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Wesselbaum, Dennis

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Time-varying volatility in the U.S. labor market

Dennis Wesselbaum

University of Otago

ABSTRACT

In state-of-the-art macroeconomic and labor market models shocks are assumed to be homoscedastic. However, we show that this assumption is much too restrictive. We estimate the conditional variance-covariance matrix using a VAR-DCC model and discuss the time-varying risk contained in a large set of labor market variables. We find significant evidence for strong time-varying volatility in all considered labor market time series. We observe that recessions tend to lead peaks of volatility for most variables. Further, the effect of the Great Moderation does not hold for all variables. We also find different effects of supply-side and demand-side recessions. The implications are relevant for modelling purposes, forecasting, welfare analysis, and the understanding of sources of fluctuations.

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KEYWORDS

Dynamic conditional correlation; multivariate GARCH; time-varying volatility; VAR-DCC

1. Introduction

In this paper we estimate the conditional variance and covariance matrix of a large set of labor market variables. A complete understanding of the behavior of uncertainty in the labor market is particularly important for welfare analysis, the validity of forecasts, and policy advice. The purpose of this paper is to discuss the time-varying volatility of a large set of key labor market variables in the United States. Further, it addresses the question whether uncertainty in one labor market variable is correlated with uncertainty in another variable; which is rather neglected in empirical and theoretical labor market research so far. Therefore, we try to shed light on the underlying uncertainty relations. This is particularly interesting for labor market policies. For example, our results show that uncertainty is substantially different for the entry (job finding) and the exit (separations) side. We can draw two conclusions from that finding. First, an uncertainty shock will have asymmetric effects and, second, policies aimed at reducing uncertainty should take those asymmetric effects into account.

Technically, we estimate a multivariate generalized autoregressive conditional heteroscedasticity (M-GARCH, for short) model, namely the dynamic conditional correlation model proposed by Engle (1999). This model allows for time-varying variance and correlations and is therefore able to shed light on the behavior of the conditional second moments over time. Although ARCH models have predominantly been used in finance, Hamilton (2008) discusses the scarce literature on ARCH in macroeconomics. There are various reasons why macro- and labor economists should be interested in second

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CONTACT Dennis Wesselbaum 🖾 dennis.wesselbaum@otago.ac.nz

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moments as well. As discussed in detail in Hamilton (2008), misspecifications of the variance-covariance matrix will make a hypothesis test on the mean invalid. Further, efficiency in estimating the first moments can be increased by including the observed heteroscedasticity. Moreover, time-varying first and second moments can be seen as evidence for non-linearities in the economy.

Empirically, Carroll and Dunn (1997) and Carroll, Dynan, and Krane (2004) show that uncertainty shocks to the risk of loosing a job can have effects on the real economy because of increased precautionary savings. Sims and Zha (2006) use a structural vector autoregression model allowing for Markov regime switching and show that the best fit is obtained with a model that features time-varying variances of structural disturbances. More recently, Fernandez-Villaverde and Rubio-Ramirez (2010) estimate the stochastic volatility present in aggregate time series and the empirical analysis by Justiniano and Primiceri (2008) show a strong stochastic volatility of shocks in the United States that vary considerably across types of shocks.

From a modelling perspective, Bloom (2009) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) show that higher risk may lead a household to defer investments because of the fear to hit a liquidity or credit constraint that may impact the optimal consumption allocation in the future. For the labor market, Takahashi (2013) shows that uncertainty shocks impact the composition of workers and, hence, affect aggregate productivity. Ravn and Sterk (2013) find the same result, however, by assuming uncertainty shocks on unemployment duration in a search model with nominal frictions.

To the best of our knowledge, this paper is the first to estimate the conditional variance-covariance matrix of a large set of labor market variables to draw a clear picture of the time-variability contained in those variables. The closest paper to ours is the work by Stock and Watson (2002) using time series for employment, unemployment, wages, and the help-wanted index and estimate an AR(4) process to address the change in the (time-varying) standard deviation. They find a significant time-varying component but they focus on a small set of labor market variables and do not estimate the dynamic interdependencies between those variables.

Finally, we would like to emphasize that we leave a (micro)foundation of the observed stochastic volatility to future research. However, let us briefly discuss some possible explanations for the presence of stochastic volatility in labor market variables. Alejandro and Primiceri (2008) suggest that the Great Moderation might have been driven by a decline in financial frictions. Similarly, our estimations show that volatility in key labor market variables decreases which might indicate that labor market frictions have decreased significantly over our sample period. To support this view, the reader should notice that labor markets reforms, aimed to increase flexibility and decrease frictions, are common policy tools used to support full employment. In the search and matching model, one might think of (non-linear) vacancy posting costs, hiring and firing costs, hours adjustments costs, efficiency wages, temporary vs. permanent contracts, or other legal restrictions to the use of labor.

Our findings show a significant decline of volatility in almost all time series in line with the Great Moderation. However, there are three exceptions: productivity, vacancies, and the job finding rate. We can cluster variables into three groups according to the size of their fluctuations. The job finding rate, separation rate, vacancies and productivity show the smallest values of conditional volatility. Then, we find a cluster consisting of employment, unemployment, wages, and GDP that is about four times as volatile as the first cluster. The time series for hours shows the largest conditional volatility. Finally, we find that the obtained errors are non-normally distributed.

The paper is structured as follows. The next section derives the model while Section 3 discusses our data and motives our modelling choice. Section 4 then presents and discusses our results for the conditional volatility, correlation, and normality of the errors. Section 5 briefly concludes.

2. Model

2.1. The VAR-DCC model

In the following we will formulate a model that describes the mean and the variance for a multivariate system of time series. Let $\{Y_t\}$ denote a $N \times 1$ dimensional vector of random variables with $\mathbb{E}[Y_t] = 0$. Then, the mean is assumed to follow a vector autoregressive model (VAR, for short) with *p* lags. The VAR (*p*) representation is given by

$$Y_{t} = \mu + \sum_{i=1}^{p} \Gamma_{i} Y_{t-i} + u_{t}, \qquad (1)$$

where Γ_i are parameter matrices of size $(N \times N)$, μ is an unrestricted constant, and u_t is an error term. Estimating this model using OLS will give us N time series of residuals, y_t . Further, let \mathcal{I}_t be the smallest σ -field generated by the history of values of y_t , i.e. $\mathcal{I}_t = \sigma(y_r, r \le t - 1)$. Moreover, assume that the time series in our vector $\{y_t\}$ are conditionally multivariate Gaussian with zero mean and covariance matrix \mathbf{H}_t . By imposing measurability of \mathbf{H}_t with respect to \mathcal{I}_t we can write the multivariate GARCH as

$$y_t | \mathcal{I}_t \sim \mathcal{N}(0, \mathbf{H}_t). \tag{2}$$

Formally, $y_t = \mathbf{H}_t^{1/2} \eta_t$, where η_t is a $N \times 1$ dimensional vector of i.i.d. errors. The next step is to put some structure on the $N \times N$ dimensional, positive semi-definite, symmetric conditional covariance matrix \mathbf{H}_t and this is done by modelling the conditional variances and correlations, i.e.

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t. \tag{3}$$

Here, \mathbf{D}_t is a $N \times N$ diagonal matrix of time-varying conditional standard deviations and \mathbf{R}_t is a $N \times N$ dimensional time-varying conditional correlation matrix.

The former matrix is given by

$$\mathbf{D}_{t} = \begin{bmatrix} \sqrt{h_{1,t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2,t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{h_{N,t}} \end{bmatrix},$$
(4)

where $\sqrt{h_{i,t}} \forall i \in \{1, ..., N\}$ is estimated from a univariate GARCH (q, p) model. This GARCH (q, p) model can be written the usual way as

$$h_{i,t} = \alpha_{i,0} + \sum_{j=1}^{q} \alpha_{i,j} y_{i,t-j}^2 + \sum_{j=1}^{p} \beta_{i,j} h_{i,t-j},$$
(5)

with $\alpha_{i,0} > 0$, $\alpha_{i,j} \ge 0$, and $\beta_{i,j} \ge 0 \forall i, j$. Further, we denote the standardized residuals as $\varepsilon_t = \mathbf{D}_t^{-1} y_t \sim \mathcal{N}(0, \mathbf{R}_t)$, where we standardize by the conditional standard deviation.

It can be shown that a necessary and sufficient condition for stationarity of those univariate GARCH processes is $\sum_{j=1}^{q} \alpha_{i,j} + \sum_{j=1}^{p} \beta_{j,j} \le 1 \forall i$.

The symmetric correlation matrix \mathbf{R}_t is given by

$$\mathbf{R}_{t} = \begin{bmatrix} 1 & \rho_{1,2,t} & \cdots & \rho_{1,N,t} \\ \rho_{1,2,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \rho_{N-1,N,t} \\ \rho_{1,N,t} & \cdots & \rho_{N-1,N,t} & 1 \end{bmatrix},$$
(6)

where $\rho_{i,j,t}$ is the correlation estimator. We would like to ensure that \mathbf{H}_t is positive definite and that all elements of the correlation matrix, \mathbf{R}_t , are less or equal to one in absolute terms.

For this purpose, it is assumed that the conditional correlation matrix follows

$$\mathbf{R}_t = \mathbf{Q}_t^{*-1} \mathbf{Q}_t \mathbf{Q}_t^{*-1},\tag{7}$$

$$\mathbf{Q}_{t} = \left(1 - \sum_{m=1}^{M} \alpha_{m} - \sum_{k=1}^{K} \beta_{k}\right) \bar{\mathbf{Q}} + \sum_{m=1}^{M} \alpha_{m} \varepsilon_{t-m} \varepsilon_{t-m}' + \sum_{k=1}^{K} \beta_{k} \mathbf{Q}_{t-k},$$
(8)

where $\bar{\mathbf{Q}} = \mathbb{E}[\varepsilon_t \varepsilon'_t]$ is estimated by the sample mean. Then, $\mathbf{Q}_t^* = diag(\sqrt{q_{11,t}}, \cdots, \sqrt{q_{NN,t}})$ re-scales the elements of \mathbf{Q}_t to ensure that the elements of the correlation matrix are less or equal to one in absolute terms, i.e. $\left|\rho_{i,j,t}\right| = \left|\frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}}\right| \leq 1$.¹ Positive definiteness of \mathbf{H}_t with probability one is ensured by $\alpha_{i,j} \geq 0$, $\beta_{i,j} \geq 0 \forall i, j$, positive definite \mathbf{Q}_0 , and the stationarity condition $\sum_{j=1}^{q} \alpha_{i,j} + \sum_{j=1}^{p} \beta_{i,j} < 1 \forall i$ as in Engle and Sheppard (2001).

2.2. Estimation

Here, we want to briefly describe the estimation strategy of the DCC model. Because we assumed our errors, η_t , to be multivariate Gaussian, we can derive the joint distribution of z_t as

$$f(\eta_t) = \prod_{t=1}^T (2\pi)^{-\frac{N}{2}} e^{-\frac{1}{2}\eta'_t \eta_t},$$
(9)

where we used the properties of the i.i.d. shock $\mathbb{E}[\eta_t] = 0$ and $\mathbb{E}[\eta_t \eta'_t] = \mathbf{I}_N$. Then, by using our original definition, $y_t = \mathbf{H}_t^{1/2} \eta_t$, we can write the likelihood function as

¹Lags M and K are choosen to minimize ARCH effects in the obtained residuals.

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$$L(\phi) = \prod_{t=1}^{T} (2\pi)^{-\frac{N}{2}} (|\mathbf{H}_t|)^{-\frac{1}{2}} e^{-\frac{1}{2}y_t' \mathbf{H}_t^{-1} y_t},$$
(10)

where $|\mathbf{H}_t|$ is the determinant of \mathbf{H}_t . Recall that $\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t$ holds. Further, ϕ contains the parameters of the univariate GARCH model for the *i*th time series, i.e. $(\phi, \psi) = (\phi_1, \dots, \phi_N, \psi)$ and $\phi_i = (\alpha_{i,0}, \alpha_{i,1}, \dots, \alpha_{i,p}, \beta_{i,1}, \dots, \beta_{i,q}) \forall i$ and $\psi = (\alpha_1, \dots, \alpha_M, \beta_1, \dots, \beta_K)$ contains the parameters of the correlation structure.

After some algebra, the log-likelihood estimator is given by

$$\ln(L(\phi)) = -\frac{1}{2} \sum_{t=1}^{T} \left[N \ln(2\pi) + \ln(|\mathbf{D}_t \mathbf{R}_t \mathbf{D}_t|) + \eta_t' \mathbf{D}_t^{-1} \mathbf{R}_t^{-1} \mathbf{D}_t^{-1} \eta_t \right].$$

The MLE is computed in two steps. First, one estimates univariate GARCH models for each residual time series. Here, one replaces the correlation matrix, \mathbf{R}_t , with the identity matrix, \mathbf{I}_N .

Then, the quasi maximum log-likelihood estimator is

$$\ln(QL_1(\phi|y_t)) = -\frac{1}{2} \sum_{n=1}^{T} \left[N \ln(2\pi) + \sum_{t=1}^{T} \left[\log(h_{i,t}) + \frac{y_{i,t}^2}{h_{i,t}} \right] \right].$$
 (11)

The first stage estimator intuitively is the summation of individual log-likelihood values of univariate GARCH models for each time series in y_t . The only remaining parameters to be estimated after the first step are the ones contained in ψ .

Consecutively, step two uses the correctly specified likelihood

$$\ln(QL_2(\psi|\hat{\phi}, y_t)) = -\frac{1}{2} \sum_{t=1}^{T} [N\ln(2\pi) + 2\ln(|\mathbf{D}_t|) + \ln(|\mathbf{R}_t|) + \eta_t' \mathbf{D}_t^{-1} \mathbf{R}_t^{-1} \mathbf{D}_t^{-1} \eta_t],$$
(12)

here, we condition on the parameters estimated in the first step. Due to conditioning on the estimated parameters, we could exclude the constant parameters from the maximization and only consider the latter two terms in Equation (12). Consistency and asymptotic normality of the two step QMLE estimator has been shown by White (1996) and Engle and Sheppard (2001). In addition, Bollerslev and Wooldridge (1992) have shown that even in the presence of skewed and leptokurtotic error terms (see Section 4.3), the QMLE estimator still gives consistent parameter estimates.

The VAR-DCC model is estimated as follows. In step 1, we estimate the VAR model using the optimal number of lags (5) selected according to the AIC criterion. Then, in step 2 univariate GARCH models are fitted to the obtained residuals from step 1. In step 3, residuals are standardized by the estimated conditional variance from the univariate GARCHs. The DCC part is then estimated using the standardized residuals using the QMLE estimator.

3. A preliminary look at the data

3.1. Data

In the subsequent chapters we will use different labor market time series, namely employment, vacancies, unemployment, wages, labor productivity, (job) separation rate, job finding rate, hours, and the industrial production (IPro, for short) as a proxy for GDP. All time series are seasonally adjusted and are on a monthly basis and cover the period from 1964:M1 to 2014:M12, which gives us 612 data points spanning the Great Moderation and the Global Financial Crisis (GFC, for short). We first-difference the time series in order to obtain the necessary zero-mean input series.

Employment is measured by the number of total private workers as constructed by the Bureau of Labor Statistics (BLS, for short). The series for vacancies is taken from Barnichon (2010) using the help-wanted advertising index. Unemployment is measured by the number of unemployed as published by the BLS in its Current Population Survey (CPS, for short). For the separation rate and the job finding rate, we follow Shimer (2012) and construct those time series from employment, unemployment, and short-run unemployment.

For wages we use the total private average hourly earnings of production and non-supervisory employees in dollars per hour. Hours are measured by average weekly hours of production and non-supervisory employees in manufacturing. The time series for output is the industrial production index. Then, we construct labor productivity (as it is not available on a monthly frequency) by dividing output by total hours.

3.2. Test on constant correlation

Engle and Sheppard (2001) suggest a test on constant correlation that standardizes the residuals of the estimate of univariate GARCH processes. The correlation of the standardized residuals is estimated, jointly standardized by the symmetric square root decomposition of the correlation matrix $(\bar{\mathbf{R}}^{-\frac{1}{2}}\mathbf{D}_t^{-1}y_t)$. If correlation would truly be constant, then the residuals would be i.i.d. with an identity matrix as variance-covariance matrix. Therefore, the hypothesis is

$$H_0: \mathbf{R}_t = \bar{\mathbf{R}},\tag{13}$$

vs.

$$H_A: vech^u(\mathbf{R}_t) = vech^u(\bar{\mathbf{R}}) + \beta_1 vech^u(\mathbf{R}_{t-1}) + \ldots + \beta_p vech^u(\mathbf{R}_{t-p}),$$
(14)

where $vech^u$ is a vech-operator that only uses elements above the diagonal. Then, the vector autoregression is

$$Y_t = \alpha + \beta_1 Y_{t-1} + \dots + \beta_s Y_{t-s} + \zeta_t, \tag{15}$$

where $Y_t = vech^u \left[\left(\bar{\mathbf{R}}^{-\frac{1}{2}} \mathbf{D}_t^{-1} y_t \right) \left(\bar{\mathbf{R}}^{-\frac{1}{2}} \mathbf{D}_t^{-1} y_t \right)' - \mathbf{I}_N \right]$. Again, if the null would be true, all regression coefficients would be zero. Finally, the test statistic is $\left(\hat{\delta} X' X \hat{\delta} \right) / \sigma^2$, where X

contains the regressors and $\hat{\delta}$ contains the estimated regression coefficients. Then, the test statistic will be asymptotically $\chi^2(s+1)$.

If we apply this test to our data, we find that the *p*-value is $7.56e^{-11}$, using five lags. Put differently, the probability that the correlation is constant is effectively zero. Therefore, we reject the null hypothesis that the correlation in our data set is constant.

We would like to make two additional points in support of the VAR-DCC modelling choice. First, after estimating a VAR-CC model there is still conditional heteroscedasticity left in the squared residuals according to the Engle LM test. Second, estimating various multivariate GARCH models (DCC, CC, BEKK, TBEKK, IDCC) the DCC model yields the highest log-likelihood value indicating that it fits the data best.

4. Discussion

4.1. Volatility

We begin by discussing the results from estimating the conditional standard deviation using the DCC model. The resulting time series are presented in Figure 1. From this figure, we can draw several interesting conclusions.

We can cluster variables into three groups according to the size of their fluctuations, i.e. their level of uncertainty. The job finding rate, separation rate, vacancies and productivity show the smallest values of conditional volatility. Then, we find a cluster consisting of employment, unemployment, wages, and industrial production that is about four times as volatile as the first cluster. Finally, the time series for hours shows the largest conditional volatility. Further, we find evidence for a significant decline of volatility in almost all time series which has been named the "Great moderation" and



Figure 1. Estimated standardized conditional standard deviations relative to mean. Shaded areas indicate NBER recession dates.

started around the mid 1980's. However, there are three exceptions: productivity, vacancies, and the job finding rate. There is no clear decline in the standard deviation of those series and, hence, no difference in its behavior before or after the starting point of the Great moderation (1984 is accepted by most researchers). The only difference is that less spikes are observed during the Great Moderation. This finding is supported by splitting the sample in pre- and post-1984, where coefficient for mean and variance equation are different for almost all parameters.

In all figures NBER recession dates are shaded in grey in order to stress the synchronicity of recessions and peaks of volatility. We observe that the seven recessions contained in our sample, more precisely the underlying disturbances associated with those recessions, have different effects across variables.

Our sample begins four years after the 1960 recession. This recession was caused by a tightening in monetary policy but also by the so-called "rolling adjustment". Consumers started to buy foreign-built cars and the industry started to decrease inventories. This recession had different impacts on the entry and exit side decisions of firms: if inventories and investment are reduced, it is less likely that the firm will hire new workers. At the same time, due to search frictions the value of a job might still be positive such that separations are less affected. Prior to the 1969 recession, the so-called "Nixon recession", we find that volatility was relatively high in employment, the job separation and finding rate, and vacancies. This might still be attributed to the aftermath of the 1960 recession. The Nixon recession was driven by fiscal adjustments. In order to drive down the budget deficit (mainly) caused by the Vietnam war, the government engaged in fiscal tightening. At the same time, monetary policy became tighter to fight inflationary pressures. Our results show that this recession had only limited effects on the volatility of productivity and hours but large effects on the remaining variables.

The first oil price shock in 1973 caused a major and long-lasting recession and is the first, uniquely supply-side driven recession in our sample. Moreover, Nixon's price-wage control kept prices and wages too high, therefore reducing demand and causing lay-offs. We find that the volatility in wages peaks around 1972 right before the recession and around Nixon's price-wage control policy. Further, the abandoning of the gold standard generated inflation. We find that this supply-side shock had large effects on the volatility of all variables. Especially, we find large peaks in the separation rate and the job finding rate. The increase in volatility in employment and vacancies is smaller compared to the 1969 recession. This implies a larger effect along the exit side (separations) of the labor market compared to the entry side (vacancies). Supply-side and demand-side recessions therefore might lead to different effects along the entry and the exit side of the labor market.

Let us now turn to the double-dip recession of the early 1980's. The recession in 1980 was mainly caused by a tightening in monetary policy under the Volcker regime and had only a very limited effect on volatility. The only large spikes can be found in the separation rate and vacancies. Again, here we see that entry and exit side are similarly affected by this demand-side shock.

Interestingly, we observe small spikes in the volatility of hours before the recession from 1976 onwards. In general, we observe in many variables a buildup of volatility from 1977 onwards. This holds true for all variables with wages being the least affected time series. This happens at the same time monetary policy shocks become more volatile as shown by Justiniano and Primiceri (2008). More severe, however, is the recession following the second oil price shock and the first savings and loans crisis in 1981. This second supply-side driven recession had large effects on the volatility of all variables. As in the first supply-side driven recession we find a stronger effect along the exit side of the economy (separation rate) compared to the entry side (vacancies, job finding rate).

The recession at the early 1990's was driven by the third oil price shock (following the Gulf war), high government debt, and the second savings and loans crisis. We find that this recession had only very limited impact on the volatility of almost all variables but peaks in vacancies and the job finding rate. This leads to the conclusion that the underlying event had stronger uncertainty effects along the entry site of the labor market. Our observation is significantly different to earlier recessions. Here, we observe a decoupling of recessions and peaks of volatility. Put differently, a decoupling of recession dates and the uncertainty contained in labor market variables.

The first recession in the twenty-first century was driven by the burst of the dot-com bubble and the 9/11 terrorist attacks. We find that this recession had only small increases in the volatility of almost all variables but vacancies and the job finding rate. Finally, the last recession in our sample, caused by the industrial production, is the Great Recession. While the standard deviation of all variables but wages and hours spike, uncertainty did not reach historical highs for all variables. Historical highs are observed for industrial production and productivity. The latter probably due to the construction of our productivity measure. Further, given that the increase in the uncertainty in employment is larger than the increase in hours we can conclude that there has been more uncertainty along the extensive labor market dimension. Along this line, the increase in the standard deviation in the separation rate is larger compared to the increase in the standard deviation in the job finding rate and vacancies. We can conclude that the Great Recession had stronger uncertainty effects along the exit site of the labor market. Some observes speak about a jobless recovery after the Great Recession. If uncertainty has been a candidate to explain the jobless recovery we do not find evidence to support this idea. Uncertainty decreases fairly quickly and is not persistently higher after output returned to pre-crisis levels.

In sum, we observe that recessions tend to lead peaks of volatility for most variables. This is particularly true for vacancies. Hence, the conditional standard deviation for vacancies could be used as an early warning indicator for recessions. Volatility prior to and including the double dip recession could have been used as an early warning indicator, as standard deviations increased sizably. In general, there is an isomorphic mapping between recessions and peaks (ignoring leads and lags), put differently every "large" peak is associated with a recession and every recession is associated with a peak of volatility. However, we should be careful not to confuse correlation with causation; a question that we cannot answer within this framework. Finally, we find no evidence that the length of a recession is correlated with the size of the peak in volatility. Moreover, we find that recessions tend to have larger effects on the volatility of the exit side (separation rate) than on the exit side (job finding rate or vacancies).

Our estimates show that supply-side shocks (for example the first two oil price shocks) affect the uncertainty of all variables and have larger effects compared to demand-side shocks (for example the recessions caused by a tightening in monetary policy) who do not necessarily affect all variables. We can identify several explanations for this observation. One interpretation is that potentially time-varying non-linearities, labor market frictions, and financial frictions (see Alejandro and Primiceri (2008)) generate different effects even for identical disturbances. Another explanation are different shocks associated with the recessions and different propagation mechanisms. For example, a supply-side shock is likely to have different effects if, additionally, the financial market is under stress, e.g., due to structural problems. Hence, it will have different effects on the uncertainty of key variables. Further, we can't exclude the possibility that sunspot shocks or multiple equilibria played a significant role in those recessions. Finally, the response of monetary and fiscal policy plays a powerful role in driving riskiness in labor market variables.

It would be interesting to think about the transmission of uncertainty of an isolated type of shock (or policy reform) onto other variables. For example, the peaks in uncertainty of the separation rate and productivity coincide with recession dates. Research has shown that variation in those variables is key driver of fluctuations in the labor market. Therefore, the transmission of uncertainty from the underlying disturbance takes time until it can affect the variables (like vacancies) via the decision problem of agents.

Finally, we want to discuss our results in relation to the existing literature. Mumtaz and Zanetti (2015) estimate the unconditional volatility of the job finding rate, the job destruction rate, industrial production, and the unemployment rate using a SVAR with time-varying coefficients and stochastic volatility. They find similar patterns in all four variables: a peak of volatility around the double dip recession of the 1980's. Apart from that, the variables also show increased volatility around the mid-1970's. Those two observations are in line with our findings for the conditional volatility. Further, Guglielminetti and Pouraghdam (2015) estimate a TVP-VAR with stochastic volatility. They find that the innovation to vacancies show sizable time-variation, again, spiking in the mid-1970's and around the double dip recession. They also document increased volatility after the turn of the millennium which is in line with our findings.

4.2. Correlations

Having discussed the conditional standard deviation we now turn to the dynamic conditional correlations between labor market variables. Figures 2–5 present the results from our VAR-DCC estimation.

Overall, we find that for most variables the conditional correlation peaks in and around recessions. This implies a stronger relationship between the two variables considered. Further, we do not find a clear cut effect of the Great Moderation on conditional correlations. For some correlations (e.g., employment and vacancies) we find a less volatile behavior while for others (e.g., vacancies and hours) volatility even increases. Moreover, we again observe that recessions and peaks in the conditional correlations coincide in timing.

We begin by describing the relation of employment with the remaining variables (Figure 2). The results for the conditional correlation of employment with the other variables are in line with intuition. For example, we observe a strong positive



Figure 2. Estimated conditional correlations. Shaded areas indicate NBER recession dates.



Figure 3. Estimated conditional correlations. Shaded areas indicate NBER recession dates.

correlation of employment with industrial production and hours worked. Further, there is a negative correlation with the separation rate. We also find a mild positive correlation with vacancies, unemployment, wages, and the job finding rate. This finding also should not be a surprise. Shocks affecting the entry side should be visible in the relation between employment, unemployment (as a mirror), vacancies, and the job finding rate. The positive correlation of employment and wages might boil down to the fact that 208 👄 D. WESSELBAUM



Figure 4. Estimated conditional correlations. Shaded areas indicate NBER recession dates.



Figure 5. Estimated conditional correlations. Shaded areas indicate NBER recession dates.

uncertainty about employment also implies uncertainty about income. The correlation with productivity fluctuates around zero.

Differences across recessions are harder to detect. It again holds true that the recession in the early 1990's and 2000's appear to have smaller effects on the conditional correlation compared to the other five recessions in our sample. Again, after the GFC

we do not observe a persistent increase in the conditional correlation of employment with other variables which might have been a factor explaining the jobless recovery.

Next, let us discuss the correlation of output with the other variables. We find a strong positive conditional correlation with hours and a weaker positive correlation with vacancies, productivity, and the job finding rate. The correlation with the separation rate, wages, and unemployment fluctuates around zero. While we do observe dampening effects of the Great Moderation on some correlations (e.g., with unemployment or the separation rate), we do observe no such effect on the correlation with productivity, hours, and the job finding rate. For the latter three we observe more volatility in the time series. Most interesting is the relation between industrial production and productivity. We observe large downward spikes for the two oil-price recessions and a large upward spike around the GFC. The double-dip recession even generated a negative correlation, while we also observe a similarly large downward spike around 1996.

For vacancies, we find a mild positive correlations with productivity and the job finding rate and a negative correlation with the separation rate. The correlation with unemployment, wages, and hours fluctuates around zero. Our findings are in line with the intuition about asymmetric effects along the entry and the exit side of the labor market. Dynamics along the entry side should affect employment, hours, vacancies, the job finding rate, and vacancies in a similar way, therefore, creating a positive correlation. In contrast, factors affecting the exit side should lead to a negative correlation between vacancies and the separation rate.

While so far we find some suggestive evidence that the Great Moderation reduced the variability in the conditional correlation we do not observe this effect on the correlation of vacancies with the other labor market variables. For example, we find a spike in the conditional correlation of vacancies with productivity, unemployment, wages, hours, and the job finding rate around 1996. The only policy change that could have caused this finding was the Personal Responsibility and Work Opportunity Act (PRWORA) passed by the Clinton administration. This reform limited welfare benefits and could have changed the behavior of agents in the labor market.

The next set of conditional correlation looks at the relation between productivity and unemployment, wages, hours, and the job finding and separation rates. We observe fluctuations around zero for all variables but hours, where we find a negative correlation. Most interesting for productivity is the relation with hours. We find a positive correlation during the GFC which was also the case in the Nixon recession and the firstoil price shock recession. It appears that in those three recessions the underlying relation between productivity and hours has changed dramatically. Along this line, those three recessions also show a stronger negative conditional correlation between productivity and the separation rate.

For unemployment we find a mild positive correlation with the job finding rate and fluctuations around zero for wages, hours, and the separation rate. Next, the conditional correlation between wages and hours, separation rate, and the job finding rate fluctuates around zero. The same holds for the correlation of hours with the separation and job finding rate as well as for the correlation of the separation and the job finding rate. Again, we find only small effects of the Great Moderation on the conditional correlation in those correlations.

Variable	Kurtosis	Skewness
Employment	5.81	-0.55
GDP	4.08	-0.29
Vacancies	4.01	-0.06
Productivity	24.94	0.23
Unemployment	5.81	0.17
Wages	5.49	-0.2
Hours	9.55	-1.43
Separation Rate	4.09	-0.08
JFR	3.46	-0.22

 Table 1. Kurtosis and Skewness of VAR-DCC errors.

4.3. Residuals

At the end of our discussion, we want to briefly discuss the resulting residuals from our VAR-DCC estimation. Table 1 presents kurtosis and skewness values. We find that all variables are leptokurtotic. Further, we find that all variables except unemployment and productivity rate have left-skewed errors.

Finally, we want to answer the question whether the resulting residuals (or errors) from our DCC estimation are normally distributed. This is of interest for modelling purposes and forecasting, where the canonical assumption is that errors are drawn from a normal distribution. For this purpose, we estimate kernel densities using the Epanechnikov-kernel from the estimated time series and plot them in black. Further, we estimate the mean and variance from the errors and plot the resulting normal distribution in red. Figure 6 compares those two estimates for our nine variables.

In order to assess whether the errors are in fact normally distributed, we use the Kolmogorov-Smirnov Test (KS, for short), the Jarque-Bera test (JB, for short), and the Lilliefors test (LF, for short). The tests are performed on a 5 percent significance level. We find that only the Lilliefors test does not reject the null of normally distributed errors for the job finding rate. We can conclude that there is strong evidence that the errors are in fact non-normally distributed. Only the errors from the job finding rate might be normally distributed.

5. Conclusion

In state-of-the-art macroeconomic and labor market models the dynamic effects of shocks are simulated by imposing the ad hoc assumption of homoscedasticity of the underlying stochastic processes. However, this assumptions seems to be arbitrary given the recent research agenda on time-varying variance in aggregate time series. Along this line, changes in volatility, or in the riskiness, in labor market variables can have substantial real effects. Bloom (2009) and Bloom et al. (2012) show that higher uncertainty significantly affects the optimal allocation problem. Takahashi (2013) and Ravn and Sterk (2013) show that uncertainty shocks in the labor market can have non-negligible effects on aggregate productivity.

This paper provides missing evidence on time-varying volatility in the U.S. labor market. Using a number of labor market time series, covering the period from 1964 to



Figure 6. Kernel density estimation (black line) vs. normal estimation (red line) of residuals – DCC.

2014, we present evidence of strong time variability. We estimate the conditional variance and covariance matrix by using the DCC model proposed by Engle (1999). This model allows for time-varying conditional variance and correlations and is therefore able to shed light on the behavior of the conditional second moments over time. We find a strong time-varying uncertainty component in all labor market variables. Nevertheless, we do observe the effects of the Great moderation in our sample. Further, we establish an isomorphic relationship between recessions and peaks of uncertainty.

Furthermore, we show that the recessions in our sample have significantly different effects on the uncertainty of the labor market. According to our results, recessions have larger effects on the uncertainty of job destruction than on the uncertainty of job creation. Along this line, we find that supply-side shocks generate sizable changes in the uncertainty of all variables, while demand-side shocks have smaller effects and not necessarily affect the uncertainty of all variables.

We have offered several explanations for the findings in unconditional and conditional second moments. Most promising are time-varying frictions in the labor and financial market. Further, non-linearities in the production technology could explain the different effects of recessions and are a starting point to build a model that – endogenously – creates time-varying volatility. Moreover, we stressed that time-varying volatility might be a consequence of unstable or multiple equilibria. Then, there are several implications for future research. First, the issue of the transmission of uncertainty of an uncorrelated shock (or policy reform) onto other variables is of interest for policy makers and researchers. One example might be the recession at the early 1990's. Second, the role played by time-varying volatility for the estimation of search and matching models, for forecasting, as well as the role played for welfare results in those models needs to be addressed.

Disclosure statement

No potential conflict of interest was reported by the author.

Notes on contributor

Dennis Wesselbaum I earned a Diploma in (Theoretical) Economics from the University in Kiel and received my Doctorate (Doctor rerum politicarum) from the University of Hamburg. In between, I worked as a researcher for the Kiel Institute for the World Economy. I'm currently a Senior Lecturer in Economics at the University of Otago.

My earlier work focused on labor market dynamics and monetary policy. Currently, my first research focus is on monetary and fiscal policy. Examples for this line of research are projects on inflation expectations, central bank communication, and heterogeneous agent models. My second research focus is on the interaction between climate and society. Here, I study the link between climate variables and migration or the link between weather, pollution, and crime.

In pursuing my research, I have used the set of tools and methodologies known as quantitative macroeconomics, i.e. calibrated and estimated dynamic stochastic equilibrium models, continuous time models, and univariate or multivariate econometric methods (e.g. Panel estimations, vector autoregression, or Markov-switching models). My work connects mathematical methods with data in order to test or quantify theoretical mechanisms, compare models, and address policy questions.

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