MACROECONOMIC EFFECTS of SECTORAL SHOCKS in GERMANY, U.K. and U.S.: A VAR-GARCH-M APPROACH.

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Abstract

A VAR-GARCH-M model for aggregate employment and employment shares is developed to explore the macroeconomic effects of sectoral shocks. Using U.S., U.K. and German data three main issues are investigated: the relevance of shocks volatility; the amount of aggregate employment growth variation accounted for by re-allocation shocks and the amount of aggregate innovation volatility explained by sectoral components. Bayesian methods are used for estimation, model selection and innovation accounting - Bayes factors for model selection and MCMC for estimation. The results favor the VAR-GARCH-M model. A significant GARCH-M component suggests the presence of volatility clustering and the feedback of volatilities on aggregate employment and sectoral shares growth rates. The innovation analysis supports sectoral shocks as a triggering force for aggregate employment fluctuations. In all three countries, 45% to 55% of aggregate employment variation is accounted for by sectoral innovations.

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1 INTRODUCTION

Lilien's (1982a) sectoral shifts hypothesis, the claim that changes in the pace of labor re-allocation between sectors could bring about unemployment (employment) fluctuations, has been widely tested over the last fifteen years. Most of this work has been carried out in a time-series context trying to create reliable dispersion measures of intersectoral re-allocation. As a modeling strategy, the use of dispersion measures has been hindered by the difficulty of disentangling the effect of sectoral shocks on such measures from their reaction to aggregate disturbances (Lilien 1982b; Abraham and Katz, 1986). Thus, this procedure has been unable to discriminate properly against conventional business cycle models that incorporate non-neutralities across sectors. As a consequence, much attention has been devoted to overcoming the observational equivalence problem embedded in the use of such indices (see Gallipoli and Pelloni, 1999, for a survey of these issues).

Campbell and Kuttner (1996), henceforth CK, has abandoned this approach and has tried to model the relationship between aggregate and sectoral employment explicitly using a VAR approach.

In Pelloni and Polasek (1999), henceforth PP, the VAR strategy is extended by trying to model the heteroscedastic component of sectoral shocks directly so as to bring to bear potential non-linearities implicit in the sectoral-shifts hypothesis. PP estimate and test a model for the U.S. over the period 1975-1990 using quarterly data. Two major results emerge from the analysis:

1. they find support for a VAR(2)-GARCH(2,2)-M(2) structure relative to other models, thus corroborating both shocks volatility clustering and volatilities feedback into employment growth rates;

2. the innovation accounting analysis, based on a Choleski decomposition, where aggregate shocks are ordered ahead of sectoral innovations, shows that sectoral shocks can account for approximately 65% of the total employment growth rate over a one-year forecast horizon. Re-allocation shocks emerge as having a large and significant role in explaining recent U.S. aggregate employment behaviour.

In this paper we expand and develop the approach of PP by applying it to German and U.K. time series as well as to a U.S. data set larger than the one used previously in PP. Although most of the empirical literature on sectoral shifts focuses on U.S. and Canadian data, work has also been carried out for other economies and for Europe in particular (Bean and Symons, 1989;

Caporale, 1997; Evans, 1988; Gross, 1993; Jimeno, 1992; Loungani, 1991; Loungani, Oyer and Rush, 1993; Mills, Pelloni and Zervoyianni, 1996, 1997; Ours and van der Tak 1992; Ottersten, 1993, 1994; Pelloni 1992; Samson, 1990; Serrano and Jimeno 1999; Schettkat, 1992; Siebert, 1997). Most of this work has been carried out in dynamic settings using ad hoc dispersion measures and none of it has addressed the issue of directly modeling sectoral shocks variability in PP for the U.S.. We begin to fill this gap by taking into account two major European economies that may be regarded as representative of two very different institutional arrangements. One, the U.K., has been characterized over the sample period by an increasingly flexible labor market, while the other, Germany, epitomises the prototype welfare structure typical of continental Europe. We draw comparisons with the U.S. economy, not by using the results in PP but rather by re-estimating the model using the 1968-98 sample, as for Germany and U.K., and applying the methodological innovations introduced in this paper.

We examine the following questions:

1. Should shocks volatilities enter the model? If so, should they enter in an GARCH or an GARCH-M form?

2. How much of the variation of aggregate employment growth can be accounted for by re-allocation shocks?

3. How much of aggregate volatility is explained by sectoral components?

Consistently with PP, our approach is Bayesian in all its aspects: estimation, model selection and innovation accounting([1]).

Model selection is carried out using the concept of the Bayes factors which is estimated exactly or numerically approximated according to the restrictions imposed by the prior distribution. The model is estimated using the Gibbs sampler and the Metropolis-Hastings algorithm (see Polasek et al. 2000).

We also introduce the following extensions:

1. cointegrating models;

2. contemporaneous effects of sectoral shocks on aggregate employment growth;

3. a new non-linear impulse response analysis;

4. augmentation of innovation analysis to incorporate the decomposition of volatilities.

2 THE MODEL

As in PP we argue that Lilien's original sectoral-shifts framework can allow for explicit modeling of the process characterizing the sectoral component of the firm is net-hiring equation. Ignoring quits, and letting the behaviour of a specific sector-reflected in the behaviour of its typical firm, we suggest that Lilien's model of the rate of change of sectoral employment could be augmented by modeling explicitly its heteroscedastic elements as

$$y_{j,t} = y_t + \varepsilon_{j,t}, \quad t = 1, \ldots, T; \quad j = 1, \ldots, M; \tag{1}$$

$$\varepsilon_{j,t} = u_{j,t}\sqrt{h_{j,t}} \tag{2}$$

$$h_{j,t} = \alpha + \sum_{i=1}^{q} \theta_{j,t}\varepsilon_{j,t}^2, \quad i = 1, \ldots, q, \quad t = 1, \ldots, T, \quad j = 1, \ldots, M \tag{3}$$

$$\alpha > 0, \quad \theta \geq 0$$

where $y_{j,t}$ is the employment growth rate of sector j at time t, y_t is an aggregate component common to all sectors, and $\varepsilon_{j,t}$ is a sector specific component characterized by a heteroscedastic structure modeled as an GARCH process (c.f. Bera and Higgins (1993) for a survey of ARCH modeling). Since Lilien's model allows for a sector-specific component with a time-dependent variance, we suggest that, at least in principle, this heteroscedasticity could be modeled as an GARCH process. Thus when a VAR procedure is implemented for the analysis of sectoral shocks, the potential presence of this GARCH component should be taken into account.

Our view is that a sectoral-shifts analysis is characterized by the presence of non-linearities imposed by variation in the variance of sectoral shocks (Lilien, 1982a, Davis, 1986). Thus it is essential to capture this feature of changing volatility for a correct representation of the sectoral-shifts hypothesis.

Earlier VAR models devoid of dispersion measures (e.g.: Campbell and Kuttner, 1996) bypass modeling the variance of sectoral shocks and its heteroscedastic structure. This modeling strategy, though important in its innovative perspective, is clearly incomplete and distorting. In fact, by not including nonlinearity as a consequence of sectoral shocks' time-dependent variance, it misrepresents the nature of the sectoral-shifts hypothesis and fails to introduce the essential triggering force of sectoral re-allocations. One of the possible ways for introducing the non-linearities connected with the time dependent variance of the shocks in a VAR model is to use a GARCH structure.

The implementation of a VAR-GARCH-M model also allows us to explore the potential presence of volatility clustering of the shocks. The sectoral-shifts hypothesis is grounded in the idea of an idiosyncratic arrival pattern of information that may be favorable or unfavorable to the existing allocation of resources. What matters is the size of the displacement disturbance: a large shock affecting the current allocations unfavorably would bring about large intersectoral movements of labor and capital. If the news, reflecting changes in sector-specific fundamentals, reaches a sector in cluster, it is reasonable to expect that allocative shocks may present a profile of changing and persisting volatility. We could also observe a profile of volatility clustering because of market dynamics in response to the flow of incoming news.

Following this insight we shall build a multivariate generalized GARCH model for aggregate employment growth and the growth of employment sectoral shares for Germany, the U.K. and the U.S. While the empirical literature on sectoral shifts for the U.S. is vast, and characterized by controversially opposing results, that for Europe is much smaller in size but more consistent in finding little, if any, support for re-allocation shocks (see Gallipoli and Pelloni 1999). For instance, to the best of our knowledge Mills, Pelloni and Zervoyianni (1996,1997) have found a significant role for sectoral shifts in the U.K.

The variables of our model are the natural logarithms of aggregate employment $\left(n_t^j,\, j=1\right)$ and of the employment shares $\left(n_t^j,\, j=2,\ldots,5\right)$ of the manufacturing, finance, trade, and construction sectors for U.S. and U.K.. For Germany it was not possible to have the same sectoral decomposition and so we used the employment shares of the manufacturing and communication sectors plus a residual sector denoted as 'Rest'. Unit root tests reveal all the variables to be $I(1)$, and so we transform them as $y_t = n_t - n_{t-4}$ to make them stationary.

The general specification of the model is provided by a M-dimensional VAR(k)-GARCH(p,q)-M(r) process:

$$
\begin{aligned}
\mathbf{y_t} &= \mu_t + \varepsilon_t \qquad (4)\\
&= \beta_0 + \sum_{i=1}^{k} \mathbf{B}_i \mathbf{y}_{t-i} + \sum_{i=0}^{r} \mathbf{\Psi_i} \text{ vech } \mathbf{H}_{t-i} + \varepsilon_t,\\
\text{vech } \mathbf{H}_t &= \alpha_0 + \sum_{i=1}^{p} \mathbf{A}_i \text{ vech } \mathbf{H}_{t-i} + \sum_{i=1}^{q} \boldsymbol{\theta}_{\mathbf{i}} \text{ vech } \left(\varepsilon_{t-i}\ \varepsilon_{t-i}^{'}\right), \qquad (5)\\
t &= 1,\ldots,T.
\end{aligned}
$$

In equation (4) $\mathbf{y}_t$ is an M-vector of observations on the variables; $\mathbf{H}_t$ is an conditional covariance matrix; ε_t is a M-dimensional process of mutually and serially uncorrelated random errors; vec (.) denotes the usual column stacking operator of a symmetric matrix, so that vech $\mathbf{H}_t$ and vech $(\varepsilon_t \varepsilon_t^{'})$ are two vectors of dimension $(M(M+1)/2)$; α_0 and β_0 are respectively

$(M(M+1)/2)$ and M-vectors of time invariant coefficients; $\mathbf{B}_i, \mathbf{\Psi}_i, \mathbf{A}_i$ and $\boldsymbol{\theta}_i$ are coefficient matrices, the first one is of dimension $M \times M$, while the other three have dimension $(M(M+1)/2) \times (M(M+1)/2)$.

For the U.S. and the U.K. the model is five-dimensional, so we have $M = 5$. For Germany, with 3 sectors, $M = 4$.

Assuming normality, the m^{th} equation of the VAR-GARCH-M model is given by $y_t^m \sim N\left[\mu_t^m, h_t^m\right], m = 1, \ldots, M$ with

$$\mu_t^m = \beta_0^m + \sum_{j=1}^{5}\left(\sum_{i=1}^{k}\beta_i^{mj} y_{t-i}^j + \sum_{i=1}^{r}\psi_i^{mj} h_{t-i}^j\right), \tag{6}$$

$$h_t^m = \alpha_0^m + \sum_{j=1}^{5}\sum_{i=1}^{p}\alpha_i^{mj} h_{t-i}^m + \sum_{i=1}^{q}\theta_i^{mj}\varepsilon_{m,t-i}^{2j}. \tag{7}$$

The crucial differences of this model from those of CK is that the conditional variances of the random shocks (h_t^m) are modeled explicitly and they enter the mean equations in (6).

If our specification of the likelihood function is viewed strictly from Lilien's perspective, the sectoral-shares growth rates y_t^j would represent the percentage change in sectoral labor re-allocation while the variances would be measures of sectoral re-allocation volatility (i.e. sectoral turbulences). If a sector experiences a large h^j at time t, then we should expect, given the sample, an amount of labor re-allocation far from its mean value. The larger the measured variance, the greater the amount of sectoral labor re-allocation.

Thus we interpret the h_t^j, the conditional variance of the sector specific shock e_t^j, as a measure of the dispersion of sector j's labor re-allocation and, as such, it should enter our specification of the model. [2] Our reading of the h_t^j's seems to be consistent with Lilien's sectoral-shifts hypothesis and, within these terms, quite uncontroversial.

The extra dimension given to the model by the persistence of the conditional variances is more open to question. Though there is not yet any rigorous theoretic support for it, we feel that it acceptable to explore this potential stylized fact empirically and test the significance of its presence. As stated above, we think it reasonable that both the idiosyncrasy of the information arrival pattern and the workings of market mechanisms may allow for its potential existence.

With respect to PP, we expand the specification of the likelihood function by capturing some of the multivariate time-series properties of the relevant processes. In this context, we can view the specification in (4)-(5) as a maintained hypothesis that aggregate employment and employment sectoral shares follow random walks without beeing cointegrated. Cointegration between processes means that they have the same stochastic trend. A lack of cointegration allows nonstationary variables to meander arbitrarily far from each other while cointegration means that there is a long-run relationship keeping together the nonstationary variables whose paths are influenced by the extent they are out of equilibrium. In our VAR, cointegration would mean that if $n_t' = (n_t^1, n_t^2, n_t^3, n_t^4, n_t^5)$ is subject to K cointegrating relations then there exists a matrix α of order $M \times K$ and rank K such that $\alpha\beta' = \Pi$, where α and β are matrices of loadings and factors. In principle we wish to embody cointegration in our VAR-GARCH-M model. However, in practice the introduction of cointegration in our framework is hampered by severe difficulties. It provides for example additional non-linearity to the model estimation and while cointegration is not a principal problem for the MCMC method of the VAR model, the estimation procedure becomes computer intensive. If M is the dimension of the model, then each additional order adds M^2 parameters to the estimation procedure. In a cointegration model, another $M \times M$ 'error correction' matrix has to be estimated, which is decomposed into a product of 2 matrices with $2 \times M \times K$ parameters, where K is the number of cointegrating vectors. In the Bayesian approach prior information must be specified for all these parameters, for the MCMC procedure one require much storage space. This shows that the 'curse of dimensionality' is fully present in high-dimensional sectoral models with volatility feedback, and therefore the principle of parsimony has to be applied for a cointegrating time-series model. Thus, the following specifications of our model do not contain the M component.

As a first step, the VAR-GARCH-M model has been augmented by an error-correction component so that the mean equation becomes:

$$\mathbf{y_t} = \mu_t + \varepsilon_t = \beta_0 + \mathbf{\Pi} n_{t-1} + \sum_{i=1}^{k} \mathbf{B}_i \mathbf{y}_{t-i} + \varepsilon_t \tag{8}$$

Where $\mathbf{\Pi}$ is an $M \times M$ matrix and $\mathbf{n}_t$ is an M-vector whose elements are the natural logarithms of aggregate employment and of employment shares. The variances are modeled as in (5). This form of the likelihood would suggest that the model's variables follow random walks and are cointegrated. We call this specification the EC-VAR-GARCH-M (or error correction) model.

We also respecify our likelihood to incorporate contemporaneous effects:

$$\mathbf{y_t} = \mu_t + \varepsilon_t = \beta_0 + \mathbf{\Pi} n_{t-1} + \tilde{\mathbf{C}} y_t + \sum_{i=1}^{k} \mathbf{B}_i y_{t-i} + \varepsilon_t, \tag{9}$$

where $\tilde{\mathbf{C}}$ is a matrix with zero restrictions along the main diagonal

$$\tilde{\mathbf{C}} = \begin{pmatrix} 0 & & C_{ij} \\ & \ddots & \\ C_{ij} & & 0 \end{pmatrix} \begin{pmatrix} n_1 \\ \\ n_2 \end{pmatrix}, \tag{10}$$

and variances modeled as in (5). We call this model the CEC-VAR-GARCH-M (or contemporaneous error correction) model.

We consider also what we call the 'general cointegration model'

$$y_t = \beta_0 + \alpha\beta' n_{t-1} + \sum_{i=1}^{k} B_i y_{t-i} + \varepsilon_t, \tag{11}$$

where α and β are $M \times r$ matrices of loadings and factors, respectively. We are interested in the rank r of the matrix $\mathbf{\Pi}$, which gives the number of cointegrating relationships. The decomposition of the $\mathbf{\Pi}$ matrix into $\alpha\beta$' is similar to a factor analysis model as in Polasek (1999). Since we are interested only in the rank of $\mathbf{\Pi}$, we take as prior distribution for α and β a data-based prior based on a singular value decomposition of $\mathbf{\Pi}$. This approach has performed favorably for a quick convergence of the MCMC algorithm.

2.1 THE PRIOR DISTRIBUTION

As an estimation method we use the Gibbs-Metropolis algorithm for a B-VAR-ARCH model, as described in Polasek et al. (2000).

As in PP our specification of the proposed prior introduces standard restrictions on the parameters of the mean and GARCH equations which should be fairly uncontroversial. Though some might not agree with our initial beliefs, we feel a reasonable consensus could exist about our assumptions.

First we follow the framework of the Litterman (1986), concentrating the coefficients around zero to avoid problems of over-fitting. Second we impose standard stationarity conditions on the vector ARCH processes. More precisely, letting β denote the coefficients of the mean equations, we assume a shrinkage normal prior of the form $\beta^m \sim N\left(0, \mathbf{H}_*^m\right)$, where β^m is the coefficient matrix and $\mathbf{H}_*^m = diag\left(1, \frac{1}{2}, \ldots, \frac{1}{k}\right)$ is the known prior covariance matrix. The assumption is that the further we move back in time the tighter is the distribution around zero so our confidence in the expected value of the coefficients being zero increases as the lags become longer.

For the GARCH part of the model, we use as a prior a truncated normal distribution so that $\alpha^m \sim N_0^\infty\left(\alpha_*^m, \mathbf{I}_N/2\right)$, where α_*^m, where N is the number of α's. We restrict the prior on the multivariate stationary condition in Engle and Kroner (1996), that is, the sum of the GARCH coefficient matrices has to be positive definite. This specification of the prior of the ARCH coefficient reflect the pure time-series restriction of covariance-stationarity. We will impose no further structure on the prior, reflecting our prior beliefs for the relative importance of aggregate and sectoral components.

2.2 MODEL SELECTION METHODOLOGY

Comparisons among different specifications of the likelihood function are carried out using the Bayes factor, BF. Letting y denote the available data set and M_j the model of interest, we compare any two models by calculating the posterior odds ratio

$$\frac{f\left(M_1|y\right)}{f\left(M_2|y\right)}=\frac{f\left(y|M_1\right)}{f\left(y|M_2\right)}\frac{f\left(M_1\right)}{f\left(M_2\right)}, \tag{12}$$

where $f(y|M_j)$ is the marginal likelihood of model j (the predictive density of the data), $f(M_j)$ is the prior density and $f(M_j|y)$ is the posterior density. The Bayes factor for M_2 versus M_1 is given by

$$B_{21}=\frac{f\left(y|M_2\right)}{f\left(y|M_1\right)}=\frac{f\left(M_1|y\right)/f\left(M_2|y\right)}{f\left(M_1\right)|f\left(M_2\right)}. \tag{13}$$

The marginal likelihood is calculated as an average of the likelihood function weighted by the prior distribution:

$$f(y\mid M_j)=\int f(y\mid \theta_j,M_j)f(\theta_j\mid M_j)d\theta_j. \tag{14}$$

Thus the Bayes factor summarizes the data evidence for Bayes tests.

Interpretative ranges have been suggested for the BF to summarize the evidence emerging from the data in favor of one hypothesis versus another (see

Kass and Raftery, 1995; Poirier 1998, p.380). The interpretative ranges for the order of magnitude of the BF for M_2 versus M_1 are provided in Table 1, which follows the so-called 9:19:99 rule. The reported scale of evidence for assessing the BF suggests that values of $\text{BF}_{21} < 1$ imply decisive evidence against M_2, while values larger than 1 would be an indication of evidence in favor of M_2. The weight of such evidence can be interpreted according to the suggested ranges of empirical evidence by BFs. From (13) the log BF is

$$\log B_{21} = \log f\left(y|M_2\right) - \log f\left(y|M_1\right) \tag{15}$$

and the orders of magnitude for the above critical points become $\log 9 = 2.2$, $\log 19 = 2.9$, $\log 99 = 4.6$.

From (14) it is clear that a BF depends on the prior distribution, $f\left(\theta_j|M_j\right)$. This dependence on the prior raises two problems: one concerning the credibility and the other the feasibility of the BF as a measure of the weight of evidence provided by the data for a hypothesis.

If the prior distributions are improper, then $f(y \mid M_j)$ in (14) is not defined and the Bayes factor cannot be interpreted. Alternative approaches have been suggested to define BFs for non-informative priors. Therefore, we calculate the posterior BF, POBF, of Aitkin (1991) and the pseudo BF, PSBF, proposed by Geisser and Eddy (1979) and implemented as in Gelfand and Dey (1994). Given the small/moderate size of our samples, we carry out exact calculations by simulating from the posterior distributions using Markov chain Monte Carlo (MCMC) techniques and, in particular, the Metropolis-Hastings algorithm.

3 IMPLEMENTATION AND RESULTS

3.1 DATA SETS

The estimation of the VAR-GARCH-M model uses German, U.S. and U.K. quarterly data sets over the period 1968-1998. We examine the three countries over the same period and let the shortest series determine the time span. The appendix provides details of the data sources.

In our analysis of the U.S. and U.K,. n_t^1 is the natural logarithm of aggregate employment ($n_t^1 = \log N_t$) and n_t^2, n_t^3, n_t^4, n_t^5 are the logarithms of employment shares in the manufacturing, construction, finance and trade sectors respectively, so that $n_t^j = \log\left(N_t^j/N_t\right)$ for j=2,...,5. For Germany we have only 3 sectors: manufacturing, communications and the 'rest'.

A Bayesian test for unit-roots is carried out along the lines of PP, where the classical augmented Dickey-Fuller (DF) regression for unit-root test is used to calculate the marginal likelihoods and the relevant Bayes factors. The 'Bayesian unit-roots test' is carried out by running regression for the $AR(p)$ in first differences, the DF model, the DF model with mean and trend, and by selecting the model with the highest marginal likelihood based on a fractional prior distribution (see O'Hagan, 1995).

By applying this procedure to the German, U.K., and U.S. data we find all the tested employment variables, $n_t^j (j = 1, \ldots, 5)$, to be non-stationary. We then test the growth rates $y_t^j (j = 1, \ldots, 5)$. For all the three countries the unit-root test indicates that all the relevant processes are stationary. Thus the univariate processes employed by the original VAR specification are all stationary while those employed for the EC model in (8) are all I(1).

3.2 ESTIMATION AND MODEL SELECTION

The M-dimensional VAR(k) model with r GARCH-in-mean components is given in (4) and the variance equation in (5). To estimate the M-dimensional time series $\{y_t, t = 1, \ldots, T\}$, we assume a conditional multivariate normal model with time-varying covariances

$$p\left(y_t|I_{t-1}\right) = N\left[\mu_t, H_t\right], \qquad t = 1, \ldots, T. \tag{16}$$

where I_t denotes the information up to time t. The likelihood function is given by

$$L\left(\theta|y\right) = \Pi_{t=1}^{T} p\left(y_t|I_{t-1}\right). \tag{17}$$

where I_0 contains information prior to time $t = 0$. The parameter vector $\theta' = (\alpha', \beta')$ is split into two parts, where in (4) $\mu_t = \mu_t(\alpha)$ with $\alpha = (\beta_0, \beta_1, \ldots, \beta_k, \Psi_0, \ldots, \Psi_r)$ a linear function in α given β, and vec H_t = vec $H_t(\beta)$ with $\beta = (\alpha_0, A_1, \ldots, A_p, \theta_1, \ldots, \theta_q)$ a linear function in β given α and I_{t-1}.

The partition of θ can be used for setting up a convenient MCMC algorithm. The β block of parameters is given by a multivariate normal distribution (conditional on α).

The full conditional distribution for the α parameters is not given in closed form. Therefore, a Metropolis-Hastings algorithm must be used. Starting from an arbitrary first proposal we update the parameters of the proposal distribution until a reasonable accept-reject ratio is obtained.

The values of the posterior and pseudo log-marginal likelihoods for all different specifications of our model (4) are reported in Tables 2.1a, 2.1b, 2.1c and 2.2a, 2.2b, 2.2c . We denote by k, p, q, r the orders of the VAR model, the GARCH process, and the M-component, respectively.

From the Tables 2.1a and 2.2a we can see that, for the U.S. data, the highest values of both marginal likelihood measures correspond to the VAR(1)-GARCH(2,1)-M(1) structure (marked by **). This is our best model for the U.S., and we call it model 2, $M2_{US}$. Similarly for Germany and the U.K., the VAR(2)-GARCH-(1,1)-M(2) process is selected as best model (marked by **) for both countries. We denote the selected likelihoods as $M2_G$ and $M2_{UK}$.

We construct the BF and compare $M2_{US}$, $M2_G$, and $M2_{UK}$ with the best models for the alternative specifications (marked by *). The results are reported in Tables 3a and 3b. The data show decisively that $M2_{US}$, $M2_G$, and $M2_{UK}$ have to be preferred to the simple VAR specification without a GARCH component ([5]). With log BF values of 100, 354 and 239 for U.S., U.K., and Germany, respectively, we see that the best VAR model for each country is far less likely than the corresponding best VAR-GARCH-M model. This suggests that the VAR-GARCH specification dominates the simple VAR model without a GARCH component.

When considering the other specifications, the BF provides substantial support for $M2_{US}$, $M2_G$, and $M2_{UK}$, with the exception of $M2_{UK}$ versus the EC-GARCH model, where there is slight evidence in favor of $M2_{UK}$.

The cointegration model is not supported by the data. This seems to be consistent with the sectoral shifts hypothesis. A cointegrating relationship would be surprising since it would imply that there exists a long run relationship between sectors and total employment, implying that no sectoral shifts would have occurred over the observed time period.

The results so far bear out the potential significance of modeling the GARCH component and the relative strength of the selected M2 models explicitly. We conclude not only that both sectoral and aggregate turbulences play a significant role within our framework, but also that we may have a high degree of confidence in choosing $M2_{US}$, $M2_G$, and $M2_{UK}$ for the subsequent innovation analysis.

So far we have decisive evidence supporting the VAR-GARCH-M model. Now we investigate whether the GARCH structure is relevant because of its aggregate component or because of its sector-specific element or both. To clarify this point, we impose two restrictions. First we examine the model with only its sectoral equations having an GARCH structure, so that aggregate volatility could not affect the system. Then we do the opposite, restricting the GARCH component only to the aggregate equations. The results are reported in Tables 4.1a, 4.1b, 4.1c and 4.2a, 4.2b, 4.2c.

The U.S. results favor the VAR-GARCH-M model in both cases, and the VAR(1)-GARCH(2,1)-M(1) model is selected as best in both cases.

Similar results are derived for the U.K. and Germany, where the VAR(2)-GARCH(1,1)-M(2) emerges as best in both countries. It should be pointed out that in both, the unrestricted VAR-GARCH-M model and the two restricted models, the level of support for the best models is always decisive in choosing the VAR model, but it varies in strength when the best models are compared with other VAR-GARCH-M processes characterized by different dynamics. We conclude that the data provide strong evidence in favor of the presence of the GARCH-M structure and that both aggregate and sectoral volatilities are relevant in characterizing it.

Before proceeding with the innovation analysis it is important to assess the importance of the GARCH-M component (the feedback of volatilities into the growth rates) of our model. Looking at the second column (VAR-GARCH-M process) of Tables 2.1a and 2.2a, we can construct the log BF for the $M2_{US}$

versus the VAR-GARCH process ($r = 0$). Decisive evidence supportive of the $M2_{US}$ model emerges from both tables. This is also true for the for the U.K. and Germany (second columns of Tables 2.1b, 2.1c, 2.2b and 2.2c).

We conclude that, within the current analytical framework, both the presence of volatility shocks and their impact on the employment growth rates are strongly corroborated by the data.

3.3 INNOVATION ACCOUNTING

We carry out an innovation accounting analysis in a nonlinear multivariate model according to the framework based on the generalized impulse response function of Koop et al. (1996) and PP. Table 5 shows the forecast error-variance decomposition for aggregate employment and employment-shares growth rates. The forecast error-variance decomposition of the conditional variances is presented in Table 6.

Looking at the 8-step ahead forecast error-variance decomposition for the aggregate employment-growth rate (column 1 of Table 5) we see that 52%, 54%, and 44% of it is accounted for by sectoral-shares innovations for Germany, the U.K. and the U.S., respectively.

Thus within the three countries, using a 2-year horizon and a triangular system with total employment ordered ahead of sectoral shares, we expect on the average, that approximately 50% of the forecast error variance of aggregate employment can be ascribed to re-allocation shocks with lower and upper limits of 44% and 54%.

The relevant role of sectoral shocks in explaining aggregate employment movements is confirmed by the results in Table 6, while the forecast error-variance decomposition of the conditional variances, which we consider to be a proper measure of labor-market turbulence, is shown. About 51%, 46%, and 58% of the 2-year horizon decomposition of aggregate-employment variability is accounted for by the combined effects of re-allocation shocks for Germany, the U.K. and the U.S. respectively. We conclude that re-allocation shocks' contributions to aggregate employment are not minor but, on the contrary, are substantial.

As far as the U.S. is concerned, our results corroborate the findings of PP. More surprisingly, we also find a considerable role for sectoral labor re-allocations in explaining aggregate employment movements in the U.K. and Germany. As mentioned above, previous empirical studies assign a limited scope to sectoral shocks in explaining aggregate employment fluctuations in

European countries. Here, however we could observe results suggesting that intersectoral labor re-allocation has a significant and substantial impact on the macroeconomic behaviour of two European economies.

Moreover, the size of the impact of sectoral re-allocation is as large, if not bigger, for Germany as for the U.K., suggesting that the different institutional arrangements of the two countries are not affecting the role of intersectoral movements in explaining aggregate behaviour. The importance of allocative shocks in explaining aggregate employment fluctuations in Germany and the U.K. is even more astonishing if we consider the strong sectoral aggregation used in our VAR. In Germany, we have only three sectors because of data restrictions, while in the U.K. we have four. Thus a large amount of intersectoral re-allocation is inevitably lost, as is its macroeconomic impact.

Within a 2-year horizon, aggregate shocks in all three countries explain only a small amount of the sectoral-shares variations, which are largely accounted for by innovations within the own sector. Though the 'own' component is always important in explaining sectoral-shares' variations, 'other sectors may account for a large amount of the fluctuations in individual sectors' employment shares.

Looking at the variance decomposition for sectoral-shares growth rates, the other sectors' contribution may at times be relatively low - as for the U.S. finance sector (26%) or the German communication sector (23%). But in general it can account for a fair amount of individual sectors' variation (40% or more). The same results hold if we look at the variance decomposition of the volatilities for the U.K. and Germany. However, for the U.S. data the other sectors' contributions to individual sector-shares changes are minor (between 5% and 25%). Thus it is reasonable to claim that there is a fairly large amount of interaction among sectors.

4 CONCLUSIONS

We have investigated the macroeconomic effects of sectoral shocks in the U.S., Germany, and the U.K. using a VAR-GARCH-M framework. In each country the GARCH-M component in the VAR-GARCH-M model is significant when compared with alternative model specifications. We find no evidence for a cointegration relationship between the sectors in any country. This is not surprising given the fact that structural changes have different impacts on employment growth rates in different sectors. The heteroscedastic structure of the shocks, the clustering of volatilities and their effects on the mean values are an essential part of this modeling strategy and should not be neglected. We interpret this result as a consequence of the GARCH component being a proxy for job re-allocations.

The innovation analysis reveals that sectoral re-allocations can account for a substantial amount of aggregate employment variations, while the effects of aggregate shocks for sectoral shares are of smaller magnitude. We conclude that multivariate VAR-GARCH models, when applied to sectoral-employment growth models, can provide new insights into the macroeconomic effects of re-allocation shocks and sectoral dynamic interactions.

NOTES

1. From a methodological point of view, PP is the first paper, within and outside the boundaries of multivariate GARCH modeling, where empirical sectoral shifts analysis is developed within a Bayesian framework.

2. A further interpretation could be given to the variances which is close to the one in sectoral uncertainty models (Topel and Weiss, 1988). An increase in future relative wage uncertainty across sectors will tend to reduce the return to sector-specific human capital investments and thus increase the willingness to switch sectors by joining the unemployment pool. The higher the sectoral turbulence, the higher the risk incurred by agents. The measured variances would represent measures of sectoral uncertainty as emerging from sectoral turbulence.

3. The identification of $\Pi = \alpha\beta'$ has been carried out by assuming normal priors $\alpha \sim N(\alpha_*, V_\alpha)$ and $\beta \sim N(\beta_*, V_\beta)$, where α_* and β_* are specified using the values from a classical eigenvalue decomposition of Π in the error correction model.

4. Let n_t be the time series we test for unit roots and let $\triangle n_t = n_t - n_{t-1}$.

Then we consider four different autoregressive processes:

$$\triangle n_t = \alpha \sum_{j=1}^{p} \alpha_j \triangle n_{t-j}, \qquad (\triangle - AR)$$

$$\triangle n_t = \alpha_0 n_{t-1} + \sum_{j=1}^{p} \alpha_j \triangle n_{t-j}, \qquad (DF - AR1)$$

$$\triangle n_t = \mu + \alpha_0 n_{t-1} + \sum_{j=1}^{p} \alpha_j \triangle n_{t-j}, \qquad (DF - AR2)$$

$$\triangle n_t = \mu + \beta t + \alpha_0 n_{t-1} + \sum_{j=1}^{p} \alpha_j \triangle n_{t-j}, \quad (DF - AR3)$$

c.f. PP section 3.2 for details of this methodology.

5. The values of the marginal likelihoods for the VAR model appearing in column 1 and in column 2 (first row) are different. The reason is due to the different estimation methods used for the two models. The simple VAR model in column 1 was estimated in closed form and therefore exact calculations were carried out. The VAR in column 2 had to be be estimated within the VAR-GARCH-M structure using the Gibbs sampler. We used the approach of Chib and Jeliazkov (1999) to calculate marginal likelihoods and the pseudo marginal likelihoods are

computed as in Gelfand and Dey (1994).

Ranges		Evidence
Bayes Factor	Log Bayes Factor	
$1 < B_{21} < 9$	$0 < \log B_{21} < 2.2$	Very Slight
$9 < B_{21} < 19$	$2.2 < \log B_{21} < 2.9$	Substantial
$19 < B_{21} < 99$	$2.9 < \log B_{21} < 4.6$	Strong
$B_{21} > 99$	$\log B_{21} > 4.6$	Decisive

Table 1. Interpretation of Bayes factors

k	r	p	q	VAR	VAR-GARCH-M	EC-VAR-ARCH
1	0	0	0	-1271.2567	-1270.5081	-1271.2295
1	1	1	0	-1271.2567	-1207.7902	-1212.6456
2	0	1	1	-1285.5548	-1108.7372	-1110.9303
2	2	1	1	-1285.5548	-1032.2107**	-1035.3662*
k	r	p	q	CEC-VAR-ARCH	Coin-VAR(r=1)-ARCH	Coin-VAR(r=2)-ARCH
1	0	0	0	-1277.9096	-1286.5573	-1281.4841
1	1	1	0	-1221.1363	-1216.8295	-1212.4651
2	0	1	1	-1132.8812	-1139.6123	-1115.9237
2	2	1	1	-1044.0053*	-1034.6264*	-1038.9707*

Table 2.1a: Model selection for with posterior marginal likelihoods for Germany

k	r	p	q	VAR	VAR-GARCH-M	EC-VAR-ARCH
1	0	0	0	-1283.7802	-1281.1256	-1282.5268
2	0	1	1	-1206.8237	-918.5263	-922.7484
2	2	1	1	-1206.8237	-853.1585**	-855.9883*
1	1	1	0	-1283.7802	-1152.6722	-1156.1035
k	r	p	q	CEC-VAR-ARCH	Coin-VAR(r=1)-ARCH	Coin-VAR(r=2)-ARCH
1	0	0	0	-1286.6291	-1298.4053	-1286.3205
2	0	1	1	-920.7964	-921.5684	-922.7389
2	2	1	1	-862.6908*	-865.6802*	-857.2938*
1	1	1	0	-1166.8749	-1161.1841	-1154.8907

Table 2.1b: Model selection with posterior marginal likelihoods for the United Kingdom

k	r	p	q	VAR	VAR-GARCH-M	EC-VAR-ARCH
1	0	0	0	-1212.2972	-1205.6256	-1208.2639
1	1	1	0	-1212.2972	-1167.5263	-1167.6770
2	0	1	1	-1234.0697	-1250.6276	-1251.6022
1	1	2	1	-1212.2972	-1112.2005**	-1116.5968*
k	r	p	q	CEC-VAR-ARCH	Coin-VAR(r=1)-ARCH	Coin-VAR(r=2)-ARCH
1	0	0	0	-1217.5562	-1223.3191	-1216.2732
1	1	1	0	-1178.0730	-1182.3694	-1176.7387
2	0	1	1	-1262.8834	-1263.7812	-1255.1109
1	1	2	1	-1116.9966*	-1114.5606*	-1122.3131*

Table 2.1c: The posterior marginal likelihood for the United States

k	r	p	q	VAR	VAR-GARCH-M	EC-VAR-ARCH
1	0	0	0	-238.7681	-238.0195	-238.7409
1	1	1	0	-238.7681	-232.5282	-237.3836
2	0	1	1	-251.0963	-198.8237	-201.3426
2	2	1	1	-251.0963	-131.7143**	-134.8698*
k	r	p	q	CEC-VAR-ARCH	Coin-VAR(r=1)-ARCH	Coin-VAR(r=2)-ARCH
1	0	0	0	-245.4210	-254.0687	-248.9955
1	1	1	0	-245.8743	-241.5675	-237.2031
2	0	1	1	-217.2731	-219.7382	-209.7281
2	2	1	1	-143.5089*	-135.1300*	-138.4743*

Table 2.2a: The pseudo marginal likelihood for Germany

k	r	p	q	VAR	VAR-GARCH-M	EC-VAR-ARCH
1	0	0	0	-124.1070	-121.4524	-122.8535
2	0	1	1	-122.7698	-89.1283	-92.6835
2	2	1	1	-122.7698	-80.7822**	-81.6120*
1	1	1	0	-124.1070	-120.1134	-123.5447
k	r	p	q	CEC-VAR-ARCH	Coin-VAR(r=1)-ARCH	Coin-VAR(r=2)-ARCH
1	0	0	0	-126.9559	-138.7321	-126.6473
2	0	1	1	-91.6273	-92.1373	-92.8635
2	2	1	1	-90.3145*	-93.3039*	-83.9175*
1	1	1	0	-134.3161	-128.6253	-122.3319

Table 2.2b: The pseudo marginal likelihood for the United Kingdom

k	r	p	q	VAR	VAR-GARCH-M	EC-VAR-ARCH
1	0	0	0	-138.7449	-132.0733	-134.7116
1	1	1	0	-138.7449	-128.6932	-128.8439
2	0	1	1	-135.1972	-122.0864	-123.7826
1	1	2	1	-138.7449	-115.5686**	-119.9649*
k	r	p	q	CEC-VAR-ARCH	Coin-VAR(r=1)-ARCH	Coin-VAR(r=2)-ARCH
1	0	0	0	-144.0039	-149.7668	-142.7209
1	1	1	0	-139.2399	-143.5363	-137.9056
2	0	1	1	-133.8291	-134.8548	-129.0111
1	1	2	1	-120.3647*	-117.9287*	-125.6812*

Table 2.2c: Model selection with pseudo marginal likelihoods for the United States

$\log BF_{21}$	Country	
	Germany	U.K.
(VAR)	239.04	353.67
(EC-VARCH)	3.15	2.83
(CEC-VARCH)	11.79	6.71
(COIN-VARCH 1)	2.41	9.7
(COIN-VARCH 2)	6.76	1.31

Table 3a Bayes factors for model selection using posterior log marginal likelihoods

$\log BF_{21}$	Country	
	Germany	U.K.
(VAR)	107.05	41.82
(EC-VARCH)	3.15	0.83
(CEC-VARCH)	11.79	9.53
(COIN-VARCH 1)	3.42	11.69
(COIN-VARCH 2)	6.76	3.13

Table 3b Bayes factors for model selection using pseudo log marginal likelihoods.

k	r	p	q	posterior marginal likelihood	pseudo marginal likelihood
1	0	0	0	-1275.8091	-253.2577
1	1	1	0	-1211.7829	-241.3133
2	0	1	1	-1128.7383	-214.8729
2	2	1	1	-1036.7737**	-132.9490**

Table 4.1a. Model selection for Germany for the

VAR-GARCH-M restricted model 1

($*$ maximum marginal likelihood)

k	r	p	q	posterior marginal likelihood	pseudo marginal likelihood
1	0	0	0	-1294.3038	-132.5717
2	0	1	1	-920.8283	-102.1132
2	2	1	1	-855.2732**	-97.1481**
1	1	1	0	-1160.1939	-124.8163

Table 4.1b. Model selection for U.K. employment for the

VAR-GARCH-M restricted model 1

($*$ maximum marginal likelihood)

k	r	p	q	posterior marginal likelihood	pseudo marginal likelihood
1	0	0	0	-1212.5321	-140.3038
1	1	1	0	-1178.4934	-143.7829
2	0	1	1	-1260.7685	-129.4529
1	1	2	1	-1112.2361**	-121.5756**

Table 4.1c. Model selection for the U.S. employment for the

VAR-GARCH-M restricted model 1

(∗ maximum marginal likelihood)

k	r	p	q	posterior marginal likelihood	pseudo marginal likelihood
1	0	0	0	-1276.7421	-254.2444
1	1	1	0	-1212.4857	-241.8822
2	0	1	1	-1127.8380	-215.2973
2	2	1	1	-1037.5769**	-133.0290**

Table 4.2a. Model selection for Germany for the

VAR-GARCH-M restricted model 2

($*$ maximum marginal likelihood)

k	r	p	q	posterior marginal likelihood	pseudo marginal likelihood
1	0	0	0	-1298.5633	-134.6011
2	0	1	1	-920.6383	-102.7377
2	2	1	1	-855.9567**	-100.1352**
1	1	1	0	-1162.6250	-125.6746

Table 4.2b. Model selection for the U.K. for the

VAR-GARCH-M restricted model 2

($*$ maximum marginal likelihood)

k	r	p	q	posterior marginal likelihood	pseudo marginal likelihood
1	0	0	0	-1214.7645	-141.8060
1	1	1	0	-1182.0382	-146.5370
2	0	1	1	-1266.2647	-129.8283
1	1	2	1	-1112.2477**	-122.6719**

Table 4.2c. Model selection for the U.S. for the

VAR-GARCH-M restricted model 2

($*$ maximum marginal likelihood)

Country	Sectors	1	2	3	4	5
	1	0.5653	0.0218	0.0071	0.1205	0.0213
	2	0.1087	0.5639	0.1190	0.1550	0.1016
U.S.	3	0.1028	0.2188	0.5737	0.1047	0.1832
	4	0.1139	0.1937	0.2080	0.6147	0.1080
	5					

Country	Sectors	1	2	3	4	5
U.S.	1	0.4160	0.0587	0.1454	0.1067	0.0920
	2	0.0929	0.7013	0.0220	0.0331	0.1756
	3	0.3830	0.1291	0.7251	0.3012	0.0151
	4	0.0041	0.0723	0.0130	0.5050	0.0574
	5	0.1036	0.0384	0.0942	0.0537	0.6598
U.K.	1	0.5433	0.1336	0.0902	0.1420	0.0437
	2	0.0178	0.4335	0.0219	0.0863	0.0600
	3	0.2097	0.1516	0.8717	0.1058	0.1931
	4	0.0871	0.1712	0.0056	0.6177	0.2837
	5	0.1419	0.1098	0.0104	0.0480	0.4192
GERMANY	1	0.4938	0.1031	0.0209	0.2124	-
	2	0.1152	0.5131	0.1380	0.2950	
	3	0.1766	0.1626	0.6155	0.1484	
	4	0.2142	0.2210	0.2254	0.3440	

Table 6. Variance decomposition of the volatilities for the U.S., U.K. and Germany for the preferred VAR-GARCH-M models; 2-year horizon ; for U.S. and U.K.: 1 = Total, 2 = Manufacturing, 3 = Construction, 4 = Finance, 5 = Trade; for Germany: 1 = Total, 2 = Manufacturing, 3 = Communication, 4 = Rest.

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