar across specifications and closely track the baseline estimate. The first alternative prior specification does not capture either spike in the 1990s or the COVID recessions to the same degree as the other priors. This is attributed to the larger hyperparameter on the rate for each of the state equations, which assumes less volatility in the state equations. We include the pairwise correlations with the baseline series; see Table (9). The high correlations indicate that the alternative specifications do not generate meaningful deviations from the baseline measure.

We then re-estimate the MSH-VAR using an alternative lag length. Relative to the baseline, the AIC selects $p = 3$ as the second best criterion. The associated IRFs are shown in Fig.

Figure 6: Impulse Response Functions for MSH(3)-VAR(3)



Notes: The figure based on 5,000 retained draws from the posterior distribution. Solid Red Line: Posterior median for $\mathcal{M}_t^u$. Solid Blue Line: Posterior median for $\mathcal{L}_t^u$. Shaded blue regions and dashed red lines represent the 90% and 68 % posterior bands.

Source: Author's own computation

(6). Overall, shocks to both labor market uncertainty and macroeconomic uncertainty generate responses that are broadly in line with those from the baseline specification.

8 Conclusion

We contribute to the growing literature on the importance of uncertainty shocks in the labor market. For this purpose, we develop a search and matching model with factor stochastic volatility. The volatility factor that spans the idiosyncratic volatilities is identified as labor market

uncertainty. By spanning the idiosyncratic volatilities of the three fundamental blocks of the labor market, the volatility factor is able to uncover uncertainty dynamics in the labor market. Our results show distinct rises in labor market uncertainty that do not occur in other volatility-based measures of uncertainty. In particular, we find that the largest rise in labor market uncertainty did not occur during any officially dated recessions.

In a VAR application identified by heteroskedasticity, we contrast labor market uncertainty shocks and macroeconomic uncertainty. We document that while both macroeconomic uncertainty and labor market uncertainty shocks lead to an increase in unemployment, they operate through different margins. Macroeconomic uncertainty shocks primarily affect the firing margin, while labor market uncertainty shocks operate through the hiring margin. In particular, labor market uncertainty shocks generate a sharp decline in the job finding rate, but only a slight decline in the stock of vacancies. This pattern points to a decline in search intensity by firms and workers. This further establishes that uncertainty shocks increase the real option value of waiting. We do not find the same result for macroeconomic uncertainty shocks. This leads us to conclude that labor market uncertainty shocks are a distinct and integral component of explaining the effects of uncertainty shocks.

In this paper, we have shown how labor market uncertainty can be extracted from labor market data. The stylized facts we have presented could be used to inform further research into the nature of uncertainty shocks in quantitative macro-labor models. Workhorse models such as the search and matching framework have established the view that the labor market is not merely an appendage of the macroeconomy. We reinforce that for the uncertainty domain: labor market uncertainty is more than the labor market's exposure to uncertainty generated by macroeconomic shocks.

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Corresponding author

Alex Parker

Email: alexander.parker2@gmail.com