Sources of German Unemployment: A Structural Vector Error Correction Analysis*

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Abstract

In this paper we analyze the sources of German unemployment within a structural vector error correction model (SVECM) framework. For this purpose we estimate a VECM model using data for unified Germany. The cointegration analysis reveals a long run relationship between real wages, productivity and unemployment which is interpreted as a wage setting relation. Based on the reduced form VECM we identify structural shocks and assess their importance for unemployment by impulse response analysis, forecast error variance and historical decompositions. We supplement the analysis with results from a subset SVECM, a SVECM with restrictions on the reduced form parameters. In contrast to previous studies for West Germany, we find that technology, labor supply and labor demand shocks are important sources of unemployment in the long run.

Keywords: Unemployment, Cointegration, Structural VECM, Subset SVECM, Bootstrap

JEL classification: C32, E24

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1 Introduction

Persistently high unemployment is one of the major economic problems in Germany. Ever since the mid 70s the unemployment rate has been increasing. While this development has been observed in most European countries, the German reunification in 1990:3 has boosted the unemployment rate to new record levels. This increase has stimulated economists to investigate the sources of unemployment more closely. A particularly interesting question from a macroeconomic point of view is whether unemployment is mainly determined by structural factors such as technology, labor supply, or wage setting shocks or by cyclical such as aggregate demand or labor demand shocks. The answer to this question has, of course, important policy implications. If unemployment is only determined by structural factors, demand side management policies cannot successfully reduce unemployment.

In this paper we try to answer this question by identifying macroeconomic shocks for the German labor market and assess their importance for unemployment within a structural vector error correction model (SVECM) by impulse response functions (IRF), forecast error variance decompositions (FEVD) as well as historical decompositions. The structural VAR (SVAR) modeling framework has been previously used to analyze the labor market of different countries. Dolado & Jimeno (1997) investigate the sources of Spanish unemployment using a VAR in first differences. They find that unemployment is explained by a mixture of supply and demand shocks. Jacobson, Vredin & Warne (1997) use a common trends model to compare the labor markets of Scandinavian countries and conclude that the only common source of unemployment in Denmark, Norway and Sweden is shocks to wage setting. Hansen & Warne (2001) conclude from their analysis that labor supply shocks are the primary source for unemployment in Denmark. Similarly, Fabiani, Locarno, Onetto & Sestito (2000) find that most of the rise in Italian unemployment can be attributed to productivity and labor supply shocks. Carstensen & Hansen (2000) analyze the West German labor market and find that unemployment is equally determined by technology and labor supply shocks in the long run. The present study differs from Carstensen & Hansen (2000) in two important respects. First, we use a model similar to the one in Jacobson et al. (1997) to derive the identifying assumption, because it implies a smaller set of variables and avoids the somewhat arbitrary concept of a goods market equation. Second, we use data for the unified Germany from the third quarter of 1990 onwards rather than West German data only. Over ten years after German reunification it seems natural to use data for the whole country even though this may imply some extra problems.

The structural VECM used in this analysis employs both, contemporaneous and long-run restrictions on the effects of structural shocks for identification. As suggested by Vlaar (1998) both restriction types can be written as linear restrictions and the usual Maximum Likelihood (ML) estimation procedure (see Breitung (2000) and Amisano & Giannini (1997)) can be employed. This setup can also be used to estimate SVECMs with restrictions on the short run parameters. These so-called subset SVECMs can be used as additional modeling tools to avoid the problems related to the large number of parameters in VAR and VECM models.

The paper is structured as follows. In Section 2 we present the econometric modeling framework and discuss briefly the estimation of SVECMs. Section 3 presents a small macroeconomic model of the labor market, which is used to derive the identifying assumptions for the structural analysis. In Section 4 we conduct the cointegration analysis before the labor market shocks are identified in Section 5, which also contains the impulse response analysis, the FEVD and the historical decompositions. Section 6 concludes.

2 Econometric Methodology

Vector Autoregressive (VAR) models have become increasingly popular after Sims's (1980) critique of the simultaneous equation approach. However, the standard VAR is a reduced form model and economic interpretation of the results is often impossible, unless the reduced form VAR is linked to an economic model. If economic theory is used to provide the link between forecast errors and fundamental shocks, we call the resulting model a SVAR. Models of this type have become an important tool in macroeconomics and have been used to analyze the effects of monetary shocks (see Christiano, Eichenbaum & Evans (1999)), the effects of technology shocks (Galí (1999)) and the effects of fiscal shocks (see Rotemberg & Woodford (1992)), for example. It is also possible to apply the SVAR technique to vector error correction models (VECM) with cointegrated variables and we describe the relation between structural and reduced form VECM more precisely in the following.

The SVECM analysis starts from the reduced form standard VAR(p) model

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + \Xi D_t + u_t, \tag{2.1}$$

where y_t is a $K \times 1$ vector of time series, D_t a vector of deterministic terms, and $A_1, \ldots, A_p$ are $K \times K$ coefficient matrices. Ξ is the coefficient matrix associated with deterministic terms, such as a constant, trend and seasonal dummies. The reduced form disturbance u_t is a $K \times 1$ unobservable zero mean white noise process with covariance matrix Σ_u. The VAR (2.1) has a vector error correction representation denoted as VECM(p)

$$\Delta y_t = \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + \Xi D_t + u_t, \tag{2.2}$$

which is obtained by subtracting y_{t-1} from both sides of (2.1) and rearranging terms (see Lütkepohl (2001) for precise formulas). In cointegrated models Π has reduced rank $r = \text{rk}(\Pi) < K$ and can be decomposed as $\Pi = \alpha\beta'$, where α and β are $K \times r$ matrices containing the loading coefficients and the cointegration vectors, respectively. We are interested in the effects of the fundamental shocks ε_t on the system variables y_t. These shocks can be expressed in terms of the structural form VECM

$$\mathsf{K}\Delta y_t = \mathsf{\Pi} y_{t-1} + \mathsf{\Gamma}_1 \Delta y_{t-1} + \cdots + \mathsf{\Gamma}_{p-1} \Delta y_{t-p+1} + \bar{\Xi} D_t + \varepsilon_t, \tag{2.3}$$

where the $K \times 1$ vector ε_t contains the unobservable structural disturbances and has the covariance matrix Σ_ε. Thus, to compute the responses to the economic shocks ε_t, we have to link the forecast errors u_t to the structural shocks ε_t. Premultiplying the system (2.3) by K^{-1} gives the reduced form (2.2) with $\Gamma_1 = \mathsf{K}^{-1}\mathsf{\Gamma}_1, \ldots, \Gamma_{p-1} = \mathsf{K}^{-1}\mathsf{\Gamma}_{p-1}$, $\Xi = \mathsf{K}^{-1}\bar{\Xi}$ and

$$u_t = \mathsf{K}^{-1}\varepsilon_t = A_0\varepsilon_t, \tag{2.4}$$

which relates the reduced form disturbance u_t to the underlying structural shock. For notational convenience we express the model in terms of the contemporaneous impact matrix $A_0 = \mathsf{K}^{-1}$.

To analyze the effects of the underlying structural shocks, we need to recover the K^2 elements of A_0. For this purpose we need identifying restrictions coming from economic theory. To see this more clearly, we use the relation (2.4) to write

$$\Sigma_u = E[u_t u_t'] = A_0 E[\varepsilon_t \varepsilon_t'] A_0' = A_0 \Sigma_\varepsilon A_0' \tag{2.5}$$

and use the standard assumption that the structural shocks are uncorrelated and have unit variances, i.e. $\Sigma_\varepsilon = I_K$, to get

$$\Sigma_u = A_0 A_0'. \tag{2.6}$$

The symmetry of Σ_u and the normalization of the structural variances impose $K(K+1)/2$ nonlinear restrictions on the K^2 parameters of A_0. To exactly identify the elements of A_0 we need to impose $K(K-1)/2$ additional, linearly independent restrictions. Since economic theory has more to say about the long run, we prefer to impose long run restrictions rather than contemporaneous restrictions. From Granger's representation theorem (see Johansen (1995)) we know that the VECM (2.2) can be represented as a Vector Moving Average (VMA) process

$$y_t = C(1)\sum_{i=1}^{t}(u_i + \Xi D_i) + C_1(L)(u_t + \Xi D_t) + y_0, \tag{2.7}$$

where y_0 depends on the initial conditions and $C(1)$ is the total impact matrix computed as $C(1) = \beta_\perp(\alpha_\perp'(I_K - \sum_{i=1}^{p-1}\Gamma_i)\beta_\perp)^{-1}\alpha_\perp'$. $\beta_\perp$ and $\alpha_\perp$ represent the orthogonal complements of β and α, respectively. Note that $C(1)$ has reduced rank $rk(C(1)) = K - r$. From (2.7) it follows that the long run effects of structural shocks ε_t can be written as

$$C(1)A_0. \tag{2.8}$$

Long run zero restrictions as implied by economic theory can now be imposed easily by setting elements of (2.8) to zero. The common trends literature (see for example King, Plosser, Stock & Watson (1991)) distinguishes between permanent and transitory effects. In particular, we know that in a system with r cointegration relations, only $k = K - r$ shocks can have permanent effects. To exactly identify permanent shocks we need $k(k-1)/2$ additional restrictions.

Similarly, $r(r-1)/2$ restrictions identify the transitory shocks. Setting elements of (2.8) to zero can be written in implicit form as

$$R_l \text{vec}(C(1)A_0) = 0,$$

where R_l is an appropriate restriction matrix. Following Vlaar (1998) in using the rules of the vec operator these restrictions can be reformulated as

$$R_l(I_K \otimes C(1))\text{vec}(A_0) = R_l^* \text{vec}(A_0) = 0,$$

such that the restrictions are linear in the elements of A_0. Replacing $C(1)$ by an estimator obtained from the reduced form, $R_l^* = R_l(I_K \otimes \widehat{C(1)})$ is a stochastic restriction matrix. These implicit restrictions can be translated into the explicit form and then be used in the maximization procedure of the SVECM. Moreover, the long-run restrictions can be combined with contemporaneous restrictions on the elements of A_0 in the form $\text{vec}(A_0) = R_{A_0}\gamma_{A_0}$. Estimates for the contemporaneous impact matrix can be found by maximizing the concentrated log-likelihood function given by

$$\ln l(A_0) = \text{constant} - \frac{T}{2}\log|A_0|^2 - \frac{T}{2}\text{tr}\left((A_0')^{-1}A_0\widetilde{\Sigma}_u\right), \tag{2.9}$$

with respect to the free structural parameters γ_{A_0} subject to the identifying restrictions, where $\widetilde{\Sigma}_u$ is the estimated residual covariance matrix from the reduced form VECM. Note that contemporaneous and long-run restrictions on the effects of shocks are written linearly. Therefore, the estimation procedure described in Amisano & Giannini (1997) and implemented for SVAR models in Malcom by Mosconi (1998) can be modified to obtain ML estimates. Concentrating the log-likelihood with respect to the reduced form parameters is no longer possible if additional restrictions for $\alpha, \Gamma_1, \dots, \Gamma_{p-1}$ are imposed. Nevertheless, residuals from a subset VECM may still give a reasonable estimate of Σ_u (see Hamilton (1994, Chapter 11)). In other words, an expression similar to (2.9) can be obtained based on VECMs with restrictions on the reduced form parameters. To be precise (2.9) is then no longer the concentrated likelihood function. Nevertheless, the same estimation technique as before can be used to form reasonable estimates for A_0.

Based on the preceding discussion the econometric analysis of the German labor market data involves the following steps: First, we determine the cointegration rank of the system of interest and impose over-identifying restrictions on the cointegrating vectors using the ML method proposed by Johansen (1995). The identified cointegration relations can be used to setup a full VECM, where no further restrictions are imposed. Residuals from the VECM are used to form an estimate for Σ_u. Second, long-run and contemporaneous identifying restrictions derived from the model presented in the next section are used to form estimates of A_0. Using the estimated contemporaneous impact matrix, the structural shocks can be recovered and their impact can be analyzed using an impulse response analysis. Moreover, the importance of different shocks is measured by FEVD and historical decompositions of forecast errors. As an additional modeling tool we also use a subset VECM as a basis for the structural analysis. Before we turn to the empirical analysis in Section 4, the theoretical model used to derive identifying assumptions is considered next.

3 A Small Labor Market Model

In this section we briefly describe a simple macroeconomic model of the labor market which is very similar to the one used by Jacobson et al. (1997). The model is the basis for the identifying restrictions imposed in the structural analysis of Section 5. It consists of a production function, a labor demand relation, a labor supply, and a wage setting relation. All variables are expressed in natural logarithms.

The production function relates output (gdp_t) to employment e_t

$$gdp_t = \rho e_t + \theta_{1,t}, \qquad (3.1)$$

where ρ measures the returns to scale. $\theta_{1,t}$ is a stochastic technology trend that follows a random walk

$$\theta_{1,t} = \theta_{1,t-1} + \varepsilon_{gdp,t}$$

and $\varepsilon_{gdp,t}$ is the pure technology shock. Labor demand relates employment to output and real wages $(w-p)_t$:

$$e_t = \lambda gdp_t - \eta(w-p)_t + \theta_{2,t}, \qquad (3.2)$$

with

$$\theta_{2,t} = \phi_d \theta_{2,t-1} + \varepsilon_{d,t}.$$

If $|\phi_d| < 1$ the labor demand is stationary. In that case the pure labor demand innovation $\varepsilon_{d,t}$ has only temporary effects on employment. Jacobson et al. (1997) do not allow for a possible nonstationary labor demand in their model and assume a priori $\phi_d = 0$. This restriction implies that the labor demand shock has no long-run effects. Clearly, this is a very strong assumption. To relax this assumption at this stage of the analysis, we use the slightly more general form of the model. The cointegration analysis in Section 4 will show, whether labor demand is stationary.

Labor force l_t is assumed to be related to real wages according to

$$l_t = \pi(w-p)_t + \theta_{3,t}. \qquad (3.3)$$

The exogenous labor supply trend $\theta_{3,t}$ follows a random walk

$$\theta_{3,t} = \theta_{3,t-1} + \varepsilon_{s,t},$$

where $\varepsilon_{s,t}$ is the underlying labor supply shock. Finally, we have the wage setting relationf:fevd

$$(w-p)_t = \delta(gdp_t - e_t) - \gamma(l_t - e_t) + \theta_{4,t}, \tag{3.4}$$

stating that real wages are a function of productivity and unemployment. The wage setting trend $\theta_{4,t}$ can be stationary or nonstationary depending on ϕ_w in

$$\theta_{4,t} = \phi_w \theta_{4,t-1} + \varepsilon_{w,t}.$$

If $|\phi_w| < 1$, the wage setting trend is stationary. Again, we use results from the empirical analysis to determine whether wage setting is stationary. To close the model we assume that $\varepsilon_{gdp,t}, \varepsilon_{d,t}, \varepsilon_{s,t}$, and $\varepsilon_{w,t}$ are identically and independently distributed with zero mean and variances $\sigma^2_{gdp}, \sigma^2_d, \sigma^2_s$, and σ^2_w, respectively. The solution of the model (3.1) – (3.4) in terms of the variables used in the empirical analysis is given by

$$\begin{pmatrix} gdp_t - e_t \\ e_t \\ l_t - e_t \\ (w-p)_t \end{pmatrix} = \psi \begin{pmatrix} (1-\lambda)(1+\gamma\pi) + \eta\gamma \\ \lambda(1+\gamma\pi) - \eta\delta \\ \eta\delta - \lambda + (1-\lambda)\pi\delta \\ \lambda\gamma + \delta(1-\lambda) \end{pmatrix} \theta_{1,t} + \psi \begin{pmatrix} (\rho-1)(1+\gamma\pi) \\ 1+\gamma\pi \\ (\rho-1)\delta\pi - 1 \\ \gamma - \delta(1-\rho) \end{pmatrix} \theta_{2,t}$$
$$+ \psi \begin{pmatrix} (\rho-1)\eta\gamma \\ \eta\gamma \\ 1 - \rho\lambda + (\rho-1)\delta\eta \\ (\rho\lambda - 1)\gamma \end{pmatrix} \theta_{3,t} + \psi \begin{pmatrix} \eta(1-\rho) \\ -\eta \\ \eta + (1-\rho\lambda)\pi \\ 1-\rho\lambda \end{pmatrix} \theta_{4,t} \tag{3.5}$$

with

$$\psi = \frac{1}{(1-\rho\lambda)(1+\gamma\pi) + \eta\gamma + (\rho-1)\eta\delta}.$$

From (3.5) we see that productivity, employment, unemployment and real wages are driven by two random walks in productivity and labor supply. As explained above, the labor demand and the wage setting component can be stationary or nonstationary. In terms of the common trends literature, there are at least two and at most four common trends in this model. This implies at most two cointegration relations: a labor demand relation and a wage setting relation.

4 Cointegration Analysis of the German Labor Market

In this paper we use quarterly, seasonally unadjusted data for the unified Germany constructed from the Deutsches Institut für Wirtschaftsforschung (DIW) database for the period from 1970 until 1998. Prior to 1970 the German labor market was characterized by full employment, which we see as a different economic regime. Accordingly, we choose the estimation start date 1970:1, because starting in the early 70s unemployment became a major problem. All data refer to West Germany until 1990:2 and to unified Germany afterwards.

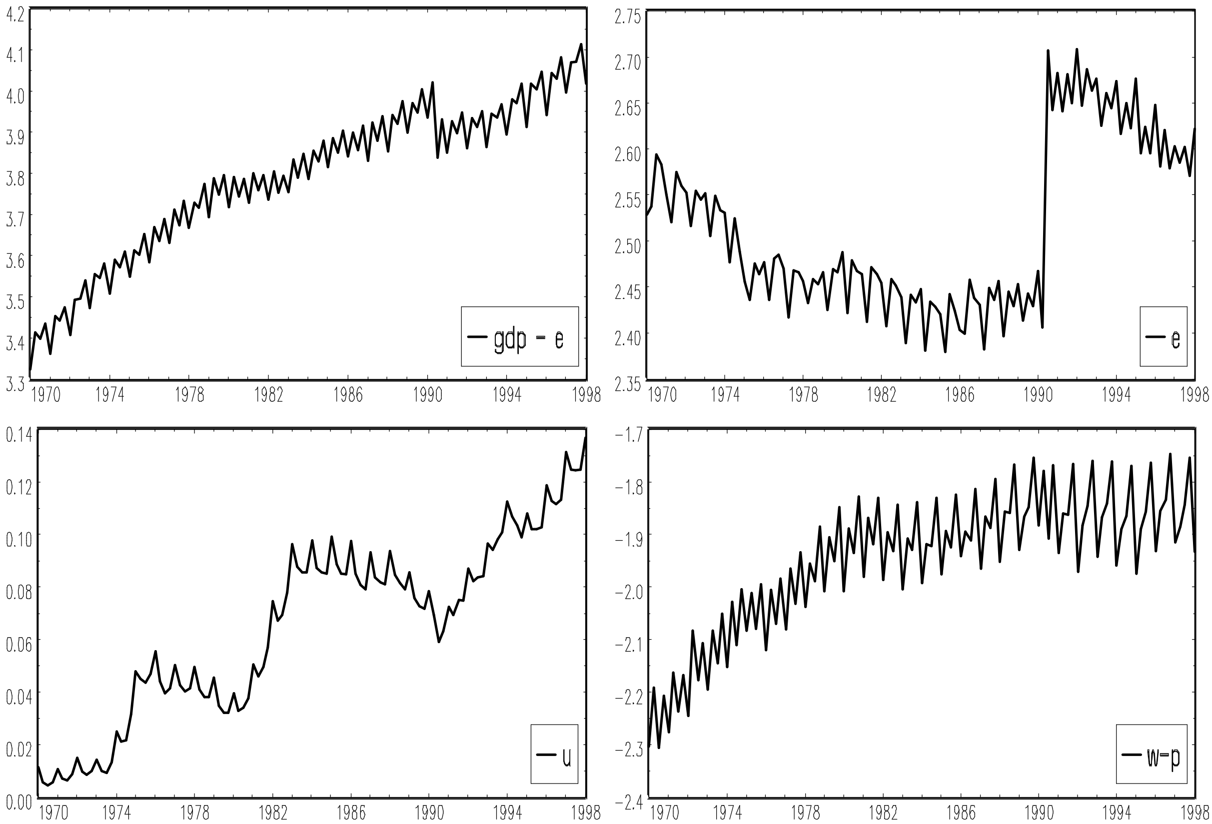

Figure 1: Labor Market Time Series Analyzed

In the empirical analysis we use four series: hourly productivity $gdp_t - e_t$, employment e_t, the unemployment rate $u_t \approx l_t - e_t$ and hourly real wages $w_t - p_t$. Appendix A gives a detailed description on how the series have been constructed. The vector we use in the cointegration analysis therefore includes

$$y_t = [(gdp_t - e_t), e_t, u_t, (w_t - p_t)]'. \tag{4.1}$$

The time series y_t are shown in Figure 1. The productivity and the employment series exhibit are clear level shift due to the German reunification that took place in the third quarter of 1990. As expected the productivity series shows a considerable downward shift, while employment (measured in hours) increases. In the unemployment series we observe a strong upward trend starting in 1990. There is also a level shift, which is not as obvious as in the other series. The hourly real wage series has a level shift as well. It is however comparably small, because the increase in hours of employment is partly offset by the increasing nominal wage bill.

Before we continue with the system analysis we investigate the integration properties of the four time series. Clearly, we have to account for the level shifts and do so by applying two types of unit root tests suggested by Perron (1989) and Lanne, Lütkepohl & Saikkonen (2002).

For the Perron test, the third column of Table 1 reports the deterministic terms used in an auxiliary regression. We use the residuals from that regression and apply an augmented Dickey-

Table 1: Unit Root Tests

		Perron / ADF Tests			τ Tests		
var.	lags	det.	statistic	5% crit.	det.	τ	5%
$gdp - e$	4	C, T, SD, s90q3	-2.72	-3.80 (a)	C, T, $f_t^{(3)}$	-0.69	-2.80
$\Delta(gdp - e)$	4	C, SD, i90q3	-6.41**	-2.89	C, SD, i90q3	-3.51*	-2.94
e	4	C, T, SD, s90q3	-2.29	-3.80 (a)	C, T, $f_t^{(3)}$	-1.63	-2.80
Δe	3	C, SD, i90q3	-8.79**	-2.89	C, SD, i90q3	-6.68**	-2.94
u	5	C, T, SD, DT, s90q3	-3.02	-4.04 (c)	C, T, $f_t^{(2)}$	-2.73	-2.80
Δu	4	C, T, SD, s90q3	-4.44**	-3.80 (a)	C, SD, i90q3	-4.40**	-2.94
$(w - p)$	5	C, T, SD, s90q3	-2.31	-3.80 (a)	C, T, $f_t^{(2)}$	-0.14	-2.80
$\Delta(w - p)$	4	C, SD, i90q3	-3.56**	-2.89	C, SD, i90q3	-4.11**	-2.94

Note: (a) and (c) denote model A and C from Perron (1989). Column 2 indicates the number of lagged differences determined according to the highest significant lag. * and ** denote significance at 5% and 1% respectively. ADF critical values are from MacKinnon (1991). The τ test statistic is τ_{int}^{+} for the levels and τ_{int}^{+0} for the first differences as proposed by Lanne et al. (2002). Critical values are from Table 1 in Lanne et al. (2002). $f_t^{(i)}$ are shift functions defined in Table 3 of Lanne et al. (2002)

Fuller test (ADF) with the number of lags indicated by the second column of Table 1. We choose the model A from Perron (1989) for productivity, employment and real wages, as this model allows for a level shift. For the unemployment series, the model C which allows for a break in the trend and in the constant seems to be more appropriate. For some of the first differences, we have applied the standard ADF test. In these cases, the third column reports the deterministic terms included in the Dickey-Fuller regression.

In addition, we also use unit root tests that allow a more flexible shift to the new level of the series. The basic idea of the tests proposed by Lanne et al. (2002) is to estimate the deterministic part including a shift function in a first step, adjust the series for these terms and apply a Dickey-Fuller type test to the adjusted series. In this study we use the test version τ_{int}^{+} that allows for a linear trend and a shift function when applied to the original series.[1] We choose the shift function by visual inspection of the adjusted series, such that the level shift is captured in the best possible way. For the first differences we compute τ_{int}^{+0}, which includes a constant and an impulse dummy only. Table 1 lists results of unit root tests applied to the levels as well as to the first differences of the series.[2] Results of both test types suggest that $gdp_t - e_t, e_t, u_t$, and $w_t - p_t$ are integrated of order one, i.e. I(1).

To test for the number of cointegration relations, we set up an initial VAR and include a constant and seasonal dummies as deterministic terms.[3] To account for the level shift, we also include a step dummy $s90q3_t$, which is one from the third quarter of 1990 and zero elsewhere and an impulse dummy $i90q3_t$ that is one in the third quarter of 1990 and zero elsewhere. We

[1]The τ_{int}^{+}-test performed relatively well in comparison to other test variants (see Lanne et al. (2002)).
[2]The unit root tests have been computed by Eviews 3.1 and GAUSS.
[3]PcFiml by Doornik & Hendry (1997) has been used for the cointegration analysis.

Table 2: Cointegration Tests

		Johansen Trace Test			S&L Test		
H_0:	H_1 :	$LR_{J\&N}$	95%	DisCo 95%	$LR_{S\&L}$	90%	95%
$r = 0$	$r > 0$	60.2**	47.2	55.9	42.5*	42.0	45.1
$r = 1$	$r > 1$	24.1	29.7	35.7	23.9	25.9	28.5
$r = 2$	$r > 2$	10.9	15.4	19.7	10.8	13.9	15.9

Note: * (**) denotes significance at the 10% (5%) level. Critical values in column 4 from Table 1 in Osterwald-Lenum (1992), values in column 5 have been simulated using DisCo by Johansen & Nielsen (1993). S&L test critical values are taken from Table 1 in Lütkepohl & Saikkonen (2000).

use the AIC, SC and HQ information criteria (see Lütkepohl (1991), Ch. 4) to determine the lag length of the VAR process. All three criteria suggest a lag length of $p = 5$ when the maximum lag length is $p_{max} = 8$. This lag length is also confirmed by a sequence of F-tests. The reduction of a VAR(6) to a VAR(5) cannot be rejected ($F(16, 254) = 1.64[0.059]$) on the 5% level while further reduction to a VAR(4) is clearly rejected ($F(16, 266) = 4.76[0.000]$). In addition a number of misspecification tests have been performed. A single equation LM-test indicates that there is some autocorrelation left in the unemployment equation. Moreover, a vector LM-test on the system indicates autocorrelated errors. Increasing the lag length of the VAR model does not fix the autocorrelation problem possibly indicating that a VARMA representation would be more appropriate. While uncorrelated errors would be desirable, they are not a precondition for the validity of the cointegration tests (see Lütkepohl & Saikkonen (1999)). Therefore, we continue the analysis using the VAR(5) model.

To test for cointegration means estimating the rank r of Π from the vector error correction representation (2.2). We use two cointegration tests that explicitly take the level shifts into account and present the results in Table 2. The first test has been proposed by Johansen & Nielsen (1993). In their test, the distribution of the statistic $LR_{J\&N}$ depends on the relative timing of the break. Therefore, we have simulated asymptotic critical values for the present case when a step dummy enters the system in restricted form using the program DisCo developed by Johansen & Nielsen (1993). According to the simulated critical values in Table 2 we reject the hypothesis of no cointegration on the 5% level. Moreover, the hypothesis that the cointegration rank is one cannot be rejected on conventional significance levels. Another test for processes with structural shifts has been proposed by Saikkonen & Lütkepohl (2000). The idea of this test is to estimate the deterministic part including the shift dummy by a GLS procedure, subtract it from the original series and apply a trace test to the adjusted series. In line with results of the Johansen & Nielsen test, the test statistic $LR_{S\&L}$ suggests one cointegration relation.

Since the theoretical model implies up to two cointegration relations, the results in Table 2 may be just the consequence of a lack of power problem of the cointegration tests. We therefore check, whether estimating under $r = rk(\Pi) = 2$ is a plausible alternative. Results for a model

Table 3: Restricted cointegration analysis

		$gdp-e$	e	u	$(w-p)$	$s90q3$	LR test
	β':	-0.973	-0.146	2.387	1	0.073	–
		(0.101)	(0.314)	(0.523)	–	(0.078)	
H1:	β':	-0.955	0	2.485	1	0.039	$\chi^2(1) = 0.17[0.68]$
		(0.085)	–	(0.485)	–	(0.015)	
H2:	β':	-1	0	2.733	1	0.039	$\chi^2(2) = 0.42[0.81]$
		–	–	(0.237)	–	(0.015)	
H3:	β':	-1	0	2.733	1	0.037	$\chi^2(3) = 1.31[0.73]$
		–	–	(0.238)	–	(0.015)	
	α':	0	0.086	-0.023	-0.252		
		–	(0.043)	(0.008)	(0.050)		
H4:	β':	-1	0	2.67	1	0.042	$\chi^2(4) = 5.98[0.20]$
		–	–	(0.247)	–	(0.016)	
	α':	0	0	-0.018	-0.222		
		–	–	(0.007)	(0.048)		
H5:	β':	-1	0	2.44	1	0.056	$\chi^2(5) = 11.22[0.04]^*$
		–	–	(0.248)	–	(0.016)	
	α':	0	0	0	-0.254		
		–	–	–	(0.051)		

Note: Standard errors in parentheses

with two cointegration vectors are given in Appendix B. It turns out, however, that the resulting labor demand function has implausible signs on the coefficients of output (gdp_t) and real wages ($w_t - p_t$). As a consequence, our preferred specification is a model with one cointegration relation and we continue to identify this cointegrating vector.

The theoretical model suggests that this cointegration relation is either a labor demand or a wage setting relation. We use the tools of restricted cointegration analysis to identify the cointegration vector. In the first row of Table 3 we report the estimated cointegration vector β, where we have normalized the real wage coefficient to unity. Associated standard errors are given in parentheses. The vector is likely to represent a wage setting relation given the coefficient estimate on e with a standard error more than twice as large as the estimate itself. In a next step, we test the exclusion of e from β, which cannot be rejected by a corresponding Likelihood Ratio (LR) test ($\chi^2(1) = 0.17[0.68]$). Moreover, we impose a $[1, -1]$ relation between real wages and productivity, which is not rejected either. The restricted cointegration vector β is identified as a wage setting relation according to the theoretical model:

$$w_t - p_t = (gdp - e)_t - 2.733u_t - 0.039s90q3_t \tag{4.2}$$

The estimated wage setting relation reflects that the German labor market is not competitive and outsiders influence the wage setting as the coefficient on unemployment suggests. $\widehat{\gamma} = 2.733$ is often interpreted as the long run elasticity of real wages with respect to unemployment. This interpretation can be problematic, nevertheless the estimated coefficient can be compared to results from other studies. Carstensen & Hansen (2000) find for the West German labor market a value of 1.824. In earlier studies Hansen (2000) finds a number of 1.95 for the preunification period in Germany, while Bean, Layard & Nickell (1986) find an estimate of 3.31. The values are not directly comparable, because estimates are derived from different estimation methods, variables and data sets. However, the comparison gives a rough indication that the estimate $\widehat{\gamma}$ is plausible. The identified cointegration vector is used to set up the VECMs used in the structural analysis.

To reduce the number of parameters we test additional exclusion restrictions on α and give the results in Table 3. Excluding α_1 from the model is easily accepted (see H3). Testing jointly the exclusion of α_1 and α_2 cannot be rejected either (H4). However, excluding α_1, α_2 and α_3 is rejected by the corresponding LR test at the 5% level. Together with the rejection of $H_0 : \alpha_3 = 0$ ($\chi^2(3) = 8.52[0.03]$) we take this result as evidence against excluding α_3. Therefore, we use the long-run structure implied by H4 as a starting point for the subset model specification.

The wage equation (4.2) represents an equilibrium relationship. The corresponding negative adjustment coefficient α_4 in the wage equation implies that excess real wages slow down real wage growth, as one would expect from economic theory. The estimate of α_3 suggests that excess wages drive down unemployment growth which seems implausible with standard economic theory. Note however that this effect is relatively small. Overall, the results from the cointegration analysis suggest that our model may be viewed as an adequate description of the German labor market data. Therefore, we use the reduced form estimates of the implied VECMs as a basis for the structural analysis.

5 Structural Analysis

5.1 Identification of the Labor Market VECM

In this section we derive identifying restrictions from the theoretical model and from the results of the cointegration analysis and use estimates of the identified model to compute impulse responses and variance decompositions for unemployment. We use both, the full SVECM and a subset SVECM and compare the results.

We know from Section 2 that we need $K(K-1)/2 = 4(4-1)/2 = 6$ additional linearly independent restrictions coming from economic theory to exactly identify the structural shocks. In addition, we know from the common trends literature that in a four-dimensional system with one cointegration relation, only three shocks can have permanent effects. Moreover, the cointegration analysis from the previous section indicates that wage setting is a stationary relation. Our theoretical model then implies that the wage setting shock $\varepsilon_{w,t}$ does not have permanent effects on the system variables which can be expressed by a zero column in $C(1)A_0$ as

$$C(1)A_0 = \begin{pmatrix} * & * & * & 0 \\ * & * & * & 0 \\ * & * & * & 0 \\ * & * & * & 0 \end{pmatrix}. \tag{5.1}$$

If we assume constant returns to scale ($\rho = 1$), it is easy to see from the solution of the theoretical model (3.5) that shocks to labor demand (ε_d), to labor supply (ε_s) and to wage setting (ε_w) have no permanent effects on productivity which can be written as

$$C(1)A_0 = \begin{pmatrix} * & 0 & 0 & 0 \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{pmatrix}. \tag{5.2}$$

(5.1) essentially sets up four linear equations involving all elements of $C(1)$. Because $C(1)$ has reduced rank (rk$(C(1)) = 3$), only three equations are linearly independent. Obviously, (5.2) imposes only two independent restrictions because $(C(1)A_0)_{14} = 0$ is imposed by (5.1) already. Consequently, (5.1) and (5.2) provide only 5 linearly independent restrictions. Therefore, we need one additional restriction. The theoretical model does not provide more long-run restrictions than already imposed by (5.1) and (5.2). Thus, we impose one contemporaneous restriction, although contemporaneous restrictions may be more difficult to justify than long-run restrictions. Nevertheless, we assume that the labor demand shock ε_d does not affect real wages in the initial quarter which means

$$A_{0,42} = 0. \tag{5.3}$$

(5.3) can be justified by the fact that wage contracts normally fix wages for more than one quarter. The restrictions (5.1)-(5.3) exactly identify the model which can now be estimated by ML as described in Section 2.

First, we estimate the standard VECM with identifying restrictions explained above. The short-run parameters $(\alpha, \Gamma_1, \ldots, \Gamma_{p-1})$ in this first model are unrestricted in the sense that we do not impose zero restrictions. Using the estimates $\hat{\alpha}, \hat{\Gamma}_1, \ldots, \hat{\Gamma}_{p-1}$ given in Table 6 (see Appendix C) and $\widetilde{\Sigma}_u$, we compute the contemporaneous impact matrix as

$$\hat{A}_0 = \begin{pmatrix} \underset{(0.167)}{1.036} & \underset{(0.174)}{-0.194} & \underset{(0.174)}{-0.149} & \underset{(0.193)}{0.158} \\ \underset{(0.261)}{-0.322} & \underset{(0.372)}{1.206} & \underset{(0.547)}{0.433} & \underset{(0.236)}{-0.525} \\ \underset{(0.044)}{-0.042} & \underset{(0.092)}{-0.097} & \underset{(0.061)}{0.166} & \underset{(0.041)}{0.109} \\ \underset{(0.319)}{0.471} & 0 & \underset{(0.411)}{-0.793} & \underset{(0.273)}{1.378} \end{pmatrix} \times 10^{-2}$$

and the identified long-run impact matrix as

$$\widehat{C(1)A_0} = \begin{pmatrix} \underset{(0.314)}{1.157} & 0 & 0 & 0 \\ \underset{(0.322)}{-0.376} & \underset{(0.375)}{1.118} & \underset{(0.470)}{-0.024} & 0 \\ \underset{(0.116)}{-0.180} & \underset{(0.127)}{-0.163} & \underset{(0.095)}{0.258} & 0 \\ \underset{(0.574)}{1.651} & \underset{(0.349)}{0.450} & \underset{(0.262)}{-0.710} & 0 \end{pmatrix} \times 10^{-2}. \quad (5.4)$$

In parentheses we provide standard errors for each point estimator obtained from $M = 1000$ bootstrap replications of the model. To be more precise, we denote the vector of free elements in $\hat{A}_0$ by

$$\hat{a}_0 = R_0 \text{vec}(\hat{A}_0).$$

The bootstrap covariance matrix of this vector is then given by

$$\hat{\Sigma}_{a_0} = M^{-1} \sum_{m=1}^{M} (\hat{a}_{0,m} - \hat{a}_0)(\hat{a}_{0,m} - \hat{a}_0)',$$

where $\hat{a}_{0,m}$ indicates the estimate in the m-th bootstrap replication. The standard errors are given by the square roots of the diagonal elements of $\hat{\Sigma}_{a_0}$. Standard errors for (5.4) can be computed accordingly. Using this bootstrap method should automatically account for the fact that the restriction matrix R_l^* is stochastic. This is important because neglecting the stochastic nature and applying standard formulas given in Amisano & Giannini (1997) may give quite misleading estimates for the standard errors (see Vlaar (1998)).

Only a few coefficients of these matrices are significantly different from zero, indicating substantial estimation uncertainty. The third row of the long-run impact matrix (5.4) shows the long-run response of unemployment after a technology, a labor demand, a labor supply and a wage shock. As imposed by (5.1) the long-run effect of a wage setting shock is zero. The long-run responses of unemployment to the other three shocks show the expected sign, however, the responses to technology and labor demand shocks are not significant according to a ± 2 standard error criterion.

Given that many coefficient of the reduced form VECM are not significant at standard levels (see Table 6 in Appendix C), applying some type of model reduction can be useful in the present situation. For the purpose of estimating impulse responses, results from Brüggemann, Krolzig & Lütkepohl (2002) and Brüggemann (2004) indicate that strategies using a 'liberal' model selection criterion (e.g. AIC) are better suited than more parsimonious alternatives (e.g. PcGets developed by Hendry & Krolzig (2001)). Therefore we use a single equation model reduction method that has performed well in the study of Brüggemann (2004). In this method the significance of loading coefficients α is tested within the Johansen framework, before the VECM is estimated. Then further restrictions on $\Gamma_1, \dots, \Gamma_{p-1}$ are imposed by sequentially deleting variables with t-ratios smaller than a threshold value. This critical value depends on the sample size and the reduction step and the information criterion that is used (see Brüggemann & Lütkepohl (2001) for details). Applying this method to our SVECM model based on the long-run structure H4 in Table 3 reduces the number of parameters by 32 and corresponding estimated are given in Table 7 (Appendix C). Clearly, the given t-ratios cannot be interpreted in the usual way, because they do not account for the uncertainty in the model selection process. The structural decomposition based on this subset model is obtained as:

$$\hat{A}_0 = \begin{pmatrix} \underset{(0.075)}{0.900} & \underset{(0.058)}{-0.190} & \underset{(0.065)}{-0.386} & \underset{(0.000)}{0.000} \\ \underset{(0.143)}{-0.112} & \underset{(0.128)}{0.952} & \underset{(0.198)}{0.935} & \underset{(0.000)}{0.000} \\ \underset{(0.019)}{-0.028} & \underset{(0.025)}{-0.156} & \underset{(0.026)}{0.081} & \underset{(0.008)}{0.103} \\ \underset{(0.138)}{0.311} & 0 & \underset{(0.193)}{-1.138} & \underset{(0.073)}{0.956} \end{pmatrix} \times 10^{-2}.$$

and

$$\widehat{C(1)A_0} = \begin{pmatrix} \underset{(0.153)}{1.154} & 0 & 0 & 0 \\ \underset{(0.203)}{0.097} & \underset{(0.138)}{1.102} & \underset{(0.175)}{0.411} & 0 \\ \underset{(0.075)}{-0.225} & \underset{(0.050)}{-0.283} & \underset{(0.046)}{0.190} & 0 \\ \underset{(0.277)}{1.753} & \underset{(0.132)}{0.754} & \underset{(0.121)}{-0.507} & 0 \end{pmatrix} \times 10^{-2}. \tag{5.5}$$

There is a change in sign for the estimate of $(C(1)A_0)_{23}$, the long-run effect of the labor supply shock on employment. The positive coefficient estimate from the subset model is economically more plausible and significant. In addition the point estimate of $(C(1)A_0)_{23}$ also switched signs, however, it is neither in the full nor is the subset model significant. Moreover, it is particularly interesting to compare the third row of (5.5) to the third row of (5.4). While estimates from the subset model show the same sign and typically similar magnitudes as in the full model, the estimated standard errors now indicate a significant long-run impact of ε_d and ε_s. One possible conclusion is that the subset VECM reduces uncertainty substantially. However, this conclusion seems risky as the standard errors do not account for the uncertainty of the model selection process and, hence, are likely to understate the true estimation uncertainty.

5.2 Impulse Response Analysis

To investigate the effects of structural shocks on unemployment, we compute impulse responses from the full SVECM as well as from a subset SVECM. We provide bootstrap confidence bands computed by the percentile method proposed by Hall (1992). To compute the confidence bands we fix the estimated cointegration relation in the bootstrap.[4] The left column of Figure 2 shows the responses of unemployment to a technology, a labor demand, a labor supply and a wage setting shock from the full SVECM together with 95% confidence intervals. A technology shock drives unemployment down. From the upper left panel we see that this negative effect is only borderline significant in the long-run. Adjustment to new equilibrium takes about eight years. A labor demand shock leads to a significant drop in unemployment and adjustment takes roughly six years. According to the bootstrap confidence bands, the effect is significant even in the long-run. The labor supply shock has a significant positive impact on unemployment and adjustment takes about 7 years. In the short-run, unemployment rises after a positive shock to wages which is in line with standard theory. However, compared to the other shocks in the system, the response is fairly small. Moreover, the wage shock has a zero long-run effect on unemployment as imposed by (5.1).

It is interesting to note that the confidence bands for responses to labor demand and labor supply shocks are somewhat asymmetric which indicates an asymmetric bootstrap distribution. In such cases interpreting impulse responses with confidence bands based on asymptotic theory would be risky because $\pm$ two standard error bands are necessarily symmetric and may draw a very misleading picture of the true dynamic interaction in the model. The asymmetry of the confidence bands may also explain why the long-run effect of a labor demand shock appears significant from the bootstrap exercise but is not significant based on the standard errors in (5.4).

The right column of Figure 2 plots the responses of unemployment from the subset SVECM. For the subset VECM we provide two different intervals. The first interval (dashed line) is based on keeping the subset restrictions fixed as given in Table 7. The second interval (dotted line) is constructed by choosing new restrictions in each bootstrap replication. The construction of the second interval is similar to the 'endogenous bootstrap' suggested by Kilian (1998) for the choice of the VAR order and is used to account for the model selection uncertainty inherent in the specification of the subset model.

The comparison in Figure 2 reveals that the shape of point estimates are basically unchanged, although we have restricted 32 coefficients to zero. The subset model estimates a slightly larger effect of the labor demand and slightly smaller effect of the labor supply shock but differences are small enough to be neglected. Thus, the subset VECM captures the same dynamics as the full model indicating that the restrictions are sensible. Moreover, the confidence intervals in the subset specification are smaller than those in the full SVECM, even if model selection uncertainty is accounted for. Similar to the results from the full SVECM we find a negative significant long-run response of unemployment to shocks in labor demand and a positive response to labor supply shocks. In contrast to the full SVECM we now also find a significant, negative long-run impact of the technology shock on unemployment.

[4]Benkwitz, Lütkepohl & Wolters (2001) find only minor differences between intervals computed with a fixed and a reestimated β.

To sum up, results from both model types, full and subset, indicate that technology and labor supply shocks are important for the determination of unemployment. In addition, we find that labor demand shocks are also important. This contrasts the result from Carstensen & Hansen (2000) for West Germany. They find that labor demand shocks are neither in the short-run nor in the long-run an important source of unemployment. The impulse response analysis indicates that adjustment is rather sluggish and takes up to 8 years. Though computed from a different model, Carstensen & Hansen (2000) obtain a substantially faster adjustment which takes only up to 4 years. A comparison to results from Jacobson et al. (1997) who find 1-2 years for Norway and Schweden, and 4 years for Denmark, shows that adjustment in Germany is considerably slower than in Scandinavian countries.

Clearly, the identifying assumptions are important in this type of empirical analysis. For instance, the response of unemployment to wage setting shocks has been governed by imposing the long-run zero restriction that wage shocks have no permanent effect on unemployment. But this restriction has been derived by using the economic model and has also been compatible with results from the cointegration analysis.

5.3 Forecast Error Variance Decomposition

To assess the importance of different shocks we compute the forecast error variance decomposition (see e.g. Hamilton (1994, Section 11.5) for details) for unemployment from the full and the subset SVECM and present the results in graphical form. Panel (a) in Figure 3 shows the variance decomposition for unemployment, i.e. the proportion of forecast error variance in unemployment, h periods ahead accounted for by the structural shocks $\varepsilon_{gdp}, \varepsilon_d, \varepsilon_s$ and ε_w. One finding is that labor demand, labor supply and wage setting shocks are important for the short-run determination of unemployment. Note, however, that for very short forecasting horizons the impact of technology and labor demand shocks is relatively small. With increasing horizon h the technology shock becomes more, while shocks to wage setting become less important. In the long-run (after 80 quarters) technology ($\approx$ 30%), labor demand ($\approx$ 20%) and labor supply shocks ($\approx$ 45%) are all important determinants of unemployment. Again, this contrasts with results from Carstensen & Hansen (2000) for West Germany. In their study labor demand is a stationary relationship and hence, they impose a zero long-run effect of labor demand shocks.

Panel (b) of Figure 3 shows the variance decomposition obtained from the subset model. We find that the labor demand shock ε_d now accounts for 45% of the variance in unemployment in the long-run, hence, is more important than in the VECM(5) model. At the same time, the importance of the labor supply shock accounts for only about 17% of the variance, i.e. is less important as in the VECM(5) model. Although there are some differences, it not clear whether these differences are significant. Nevertheless, the main conclusion is robust across different model specifications: Unemployment is determined by a mixture of technology, labor demand and labor supply shocks in the long-run.

5.4 Historical Decomposition of Forecast Errors

From (2.4) it is obvious that the reduced form forecast errors can be expressed as linear combinations of structural shocks. Therefore, an alternative way of assessing the importance of different shocks over time is to evaluate the portion of the forecast error attributable to each of the structural shocks (see e.g. King et al. (1991)). In other words, the forecast errors are decomposed into different structural components. In the SVAR literature this type of analysis is sometimes called historical decomposition. Clearly, in comparison with the FEVD the advantage of the historical decomposition is its ability to reveal the relative importance of shocks in different periods of the sample. In contrast to the FEVD, however, this technique only provides insights on a specific forecasting horizon.

We give the historical decomposition of unemployment based on our SVECM in the left column of Figure 4, where the unemployment forecast errors at a one year horizon, $h = 4$, (dotted line) are plotted together with the respective portion attributable to each of the structural shocks (solid lines). The plots illustrate the explanatory power of labor supply shocks (ε_s) at the one year horizon over the entire sampling period. In contrast the role played by technology shocks (ε_{gdp}) is negligible at this horizon. In addition, labor demand (ε_d) and wage setting shocks (ε_w) seem to be typically less important than the supply shocks although they played some role in the period after the first oil shock. It is also interesting to note that shocks to wage setting have some explanatory power for the time after German reunification.

The right column of Figure 4 shows the decomposition based on the subset SVECM. The role indicated for technology and wage shocks is virtually unchanged by using the subset restrictions. However, using the subset model indicates a more important role of the labor demand shock. Especially for the period before German reunification the forecast errors in unemployment are governed by labor demand shocks (at the four year horizon). In comparison with results from the full SVECM the labor supply shocks are now less important. Note that these results are in line with FEVD results obtained earlier for $h = 4$.

6 Conclusion

In this paper we have analyzed German labor market data to investigate the main sources of persistently high unemployment. For this purpose we have used the framework of structural vector error correction models. A cointegration analysis has shown that hourly real wages, productivity and unemployment are cointegrated and form a sensible wage setting relation. Based on the corresponding VECM we have identified structural shocks and analyzed their effects and importance for German unemployment by impulse response analysis, forecast error variance and historical decompositions. In addition to the SVECM we have also analyzed a subset SVECM with restrictions on the reduced form parameters.

We have found from the structural analysis that technology, labor demand and labor supply shocks are all important determinants for unemployment in the long-run. For shorter horizons, however, the historical decomposition revealed that wage shocks have played some role in the period after the first oil price shock and after German reunification. In contrast, technology shocks are not particularly important in the short-run.

Results from the impulse response analysis indicate rather sluggish adjustment to a new labor market equilibrium which takes up to eight years supporting the conventional wisdom that the German labor market is rather sluggish. Using a subset SVECM changes some of the results: The confidence intervals obtained from the subset model have typically been smaller than those from the full VECM even when model selection uncertainty has been accounted for. Thus, by using the subset model a clear significant negative long-run effect of technology shocks on unemployment can be observed. Moreover, the subset model has indicated that labor demand shocks have been more important for unemployment than suggested by the full SVECM.

Overall, the empirical analysis does not suggest that unemployment in Germany is mostly driven by one single factor. Instead, the results indicate that a number of demand and supply factors are important and therefore a mixture of demand and supply side management policies can be regarded as a promising strategy to reduce unemployment.

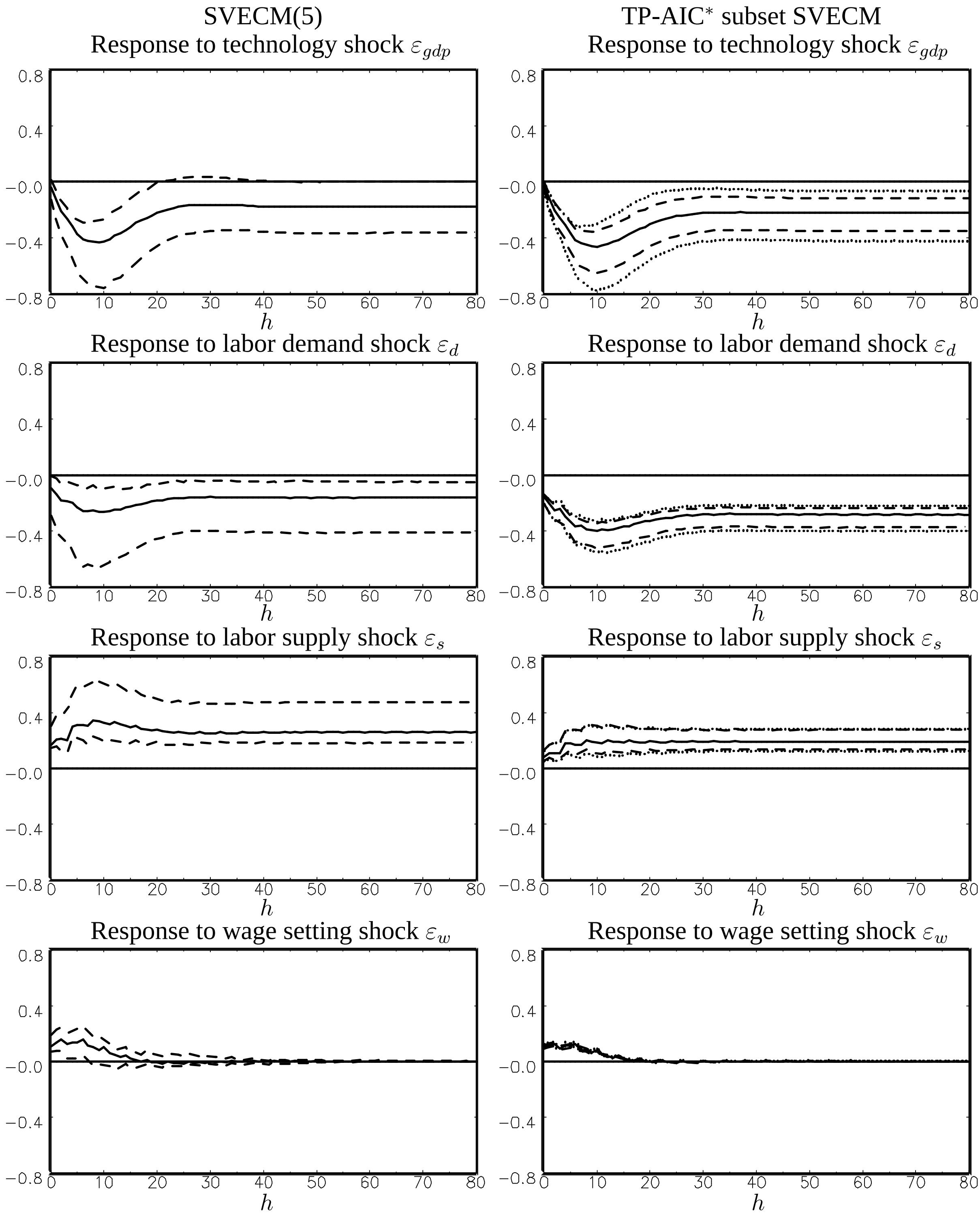

Figure 2: Responses of unemployment in SVECM(5) and subset VECM.

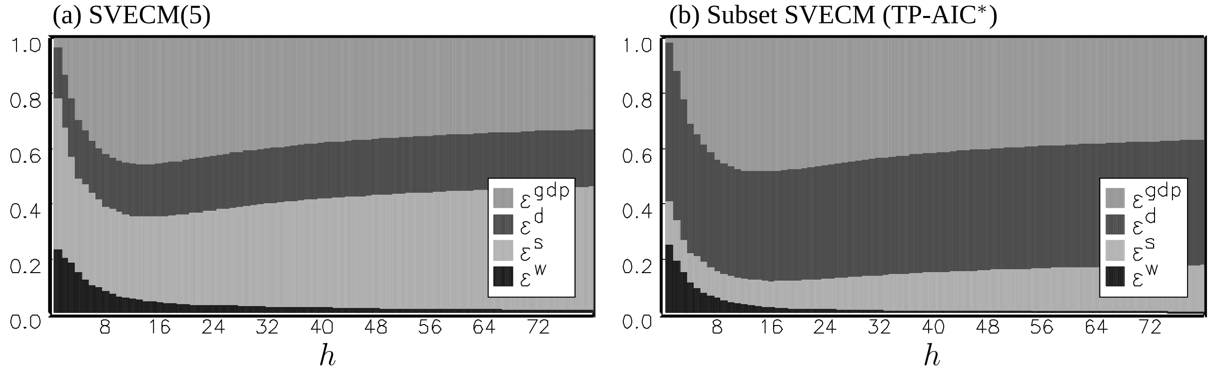

Figure 3: Variance decompositions of unemployment in full SVECM and subset SVECM.

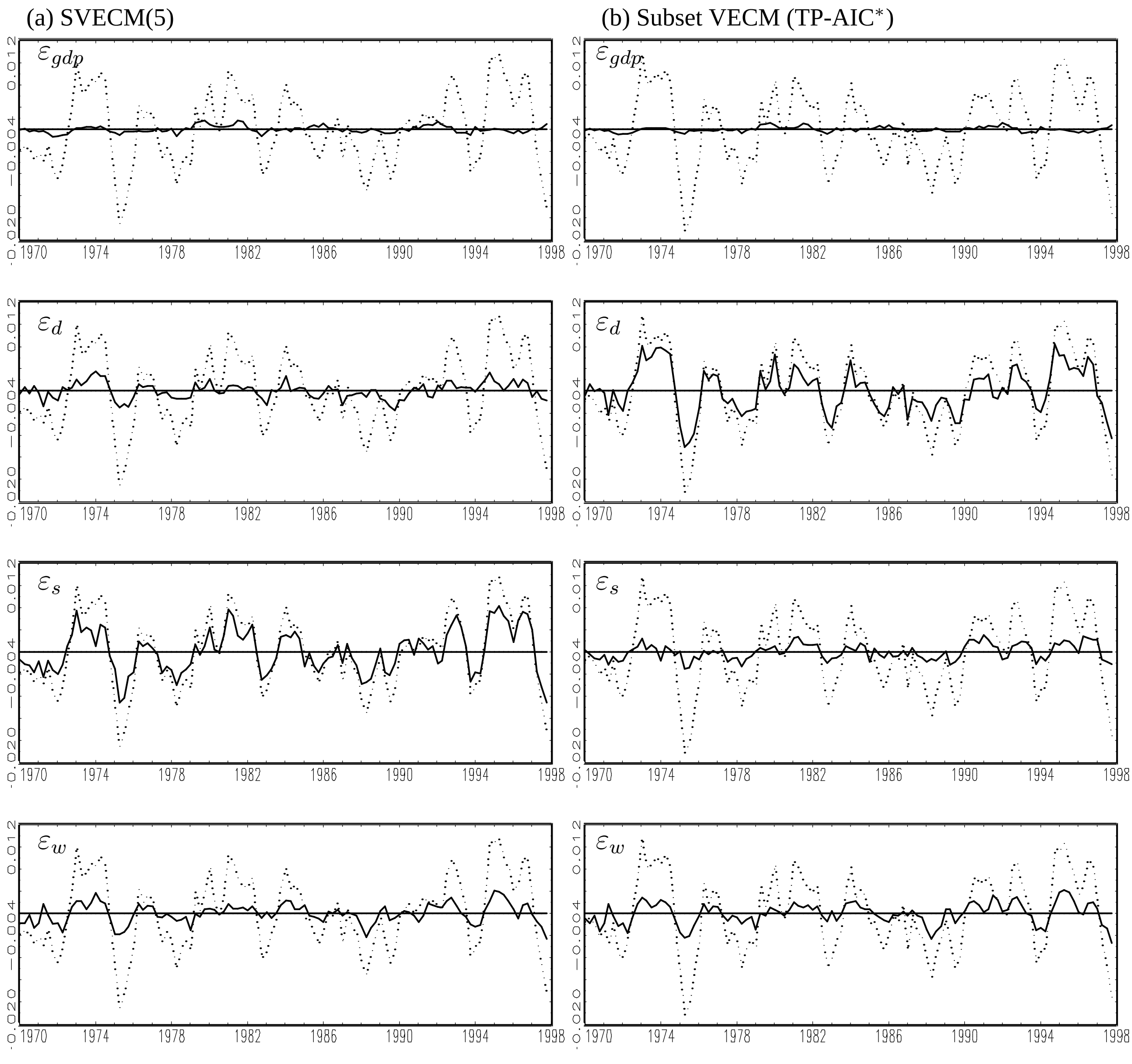

Figure 4: Historical decompositions of unemployment in full SVECM and subset SVECM.

References

Amisano, G. & Giannini, C. (1997). *Topics in Structural VAR Econometrics*, 2nd edn, Springer–Verlag.

Bean, C., Layard, P. R. G. & Nickell, S. J. (1986). The rise in unemployment: A multicountry study, *Economica* **53**: 1–22.

Benkwitz, A., Lütkepohl, H. & Wolters, J. (2001). Comparison of bootstrap confidence intervals for impulse responses of German monetary systems, *Macroeconomic Dynamics* **5**: 81–100.

Breitung, J. (2000). *Structural Inference in Cointegrated Vector Autoregressive Models*, Habilitationsschrift, Humboldt-Universität zu Berlin.

Brüggemann, R. (2004). *Model Reduction Methods for Vector Autoregressive Processes*, Vol. 536 of *Lecture Notes in Economics and Mathematical Systems*, forthcoming: Berlin: Springer-Verlag.

Brüggemann, R., Krolzig, H.-M. & Lütkepohl, H. (2002). Comparison of model specification methods, *Discussion Paper 80*, Sonderforschungsbereich 373, Humboldt-Universität zu Berlin.

Brüggemann, R. & Lütkepohl, H. (2001). Lag selection in Subset VAR models with an application to a U.S. monetary system, *in* R. Friedmann, L. Knüppel & H. Lütkepohl (eds), *Econometric Studies - A Festschrift in Honour of Joachim Frohn*, LIT: Münster, pp. 107–128.

Carstensen, K. & Hansen, G. (2000). Cointegration and common trends on the West German labour market, *Empirical Economics* **25**: 475–493.

Christiano, L. J., Eichenbaum, M. & Evans, C. (1999). Monetary shocks: What have we learned and to what end?, *in* J. Taylor & M. Woodford (eds), *The Handbook of Macroeconomics*, Amsterdam: Elsevier Science Publication.

Dolado, J. J. & Jimeno, J. F. (1997). The causes of Spanish unemployment: A structural VAR approach, *European Economic Review* **41**: 1281–1307.

Doornik, J. A. & Hendry, D. F. (1997). *Modelling Dynamic Systems Using PcFiml 9 for Windows*, Timberlake Consulting, London.

Fabiani, S., Locarno, A., Onetto, G. & Sestito, P. (2000). The sources of unemployment fluctuations: An empirical application to the Italian case, *Working Paper No. 29*, European Central Bank.

Galí, J. (1999). Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations?, *American Economic Review* **89**(1): 249–271.

Hall, P. (1992). *The Bootstrap and Edgeworth Expansion*, New York: Springer.

Hamilton, J. D. (1994). *Time Series Analysis*, University Press Princeton, New Jersey.

Hansen, G. (2000). The German labour market and the unification shock, *Economic Modelling* **17**(3): 439–454.

Hansen, H. & Warne, A. (2001). The cause of Danish unemployment: Demand or supply shocks?, *Empirical Economics* **26**: 461–486.

Hendry, D. F. & Krolzig, H.-M. (2001). *Automatic Econometric Model Selection with PcGets*, Timberlake Consultants Press, London.

Jacobson, T., Vredin, A. & Warne, A. (1997). Common trends and hysteresis in Scandinavian unemployment, *European Economic Review* **41**: 1781–1816.

Johansen, S. (1995). *Likelihood-Based Inference in Cointegrated Vector Autogressive Models*, Oxford University Press.

Johansen, S. & Nielsen, B. (1993). Manual for the simulation program DisCo, Institute of Mathematical Statistics, University of Copenhagen.

Kilian, L. (1998). Accounting for lag order uncertainty in autoregressions: The endogenous lag order bootstrap algorithm, *Journal of Time Series Analysis* **19**(5): 531–548.

King, R. G., Plosser, C. I., Stock, J. H. & Watson, M. (1991). Stochastic trends and economic fluctuations, *American Economic Review* **81**(4): 819–840.

Lanne, M., Lütkepohl, H. & Saikkonen, P. (2002). Comparison of unit root tests for time series with level shifts, *Journal of Time Series Analysis* **23**(6): 667–685.

Lütkepohl, H. (1991). *Introduction to Multiple Time Series Analysis*, Berlin: Springer-Verlag.

Lütkepohl, H. (2001). Vector autoregressions, *in* B. Baltagi (ed.), *Companion to Theoretical Econometrics*, Blackwell, Oxford, pp. 678–699.

Lütkepohl, H. & Saikkonen, P. (1999). Order selection in testing for the cointegrating rank of a VAR process, *in* R. F. Engle & H. White (eds), *Cointegration, Causality, and Forecasting - A Festschrift in Honour of Clive W. J. Granger*, Oxford University Press, pp. 168–199.

Lütkepohl, H. & Saikkonen, P. (2000). Testing for the cointegrating rank of a VAR process with a time trend, *Journal of Econometrics* **95**: 177–198.

MacKinnon, J. (1991). Critical values for co-integration tests, *in* R. Engle & C. Granger (eds), *Long-Run Economic Relationships*, Oxford University Press, pp. 276–276.

Mosconi, R. (1998). *Malcom: The Theory and Practice of Cointegration Analysis in RATS*, Milano: Cafoscarina.

Osterwald-Lenum, M. (1992). A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics, *Oxford Bulletin of Economics and Statistics* **54**: 461–472.

Perron, P. (1989). The great crash, the oil price shock, and unit root hypothesis, *Econometrica* **57**(6): 1361–1401.

Rotemberg, J. & Woodford, M. (1992). Oligopolistic pricing and the effects of aggregate demand on economic activity, *Journal of Political Economy* **100**(6): 1153–1207.

Saikkonen, P. & Lütkepohl, H. (2000). Testing for the cointegrating rank of a VAR process with structural shifts, *Journal of Business and Economic Statistics* **18**(4): 451–464.

Sims, C. A. (1980). Macroeconomics and reality, *Econometrica* **48**: 1–48.

Vlaar, P. (1998). On the asymptotic distribution of impulse response functions with long run restrictions, *DNB Staff reports 22*, De Nederlandsche Bank.

A Data Sources

All series in this paper are quarterly data and have been constructed from the Deutsches Institut für Wirtschaftsforschung (DIW) database. The data refer to West Germany until 1990:2 and the unified Germany afterwards. West German (unified German) series have a WH (GH) prefix in the DIW database codes, which are omitted from the following list.

1. gdp: Real gross domestic product GDP, DIW code: 12011. gdp is log(GDP).
2. p: GDP price deflator (1991 = 100), DIW code: 12011X. p is log(GDP price deflator).
3. e: Employment in hours in, DIW code: 1101. e is log(Employment in hours).
4. u: The unemployment series is constructed dividing the number of unemployed by the sum of people in employment and unemployment. DIW code: u = 1110/(1110 + 1102).
5. w: We use the net nominal wage bill (DIW code: 2005) and divide by the hours in employment (DIW code 1101) to compute the nominal hourly wages. w is log(2005/1101).

From these series we construct

$$y_t = [(gdp - e)_t, e_t, u_t, (w - p)_t]'$$

that is used in the analysis.

B Two Cointegrating Vectors

In this section we allow for the possibility of two cointegrating vectors, to check whether this is a plausible alternative to the model used in the text. For this purpose we assume that $r = 2$ and present results from the restricted cointegration analysis in Table 4. First, we impose just identifying restrictions by excluding e_t from the first and u_t from the second cointegration vector and normalizing on $(w_t - p_t)$. The coefficients of the wage setting relation closely resemble those from the text when we restrict the coefficient on productivity to be -1. If we rewrite the second cointegration vector β_2 in form of the labor demand function (3.2) we get

$$e_t = -1.118 gdp_t + 1.199(w_t - p_t) + .555 s90q3_t,$$

which has implausible signs on gdp_t and $(w_t - p_t)$. We therefore regard a model with one cointegrating vector as the preferred specification. Nevertheless, we compute identified impulse responses and the FEVD of unemployment under the assumption $r = 2$. Of course, we have to adjust our identification scheme from the text accordingly. With $r = 2$ only $k = K - r$ shocks have permanent effects. Moreover, to identify the two permanent shocks we need $k(k-1)/2 =$

1 additional restriction and again assume constant returns to scale. These two restriction sets can be written as:

$$C(1)\bar{A}_0^{-1} = \begin{pmatrix} * & 0 & 0 & 0 \\ * & 0 & * & 0 \\ * & 0 & * & 0 \\ * & 0 & * & 0 \end{pmatrix}. \tag{B.1}$$

To identify the two transitory shocks we imposes $r(r-1)/2 = 1$ restriction on the contemporaneous impact matrix. In particular, we choose the same restriction as in the Section 5:

$$(\bar{A}_0^{-1})_{42} = 0. \tag{B.2}$$

Note that this restriction was needed in Section 5 to identify the permanent shocks. Here, however, it identifies the transitory shocks. The impulse responses are depicted in Figure 5. Compared to the preferred model, the responses of unemployment to a productivity, a labor supply, and a wage shock are virtually unchanged. As imposed the labor demand shock has now a zero long run impact on unemployment. Unemployment responds positively to a positive shock in labor demand in the short run, which is somewhat puzzling and might be due to the implausible signs of the identified labor demand relation. The result from the FEVD in Table 5 basically reflects the imposed restrictions: Labor demand and wage setting shocks are not an important source of unemployment in the long run.

Table 4: Restricted Cointegration Analysis, $r = 2$

	$gdp - e$	e	u	$(w - p)$	$s90q3$	LR-test
β_1'	-0.978	0	2.608	1	0.038	–
	(0.082)	–	(0.431)	–	(0.015)	
β_2'	-0.921	-1.726	0	1	0.453	
	(0.184)	(0.575)	–	–	(0.141)	
H1:						
β_1'	-1	0	2.730	1	0.038	
	–	–	(0.237)	–	(0.015)	
β_2'	-0.932	-1.766	0	1	0.463	
	(0.183)	(0.585)	–	–	0.143	
						$\chi^2(1) = 0.04[0.84]$

Note: Standard error in parentheses

Table 5: Variance decomposition of unemployment, $r = 2$

	Full VECM			
h	ε_{gdp}	ε_d	ε_s	ε_w
1	0.043	0.107	0.697	0.152
2	0.136	0.135	0.611	0.118
3	0.232	0.132	0.531	0.105
4	0.306	0.127	0.485	0.082
5	0.321	0.135	0.482	0.061
6	0.347	0.128	0.475	0.049
7	0.374	0.119	0.462	0.045
8	0.398	0.108	0.456	0.038
10	0.416	0.090	0.465	0.029
30	0.376	0.041	0.570	0.013
50	0.337	0.029	0.625	0.009
70	0.316	0.022	0.655	0.007
80	0.308	0.020	0.666	0.006

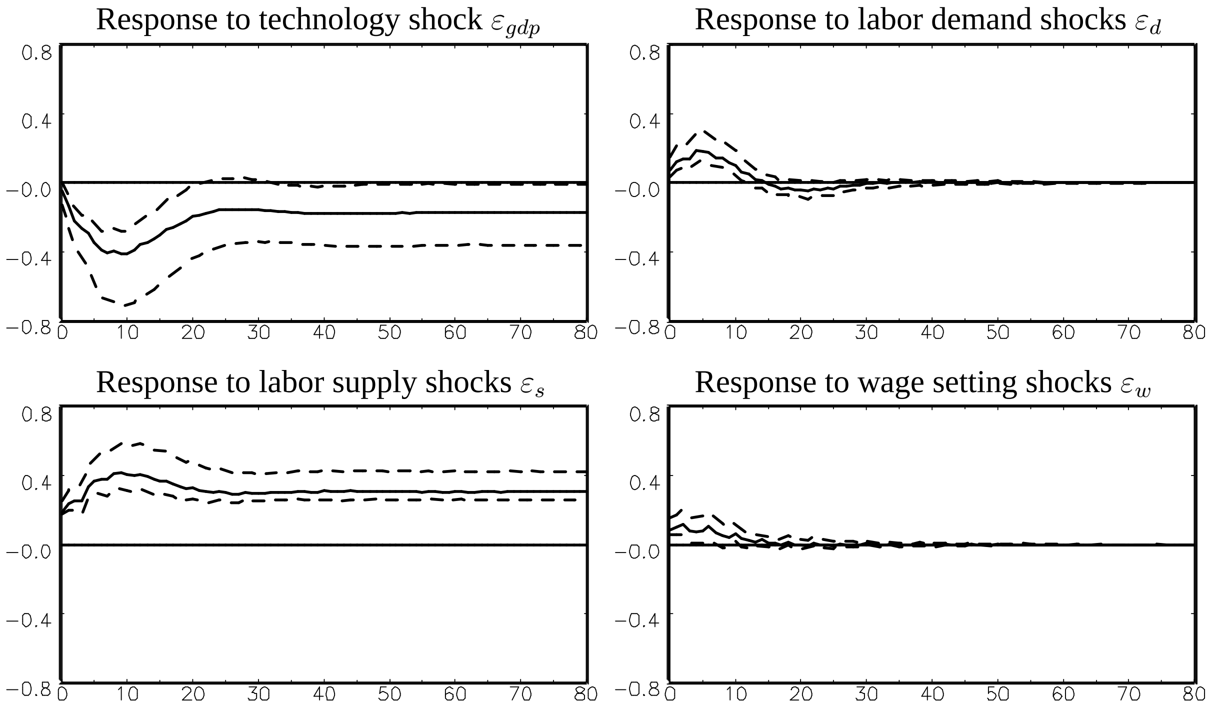

Figure 5: Responses of unemployment in full SVECM, $r = 2$.

C VECM Estimates

Estimated coefficients of the full VECM and the subset VECM for the model with one cointegration vector are listed in Table 6 and Table 7.

Table 6: OLS estimates of Full VECM

	$\Delta(gdp-e)_t$	Δe_t	Δu_t	$\Delta(w-p)_t$
ec_{t-1}	-0.031 (-0.855)	0.104 (2.150)	-0.022 (-2.819)	-0.273 (-4.837)
$\Delta(gdp-e)_{t-1}$	-0.124 (-1.095)	-0.102 (-0.680)	-0.111 (-4.716)	-0.252 (-1.445)
$\Delta(gdp-e)_{t-2}$	-0.054 (-0.450)	-0.163 (-1.035)	-0.103 (-4.119)	0.109 (0.592)
$\Delta(gdp-e)_{t-3}$	-0.115 (-0.986)	0.131 (0.846)	-0.079 (-3.241)	-0.002 (-0.008)
$\Delta(gdp-e)_{t-4}$	0.370 (3.367)	0.125 (0.861)	-0.065 (-2.826)	-0.095 (-0.562)
Δe_{t-1}	0.157 (2.096)	-0.397 (-4.019)	-0.031 (-1.970)	0.006 (0.050)
Δe_{t-2}	-0.064 (-0.814)	0.014 (0.139)	-0.036 (-2.212)	-0.136 (-1.123)
Δe_{t-3}	-0.106 (-1.410)	0.147 (1.486)	-0.021 (-1.343)	-0.266 (-2.301)
Δe_{t-4}	0.185 (2.547)	0.191 (1.986)	0.019 (1.224)	0.071 (0.633)
Δu_{t-1}	0.979 (2.341)	-1.835 (-3.319)	0.299 (3.426)	0.791 (1.227)
Δu_{t-2}	-0.513 (-1.168)	0.295 (0.509)	0.102 (1.117)	0.556 (0.822)
Δu_{t-3}	-0.270 (-0.648)	0.425 (0.773)	-0.107 (-1.228)	-1.347 (-2.100)
Δu_{t-4}	0.499 (1.196)	-0.294 (-0.533)	0.537 (6.166)	0.260 (0.404)
$\Delta(w-p)_{t-1}$	0.017 (0.267)	0.012 (0.147)	0.022 (1.649)	-0.308 (-3.163)
$\Delta(w-p)_{t-2}$	-0.123 (-1.965)	0.361 (4.354)	0.027 (2.040)	-0.702 (-7.264)
$\Delta(w-p)_{t-3}$	-0.020 (-0.292)	0.129 (1.404)	0.007 (0.485)	-0.465 (-4.329)
$\Delta(w-p)_{t-4}$	0.014 (0.196)	0.129 (1.370)	0.017 (1.119)	0.159 (1.450)

Note: t-ratios in parentheses

Table 7: EGLS estimates of TP-AIC* subset VECM

	$\Delta(gdp-e)_t$	Δe_t	Δu_t	$\Delta(w-p)_t$
ec_{t-1}			-0.025 (-4.294)	-0.230 (-6.069)
$\Delta(gdp-e)_{t-1}$		-0.274 (-2.973)	-0.122 (-6.450)	-0.197 (-2.398)
$\Delta(gdp-e)_{t-2}$		-0.174 (-2.809)	-0.114 (-5.737)	
$\Delta(gdp-e)_{t-3}$			-0.079 (-3.998)	
$\Delta(gdp-e)_{t-4}$	0.503 (8.175)		-0.075 (-6.382)	
Δe_{t-1}	0.205 (6.663)	-0.448 (-7.521)	-0.040 (-3.122)	
Δe_{t-2}			-0.042 (-3.051)	-0.172 (-2.949)
Δe_{t-3}			-0.024 (-2.026)	-0.175 (-3.190)
Δe_{t-4}	0.242 (5.380)	0.080 (1.856)		0.155 (2.573)
Δu_{t-1}	0.766 (2.891)	-1.226 (-3.548)	0.266 (3.774)	
Δu_{t-2}			0.141 (2.078)	0.980 (2.109)
Δu_{t-3}			-0.115 (-1.572)	-0.890 (-1.943)
Δu_{t-4}			0.520 (7.338)	
$\Delta(w-p)_{t-1}$			0.016 (2.003)	-0.291 (-4.810)
$\Delta(w-p)_{t-2}$	-0.113 (-4.005)	0.277 (7.032)	0.019 (2.530)	-0.657 (-9.140)
$\Delta(w-p)_{t-3}$				-0.358 (-4.950)
$\Delta(w-p)_{t-4}$				0.222 (2.945)

Note: t-ratios in parentheses. Estimates for deterministic terms (constant, seasonal dummies, $i90q3$) are not listed.