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Uncertainty and Labor Market Fluctuations

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Uncertainty and Labor Market Fluctuations*

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Abstract

We investigate how a macroeconomic uncertainty shock affects the labor market. We focus on the uncertainty transmission mechanism, for which we employ a set of worker flow indicators in addition to labor stock variables. We incorporate common factors from such indicators into a framework that can simultaneously estimate historical macroeconomic uncertainty and its impacts on the macroeconomy and labor market. We find firms defer hiring as the real option value of waiting increases. Moreover, significantly more workers are laid off while voluntary quits drop, suggesting other mechanisms such as the aggregate demand channel play a crucial role.

Keywords: Business cycle, Labor market, Uncertainty, Stochastic volatility

JEL Classifications: C32, D80, E24, E32

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1 Introduction

Recent studies have found that an unexpected increase in uncertainty impacts the labor market negatively through a variety of channels.[1] In this paper, we empirically investigate how such channels operate, using a comprehensive set of labor flow statistics.

One of the important channels discussed in theoretical studies is the *real option* channel (Bernanke (1983) and Bloom (2009)). High uncertainty widens the inaction region between investment/disinvestment for capital and hiring/firing for labor, due to irreversible, non-convex adjustment costs. Thus, more firms pause their investment, hiring and firing decisions, which lowers economic growth. On the demand side, households lower consumption and increase precautionary savings (the *aggregate demand* channel: see Basu and Bundick (2017) and Leduc and Liu (2016)). The *reallocation* channel highlights that the probability of acquiring extreme returns intensifies the reallocation process during the times of high uncertainty; firing and quitting increase more than hiring does (Schaal (2017)). These channels yield an observationally-equivalent prediction of increased unemployment in response to an uncertainty shock.

As such, previous empirical studies have used changes in (un)employment at the aggregate level to examine the uncertainty shock impacts. However, such aggregate indicators provide little information on the transmission channels of uncertainty (Bloom (2009) and Choi and Loungani (2015)). That is, they capture how the stock of the unemployed changes in each period, without revealing inflows and outflows driving the changes. For example, unemployment goes up when inflows into unemployment increase and outflows from the pool decrease. However, it can also rise when the inflows increase more than the outflows, as demonstrated by the reallocation channel. Unemployment can also increase when both flows decline in line with the real option channel, with a larger drop in outflows than the inflows.

To shed light on the transmission channels, we employ a variety of labor flow as well as stock variables. For example, we make use of worker transition probability and employment hazard rate series as introduced in Elsby, Michaels, and Solon (2009) and Elsby, Hobijn,

[1] Examples include Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), Caggiano, Castelnuovo, and Groshenny (2014), Schaal (2017), Choi and Loungani (2015), Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016), Carriero et al. (2018), and Mumtaz (2018).

and Şahin (2015), to gauge how unemployment increases. We also include the number of unemployed for less than five weeks, which reflects a new inflow into the unemployment; we further disaggregate this series by reasons for separation to gauge potential heterogeneity.

One concern in all empirical studies of uncertainty is how to measure uncertainty and to identify an uncertainty shock. Many use a proxy, such as implied volatility in the stock market (i.e., VIX) or forecast dispersions, and include it in a vector autoregressive (VAR) model along with other macroeconomic/financial variables (see Bloom (2009), Bachmann, Elstner, and Sims (2013), Caggiano et al. (2014), and Riegler (2018), for example). The uncertainty shock is then identified via the Cholesky decomposition. However, this approach suffers from several problems. First, many uncertainty measures capture distinct phenomena although they tend to co-move largely (Kozeniauskas, Orlik, and Veldkamp (2018)). Second, while most proxies are constructed from time-varying volatilities of macroeconomic and financial variables, the latter step of using a simple VAR contradicts this idea, as it implicitly assumes their variances do not change over time (Carriero et al. (2018)). Finally, this approach does not explicitly control for whether an increase in uncertainty is due to an exogenous uncertainty shock or a response to a first-moment shock. In other words, this setup insufficiently address the simultaneity problem between uncertainty and the state of the economy, as highlighted in Piffer and Podstawski (2016).

We address this issue by using a stochastic volatility (SV)-in-mean type model that allows simultaneous estimation of historical macroeconomic uncertainty and its impacts, as in Carriero et al. (2018). Macroeconomic uncertainty is defined as a common factor driving the SVs of many macroeconomic indicators. In addition, since the uncertainty evolves as SV that has its own innovation term, the model can identify an uncertainty shock that is not caused by other first-moment shocks. We extend the model by adding common labor factors to the macro indicators, which are estimated from a large panel of worker flows variables. Our model is thus similar in spirit to a factor-augmented VAR model in Bernanke, Boivin, and Eliasz (2005), and enables us to estimate the impacts of the uncertainty shock on labor flow variables in one consistent step. The model is widely applicable to examinations of the effects of macroeconomic and/or financial uncertainty shocks on a set of variables of a similar property, such as production and prices of different industries.[2]

Similar papers include Martínez-Matute and Urtasun (2018) and Riegler (2018), which focus on labor flows. Using a survey of European firms, Martínez-Matute and Urtasun (2018) find firms were more likely to freeze hiring and not renew temporary contracts, when uncertainty was high during the period of 2010–2013. Riegler (2018) estimates a VAR model where uncertainty is proxied by implied volatility of stock returns and finds high uncertainty increases the job separation rate while lowering the job finding rate. He then builds a search model differentiating job flows and worker flows to understand such findings. Our paper differs in that the measure of uncertainty is estimated inside of the model. Moreover, to the best of our knowledge, our paper is the first one to use a comprehensive set of labor flow indicators in the U.S to examine the uncertainty transmission channel.

We find that firms decrease hiring during periods of high uncertainty, implying that the real option channel is at work. In addition, the positive responses of various inflows to unemployment highlight the importance of the role other channels play. A greater number of laid-off workers mainly drive the inflows increase. Firms fire more workers, possibly due to lower consumption by households that increase precautionary savings in response to uncertainty. This demand-side propagation mechanism is also supported by drops in voluntary quits as well as increases in entrants switching from non-participation. Firms may find it easy to adjust labor in response to lower demand rather than to adjust capital, where costs could be larger. Finally, demand for labor could decrease due to its complementarity with capital which declines following an uncertainty shock. As such, it will be crucial to highlight these mechanisms in addition to the option value channel to understand and quantify the impacts of the uncertainty shocks more precisely. Our findings also suggest that assuming asymmetric hiring and firing costs can be helpful when building a theoretical model of uncertainty.

The rest of the paper is organized as follows: Section 2 illustrates our econometric model used to estimate macroeconomic uncertainty and its impacts on the labor market;

[2] Mumtaz, Sunder-Plassmann, and Theophilopoulou (2018) presents a model that can be applied to a similar setup as ours. Here, macroeconomic uncertainty is defined as the common uncertainty of unobservable factors that are drawn from both the aggregate- and state-level indicators, i.e, the volatility of the factors. In contrast, our macroeconomic uncertainty is a factor of the volatilities of macroeconomic indicators.

section 3 describes the data set of macroeconomic and labor market indicators; section 4 presents the estimated macroeconomic uncertainty series and labor factors, and section 5 discusses the impacts of uncertainty on macroeconomic and labor market indicators and the transmission mechanism. The last section concludes.

2 Model

Our model is built upon the framework introduced by Carriero et al. (2018). It models macroeconomic uncertainty as common factors of the stochastic volatilities (SV) of many different economic indicators comprising a VAR. The common volatility factor is then included in the mean equations of the VAR to capture its impacts on the indicators. One of the main advantages of this setup lies in the modeling of the volatility process. A SV process has its own error terms that can potentially have a separate volatility shock unrelated to any first-moment shocks. In a GARCH-type volatility model often used as an alternative, the shock that changes the first moment in the past is the source of variations in volatility. As a result, it is not possible to clearly discern the effects of second moment shocks from those of the first moment shocks (see Jo (2014) and Carriero et al. (2018) for detailed discussions on the comparison of SV and GARCH models).

It is important to note that our focus is estimating the impacts of an uncertainty shock on a set of labor flow indicators, which outnumbers macroeconomic indicators we include in the model. To address this issue, we first impose a factor structure on the set of labor indicators:

$$\begin{aligned} X_{i,t} &= \lambda_i F_t + e_{i,t}, \\ e_{i,t} &\sim N(0, \Sigma). \end{aligned} \tag{1}$$

Here, $X_{i,t}$ is i-th labor indicator in the panel in time t. We assume that common dynamics across different labor variables in period t are captured by M unobservable labor factors F_t. Any idiosyncratic movements of $X_{i,t}$ are reflected in $e_{i,t}$.

The factors, F_t, are then augmented to vector Y_t along with N_M observable macroeconomic variables (i.e., $N \equiv N_M + M$). In particular, we order F_t after macro variables in Y_t. Then, the dynamics of a N-dimensional vector Y_t is modeled using a VAR process following Carriero et al. (2018):

$$
\begin{aligned}
Y_t &= \Pi(L)Y_{t-1} + \Pi_m(L)\ln m_t + v_t, \qquad (2)\\
& v_t \sim N(0, \Omega_t),\\
& \Omega_t = A^{-1}H_tA',\\
& H_t = \begin{bmatrix} \lambda_{1,t} & 0 & 0 & \cdots & 0 \\ 0 & \lambda_{2,t} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \cdots & \vdots \\ 0 & 0 & 0 & \cdots & \lambda_{N,t} \end{bmatrix}.
\end{aligned}
$$

The first notable difference of our setup (2) from a usual VAR model is that the errors associated with each variable in Y_t have time-varying volatilities $\lambda_{i,t}$, similar to Kim, Shephard, and Chib (1998) and Primiceri (2005), among others. Moreover, we postulate such time-varying volatilities of each variable have a common factor, imposing the second factor structure in our model. Both the common volatility factor ($\ln m_t$) and the idiosyncratic components ($\ln h_{i,t}$) evolve following stochastic volatility processes:

$$
\begin{aligned}
\ln \lambda_{i,t} &= \beta_{m,i} \ln m_t + \ln h_{i,t}, \qquad i = 1, \cdots, N\\
\ln h_{i,t} &= \gamma_{i,0} + \gamma_{i,1} \ln h_{i,t-1} + u_{i,t},\\
\ln m_t &= \upsilon(L) \ln m_{t-1} + \delta_m' y_{t-1} + \epsilon_{m,t}. \qquad (3)
\end{aligned}
$$

The volatility factor, $\ln m_t$, represents a component capturing common dynamics in the volatilities of all N variables. We define this common volatility factor *macroeconomic uncertainty*, similar in spirit to Jurado, Ludvigson, and Ng (2015). The loadings on the macro uncertainty are noted as $\beta_{m,i}$. We set the order of $\upsilon(L)$ to 2. Finally, the term $\delta_m' y_{t-1}$ shows that the previous realization of y_t has impacts on the dynamics of macroeconomic uncertainty.

With F_t augmented to Y_t, our model is similar in spirit to a factor-augmented VAR (FAVAR) model approach in Bernanke et al. (2005). More specifically, it is closer to the approximate factor models in Forni and Reichlin (1998) and Foerster, Sarte, and Watson

(2011), in that we do not include any observable factors in F_t. Given the interest of our paper, we focus explicitly on the commonality captured by unobserved factors and do not rotate the factors to remove the correlation with observable macroeconomic variables from them. In fact, we expect the labor factors to be correlated with those indicators, rather than providing additional information content to the macro panel. We discuss more on such correlations in Section 4.2.

It is important to note that we refrain from adding labor flow indicators directly to Y_t. Adding all of the labor indicators to the main VAR will make its dimensions too large, with almost 50 variables. More importantly, the common uncertainty factor estimated under this circumstance will not likely represent "macroeconomic uncertainty", as its dynamics will be mostly driven by the labor indicators' volatilities. Adding common labor factors to Y_t alleviates such problems.

Macroeconomic uncertainty then appears in the mean equations of the VAR, as in equation (2).[3] The model allows the joint estimation of the macroeconomic uncertainty as well as its impacts on macroeconomic variables and common labor factors. Based on these estimates, we can further gauge the impacts of a macroeconomic uncertainty shock on labor flow indicators. Our setup, thus, extends Carriero et al. (2018) and would be useful for a similar analysis where the interest lies in estimating the dynamic impulse responses of a variety of variables that share similar characteristics to a common uncertainty shock. For instance, it can be particularly helpful for assessing the impact of uncertainty on the panel of companies' capital investment decisions as well as changes in sales. A summary of estimation algorithm is provided in Appendix.

3 Data

We include 18 macroeconomic indicators in vector Y_t in our main VAR (i.e., equation (2)), ranging from the real economic activity to price indexes. Our selection of the macro

[3] While Carriero et al. (2018) have two volatility factors capturing macroeconomic and financial uncertainties, we keep one volatility factor representing macroeconomic uncertainty only. Our focus is on understanding the channels that macroeconomic uncertainty transmits to the labor market, but not on distinguishing the impacts of macro and financial uncertainties. Therefore, we abstain from the financial variables as well as financial uncertainty and keep the model concise.

variables is similar to that of Carriero et al. (2018). See Table A1 in Appendix for the full list of macroeconomic indicators.

We estimate three factors from a variety of labor market indicators to include in Y_t. A complete list of all labor indicators is documented in Table A2 in Appendix, some of which we highlight here. First, the indicators consist of the number of unemployed by duration. The Current Population Survey (CPS) is a monthly survey of about 60,000 households in the U.S., and provides pertinent information about the labor market. BLS publishes seasonally-adjusted data showing people unemployed by the duration of joblessness, i.e., unemployed for less than five weeks, for between five and 14 weeks, for 15 weeks or longer. For the number of unemployed for less than five weeks, we further disaggregate the series by reasons for separation, i.e., job losers, job leavers, and entrants. Job leavers are those who quit or otherwise terminated their employment voluntarily and immediately began looking for work. Entrants include both re-entrants and new entrants; reentrants worked previously but were out of the labor force prior to beginning their job search, while new entrants have never worked. These series thus capture new flows into the unemployment due to the different reasons.[4]

We also include the transition probability of worker flows across employment states, which are constructed following Elsby et al. (2015). CPS keeps a selected household in sample for four consecutive months, and then re-surveys the household for another four months after an eight-months break. This rotating-panel element allows the construction of the monthly transition probability of workers within employment, unemployment, and nonparticipation.

Finally, we use inflow and outflow hazard rates disaggregated by the three reasons noted above. In particular, we follow Elsby et al. (2009) for the construction of the series, where the authors highlight distinct dynamics in the cyclical properties of the three groups' flows series. This enables us to more precisely account for potential heterogeneity in the uncertainty transmission mechanism across unemployment groups by different reasons. We

[4]Following Elsby et al. (2009) and Elsby et al. (2015), we apply correction factors to unemployment series disaggregated by duration, reason, or both. This is to account for the well-known discontinuity in the short-term unemployment series, due to the redesign of the CPS in 1994. See Elsby et al. (2009), Elsby, Hobijn, and Şahin (2013, 2015), Shimer (2012) and Ahn and Hamilton (2019) for details about the CPS redesign and suggested treatments.

also include the job finding and separation rates, constructed following Elsby et al. (2009).

We calculate year-over-year growth rates of all labor variables by taking log differences from the prior year. We standardize the growth rates before estimating factors, as commonly done in the studies applying a factor model. Our data span the period from June 1969 to June 2018.

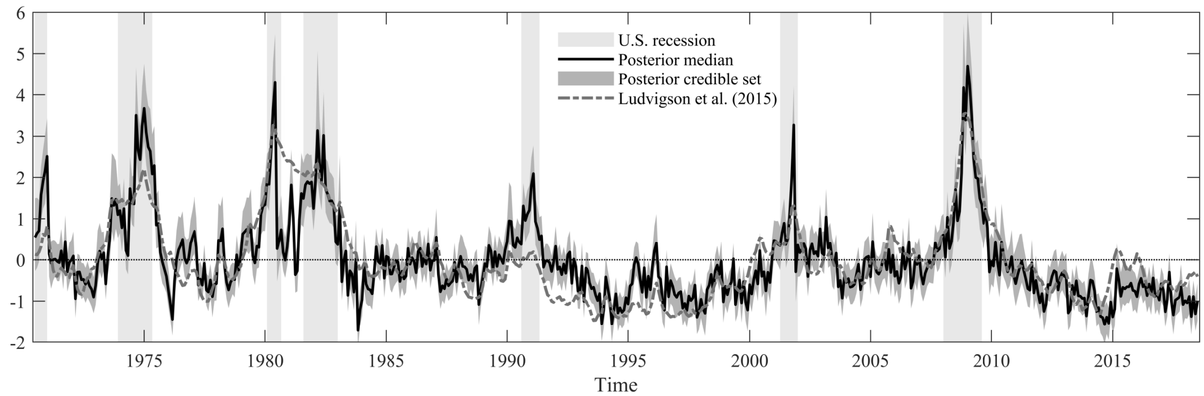
4 Estimated Uncertainty and Labor Factors

4.1 Macroeconomic Uncertainty

Figure 1 plots the median posterior draws of macroeconomic uncertainty series ($\{\sqrt{m_t}\}_{t=1}^{T}$) from the baseline model, along with the 70% posterior credible set. The uncertainty series is fairly tightly estimated, consistent with Carriero et al. (2018). It has several large peaks that coincide with recessions in the 1980s, 2001, and the recent Great Recession. In addition, the macroeconomic uncertainty series jumps quite often outside of recession periods, e.g. prior to the 1980 recession and around 1996.

We also plot the macroeconomic uncertainty series from Ludvigson, Ma, and Ng (2015) in Figure 1. Overall, both measure of uncertainty move closely together, with a correlation of 0.71. However, our series is more volatile and has more frequent jumps; the difference is particularly noticeable in 1990s and early 2000s.

Figure 1: Macroeconomic Uncertainty Series

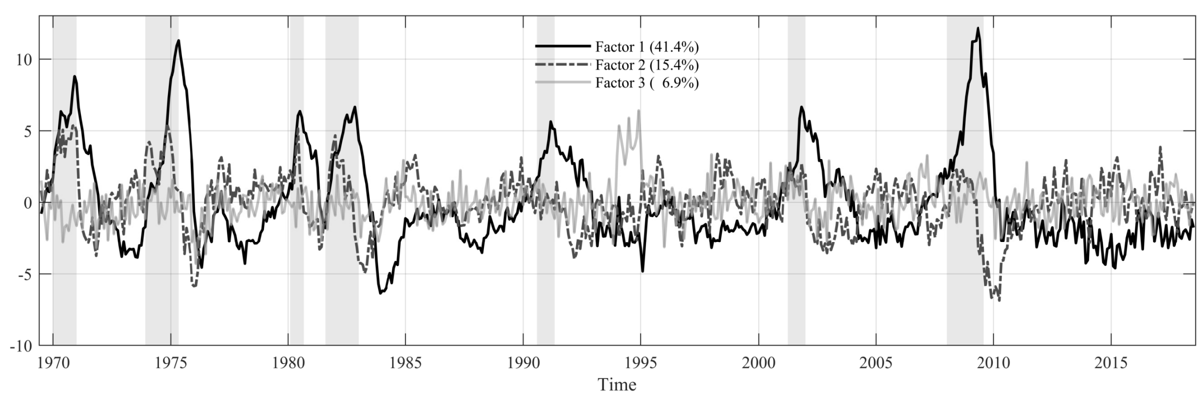


NOTE: The solid line represents the median posterior draws of monthly macroeconomic uncertainty series (i.e., $\sqrt{m_t}$). The shaded bands are the 70% posterior credible set. The dotted line is the macroeconomic uncertainty series from Ludvigson, Ma, and Ng (2015). All series are standardized for comparison. The shaded areas are the NBER recession periods.

4.2 Common Factors in the Labor Series

Figure 2 plots three factors estimated from the panel of the labor indicators. Together, the factors capture about 50% of total variations in all labor market indicators.[5] Results shown below do not significantly change as we add more factors.

Figure 2: Factors Estimated from the Labor Market Variables



NOTE: This figure plots the three common factors of the labor market indicators, obtained via principal component analysis. The shaded regions are the NBER recession periods.

[5]The factors are estimated using principal component analysis (PCA). We choose to use the first three factors, which explain 41.4%, 15.4%, and 6.8% of the total variations, respectively. Each of the remaining factors explains less than 6% of total variations.

Table 1: Correlation Coefficients between Labor Factors and Selected Macroeconomic Indicators

Variables	Factor 1	Factor 2	Factor 3
Employment	−0.68*	−0.10*	−0.06
Hours worked	−0.63*	0.02	0.13*
ISM: new orders	−0.55*	−0.41*	−0.07*
Industrial production	−0.36*	−0.32*	−0.08*
Capacity utilization: manufacturing	−0.33*	−0.38*	−0.09*
Vacancy rate	−0.24*	−0.23*	−0.13*
Unemployment rate	0.50*	0.31*	−0.02

NOTE: This table shows the correlation coefficients between the three factors estimated from the labor panel and the selected macroeconomic indicators in the main VAR. The asterisks denote that the correlation coefficients are statistically different from zero at the 95% significance level.

Table 1 shows correlation coefficients between each labor factor and other selected macroeconomic indicators included in the main VAR. The first factor closely comoves with total non-farm employment as well as with hours worked. Interestingly, the second factor has the highest correlation with the ISM new orders index, followed by capacity utilization and industrial production index. Finally, the third factor captures high-frequency, volatile fluctuations in the labor market. The variables with which it is most closely correlated are the vacancy rate and the hours worked.

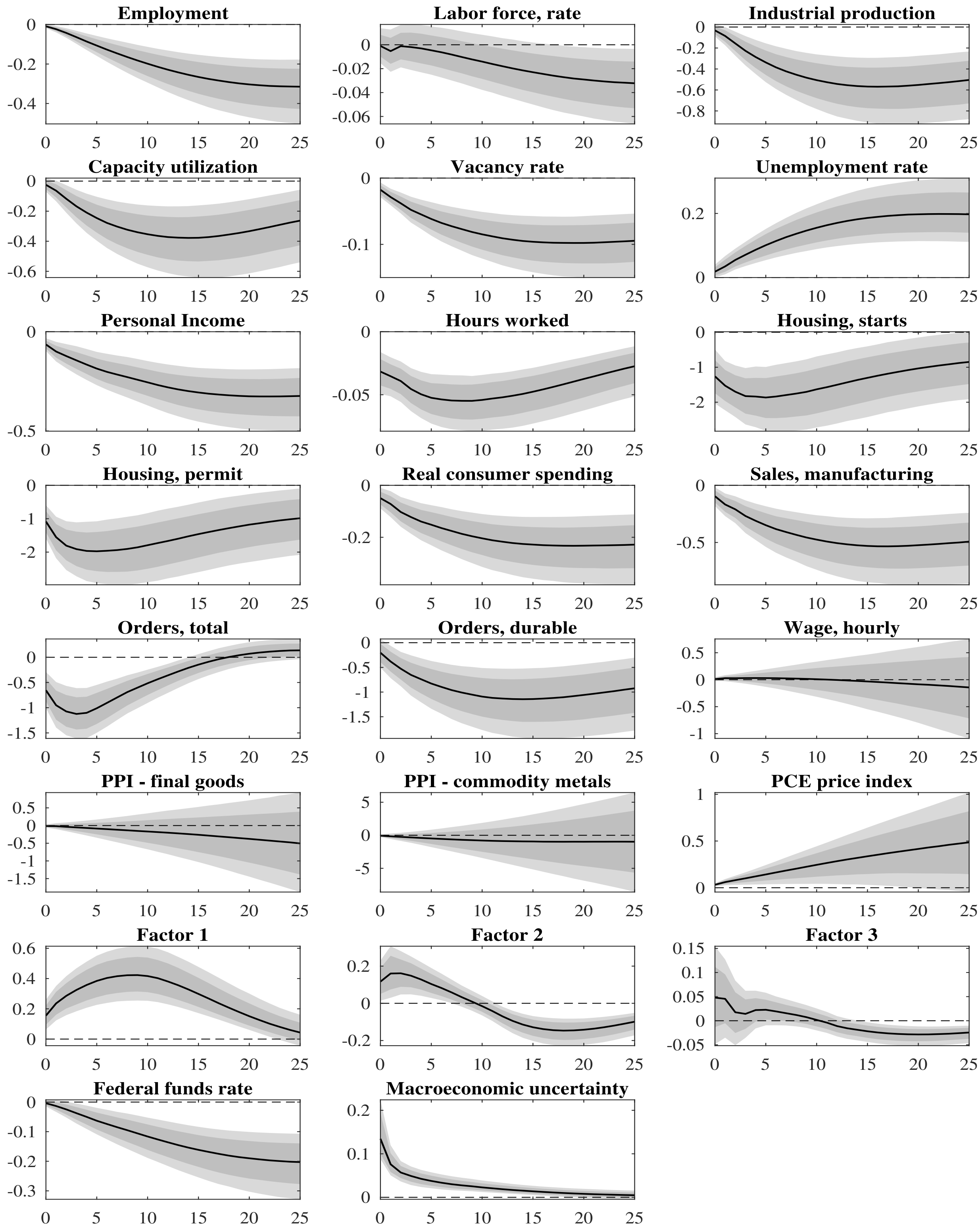
5 Dynamic Impacts of Macroeconomic Uncertainty

5.1 Impacts on Macroeconomic Variables

Figure 3 plots the impulse responses of the variables in the main VAR to a one-standard deviation shock to the log macroeconomic uncertainty ($\ln m_t$).[6] The increase in macroeconomic uncertainty dissipates in about a year after the impact. In general, the dynamic responses of the macroeconomic variables are very similar to those documented in Carriero et al. (2018). An unexpected increase in the macroeconomic uncertainty has significant

[6]The impulse responses of macro variables are in levels or log levels, and the units are percentage point changes. Similar to Carriero et al. (2018), we conduct the following steps. First, we obtain impulse responses in standardized data; note that for some variables, the data are differenced once or twice. We then multiply the resulting impulse responses of each variable by its original standard deviations and accumulate the impulse responses if the corresponding variable entered the VAR in differences.

Figure 3: Macroeconomic Responses to an Uncertainty Shock



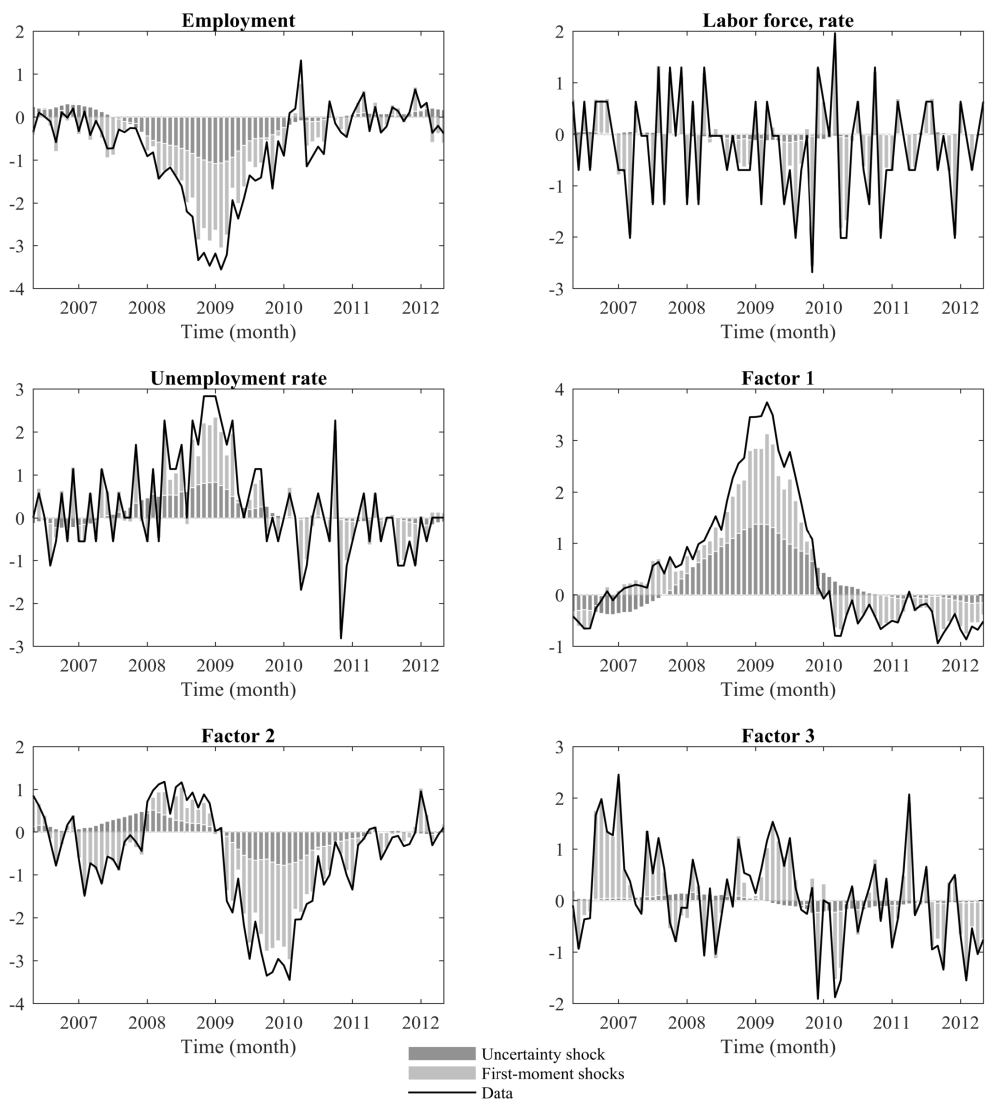
NOTE: This figure plots the impulse responses of macroeconomic indicators as well as the three labor factors to a one-standard deviation macroeconomic uncertainty shock. The dark shaded areas represent the 70% posterior credible sets, and the light areas 90%.

negative impacts on most economic indicators such as industrial production, capacity utilization and orders of durable goods and the new orders component of the ISM index. Some indicators show rather immediate and large declines (e.g., housing starts and new orders), while others have more persistent effects that peak around 15 months after the impact (e.g., capacity utilization and employment). Looking at the aggregate labor market variables, the shock decreases employment, hours worked, as well as vacancy rate, while increasing the unemployment rate. Hourly wage declines slightly, but the impacts are estimated rather imprecisely as are other price indices, possibly due to stickiness upon arrival of an uncertainty shock, as noted in Carriero et al. (2018).

To see how important uncertainty shocks are in explaining fluctuations in the labor market and more broadly in the macroeconomy, we compute a historical decomposition for the period around the Great Recession. As noted in detail in Carriero et al. (2018), however, the computation of a historical decomposition in our framework is not as straightforward as it is for a linear time-invariant VAR model. The variables in the VAR part of our model are affected by three different terms: i) first-moment shocks ν_t, ii) a macroeconomic uncertainty shock via the SV-in-Mean term, and iii) the interaction between the first and the second moment shocks. The final term reflects that both macroeconomic and variable-specific second-moment shocks influence the variance-covariance matrix Ω_t from which the first moment shocks are drawn. However, it is not simple to further discern the impacts of macroeconomic uncertainty from interaction terms, as variable-specific volatilities are multiplied to the macroeconomic uncertainty. Thus, following the approach in Carriero et al. (2018), we leave out the interaction term from the historical decomposition, and use the first two direct impacts of uncertainty only. Thus, our estimates can be hence interpreted as a lower bound.

Figure 4 shows the historical decomposition results for selected labor indicators and labor factors, computed from May 2006 to May 2012. We find that the uncertainty shock was as pertinent as first-moment shocks for some variables during this period. For instance, it explains about 40 percent of the decline in employment on average during the Great Recession. Interestingly, uncertainty contributed substantially negatively to the dynamics of employment for an extended period after the trough around 2009; sometimes it more than offset the positive contributions from the first moment shocks, as the economy emerges from the bottom of the Great Recession. This suggests that high macroeconomic uncertainty could be a crucial factors for the observed sluggish labor market recovery. The unemployment rate and the first labor factor are also affected materially, while the labor force participation as well as the other factors are less so.

Figure 4: Historical Decomposition

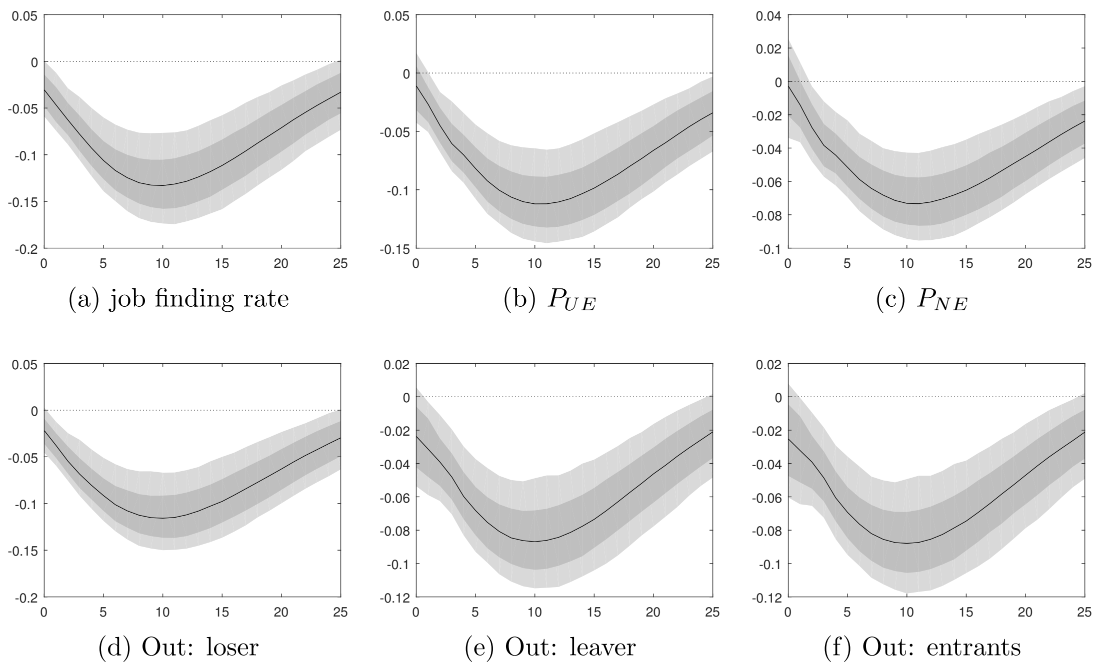


NOTE: This figure plots the historical decomposition for the period of 2006 May to 2012 May for selected labor indicators and the three labor factors. The charted estimates are the posterior median decomposition values based on all draw from the posterior distribution.

5.2 Impacts on the Labor Market

Now we shift our focus to the labor market. We note again that our model estimates such effects based on the dynamic responses of three common labor factors, which are determined in the main VAR. For each posterior draw of VAR parameters and volatilities, we compute the responses of the three labor factors and plug those back into equation (1) to assess the impacts on the labor flow series. The factors affect each labor series differently based on factor loadings.

Figure 5: Impulse Responses of Outflows from Unemployment

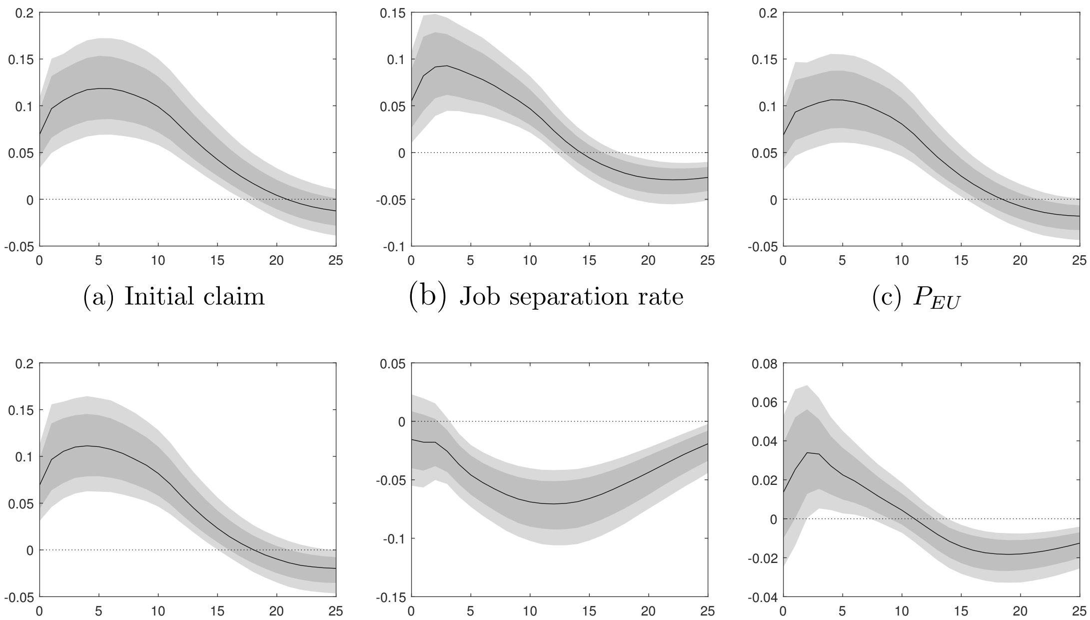


NOTE: This figure plots the impulse responses of the (a) job finding rate, (b) transition probability from unemployment to employment (UE), (c) that from not-in-labor-force (NE), outflow rate from unemployment (d) of job losers, (e) of job leavers, and (f) of entrants to the labor force, to a one-standard deviation macroeconomic uncertainty shock. The dark and light shaded areas represent the 70% and 90% posterior credible sets, respectively.

We start by examining the responses of six different outflows from unemployment in Figure 5. All series consistently point that hiring decreases significantly. The job finding rate drops significantly and so do the transition probabilities to employment from unemployment and nonparticipation. All outflow hazard rates from three unemployment-by-reason groups decrease. Note, that the vacancy rate also drops significantly as shown earlier, suggesting that firms post fewer jobs. The declines observed consistently across all

6 series evidence that the real option value of waiting increases in the case of hiring when uncertainty is high, in line with Bloom (2009).

Figure 6: Impulse Responses of Inflows into Unemployment



(a) Initial claim (b) Job separation rate (c) P_{EU}

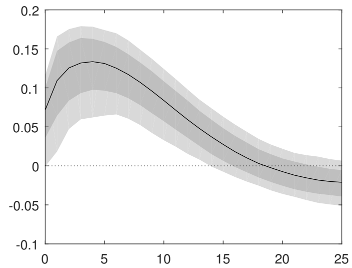
(d) In: loser (e) In: leaver (f) In: entrants

NOTE: This figure plots the impulse responses of the (a) initial unemployment insurance claims, (b) job separation rate, (c) transition probability from employment to unemployment (EU), inflow hazard rate of (d) job losers, (e) of job leavers, and (f) of entrants to the labor force. The responses are to a one-standard deviation macroeconomic uncertainty shock. The dark and light shaded areas represent the 70% and 90% posterior credible sets, respectively.

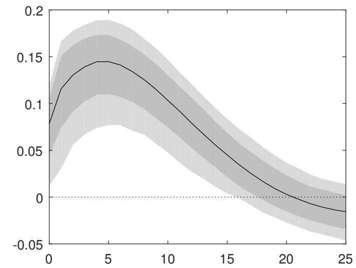
Figure 6 reports the impulse responses of the labor indicators capturing inflows to unemployment. We see that the number of initial unemployment insurance claims increases significantly (panel (a)). So does the job separation rate (panel (b)) as well as the transition rate from employment to unemployment (panel (c)). We also find that the inflow hazard rate of the job losers (panel (d)) increases significantly. This indicates that firms are likely to terminate employment at a significantly higher rate when an uncertainty shock hits. In contrast, panel (e) highlights that inflow hazard rates of job leavers drops significantly; those who would otherwise consider quit their jobs voluntarily are now more likely to stay at the current positions. Finally, panel (f) shows that significantly more workers not participating in the labor force are expected to enter unemployment.

Figure 7 plots the impulse responses of short-term unemployment, i.e., the number of

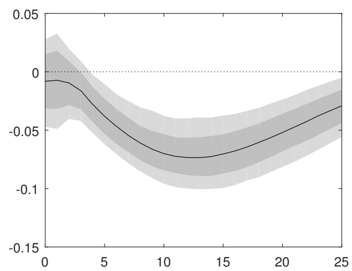
Figure 7: Impulse Responses of Short-Term Unemployment Series to an Uncertainty Shock



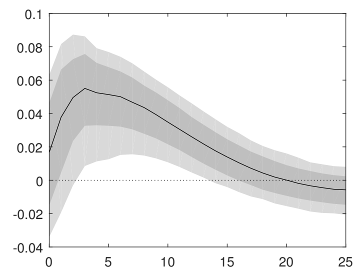
(a) Total



(b) Job losers



(c) Job leavers



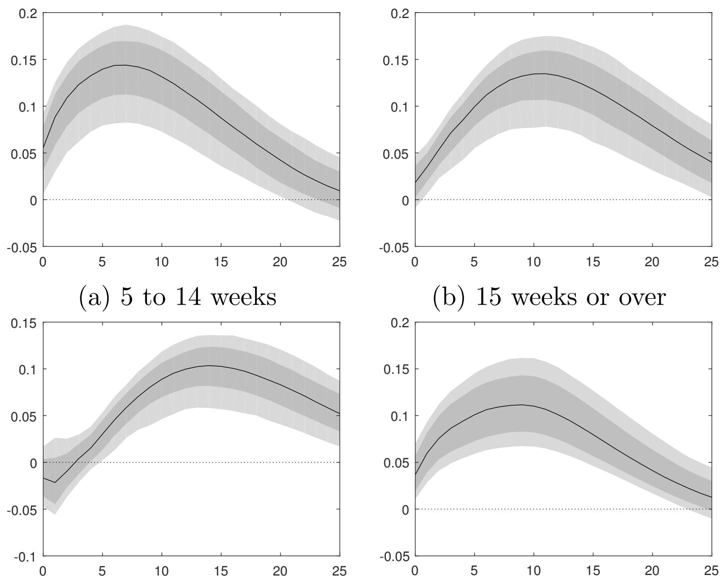
(d) Entrants

NOTE: This figure plots the impulse responses of four less-than-five-week unemployment series to a one-standard deviation macroeconomic uncertainty shock. The dark and light shaded areas represent the 70% and 90% posterior credible sets, respectively.

unemployed for less than 5 weeks. This captures those who just entered the unemployment pool in the past month. The first notable finding is that the total number of short-term unemployment increases significantly (panel (a)), with the median response peaking at around 13 basis points. We further look at the less-than-5-week unemployment series disaggregated *by reasons*, and the impulse responses of these are in line with those of the inflows series examined above. Short-term job losers (panel (b)) increase very significantly, driving the responses of total short-term unemployment. The number of job leavers in the past 4 weeks declines (panel (c)) and those who enter the labor force also increase significantly (panel (d)).

All in all, the real option channel does not seem to be the main transmission mechanism of uncertainty for the inflows of workers to unemployment. This channel would rather lead firms to retain workers, as an uncertainty shock shifts out the firing threshold due to high adjustment costs. Our results are also at odds with the reallocation channel (e.g., Schaal (2017)); high uncertainty increases the dispersion of wage distribution and leads to the higher probability of getting a high wage offer. As a result, it would incentivize more workers to voluntarily quit their current jobs through the reallocation channel. Instead, our findings support the idea that other mechanisms, such as the aggregate demand channel, can also be important to understand the transmission of uncertainty. Firms fire more workers, as households lower consumption and increase precautionary savings under uncertainty. In addition, uncertain income flow prospects may stop more workers from voluntarily terminating current employment and push those who had not participated in the labor force to look for a job.

Figure 8: Impulse Responses of Medium- and Long-Term Unemployment and Duration



(a) 5 to 14 weeks (b) 15 weeks or over

(c) Duration (d) Part-timers

NOTE: This figure plots the impulse responses of (a) the number of civilian unemployed for 5 to 14 weeks, (b) that for 15 weeks and over, and (c) average duration of unemployment to a one-standard deviation macroeconomic uncertainty shock. The dark and light shaded areas represent the 70% and 90% posterior credible sets, respectively.

As worker outflow from the pool declines substantially while inflow increases, the pool of unemployed balloons, and unemployment duration goes up. Medium- and long-run unemployment, as well as average unemployment duration, increase substantially, as shown in panels (a) to (c) in Figure 8. It would be worthwhile to point out that we do not restrict a priori the impulse responses of these variables to change systematically in accordance with the short-term unemployment.

Finally, while less evident from the responses of the inflows, it is important to note again that the real option channel is still one of the crucial transmission mechanisms of uncertainty. Panel (d) in Figure 8 shows that firms switch to part-time employees when uncertainty is high. Part-time workers in general do not incur as high adjustment costs as full-time workers, so firms switch to this flexible group when uncertainty is high. This, in turn, illustrates the real option channel can have differential impacts depending on the size of the adjustment costs (see Bloom (2014)).

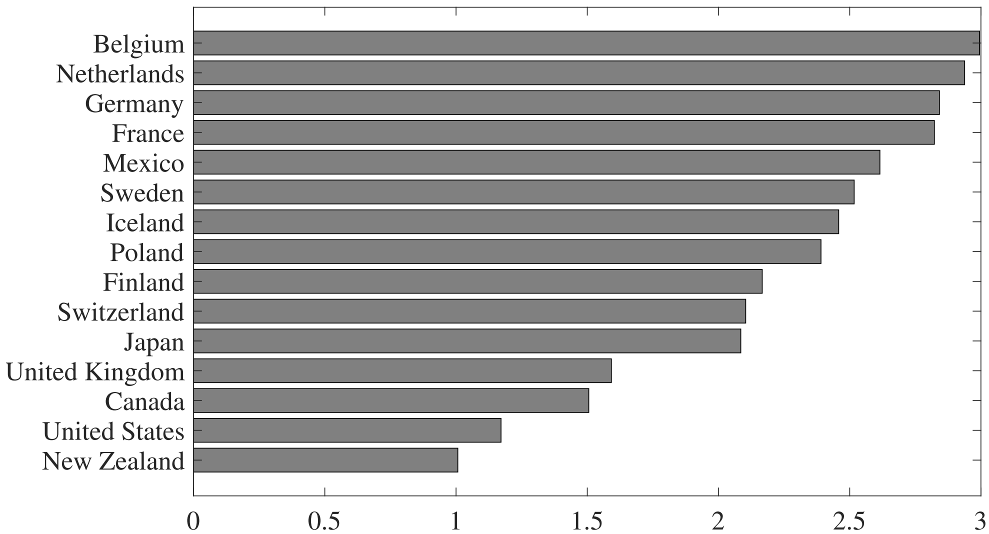
5.3 Uncertainty Transmission and Labor Adjustment Cost

So far we have shown that firms defer hiring and switch to part-time workers, as the real option value of waiting increases during the period of high uncertainty. In addition, results from worker inflows to unemployment show that other mechanisms such as the aggregate demand channel play a crucial role.

Related to this, one notable characteristic of the U.S. labor market is that it is much more flexible and workers are highly mobile, relative to other advanced countries. For instance, Elsby et al. (2013) show that the U.S. stands out as an outlier among Organization for Economic Co-operation and Development (OECD) countries, as worker flows into and out of unemployment account for about 40% of the labor force, while the same flows explain less than 10% in continental Europe. In addition, OECD publishes *Indicators of Employment Protection* that quantify the procedures for hiring and dismissing workers as well as costs involved in dismissing them. As shown in Figure 9, this index for the U.S. is among the lowest, indicating that it is fairly easy for firms in the U.S to lay off workers. This implies that labor adjustment costs in the U.S. would likely be much lower than in European countries. This low adjustment costs may have led us to overestimate the role of other uncertainty transmission channels.

For this reason, we estimate a similar model using data from Germany. As shown in Figure 9, the index for Germany ranked the third, suggesting it is highly restrictive and costly to terminate employment. We use two labor flow indicators, the job finding and separation rates in Germany, since most other labor market indicators are not available

Figure 9: OECD Indicators of Employment Protection



NOTE: This figure plots selected OECD countries' indicator of employment protection legislation for 2013. This indicator measures the procedures and costs involved in dismissing individuals or groups of workers and the procedures involved in hiring workers on fixed-term or temporary work agency contracts. The index can have values ranging from 0 (least restricted) to 6 (most restricted).

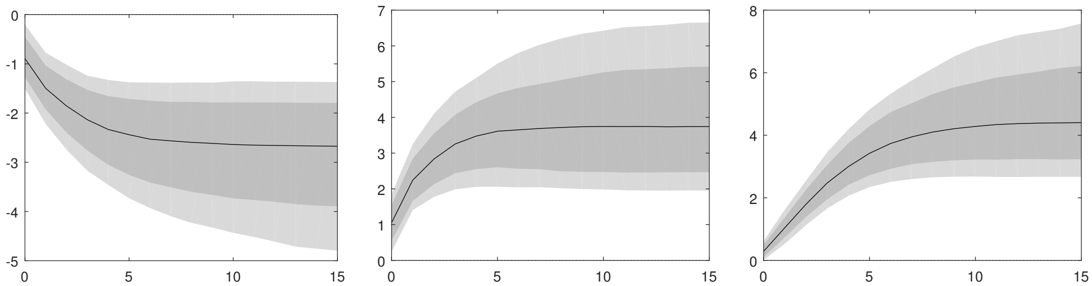
especially at a monthly/quarterly frequency for Germany.[7]

Figure 10 shows the impulse responses of the German job finding and separation rates as well as unemployment. The responses are consistent with those based on the U.S. data, despite Germany's high labor adjustment costs. We see that the job finding rate decreases and the job separation rate significantly increases, contributing together to increases in the unemployment rate.

This result again supports the idea that other demand-driven channels are also crucial for the uncertainty transmission and may dominate the real option channel when it comes to the inflows to unemployment. However, it is also possible that firms use labor as a flexible margin of adjustment during the high uncertainty, as the adjustment costs of labor are lower relative to those of capital. One simple way of accounting for such possibility is to include capital investment in the model to control for its changes. However, when we estimate a model with investment, the baseline results did not change (see Figure A2 in

[7]Since only two labor indicators are available, we do not estimate factors from those labor indicators and run a VAR model with stochastic volatility in mean. The model is estimated at the quarterly frequency due to the availability of some macroeconomic series for Germany, for the period from 1979Q1 to 2013Q1. See Table A1 in Appendix for the German macroeconomic indicators included in the model and their sources.

Figure 10: Impulse Responses from the Model Estimated with German Data



(a) Job finding rate (b) Job separation rate (c) Unemployment

NOTE: This figure plots the impulse responses of the (a) job finding rate, (b) job separation rate, and (c) total unemployment rate. The dark and light shaded areas represent the 70% and 90% posterior credible sets, respectively.

the Appendix for the impulse responses of selected variables).[8] We also run a battery of robustness checks as noted in Appendix, and the main results remain little changed.

6 Conclusion

This paper examines how uncertainty affects the labor market. While previous studies commonly pointed to a negative impact on total employment and an increase in the total unemployment rate, the transmission channels of the uncertainty to the labor market has not been empirically investigated. We employ a set of labor flow indicators in addition to previously-used labor stock variables, from which we estimate common factors. These factors are then used wih macroeconomic indicators to estimate a model that allows the simultaneous estimation of macroeconomic uncertainty and its effects.

We find that firms defer hiring during the period of high uncertainty: Various outflows from the unemployment decline significantly, implying that the real option channel is at work. In addition, more people flow into the unemployment pool. The increase of the inflows is mainly driven by increased number of workers who are laid off. Firms let go more workers, as households lower consumption and increase precautionary savings amid

[8] It is still feasible at the industry level that the relative adjustment cost of labor is minimal, compared to that of capital. In this case, it is expected that one is unable to find any evidence supporting the option value channel for labor. Investigating the joint adjustment mechanism of labor and capital under uncertainty at the industry level would be an interesting future study. See Byun and Jo (2018) for the sectoral impacts of uncertainty on investment.

uncertainty. This demand-side propagation mechanism is also reflected in the drops in voluntary quit as well as increases in entrants. Also, it is possible that firms may find it easy to adjust labor in response to lower demand rather than capital, where adjustment costs could be much larger. Finally, the demand for labor could be also lower due to its complementarity with capital that declines after the uncertainty shock.

As such, our findings imply that macroeconomic uncertainty likely propagates to the labor market through a variety of channels. Hence, it would be crucial to account for these mechanisms, in particular the aggregate demand channel, in addition to the popular option value channel in theoretical studies. This will further understanding and quantify the impacts of the uncertainty shocks more precisely.

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A Data

Table A1: Macroeconomic Indicators in the VAR

Macroeconomic variables (Transformation)	U.S.	Germany
Employment, total non-farm ($\Delta \ln$)	[1]LNS12035019	[1]LFEMTTTTDEQ647S
Industrial production index ($\Delta \ln$)	[1]INDPRO	[1]DEUPROMANMISMEI
Capacity utilization: manufacturing (Δ)	[1]TCU	[1]BSCURT02DEQ160S
Vacancy rate (Δ)	Barnichon (2010)	[1]LMJVTTUVDEQ647S
Unemployment rate, total (Δ)	[1]UNRATE	[1]LMUNRRTTDEM156S
Personal income, real ($\Delta \ln$)	[1]RPI	N/A
Hours worked, weekly goods-producing	[1]CES0600000008	N/A
Housing starts (ln)	[1]HOUST	[1]DEUPROCONQISMEI
Housing permits (ln)	[1]PERMIT	[1]ODCNPI03DEQ180S
Personal consumption expenditure index, real ($\Delta \ln$)	[1]DPCERA3M086SBEA	[1]NAEXKP02DEQ661S
Sales, real manufacturing and trade ($\Delta \ln$)	[2]CMRMTSPLx	[1]SLMNTO01DEQ661S
New orders index	Conference Board/Haver	[1]BSOITE02DEM460S
Orders, durable goods ($\Delta \ln$)	[2]AMDMNOx	[1]DEUODMNTO01IXOBSAM
Earnings, average hourly ($\Delta^2 \ln$)	[1]CES0600000008	[1]DEUHOUREAQISMEI
Producer Price Index, Finished goods ($\Delta^2 \ln$)	[1]WPSFD49207	N/A
Producer Price Index, Commodities - metal ($\Delta^2 \ln$)	[1]PPICMM	[1]DEUPPDMMINMEI
Personal Consumption Expenditure index ($\Delta^2 \ln$)	[1]PCEPI	[1]DEUCPIALLMINMEI
Federal funds rate (Δ)	[1]FEDFUNDS	IRSTCI01DEM156N

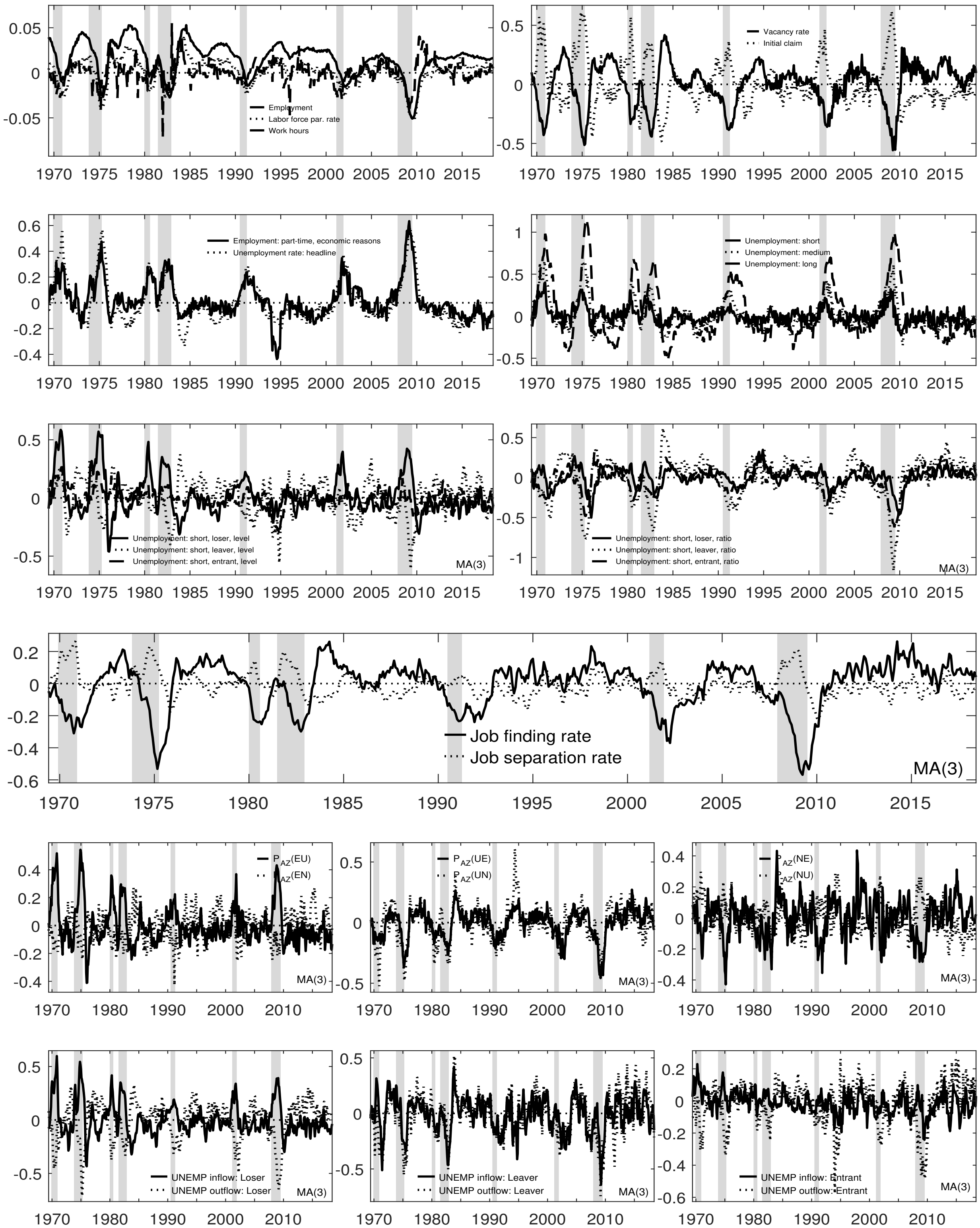
NOTE: This table shows 18 macroeconomic variables included in the main VAR (i.e., equation (2)) in our baseline analysis using the U.S. data. The middle column reports corresponding mnemonics from the Federal Reserve Economic Data ([1]) and FRED-MD ([2]). The vacancy rate is calculated by authors following Barnichon (2010). The right column documents the mnemonics of German macroeconomic indicators used for a robustness check, in addition to the job finding and separation rates. The case study of Germany excludes some macroeconomic data that are not available ('N/A').

Table A2: List of Labor Market Indicators

Labor market variables	Mnemonics
Unemployment insurance initial claims	[1]ICSA
Part-time, nonagricultural employment for economic reasons	[1]LNS12032197
Job finding rate (constructed following Elsby, Michaels, and Solon (2009))	
Job separation rate (constructed following Elsby, Michaels, and Solon (2009))	
Number of civilians unemployed for less than 5 weeks	[1]UEMPLT5
Job losers*	[2]LNU03023633
Job leavers*	[2]LNU03023717
Entrants* (Reentrants + New entrants)	[2]LNU03023581 + [2]LNU03023585
Number of civilians unemployed for 5 to 14 weeks	[1]UEMP5TO14
Number of civilians unemployed for 15 weeks and over	[1]UEMP15OV
Worker transition probability (constructed following Elsby, Hobijn, and Şahin (2015))	
Employment to unemployment	
Employment to not in labor force	
Unemployment to employment	
Unemployment to not in labor force	
Not in labor force to employment	
Not in labor force to unemployment	
Flow hazard rates (constructed following Elsby, Michaels, and Solon (2009))	
Inflow & outflow - job losers	
Inflow & outflow - job leavers	
Inflow & outflow - entrants	
Average duration of unemployment	[1]UEMPMEAN

NOTE: This table lists the labor market variables included in X_t in equation (1). The left column shows the data sources as well as corresponding mnemonics, if available; [1] indicates Federal Reserve Economic Database (FRED) at the Federal Reserve Bank of St. Louis, and [2] the Bureau of Labor Statistics (BLS). * denotes that we include both the level and the share of the corresponding group in the number of unemployed for less than 5 weeks. For the levels of the number of unemployed for less than 5 week by different reasons from 1968 June to 1976 June, we take the series from Elsby, Michaels, and Solon (2009). All variables are converted into year-over-year growth rates by taking log differences from a year before.

Figure A1: Labor Market Indicators

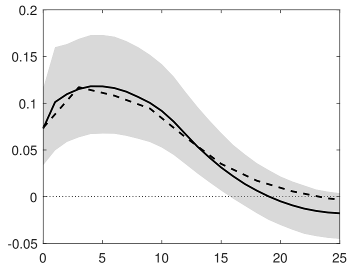


NOTE: All data are monthly from 1979 June to 2018 June. Those denoted as 'MA(3)' are transformed to three-month moving averages for the plotting purpose only.

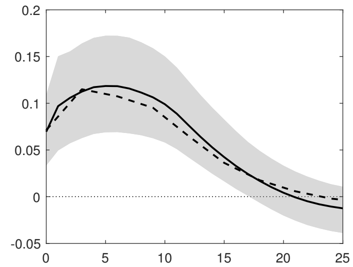
B Robustness Checks

Here we present results from a quarterly model including the investment series. Our baseline model is estimated using monthly data, and does not include quarterly private investment series from the national account. All monthly series used in the baseline model are converted to quarterly series by taking averages.

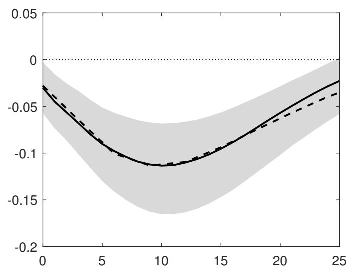
Figure A2: Robustness Check Including Capital Investment



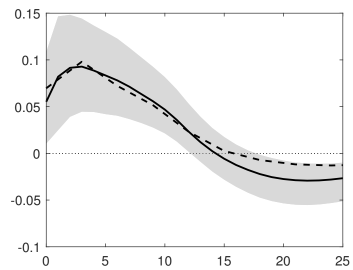
(a) short-term job losers



(b) initial claims



(c) job finding rate



(d) job separation rate

NOTE: This figure compares the impulse responses of the (a) job losers unemployed for less than five weeks, (b) initial jobless claims, (c) job finding rate, and (d) job separation rate. The solid line and its associated shaded area are the median responses obtained from the baseline model and its 90% posterior credible sets, respectively. The dotted line is the median responses from the quarterly model including investment.

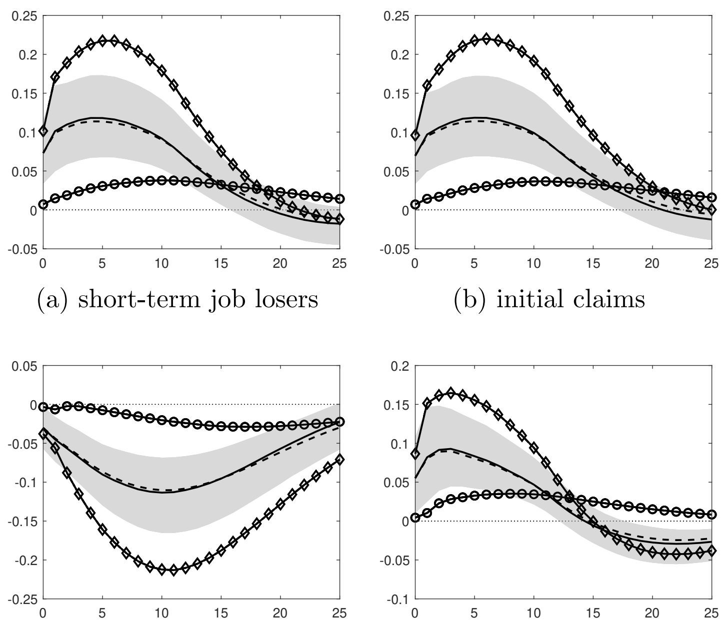
Our finding is also robust to other changes. We first run a model where we shut down the feedback from the changes in levels. Our baseline model assumes that the process of the volatility factor is also affected by the past values of macroeconomic indicators, as shown by the term $\delta_m' y_{t-1}$ in Equation (3). While this channel captures a potential feedback from macroeconomic fluctuations to the level of uncertainty, one may argue that it may amplify the effects of an uncertainty shock. Therefore, we re-estimate the model after setting all elements of δ_m equal to zero and shuts down the feedback channel.

We also exclude the Great Recession period and re-estimate the same model. The Great

Recession is characterized by a period with extremely high uncertainty, at the same time as the labor market showed unusually slow recovery. One consequent concern could be that this period may drive most baseline results. To make sure that the results are not purely driven by the Great Recession period, we re-estimate the model excluding this period, so that the sample spans from July 1976 to December 2006.

Finally, we shut down the price channels in the main VAR. The baseline impulse responses represent the impacts of uncertainty in general equilibrium. This implies that price changes may have affected the results we previously saw, potentially mitigating the effects of an uncertainty shock on the labor market. As such, we re-estimate our baseline model while fixing all coefficients of price variables to be zero. In all three cases, our baseline results remain little changed. The impulse responses for selected variables are presented in Figure A3.

Figure A3: Other Robustness Checks



(a) short-term job losers

(b) initial claims

(c) job finding rate

(d) job separation rate

NOTE: This figure compares the impulse responses of the (a) job losers unemployed for less than five weeks, (b) initial jobless claims, (c) job finding rate, and (d) job separation rate from different model setups. The solid line and its associated shaded area are the median responses obtained from the baseline model and its 90% posterior credible sets, respectively. The line with diamonds denotes the median responses from the model where we excluded the feedback from the first moment; the dashed line is from the model where the price responses were muted; the line with circles is from the model where we stop the sample before the Great Recession.

C Model Estimation

We estimate the model in two steps. First, we estimate (three) common factors of the labor market indicators by the principal component analysis. Factor loadings are thus given as the corresponding principal component coefficients. Second, conditional on the estimated factors, we estimate the VAR parameters as well as the time-varying idiosyncratic and macroeconomic volatilities. We use the Bayesian Markov Chain Monte Carlo (MCMC) sampler, which iteratively generates sample draws from the joint posterior distribution. We discard the first 5,000 draws and save every fifth draw until we collect 5,000. Here we provide a short description of the MCMC sampler.

1. Draw factor loadings of macroeconomic uncertainty conditional on the macroeconomic and idiosyncratic volatility draws from the previous iteration. This boils down to a Bayesian regression with known mean and variance, where the mean and variance are determined by the state variable for the mixture of Normal approximation.

2. Conditional on other draws, obtain a posterior draw of the VAR coefficients. This again becomes a Bayesian regression with time-varying variance-covariance. Since we have a fairly large VAR, we apply triangularization that allows the equation-by-equation estimation of the VAR coefficients. See Clark, Carriero, and Marcellino (2016) for the details of the triangularization.

3. Draw the elements in the lower-triangular matrix A again equation by equation after the triangularization. Given VAR coefficients and the series of volatilities, reduced-form errors ν_t as well as the structural error variances λ_t for each equation are known. This step hence becomes estimating Bayesian regressions for each equation.

4. Draw AR coefficients in the stochastic volatility equations. One can then also update the error terms in these equations based on the new draws, which will be used in drawing macroeconomic volatility in the next step.

5. Given all other parameters, draw a series of macroeconomic uncertainty. This step is done by exploiting the particle Gibbs sampler, following Andrieu, Doucet, and Holenstein (2010).

6. Update the state variable for the Normal approximation, which will be used in the next step for drawing idiosyncratic volatilities.

7. Given other parameter values as well as macroeconomic uncertainty, draw series of idiosyncratic volatilities in a state-space framework. As the state-space model is linear, but not Gaussian, the volatility draws can be generated by using Kim et al. (1998)'s mixture of Normal approximation.

See Carriero et al. (2018) for a detailed description about the estimation of the VAR part of the model, prior distributions and initial values.