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A Cross-Country Study on Okun's Law

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A Cross-Country Study on Okun's Law

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Abstract

Okun's Law postulates an inverse relationship between movements of the unemployment rate and the real gross domestic product (GDP). In this article we investigate Okun's law for 15 OECD countries and check for its the structural stability. By using data on employment and the labor force we infer whether structural instability is caused either from the demand side or the supply side.

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1 Introduction

Okun's law postulates a negative relationship between movements of the unemployment rate and the real gross domestic product (GDP). This empirical relationship is a major part of every traditional macro-model as the aggregate supply curve is derived by combining Okun's law with the Phillips curve. Moreover, this relationship has also important implications for macroeconomic policy. It is simply very interesting to know the growth rate necessary to reduce unemployment (if this is even possible). Furthermore, the effectiveness of disinflation policy depends on the responsiveness of unemployment on the output growth rate (*sacrifice ratio*). In this article we investigate Okun's law for 15 OECD countries. We check whether there are significant differences in this relationship among the 15 countries and look for possible causes of these differences. In a second step we examine the stability of Okuns's law. This second question is important as well, since an analysis of stability provides us with an indirect check whether external shocks result in an unstable unemployment-GDP relationship. Moreover, by investigating labor supply and labor demand we are able to assign whether changes in the Okun relationship are either labor supply or labor demand based.

First let us relate this paper to recent work on Okun's law: Even in economic textbooks e.g. Blanchard (1999)[pp.170] the stability of the Okun coefficient is supposed to have decreased over time. The author claims that we are currently confronted with stronger effects on unemployment by GDP variations. The reasons for this are stronger international competition, less legal protections of the employed and generally less turn over costs leading firms to reduce labor hoarding. In Moosa (1997) the Okun coefficients for 7 OECD countries are estimated while the stability is checked by means of "rolling" OLS and Chow break point tests. For Germany and France he infers a significant decline of the Okun coefficient. Weber (1995) estimated Okun's law of the US economy and checks whether the unemployment-GDP relationship has changed in 1973, with the result that no indication for a structural break in 1973 can be supported by the data. Furthermore the author provides a brief overview on former estimates of Okun's law.

In this paper we use Bayesian methods to check for discrete changes in the Okun relationship (*structural breaks*) and *Kalman filtering* to check for "continuous" changes. Furthermore we use labor force and employment data to investigate whether cross-country differences and changes in Okun's law are based on the demand or supply side effects. Since the labor force is the sum of employment and the number of unemployed within an economy, changes in the unemployment–output relationship could either be caused by changes in employment or by shifts in the labor force. In a final step, we relate our estimation results to *labor hoarding* policy and to the persistence in the unemployment rate (*hysteresis effect*) by using the OECD employment protection index and the first order autocorrelations in the unemployment rates. We regress both on our estimates of the employment coefficients.

This article is organized as follows: In section 2 a brief motivation on the relationship between GDP and unemployment is provided. While Okun (1962) motivated this relationship in an empirical analysis, we briefly discuss Okun's law from a neoclassical and a Keynesian perspective. Section 3 discusses the empirical implementation and motivates the statistical models to be estimated. In section 4 we present a brief description of the estimation techniques used in our work, while section 5 provides the estimation results.

2 Theoretical Foundations

It was Okun (1962) who focused the discussion on the empirical relationship between unemployment and GDP variations. Although a stable empirical relationship may be important for policy modeling, macroeconomic theory provides us with relatively few models linking the unemployment rate to GDP growth. From an old fashioned *Keynesian* perspective the explanation of Okun's law is very simple. Due to changes in aggregate demand firms alter their output plans. This leads to changes in labor demand and therefore affects the unemployment rate. The drawback of this explanation is that implicitly fixed prices and wages are assumed. By the introduction of nominal and real rigidities New Keynesian Economics tries to overcome this drawback. E.g. let us consider a model of monopolistic competition like in Blachard and Kiyotaki (1987). If we introduce menu costs (*nominal rigidity*) on the market for goods and a *real rigidity* on the labor market (e.g. efficiency wages) it is easy to show that changes in aggregate demand will affect output and employment and therefore unemployment. An interesting aspect of such a model is that productivity shocks can lead to an Okun relationship as well, since output and employment move in the same direction as long as the effects of productivity shocks on efficiency-wages are not too strong.

From a purely *neoclassical* point of view with a permanently cleared labor market only structural and frictional unemployment can exist. A foundation of Okun's law is therefore much harder. I.e. economic theory has to explain why structural or frictional unemployment declines in upswings and increases in downswings. One usual measure of structural problems is the standard deviation of sectural employment growth rates (*Lilien Index* - see Lilien (1982)). In an upswing this standard deviation has to decline in order to justify Okun's law. However there is no obvious argument why this should always be the case. Investigating frictional unemployment – especially search unemployment – one can argue that in an upswing people searching for a new job still have low wage aspirations and are therefore more willing to take a particular job. This results in shorter search times in upswings with lower unemployment. It is clear that this argument crucially depends on the formation of the agents' expectations.

In recent times there have been also some attempts to point out a relationship between unemployment and output growth within the framework of endogenous growth models. Although such a relationship is meant to be a long run one and is therefore not in the spirit of Okun's original contribution these attempts are nonetheless interesting. Aghion and Howitt (1994) analyze the effects on long run unemployment in a search model. Within their work they derive two competing effects such as that (i) higher growth due to higher technical progress leads to more structural problems (e.g. automation, depletion of skills, bankruptcies) resulting in a higher job-turnover. (ii) On the other hand growth reduces the duration of a job match (higher exit rate), caused by an increase in labor demand. In Schaik and Groot (1998) the effect of different degrees of competition on the unemployment GDP relationship is investigated. Zagler (1999) considers a monopolistically competitive economy with efficiency wages. A fall in the internal efficiency of firms gives rise to higher efficiency wages, which causes a decrease in employment within the research and development sector. This results in less economic growth and a negative correlation between growth and unemployment.

3 Empirical Implementation

The standard specification for estimating Okun's law is

$$\Delta u_t = a_0 + a_1 \Delta y_t + v_t \tag{1}$$

where Δu_t is the yearly change in the unemployment rate, Δy_t is the yearly change in the $\log GDP_t$ and v_t is an error term. Since there are significant time lags involved, especially in the reaction of labor demand, the following specification should be preferred (see also Weber (1995)):

$$\begin{aligned} \Delta u_t &= a_0 + a_1 \Delta y_t + a_2 \Delta y_{t-1} + v_t \\ &= a_0 + a_1 \Delta^2 y_t + (a_1 + a_2) \Delta y_{t-1} + v_t \ . \end{aligned} \tag{2}$$

This allows for a *delayed* reaction of unemployment (employment) on output changes. The coefficient a_1 refers to the *impact effect* on output growth and the coefficient $a_1 + a_2$ to the *total effect*. This distributed lag specification also reduces the *simultaneous equation bias* for the total effect, as long as Δy_t is positively autocorrelated. In this case the bias in the estimator $\hat{a}_1$ is reduced by an opposite bias in $\hat{a}_2$.
Within this article the structural stability of Okun's law will be related to structural changes in labor demand and supply. Note that

$$\begin{aligned} u_t &\approx n_t - l_t \ \Rightarrow \\ \Delta u_t &\approx \Delta n_t - \Delta l_t \ , \end{aligned} \tag{3}$$

with unemployment rate u_t, the logarithm of the labor force n_t and the log of employment l_t. Changes in unemployment are therefore due to changes in the labor force (*labor supply*) and changes in employment (*labor demand*). Suppose that the changes in n_t and l_t depend on changes in real GDP. To investigate these relationships the following specifications are used:

$$\begin{aligned} \Delta n_t &= \alpha_0 + \alpha_1 \Delta y_t + \alpha_2 \Delta y_{t-1} + v_{n,t} \\ &= \alpha_0 + \alpha_1 \Delta^2 y_t + (\alpha_1 + \alpha_2) \Delta y_{t-1} + v_{n,t} \end{aligned} \tag{4}$$

$$\begin{aligned} \Delta l_t &= \beta_0 + \beta_1 \Delta y_t + \beta_2 \Delta y_{t-1} + v_{l,t} \\ &= \beta_0 + \beta_1 \Delta^2 y_t + (\beta_1 + \beta_2) \Delta y_{t-1} + v_{l,t} \ . \end{aligned} \tag{5}$$

Using (3) the reader can easily verify that the coefficients a_1 and a_2 in (2) are approximately equal to $\alpha_1 - \beta_1$ and $\alpha_2 - \beta_2$ respectively. So, the coefficients in Okun's law depend on the parameters in labor demand and supply relationships.
The dependence of labor supply on GDP growth in (4) can be motivated by the arguments that (i) an increase in output growth generally leads to higher wages and therefore higher labor supply and (ii) in some countries migration effects can play a major role – i.e. more output growth results in higher immigration and higher labor supply. Thus, the coefficients

α_1 and α_2 in the labor supply equation (4) primarily depend on the wage setting behavior and migration effects.
To investigate the effects of output growth on employment (labor demand) as stated with (5) we consider a standard production function:

$$y_t = F(\gamma_t + k_t, \varepsilon_t + l_t) \tag{6}$$

where l_t refers to log employment, ε_t to log labor utilization, k_t to log capital and γ_t to log capital utilization. By differentiating (6) with respect to time we derive:

$$\dot{y}_t = \varphi(\dot{\gamma}_t + \dot{k}_t) + \psi(\dot{\varepsilon}_t + \dot{l}_t) \tag{7}$$

with $\varphi = \frac{\partial F}{\partial(\gamma_t + k_t)}$ and $\psi = \frac{\partial F}{\partial(\varepsilon_t + l_t)}$ equal to the elasticities of output on capital and employment respectively. Solving (7) for employment growth results in:

$$\dot{l}_t = -\left(\frac{\varphi}{\psi}\dot{\gamma}_t + \dot{\varepsilon}\right) + \frac{\dot{y}_t}{\psi} - \frac{\varphi \dot{k}_t}{\psi} \ . \tag{8}$$

Now suppose that capital growth in some fixed proportion ϱ to output growth, i.e.

$$\dot{k}_t = \varrho \dot{y}_t \ . \tag{9}$$

According to neoclassical growth theory ϱ should be equal to 1 in the long run growth equilibrium, while in the short run ϱ varies with relative factor prices. Furthermore assume that changes in labor and capital utilization vary with GDP, yielding:

$$\dot{\gamma} = \bar{\gamma} + \lambda_k \dot{y}_t \tag{10}$$

$$\dot{\varepsilon} = \bar{\varepsilon} + \lambda_l \dot{y}_t \ . \tag{11}$$

Inserting (7), (10) and (11) into (8) we finally get the employment-GDP relationship

$$\dot{l}_t = -\left(\frac{\varphi}{\psi}\dot{\gamma}_t + \dot{\varepsilon}\right) + \frac{1 - \varphi\lambda_k - \psi\lambda_l - \varrho\varphi}{\psi}\dot{y}_t \ . \tag{12}$$

Remark 1 *Note that equation (12) is not a ceteris paribus relation between l_t and y_t since the co-movements in the capital stock and the utilizations are taken into account. The parameters ϱ, λ_k and λ_l describe the strength of these co-movements.*

From (12) we conclude that the reaction of employment to output growth depends on the parameters φ, ψ, ϱ, λ_k and λ_l. Therefore, country specific differences may be due to different production functions (not very likely for developed OECD countries) or differences in ϱ, which in turn is linked to wage policies. Furthermore different reactions of productivity, especially labor productivity, on output growth can play a major role. For instance, if firms try to smooth employment over the business cycle (*labor hoarding*) the parameter λ_l would be high. Then the term $(1 - \varphi\lambda_k - \psi\lambda_l - \varrho\varphi)/\psi$ in (12) becomes small. Our employment equation (5) is a dynamic specification of (12), where we allow for a delayed reaction as already discussed above.

Summing up, we conclude from this section that the coefficients in Okun's law (2) depend on the labor supply and demand relationships (4) and (5) respectively. These relationships in turn are likely to depend on wage policies, migration effects and policies and labor hoarding. So institutional factors like union density and power, turnover costs, legal employment protections or redundancy payments can play a major role in explaining country specific differences in Okun's law or in explaining changes over time.

4 Time Variing Parameter Models

Within this section we provide a brief overview of the methods to estimate a model of the type:

$$x_t = \beta_t' z_t + \varepsilon_t \tag{13}$$

where x_t is the response and $z_t \in \mathrm{R}^d$ is the vector of prediction variables. $\beta_t \in \mathrm{R}^d$ is the d-dimensional vector of regression parameters, where some components of β_t should be allowed to vary with time t. The noise term is given by ε_t with a variance of σ_t^2. In subsection 4.1 we describe how the model parameters (β_t, σ_t^2) are estimated if they are assumed to change continuously with time while subsection 4.2 gives a brief overview to derive (β_t, σ_t^2) if the parameters are allowed to switch between a finite number of states (*structural breaks*). The reader who is already familiar with these tools or only interested in the results could skip to the next section.

4.1 Kalman Filter Analysis

Our starting point is the relationship (13): The parameter vector β_t evolves as a random walk

$$\beta_t = \beta_{t-1} + \epsilon_t \ , \tag{14}$$

where ϵ_t is a vector valued error term; the $(d \times d)$ covariance matrix is given by $\Sigma_{\epsilon\epsilon}$. The difference of this model to the ordinary least squares approach is that the parameter vector β_t now depends on time. If all the variances of ϵ_t are zero, the model is identical to an OLS model. Note that the covariance matrix $\Sigma_{\epsilon\epsilon}$ is assumed to be diagonal for identification purposes (for further information the reader is referred to Harvey (1989)). To estimate such a model we first maximize the likelihood function, which is derived from the *error prediction decomposition*, with respect to $\sigma^2_{\epsilon_t}$ and to $\sigma^2_{\varepsilon_t}$. Having estimated these variances, the time path of β_t can be obtained by the Kalman filter and smoothing algorithms. Compared to the rolling OLS method applied in Moosa (1997) this approach provides an efficient use of the whole information contained in the data. For a more detailed description of these estimation techniques and its statistical properties see Harvey (1989) and Stiassny (1993).

4.2 Bayesian Analysis

This subsection provides a brief description into Bayesian estimation of the parameters if (β_t, σ_t^2) is allowed to switch between a finite number of states (*switching regression model*).

Since the posterior cannot be derived analytically for the underlying switching regression model Markov-chain Monte Carlo (MCMC) methods are applied. The goal of these methods is to construct an ergodic Markov chain by means of sampling from known conditional distributions, resulting in the desired posterior distribution of the model parameters. Further information on MCMC methods is provided in Greene (1997), Casella and George (1992) and Albert and Chib (1993). For switching models the reader is referred to Hamilton (1989), Chib and Greenberg (1996), or Frühwirth-Schnatter (1998).
First of all, let us consider a Bayesian statistical model with the conditional density $f(X^N|\theta)$, with the data $X^N = (x^N, z^N)$ where $x^N = (x_t)_{t=1}^N$ is the response data and $z^N = (z_t')_{t=1}^N$ is the prediction data, the unknown vector of parameters θ, and the prior distribution of parameters, represented by the density $\pi(\theta)$. The a-postiori density is $\pi(\theta|X^N)$.
To investigate structural breaks, we augment the set of parameter by a latent switching variable I_t following a homogenous Markov process in discrete time. The transition probabilities $\eta_{11}, \ldots, \eta_{kk}$ are summarized in the matrix of transition probabilities η. Each row η_i of this matrix provides us with the probabilities η_{il} that the process switches from $[I_{t-1} = i]$ to state $[I_t = l]$, $l = 1, \ldots, k$.. Each η_i takes values on a k-dimensional simplex $\mathcal{E}$. Since we only observe data X^N the corresponding sequence of switching variables is defined by $I^N := (I_t)_{t=1}^N$. This results in the *augmented vector of parameters* $\Psi = (\theta, I^N)$, where θ consists of common parameters β_i, σ_i^2, $i = 1, \ldots, k$ and the matrix of the Markov transition probabilities η.
Prior distribution: We assume the following prior structure: (i) Independence of the state specific parameters and the switching probabilities, (ii) I^N is Markov; $\pi(i_0)$ is the starting distribution, where we assign equal starting probabilities to every state. (iii) $\pi(\beta, \sigma^2)$ and $\pi(\eta)$ are invariant to permutations in the indices. As usual with switching regression model, we assume that $\pi(\eta_i)$ is Dirichlet $\mathcal{D}(e_{0,i1}, ..., e_{0,ik})$, $\pi(\sigma_i^2)$ is inverse gamma $\mathcal{IG}(\nu_0, D_0)$ and $\pi(\beta_i|\sigma_i^2)$ is Gaussian $\mathcal{N}(b_0, B_0\sigma_i^2)$.
Sampling from the posterior: Due to the hierarchical structure of the Bayesian switching regression model (13) samples from the posterior of Ψ can be derived by successive sampling from the conditional distributions of the parameters (MCMC). The whole sampling process is a recursive procedure which converges due to geometric ergodicity of this Markov chain (see Robert (1994)). Let us denote the samples of sampling period j by the superscript $[j]$. We sample (i) $I^{N,[j]}$ from $\pi(i^N|X^N, \theta^{[j-1]})$, (ii) $\eta^{[j]}$ from $\pi(\eta|X^N, I^{N,[j]}, (\sigma_i^2)^{[j-1]}, \beta_i^{[j-1]})$, (iii) $\sigma_i^{2\ [j]}$ from $\pi(\sigma_i^2|I^{N,[j]}, X^N, \eta^{[j]}, \beta_i^{[j-1]})$ and (iv) $\beta_i^{[j]}$ from $\pi(\beta_i|I^{N,[j]}, X^N, \eta^{[j]}, (\sigma_i^2)^{[j-1]})$. For the underlying regression model (13) we use conjugate priors as described in Robert (1994). This implies: (i) $\pi(i^N|X^N, \theta^{[j-1]})$ is derived by applying the methods proposed in Chib and Greenberg (1996). (ii) $\pi(\eta|X^N, I^{N,[j]}, (\sigma_i^2)^{[j-1]}, \beta_i^{[j-1]})$ is Dirichlet $\mathcal{D}(e_{0,i1}+N_{i1}^{[j]}, ..., e_{0,ik}+N_{ik}^{[j]})$, where $N_{il}^{[j]} := \#(I_t = l|I_{t-1} = i)$ is the number of jumps from $[I_{t-1} = i]$ to $[I_t = l]$ in $I^{N,[j]}$. (iii) $\pi(\sigma_i^2|I^{N,[j]}, X^N, \eta^{[j]}, \beta_i^{[j-1]})$ is inverse gamma with parameters ν_i and D_i. For the jth sampling period these parameters are derived as follows: $\nu_i^{[j]} := \nu_0 + 0.5N_i^{[j]}$ and $D_i^{[j]} := D_0 + 0.5 \sum_{t=1}^N S_{t,i}^{N,[j]}(x_t - \beta_i^{'\ [j-1]} z_t)^2$, where $N_i^{[j]} := \#(I_t = i)$ is the frequency the chain has hit state i. $S^{N,[j]}$ is a $(N \times k)$ matrix. The w-th element, $w = 1, \ldots, k.$, of the t-th row of $S_N^{[j]}$, $t = 1, \ldots, N.$, is equal to 1 if $[I_t = w]$ and zero if $[I_t \neq w]$. $S_i^{N,[j]}$ is the i-th column of $S^{N,[j]}$ sampled at step j, while $S_t^{N,[j]}$ is the t-th row of this matrix. $S_{t,i}^{N,[j]}$ is the i-th element of $S_t^{N,[j]}$. (iv) For the regression parameters $\beta_i^{[j]}$, $\pi(\beta_i|I^{N,[j]}, X^N, \eta^{[j]}, (\sigma_i^2)^{[j-1]})$ has normal law

$\mathcal{N}(\kappa_i^{[j]}((Z_i')^{[j]}x^N + B_0^{-1}b_0), \kappa_i^{[j]}(\sigma_i^2)^{[j]})$, where $Z_i^{[j]} = S_i^{N,[j]}z^N$ and $\kappa_i^{[j]} =: ((Z_i')^{[j]}Z_i^{[j]} + B_0^{-1})^{-1}$. Since the unrestricted model is not identifiable we impose a restriction $\mathcal{R}$ on θ. In this article we follow Frühwirth-Schnatter (1998) (*permutation sampling*) to get the model identifiable; the restriction is put on the intercept $\beta_{0,i}^{[j]}$. This implies that state 1 is the state with the lowest intercept $\beta_{0,1}^{[j]}$, etc.

Model selection and parameter estimation: To get samples from the posterior only samples of Ψ after a burn-in phases of 2000 time steps are used. Parameter estimates $\hat{\theta}$ are obtained by taking the expectation of θ. This is the mean value of the samples from the posterior. The number of states k will be estimated by taking the model with the highest model likelihood $L_k(X^N)$. In our analysis $L_k(X^N)$ is derived by means of the so called *candidate's formula* as described in Chib (1995); an estimate of the natural logarithm of the model likelihood is derived by calculating $\log \hat{L}_k(X^N) = \log \hat{f}(X^N|\theta^*) + \log \hat{\pi}(\theta^*) - \log \hat{\pi}(\theta^*|X^N)$, where $\hat{f}(X^N|\theta^*)$ is the estimated marginal likelihood after I^N has been integrated out, $\hat{\pi}(\theta^*)$ is the estimated a-priori density at parameter values θ^* selected from MCMC output, and $\hat{\pi}(\theta^*|X^N)$ is the estimated posterior density from MCMC output; $\hat{\theta}$ is used for θ^*.

5 Results

5.1 OLS Estimates

In a first step we present the OLS estimates (corrected for autocorrelations - Cochrane-Orcutt method) for 15 OECD countries. The estimation period was 1960 - 1999 (for Germany we used 1960 - 1989) and the data were taken from the OECD economic outlook database; estimates are denoted by the superscript ˆ. [1]

Table 1 presents the estimates for Okun's law. The second column shows the estimates of the intercept, the third one the impact effects of GPD growth and the forth one the total effect of GPD growth (*Okun coefficient*). The fifth column presents the results of a Chow break point test, where the null-hypothesis of a structural break between 1982 and 1983 was tested against the alternative of no break point at this period of time. Break points at significance levels of 10%, 5% and 1% are abbreviated by $*$, $**$ and $***$. These Chow-tests are a first indication whether these relationships have been stable over time. Table 1 is ordered by the coefficient $(a_1 + a_2)$. This *Okun coefficient* varies between -0.12 and -0.82. In Japan and Austria we found the lowest reaction of unemployment on GDP growth and in the Netherlands the strongest reaction. As the Chow tests indicate, there are several countries where this relationship seems to have changed over time.

Table 2 displays the effects of output variations on the labor force. We observe strong country specific differences; but the ordering of the countries is different. The countries with the weakest effects of output growth on labor force changes are the Netherlands and GBR. We find a relatively high elasticity of the labor force on output – among others – in Austria, Germany, the USA, the Switzerland and Sweden. For some of this countries migration effects are very likely. Table 3 presents the employment equations. Also here we observe extraordinary differences among these OECD countries. The weakest effects of

[1] For OLS the EViews 3.1 package was used. For MCMC we used MATLAB 5.2 while the Kalman filter analysis was carried out by TVP (see Stiassny (1993)).

Table 1: Okun's Law: $\Delta u_t = a_0 + a_1 \Delta^2 GDP_t + (a_1 + a_2)\Delta GDP_{t-1} + v_t$, $v_t = \rho v_{t-1} + \varepsilon_t$.

Country	$\hat{a}_0$	$\hat{a}_1$	$\hat{a}1 + \hat{a}_2$	Break 82
JPN	0.006	-0.05	-0.12	**
AUT	0.006	-0.10	-0.15	
CHE	0.004	-0.08	-0.16	
ITA	0.009	-0.09	-0.21	
NOR	0.011	-0.16	-0.31	**
SWE	0.008	-0.28	-0.35	***
DEU	0.013	-0.29	-0.38	**
FRA	0.014	-0.30	-0.43	***
DNK	0.013	-0.31	-0.47	**
USA	0.016	-0.41	-0.52	**
BEL	0.013	-0.33	-0.57	
GBR	0.015	-0.31	-0.58	*
CAN	0.021	-0.48	-0.60	*
FIN	0.022	-0.35	-0.61	***
NDL	0.019	-0.42	-0.82	**

output variations on employment we found again in Japan and Austria, the strongest effects in the USA and Canada. Note, that the values of the forth column in Table 1 are roughly the difference of the corresponding values of Tables 2 and 3, since $a_1 + a_2 \approx \beta_1 + \beta_2 - \alpha_1 - \alpha_2$. For instance for Austria we get an Okun coefficient of -0.15 which is roughly $0.28 - 0.45$.

Table 2: Labor Force vs. GDP: $\Delta n_t = \alpha_0 + \alpha_1 \Delta^2 GDP_t + (\alpha_1 + \alpha_2)\Delta GDP_{t-1} + v_{n,t}$, $v_{n,t} = \rho_n v_{n,t-1} + \varepsilon_{n,t}$.

Country	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_1 + \hat{\alpha}_2$	Break 82
NDL	0.010	-0.001	-0.01	
GBR	0.002	0.04	0.01	
BEL	0.003	0.09	0.12	*
JPN	0.011	0.03	0.17	
DNK	0.005	0.12	0.19	*
ITA	0.001	0.20	0.23	
FIN	-0.000	0.17	0.26	**
AUT	0.002	0.13	0.28	
FRA	0.005	0.24	0.28	*
CAN	0.013	0.24	0.32	***
DEU	-0.002	0.20	0.36	
USA	0.010	0.16	0.37	***
NOR	0.000	0.17	0.43	
CHE	-0.003	0.27	0.45	**
SWE	-0.004	0.20	0.48	***

Table 3: Employment vs. GDP: $\Delta l_t = \beta_0 + \beta_1 \Delta^2 GDP_t + (\beta_1 + \beta_2)\Delta GDP_{t-1} + v_{l,t}$, $v_{l,t} = \rho_l v_{l,t-1} + \varepsilon_{l,t}$.

Country	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_1 + \hat{\beta}_2$	Break 82
JPN	0.006	0.07	0.25	**
AUT	-0.005	0.24	0.45	
ITA	-0.010	0.31	0.49	
CHE	-0.005	0.31	0.54	**
NOR	-0.011	0.35	0.74	
BEL	-0.012	0.35	0.52	***
GBR	-0.015	0.37	0.65	
NDL	-0.009	0.44	0.84	
DNK	-0.008	0.45	0.69	
GER	-0.015	0.49	0.76	
SWE	-0.013	0.50	0.83	***
FRA	-0.007	0.52	0.63	**
FIN	-0.024	0.54	0.94	**
USA	-0.009	0.61	0.96	
CAN	-0.011	0.73	0.97	*

5.2 Structural Breaks

By means of MCMC we check for structural breaks for models (2), (4) and (5). The prior distribution of the parameters is the following: $e_{0,il} = 1$ for all i, i.e. $\eta_i = \mathcal{D}(1, ..., 1)$. For the priors of the state specific parameters we use the ordinary least squares estimator and the corresponding variance of the residuals s_y^2 in the following way: b_0 is equal to the OLS estimate, $B_0 = diag(1, 1, 1)$, $\nu_0 = 2$, $D_0 = s_y^2$; $diag(.)$ stands for diagonal matrix. Thus, we use relatively vague priors on the switching probabilities η and informative priors on the state specific parameters β and σ^2. Since we claim an inversely related interdependence in the data, we use this additional information in our sampler.

Remark 2 *It is worth noting that altering the state specific prior assumptions to diffuse priors, i.e.* $b_0 = (0\ 0\ 0)'$ *and* $D_0 = 1$*, does not alter the inference of the number of states* k*.*

Model Selection: As already stated in section 4 model selection is performed by means of the model likelihood $L_k(X^N)$. We derived estimates $\hat{L}_k(X^N)$ and its standard deviation for models with $k = 1, \ldots, 4$. The estimates of the model likelihood for models with one and two states are presented in Table 4. From these estimates we conclude that *regime switching* – i.e. discrete changes – in Okun's law cannot be inferred from the underlying data. The parameter estimates for the models with *one* state correspond to the OLS estimates.

Remark 3 *By comparing Tables 1-3 to Table 4 we observe no structural breaks. Although we observe switching behavior in the latent process* (I_t) *between 1982 and 1983 for countries with a significant Chow statistic (Tables 1-3), this was not sufficient to increase* $\log \hat{f}(X^N|\theta)$ *to compensate for the decrease in* $\log \hat{\pi}(\theta^*) - \log \hat{\pi}(\theta^*|X^N)$ *due to the higher number of parameters (which acts like a penalty term in the model likelihood for larger models) such that the model likelihood* $\log \hat{L}_k(X^N)$ *is the highest with* $k = 1$*. The difference between this Bayesian analysis and ordinary Chow tests arises from the fact that the Chow break point test presupposes one break point while this Bayesian approach allows for switching between different states such that many break points are possible. Therefore MCMC requires more parameters to be estimated. A second explanation for differences between this Bayesian and the Chow analysis is that the Chow break point test is leads to a false inference on break points if continuous changes are in the data.*

Table 4: Estimates of the Model Likelihoods $\hat{L}_k(X^N)$ (standard deviations in parantheses).

Country	Okun's Law		Labor Force		Employment	
	$k=1$	$k=2$	$k=1$	$k=2$	$k=1$	$k=2$
AUT	-49.5985	-52.8958	-49.7518	-53.4936	-50.1679	-54.3211
	(0.0311)	(0.1244)	(0.0373)	(0.1277)	(0.0370)	(0.1402)
BEL	-43.0740	-46.0901	-54.5247	-57.0036	-42.8955	-46.3442
	(0.0388)	(0.1415)	(0.0353)	(0.1343)	(0.0385)	(0.1473)
CAN	-54.0064	-57.0898	-54.3763	-56.5213	-53.8854	-57.6945
	(0.0340)	(0.1055)	(0.0269)	(0.2073)	(0.0370)	(0.1088)
CHE	-55.6405	-58.9019	-54.5003	-56.8974	-54.3916	-57.6123
	(0.0328)	(0.1286)	(0.0367)	(0.1173)	(0.0276)	(0.1505)
DEU	-54.1963	-56.8936	-54.4440	-57.0460	-54.5012	-57.8263
	(0.0333)	(0.1199)	(0.0287)	(0.1441)	(0.0312)	(0.1420)
DNK	-54.2352	-57.1394	-54.3273	-57.3810	-55.1860	-59.4026
	(0.0323)	(0.1439)	(0.0331)	(0.1459)	(0.0324)	(0.1289)
FRA	-51.5482	-54.7653	-51.0840	-53.5579	-51.4580	-53.9223
	(0.0325)	(0.1418)	(0.0351)	(0.1335)	(0.0344)	(0.1428)
GBR	-54.2968	-57.5310	-54.5903	-56.8884	-55.8826	-60.1629
	(0.0297)	(0.1317)	(0.0318)	(0.1429)	(0.0284)	(0.1683)
ITA	-54.1602	-58.1199	-54.0953	-57.5546	-54.7358	-58.5375
	(0.0346)	(0.1004)	(0.0392)	(0.0976)	(0.0323)	(0.1103)
JPN	-49.8030	-53.5570	-50.6759	-52.6954	-50.3769	-53.7199
	(0.0346)	(0.1354)	(0.0332)	(0.1190)	(0.0349)	(0.1536)
NDL	-44.4784	-47.0104	-44.1023	-47.3185	-45.5407	-49.1416
	(0.0388)	(0.1686)	(0.0404)	(0.1329)	(0.0449)	(0.1555)
SWE	-54.1693	-57.1559	-54.1728	-56.8290	-54.1188	-56.9449
	(0.0280)	(0.1380)	(0.0334)	(0.1286)	(0.0340)	(0.1138)
USA	-54.4068	-56.8510	-54.2857	-56.5913	-54.1737	-57.0545
	(0.0353)	(0.1505)	(0.0341)	(0.1169)	(0.0286)	(0.1703)
FIN	-54.6250	-56.8426	-54.2201	-56.8950	-54.5755	-57.9913
	(0.0318)	(0.1775)	(0.0257)	(0.1676)	(0.0280)	(0.1759)
NOR	-54.1706	-57.0998	-54.3262	-57.5524	-54.3550	-57.7974
	(0.0303)	(0.1317)	(0.0335)	(0.1511)	(0.0343)	(0.1322)

5.3 Continuous Parameter Changes

This subsection presents the Kalman filter estimates of the models (2), (4) and (5) for each country. Figures 1-4 present the estimated time paths for the parameters a_1+a_2, $\alpha_1+\alpha_2$ and $\beta_1+\beta_2$, along with their 90% confidence intervals.[2] Within these figures the first columns represent the effect of Δy_{t-1} on Δu_t (*Okun coefficient*), the second columns refer to the effect of Δy_{t-1} on Δl_t (*employment coefficient*) and the third ones describe the effect of Δy_{t-1} on Δn_t (*labor force coefficient*). By considering Figures 1-4 only for Italy all parameters exhibit a stable relationship over time (i.e. the estimates are identical to the OLS estimates). For all other countries we estimated more or less significant changes in the parameter values. Thus, let us draw our attention to the following interesting cases: For the US economy the Okun coefficient is stable over time at a high level. There are some variations in the coefficients $\alpha_1+\alpha_2$ and $\beta_1+\beta_2$. However these variations cancel each other such that there is no net effect on the Okun coefficient. For the French economy we expect a change in Okun's law simply by a visual inspection of a scatter-plot of Δu_t on Δy_t. Our estimates confirm this visual inspection. There has been a significant decline in the Okun's coefficient in France from -0.3 to -0.6. This decline is only partially due to a stronger reaction of employment to output variations. There has also been a significant reduction of the elasticity of the labor force on GDP variations (maybe due to more restrictive immigration policy or changes in wage setting behavior). For Denmark we found a significant decrease in the Okun coefficient but no variation in the labor force and the employment coefficients. A possible interpretation of this result is that changes in labor demand and supply are too weak to be detected by the statistical procedure, while the combined effect on the Okun coefficient is strong enough to be detected. Another interesting case is Finland. Here we also have a significant decline in the Okun coefficient. But this decline is mainly due to a stronger reaction of employment to GDP variations.
To summarize, for most countries we have found a decrease of the Okun coefficient over time as many economist would expect. However, there are some countries were the stronger effects of GDP variations on employment are partly offset by an increase of the labor force elasticity (for instance in Austria, Japan, Norway and Sweden). This results in only moderate declines in the Okun coefficients. However, in Germany, Switzerland and France the decrease in the Okun coefficient seems to be reinforced by a *decrease* in the labor force elasticity.

[2]To save space only these estimates are presented. The estimates for the other parameters are available from the authors on request.

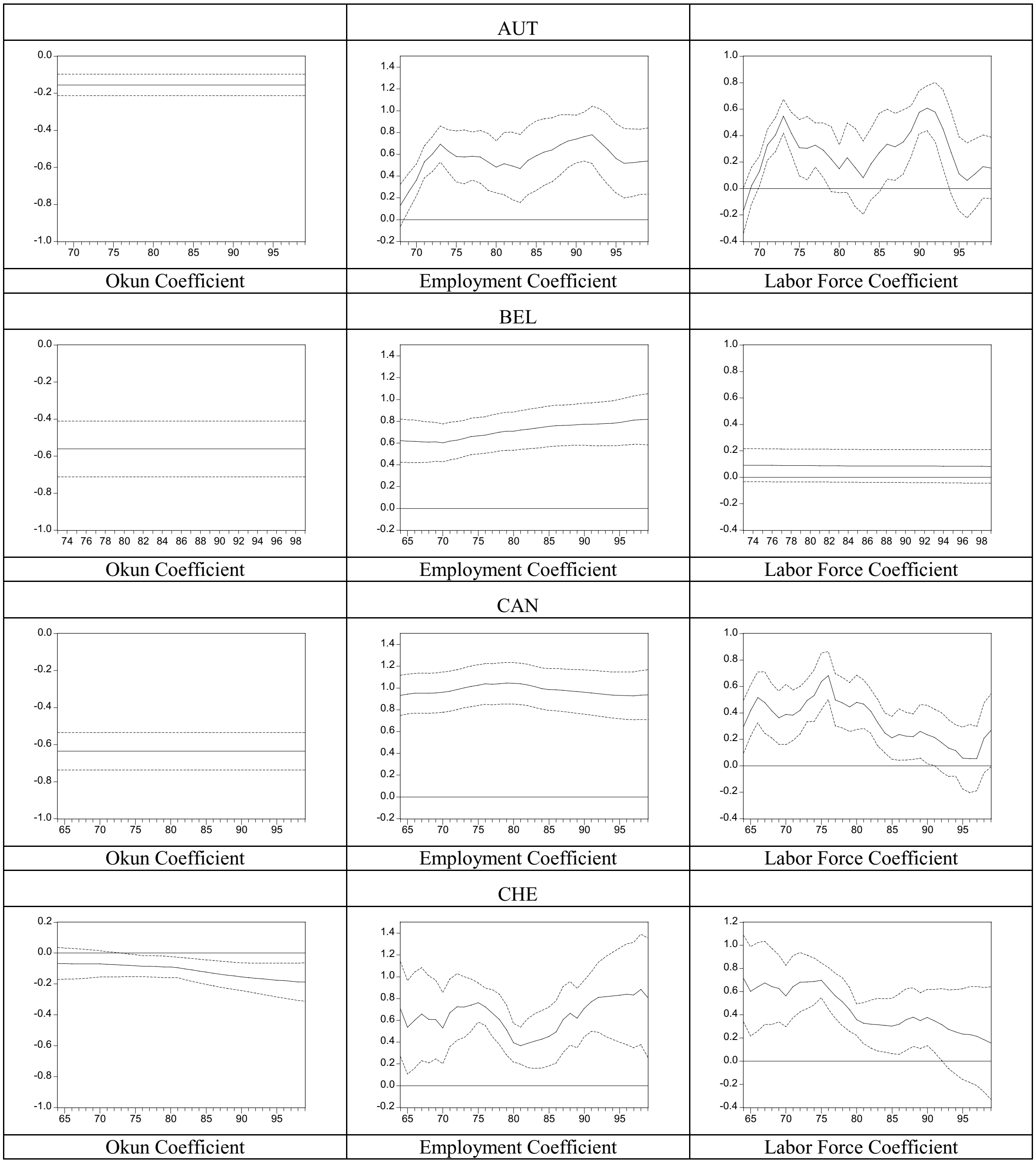

Figure 1: Kalman Filter estimates of the parameters $a_1 + a_2$, $\alpha_1 + \alpha_2$ and $\beta_1 + \beta_2$ (I).

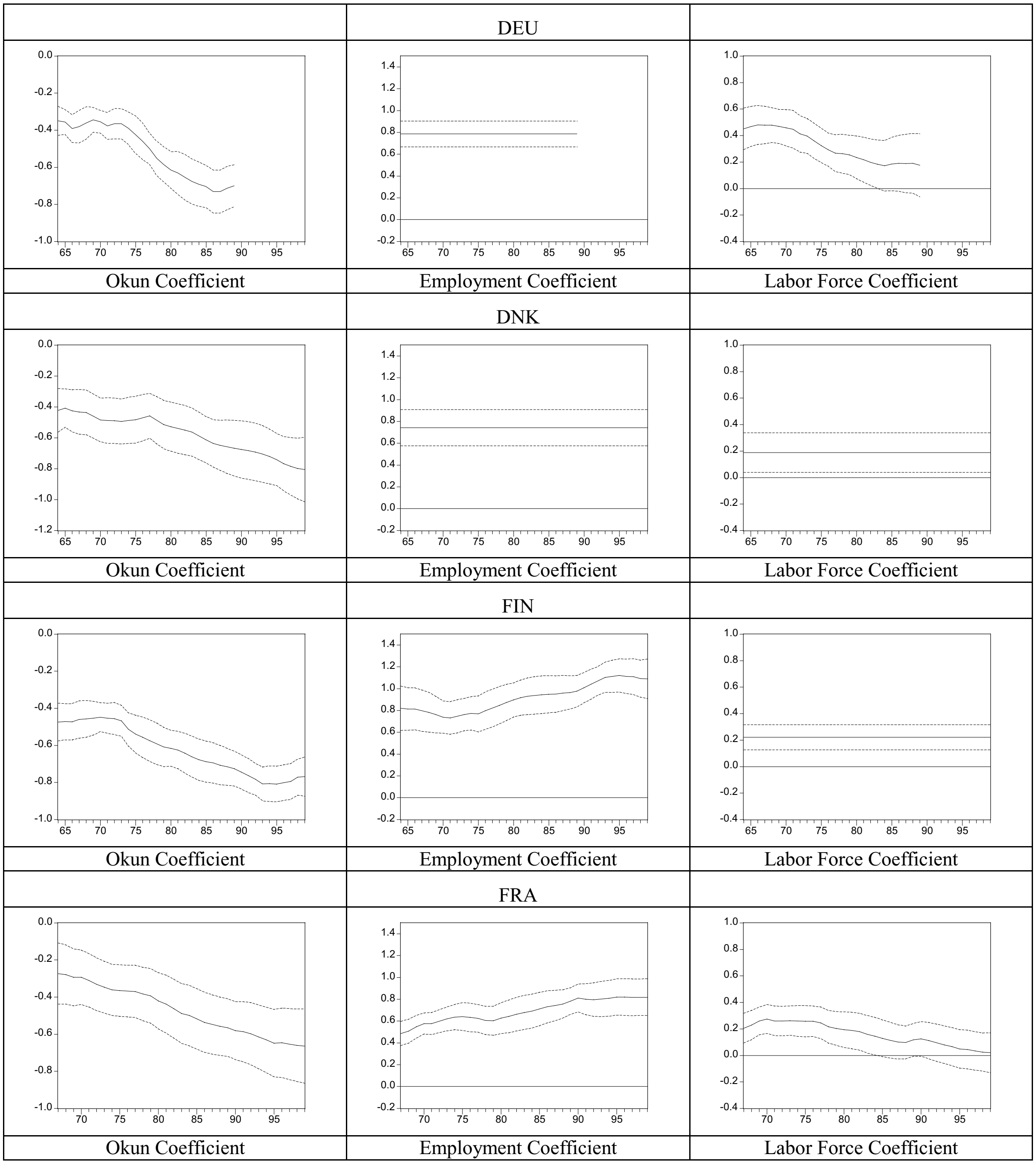

Figure 2: Kalman Filter estimates of the parameters $a_1 + a_2$, $\alpha_1 + \alpha_2$ and $\beta_1 + \beta_2$ (II).

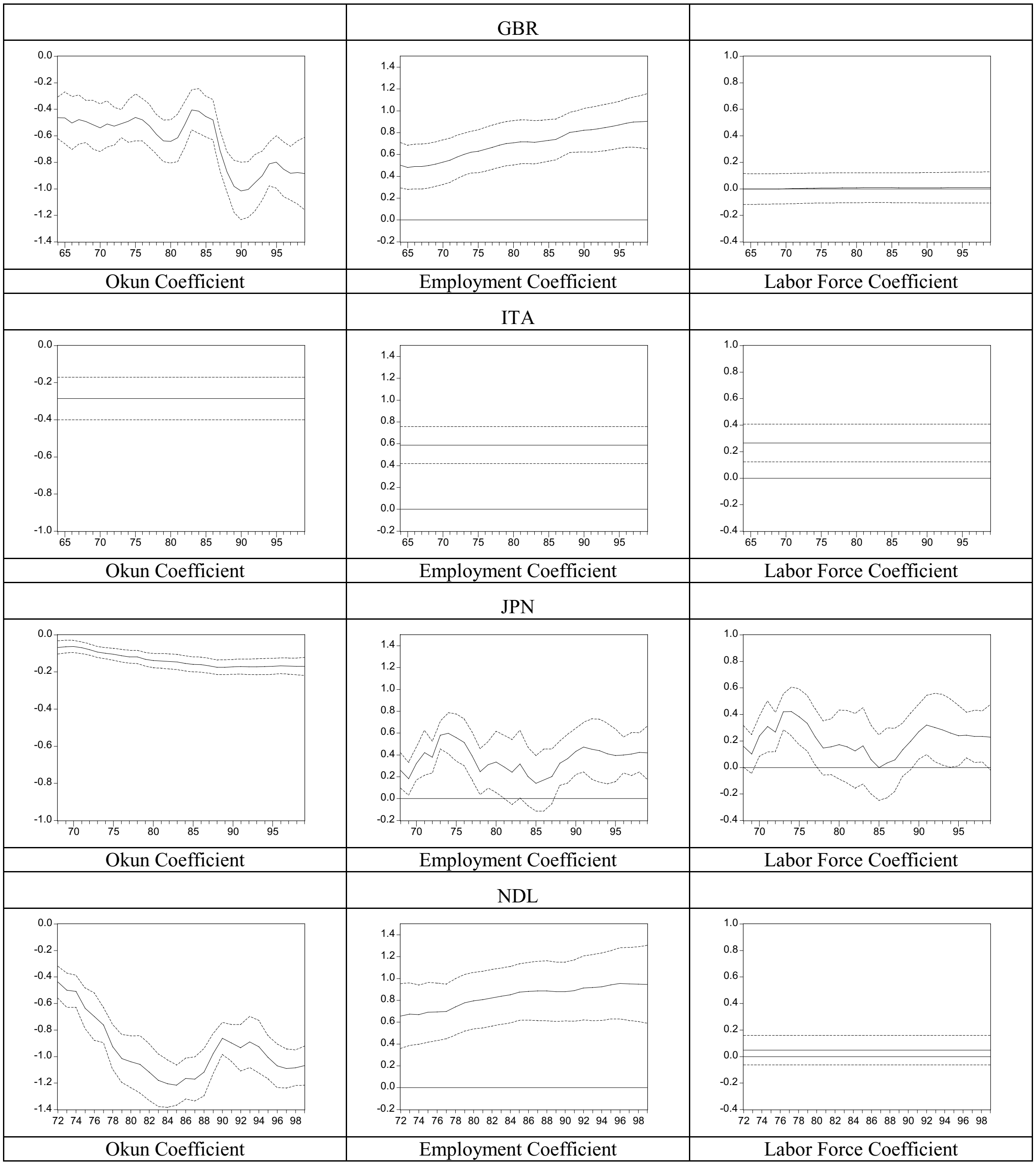

Figure 3: Kalman Filter estimates of the parameters $a_1 + a_2$, $\alpha_1 + \alpha_2$ and $\beta_1 + \beta_2$ (III).

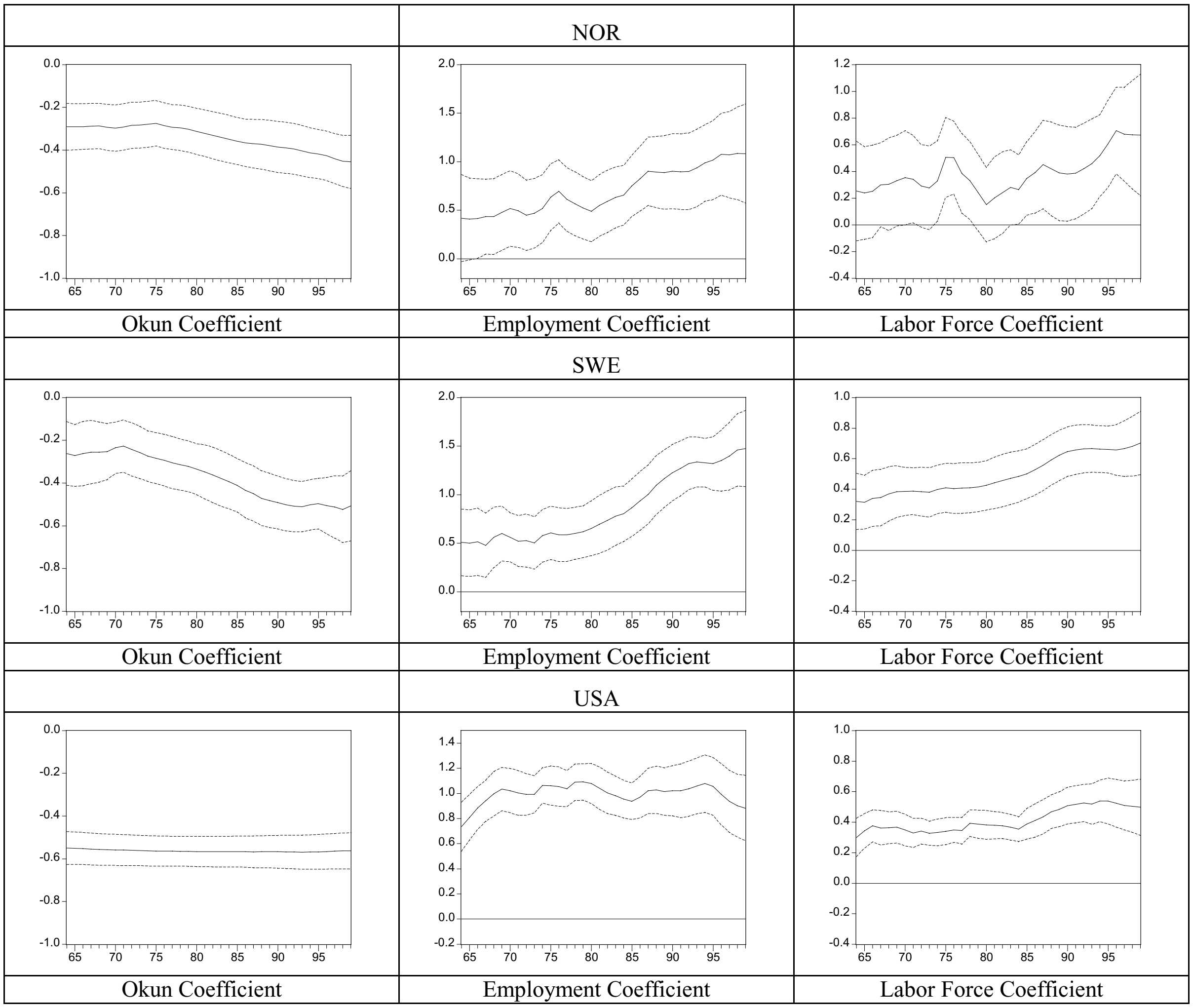

Figure 4: Kalman Filter estimates of the parameters $a_1 + a_2$, $\alpha_1 + \alpha_2$ and $\beta_1 + \beta_2$ (IV).

How can the differences in the Okun coefficients be explained? The cross-country differences and the development of the Okun coefficients over time are quite considerable. These differences could be due to differences in employment or the labor force reaction on GDP variations. Let us focus on the employment effects. As we argued in section 3 the employment-GDP relationship depends, among other factors, on wage policies (ϱ) and labor hoarding effects (λ_l, see equation (12)). So we could expect a negative correlation between factors leading to labor hoarding and the employment coefficient $\beta_1 + \beta_2$ (a high employment coefficient means less labor hoarding). This is exactly the effect stressed in literature (e.g. Blanchard (1999)). To measure the factors leading firms to follow a restrictive labor hoarding policy we used the OECD employment protection index, which is a measure of legal employment protection and firing cost (see OECD (1994)). The second column of Table 5 presents this index. Figure 5 plots the OECD employment protection index against the OLS-estimates of $\beta_1 + \beta_2$ for each country. As Figure 5 shows, this correlation is actually observed. Running an OLS-regression on these data, we get a t-value of -1.77, which is significant at a 10% level. However, there is one outlier in Figure 5 corresponding to Japan. For Japan we found a very low employment coefficient (high amount of labor hoarding) but the OECD protection index is also low for this country. Possibly there are other – social – protection forces at work in Japan, which are not measured by the OECD index. After including a dummy for Japan for that reason, an OLS regression leads to a highly significant t-value of -2.77, the coefficient of determination $R^2 = 0.59$. So we conclude that major parts of the cross-country differences in the reaction of employment to GDP variations can be explained by different degrees of labor market protections.

It is interesting to note that factors leading to more labor hoarding (higher turn over costs) also increase insider power of the employed which in turn could lead to *hysteresis* problems as is well documented in the literature (see e.g. Blanchard and Summers (1986) and Cross (1988)). So we expect a negative correlation between the employment coefficient and hysteresis in unemployment. To get a crude measure for this hysteresis effects we run regressions of u_t on u_{t-1} for every country. The higher the regression coefficient ζ of u_{t-1} (i.e. the nearer to one) the higher the hysteresis problem. Table 5 presents the estimates of ζ. In Figure 6 this crude measure for hysteresis problems is plotted against our estimated employment coefficient $\hat{\beta}_1 + \hat{\beta}_2$ for each country (including Japan). As we can see, there actually seems to be strong negative correlation. Running an OLS regression on threes data we get a t-value of -4.08.

Table 5: OCED Protection Index (PI.) and Measure for Hysteresis

Country	PI.	ζ	$\hat{\beta}_1 + \hat{\beta}_2$
AUT	16	1.000	0.45
BEL	17	0.915	0.52
CAN	9	0.916	0.97
CHE	6	0.930	0.54
DEU	15	0.970	0.76
DNK	5	0.950	0.69
FRA	14	0.968	0.63
GBR	7	0.938	0.65
ITA	20	1.000	0.49
JPN	8	1.080	0.25
NDL	9	0.890	0.84
SWE	13	0.940	0.83
USA	1	0.810	0.96
FIN	10	0.945	0.94
NOR	11	0.930	0.74

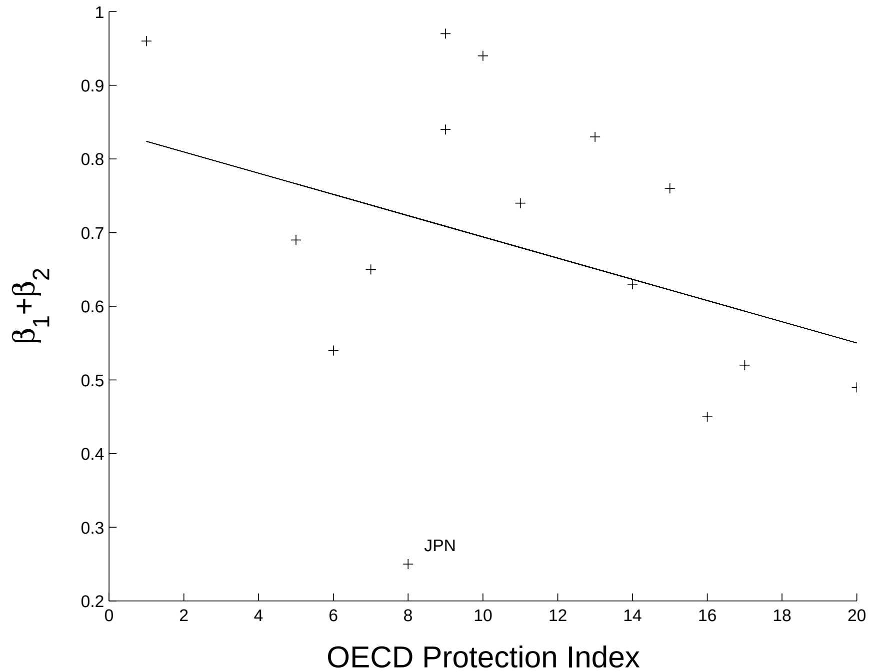

Figure 5: OECD employment protection index vs. the employment coefficient $\beta_1 + \beta_2$.

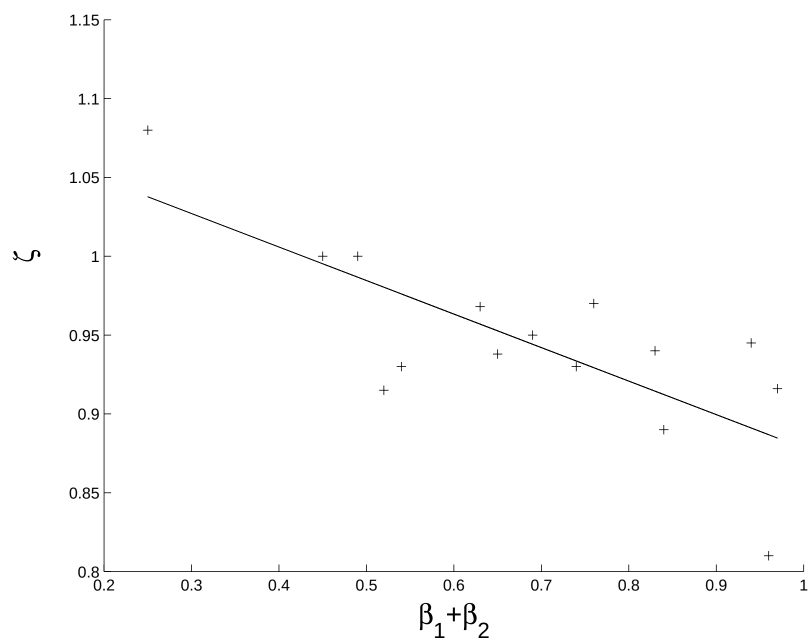

Figure 6: Persistence in unemployment ζ vs. the employment coefficient $\beta_1 + \beta_2$.

6 Conclusions

In this article we estimated Okun's Law for 15 OECD countries. From our estimates we conclude that the reaction of the unemployment to changes in GDP differs substantially between the countries considered. Furthermore we investigated the structural stability of this unemployment - GDP growth relationship by means of Bayesian methods and Kalman filtering. By the former analysis we cannot detect regime switching (no structural breaks in a strict sense) within the Okun relationship, while by applying the latter methods – where continuous changes are considered – we obtained changes in Okun's law for the Switzerland, Germany, Denmark, Finland, France, Great Britain, Japan, the Netherlands, Norway and Sweden. For Austria, Belgium, Canada, Italy and the US we inferred a stable Okun relationship. Furthermore, by considering labor demand and labor supply as functions of GDP growth we are able to assign changes in Okun's law to demand and supply side changes. By our econometric analysis this causes for changes differ considerably between the countries considered in this article. For most countries the changes in the Okun coefficients are mainly due to an increased reaction of employment (labor demand) on GDP variations. Labor force effects partially offset this effect, such that the changes in the Okun coefficients are moderate or completely compensated for some countries. Only for France, Switzerland and Germany the changes in Okun's law were enforced by labor force effects. In Italy all the relationships are stable over time.

In a final step, we relate our estimation results to *labor hoarding* policy and to the persistence in the unemployment rate (*hysteresis effect*) by using the OECD employment protection index and the first order autocorrelations in the unemployment rates. We regress both on our estimates of the employment coefficient. We derived a negative correlation between these two measures and the estimated employment coefficients. This implies that countries with a highly protected labor market actually exhibit a low reaction of employment to GDP variations (mainly due to labor hoarding), while the persistence in the unemployment rate is stronger for these countries.

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