Labour market institutions and business cycle dynamics, VAR analysis

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Abstract

This paper studies how labour market institutions are related to business cycle dynamics. I estimate for a panel of OECD countries a vector autoregressive (VAR) model of which parameters are assumed to depend on labour market institution and control variables. I study how employment protection, generosity of unemployment benefits and degree of coordination and centralization in the wage setting are related to short run dynamics of wages, unemployment, GDP and labour productivity. Results suggest that labour market institutions have explanatory power for the heterogeneity in the volatilities of macroeconomic variables and in shock adjustment. In countries with high coordination in the wage bargaining wages are less volatile and respond less on productivity shocks. In countries with strict employment protection legislation wages are less volatile and unemployment is less responsive on external demand shocks. If unemployment benefits are generous unemployment and wages are more responsive to productivity shocks. The explanatory power of labour market institutions for business cycle heterogeneity seems to comparable to that of used control variables (trade to GDP, government consumption to GDP and Euro dummy). When trying to asses the scope that labour marker reforms could achieve in changing the shock adjustment process of an economy, the results speak for only modest changes. It is illustrated that whether the relation between institutional variables and VAR parameters is assumed as deterministic or stochastic has a large impact for the inference.

Keywords: Labour market institutions, business cycles, hierarchical Bayesian modeling

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1 Introduction

One major distinction across developed economies lies in labour market institutions. Countries differ in the degree and the practices of collective bargaining, in unemployment insurance schemes and in the strictness of employment protection legislation. Labour market institutions are widely used as an explanation for differences in economic performance of countries and labour market reforms have a big weight in the policy suggestions of international institutions. [1]

The long run out comes of labour market institutions are intensively studied but the business cycle outcomes have considered less attention in the academic literature. [2]Main lesson from the modern business cycle literature has been that economic fluctuations are not undesirable as such but the imperfections and rigidities may lead to suboptimal responses of an economy on driving shocks. Therefore it is necessary to understand how labour market institutions shape the business cycle dynamics of economies in order to know the aggregate welfare consequences of different labour market institutions. Also the creation of the Euro area gives reasons to study the effects labour market institutions on business cycle dynamics. Due to the common monetary policy the member countries of monetary union have less stabilization tools. Hence it is important to know if certain labour market institutions amplify or mitigate the responses of member countries on common shocks and hence potentially create asymmetric responses. In addition, given the limited ability of the member countries to introduce stabilization policies on country specific shocks it is useful to understand which labour market institutions are desirable and undesirable from this perspective. Certain labour market institutions might lessen the need for stabilization policies and others increase it.

The introduction of search and matching framework of labour market into dynamic stochastic general equilibrium (DSGE) models has made it possible to model labour market in contemporary macroeconomic models in more detail. There are studies that also incorporate labour market institutions into DSGE models with search and matching framework, most notably Zanetti (2011) and Campolmi and Faia (2011). One aim of this paper is to test empirically implications of these models. Recently Amaral and Tasci (2016) provide evidence that labour market related business cycle statistics display significant heterogeneity among OECD countries and that a calibrated search and matching model matches the data poorly. One scope of this paper is to asses if labour market institution variables are so strongly linked to the heterogeneity in labour market dynamics that inclusion of relevant labour market institutions to theoretical models is needed to improve the empirical properties of these models.

In this study, I estimate a hierarchical Bayesian VAR model where the parameters are allowed to vary according to institutional characteristics of the countries in the sample. In the context of labour market institutions similar approach has been taken in Abbritti and Weber (2010, 2017) and Georgiadis (2014). Also Towbin and Weber (2010) and Sa, Towbin and Wieladek (2014) apply similar methodology but the subject is different. Compared to existing studies that link parameter variation

[1]See Blanchard, Jaumotte and Loungani (2013) for the role of labour market institutions in IMF country recomendations

[2]See Layard, Nickell and Jackman (2005) and Boeri and van Ours (2013) for a survey on the literature on labour market institutions and equilibrium unemployment

of a VAR to institutional variables, two differences stand out. First, I allow *all* the parameters of the VAR to vary according to institutional variables. Georgiadis (2014) allows only the VAR coefficients (that is dynamic relations) to vary with institutional variables. Abbritti and Weber (2017), Towbin and Weber (2010), Sa, Towbin and Wieladek (2014) estimate the VAR in the recursive form and allow also the contemporaneous relations in the VAR to vary with institutional variables, but keep the (diagonal) variance-covariance matrix of the errors fixed. In the estimation I allow for variation for all the elements of the variance covariance matrix, including the diagonal elements. The difference is crucial for the analysis presented here, since the analysis is based on comparing moments that are calculated from the VAR parameters and impulse response functions, which both are functions of all the VAR parameters.

The second difference to existing literature is that the relation between institutional variables and VAR parameters is assumed to be stochastic whereas in Abritti and Weber (2010,2017) and Georgiadis (2014) it is assumed to be deterministic. This assumption is crucial for the statistical inference and it has been pointed out also in Western (1998) and Wieladek (2016).

The variables that enter the VAR are real wages, unemployment rate, GDP and labour productivity growth rates. Existing studies, Abbritti and Weber (2010,2017) and Georgiadis (2014) that use VAR approach to study the relation between labour market institutions and business cycle have not included wages or labour productivity to their estimations.[3] I include also wages in the VAR since understanding the effects of labour market institutions on aggregate wage dynamics might be crucial as collective bargaining institutions are directly linked to the wage setting and can influence macroeconomy mainly through wages. Labour productivity is included since Amaral and Tasci (2016) show that the persistence of labour productivity varies greatly among OECD countries and when calibrating a search and matching model the labour productivity persistence is major determinant for the model implied volatilities. Hence it is of interest to see if the differences in labour productivity persistence are related to differences in labour market institutions.

The labour market institutions that are studied in this paper are the strictness of employment protection legislation, unemployment benefits replacement rated and wage setting coordination and centralization. The effects of the two first ones on business cycle dynamics in a DSGE model are studied in Zanetti (2011) and Campolmi and Faia (2011). Wage setting coordination and centralization has not been studied yet quantitatively in DSGE models but it is included since countries differ greatly in that institutional dimension and it is of importance in the policy discussion.[4] Also other labour market institutions could have been studied but already with these three institutional variables the empirical model is relatively large. In Abbritti and Weber (2010) and Gnocchi, Lageborg and Pappa (2015) the curse of dimensionality is dealt with constructing factors from labour market institution variables. I chose not to follow that approach in order to identify the relation between business cycle dynamics and individual institutions directly. In addition, wage set-

[3]The VAR in Abbritti and Weber (2010,2017) includes unemployment rate, inflation and interest rate. Georgiadis (2014) includes GDP, price level and interest rate.

[4]For the importance of wage setting institutions in the policy discussion see e.g. Blanchard *et al.* (2013)

ting and coordination measures are not treated as continuos variables but instead as categorial variables.

The data consists of 23 OECD countries and time period covers 1995-2013. Previous studies have used longer data sets but fever countries. In particularly restring to shorter time period allows to include Czech Republic, Hungary, Poland and Slovakia. This is beneficial since these countries have weaker labour market institutions than the majority of the older OECD countries that have longer data available. Including these countries increases the heterogeneity in the data set. Overall the variation in the labour market institution data over time within a country is very limited compared to variation across countries. Hence it is preferable to increase the cross-sectional dimension than time dimension.

Gnocchi *et al.* (2015) find that labour market institution variables are linked to differences in business cycle dynamics. They estimate business cycle statistics for 19 OECD countries and use rank correlation coefficient analysis to study the relation between labour market institution variables and business cycle statistics. Rank correlation coefficient analysis is robust but it does not allow for quantitative evaluation of the magnitudes. In this paper the aim is also to quantify how large changes in business dynamics could labour market institutions potentially cause.

Abbritti and Weber (2017) obtain stronger results for the relation between labour market institutions and business cycle dynamics than the results that I obtain in this paper. To some extend Abritti and Weber (2017) are able to show stronger results than in the previous literature. The methodology in this paper is close to methodology in Abbritti and Weber (2017), but one large difference stands out. Abbritti and Weber (2017) assume the relation between labour market institutions and VAR parameters to be deterministic, whereas I assume it to be stochastic. This has a large impact for the inference. Also my results are much stronger if the relation is assumed to be deterministic, which is in line what Western (1998) and Wieladek (2016) have documented with their applications.

Results suggest that labour market institutions have explanatory power for the heterogeneity in the volatilities of macroeconomic variables and in shock adjustment. In countries with high coordination in the wage bargaining wages are less volatile and respond less on productivity shocks. In countries with strict employment protection legislation wages are less volatile and unemployment is less responsive on external demand shocks. If unemployment benefits are generous unemployment and wages are more responsive to productivity shocks. The explanatory power of labour market institutions for business cycle heterogeneity seems to be comparable to that of used control variables (trade to GDP, government consumption to GDP and Euro dummy). When trying to asses the scope that labour marker reforms could achieve in changing the shocks adjustment process of an economy, the results speak for only modest changes.

Rest of the paper is organized as follows. The next section explains the methodology used in the estimation. Section 3 presents the data used in this paper and section 4 reports the results. Section 5 concludes.

2 Methodology

The methodology is based on the time-varying parameter VAR framework outlined originally in Cogley and Sargent (2002) and Primiceri (2005). These studies estimate a TVP VAR model for the US economy and assume that the parameters of the VAR follow driftless unit root processes. Recently, Mumtaz & Zanetti (2015) have used TVP VAR model to detect time-variation in the business cycle dynamics of US labour market variables. The aim of this paper is not to detect variation in VAR parameters *per se*, but to link the parameter variation to observable institutional variables. I specify a VAR model with an assumption that part of the parameter variation is explained by labour market institution variables.The model features error processes for the VAR parameters and these error processes account for the parameter variation that is not captured by the institutional variables. The data covers 23 OECD countries. Since labour market institutions display very little variation over time, it is mostly the parameter variation across the cross-sectional units that labour market institution variables can be assumed to capture.

The model neglects from potential interdependencies between countries. Taking this into account in a manner that is still feasible to estimate requires specific techniques, since modeling interdependencies between countries increases dramatically the number of parameters. Canova and Ciccarelli (2009) offer a panel VAR model to account for cross-country interdependencies, but applying it to the analysis in this paper would encumber the already complex model further. Since the cross-country interdependencies are neglected, the model is naturally misspecified. However it does not seem reasonable to believe that this would affect the results systematically in favor of strengthening or decreasing the relation between labour market institutions and business cycle dynamics. Typically in the literature in the field of this study cross-country interdependencies are neglected.[5] To decrease the concerns, the largest economy, USA is omitted from the sample, since fluctuations in the US economy can have large spillovers to rest of world (for a recent empirical documentation, see e.g. Feldkircher and Huber (2016)). Instead, US GDP is included to the VAR as an exogenous variable to control for common shocks in the data.

For each cross-section unit (country) i the data generating process is assumed to be a vector autoregression of form

$$y_{\mathrm{i,t}} = X_{\mathrm{i,t}}\beta_{\mathrm{i,t}} + e_{\mathrm{i,t}}, \qquad e_{\mathrm{i,t}} \sim \mathrm{N}(0, \Omega_{\mathrm{i,t}}) \tag{1}$$

where $X_{i,t}$ includes lags of depended variables and a constant and exogenous variables. As is common in time-varying parameter VAR literature (e.g. Primiceri 2005) the variance-covariance matrix $\Omega_{\mathrm{i,t}}$ is decomposed with

$$A_{\mathrm{i,t}}\Omega_{\mathrm{i,t}}A'_{\mathrm{i,t}} = \Sigma_{\mathrm{i,t}}\Sigma'_{\mathrm{i,t}} \tag{2}$$

where $A_{\mathrm{i,t}}$ is a lower diagonal matrix with ones on the diagonal and $\Sigma_{\mathrm{i,t}}$ is a diagonal matrix. The evolution of the coefficients $\beta_{\mathrm{i,t}}$, and elements in $A_{\mathrm{i,t}}$ ($a_{i,t}$'s) and $\Sigma_{\mathrm{i,t}}$ ($\sigma_{\mathrm{i,t}}$'s) is given by the constants and the labour market institution and control

[5]Neither Abbritti and Weber (2010,2017) or Georgiadis (2013) models cross-sectional interdependencies.

variables in $Z_{i,t}$ and innovations $\eta_{\mathrm{i,t}}$

$$\begin{bmatrix} \beta_{\mathrm{i,t}} \\ a_{\mathrm{i,t}} \\ log(\sigma_{\mathrm{i,t}}) \end{bmatrix} = Z_{\mathrm{i,t}} \begin{bmatrix} \theta_\beta \\ \theta_a \\ \theta_\sigma \end{bmatrix} + \begin{bmatrix} \eta^{\beta *}_{\mathrm{i,t}} \\ \eta^{a*}_{\mathrm{i,t}} \\ \eta^{\sigma *}_{\mathrm{i,t}} \end{bmatrix} \tag{3}$$

Parameters of the VAR are assumed to vary over time and across countries. $Z_{i,t}\theta$ captures the variation that can be explained with institutional variables and η captures all the remaining variation. If equation (3) is substituted to equations (1)-(2) this gives a model with interaction terms. This kind of approach with VAR is taken in Sa, Towbin and Wieladek (2014) and Abbritti and Weber (2010, 2017).[6] However in these papers the elements in $\Sigma_{i,t}$, the "volatilities" are not modeled to depend on institutional variables. This is an important extension since assuming constant, country specific σ_i's, as in Sa, Towbin and Wieladek (2014), leads to unintended restrictions for the terms in Ω. Given the decomposition in (2), terms in Ω are non-linear functions of terms in A and Σ. On prior it is difficult to justify why some of these parameters would be related to labour market institutions whereas some would not be.[7]

A limitation of the models in the previous literature is that the η error term in (3) is neglected and hence it is assumed that the parameters of the VAR depend deterministically on the variables in $Z_{i,t}$ in equation (3). This is a strong assumption but allows for straightforward estimation. In the context of univariate models there is a variety of studies that have used interaction term approach to study the role of institutions on economic relations (e.g. Blanchard and Wolfers 2000) and Nunziata () employ interaction term approach)

I consider allowing for an error term in equation (3) important since given that one is ready to assume that the parameters of an econometric model vary according to some institutional variables, it is hard to justify why these variables could be the only variables causing the variation. Even if there was no omitted variables, there might be significant measurement errors, since mapping institutional structures on the numerical measures is not trivial. Hence the data might easily differ from the theoretical variables. The inclusion η matters also for the inference. As will be seen in Section 4, neglecting η implies much stronger statistical relation between labour market institution variables and business cycle statistics than when η is included to the model.

The error term $\eta_{i,t}$ captures parameter variation in that data that is not explained by the labour market institution variables. If this residual variation originates from the institutional characteristics that are not included in $Z_{i,t}$ it suggests that $\eta_{i,t}$ should be a persistent process, since institutions display very little variation on quarterly frequencies. Also if the residual variation originates from measurements

[6]Georgiadis (2014) assumes a nonlinear relationship between VAR coefficients and institutional variables.

[7]Let a_1, a_2, a_3 be the non-constant elements in A and $\sigma_1, \sigma_2, \sigma_3$ be the non-zero elements in Σ. Then with a decomposition $A\Omega A' = \Sigma\Sigma'$ it leads to that $\Omega(1,1)$ element is σ_1^2, but $\Omega(3,3)$ is given by $(a_2 - a_1 a_3)^2\sigma_1^2 + a_3^2\sigma_2^2 + \sigma_3^2$. If a_1, a_2, a_3 are allowed to depend on institutional variables and $\sigma_1, \sigma_2, \sigma_3$ are not allowed, this leads to a restriction that the variance of errors of the first variable in the VAR is unrelated to institutional variables whereas that of the third (and second) variable is not restricted to be unrelated to institutional variables.

errors in the institution variables, this implies too that residuals in (3) follow persistent process. Finally, if there are changes in the institutions or other country characteristics that are not captured in $Z_{i,t}$ it is probable that these changes are persistent changes in turn. A process that captures both of these features, persistence and persistent changes, is unit root process. Hence it is assumed that $\eta_{i,t}$ follow uncorrelated unit root processes:

$$\eta^*_{i,t} = \eta^*_{i,t-1} + u^*_{i,t}, \qquad u^*_{i,t} \sim N(0, \Omega_{u^*}) \tag{4}$$

where $\eta^*_{i,t} = \begin{bmatrix} \eta^{\beta*}_{\mathrm{i,t}} & \eta^{a*}_{\mathrm{i,t}} & \eta^{\sigma*}_{\mathrm{i,t}} \end{bmatrix}'$ and Ω_{u^*} is a diagonal matrix. This assumption is also in line with the original TVP VAR methodology in Primiceri (2005). If none of the parameter variation was explained by the variables in $Z_{i,t}$, the model reduces to a estimation of country specific TVP VARs.

Model is very generous, since the parameters of the VAR are allowed to depend on observable institutional characteristics and in addition country specific time variation is allowed. This is to make the estimation more robust. By omitting $\eta^*_{i,t}$ I would force all the variation in the parameters of the VAR to originate from labour market institutions variables and this could lead to spurious results. Also the relation between VAR parameters and institutional variables would be deterministic without an error term in (3), which would mitigate the estimation uncertainty. The natural drawback is that the model is certainly over-parameterized and this could lead to estimation uncertainty to a degree that meaningful inference is no longer possible.

Bayesian shrinkage offers a solution to circumvent a problem of this sort. A researcher has possibility to start with a parameter rich model but the estimation proceeds data drivenly towards a more parsimonious model. A recent contribution to Bayesian shrinkage estimation is the Bayesian Lasso by Park and Casella (2008).[8] Belmonte, Koop & Korobilis (2014) provide an application to TVP framework and their approach is followed closely in what follows. The approach in Belmonte *et al.* was chosen to induce shrinkage since it provides variable selection over time varying and time invariant parameters. Following Belmonte *et al.* (2014) shrinkage is applied to $\eta^*_{i,t}$ terms with a transformation that allows to decompose the time varying $\eta^*_{i,t}$ to initial condition and deviations from the initial condition. Initial condition captures the cross-sectional (residual) variation in parameters and deviations from the initial condition capture the variation over time within a cross-sectional unit.

To decompose the $\eta^*_{i,t}$ process to initial conditions and deviations from it, simply define $\eta_i = \eta^*_{i,0}$ and $\eta_{i,t} = \eta^*_{i,t} - \eta_i$, $\eta_{i,0} = 0$. Following Belmonte *et al.* (2014) and Frühwirth-Schnatter and Wagner (2010) a further transformation is implemented for $\eta_{i,t}$ terms. For a j'th element in $\eta_{i,t}$ vector, $\tilde{\eta}_{j,i,t} = \frac{\eta_{j,i,t}}{\omega_{j,i}}$, where $\omega_{j,i}$ is a diagonal element in Ω^*_u. Frühwirth-Schnatter and Wagner (2010) refer this as non-centered parameterization.

Then equations (3) and (4) can be re-written as

$$\begin{bmatrix} \beta_{\mathrm{i,t}} \\ a_{\mathrm{i,t}} \\ log(\sigma_{\mathrm{i,t}}) \end{bmatrix} = Z_{\mathrm{i,t}} \begin{bmatrix} \theta_\beta \\ \theta_a \\ \theta_\sigma \end{bmatrix} + \omega_{\mathrm{i}} \tilde{\eta}_{\mathrm{i,t}} + \eta_{\mathrm{i}} \tag{5}$$

[8] LASSO is an acronym for least absolute shrinkage and selection operator

$$\tilde{\eta}_{i,t} = \tilde{\eta}_{i,t-1} + u_{i,t}, u_{i,t} \sim N(0, I) \tag{6}$$
$$\eta_{i,0} = 0 \tag{7}$$

Now the $\eta^*_{i,t}$ error terms are divided into unit specific time-invariant η_i and unit specific time-varying $\tilde{\eta}_{i,t}$ parts. Rationale for using the non-centered parameterization for η's is that one is able to assume inverted normal prior for ω's. Usually the variances of the errors are assumed to be inverted Gamma distributions. Frühwirth-Schnatter and Wagner (2010) provide evidence that when working with shrinkage priors, the use of Normal priors leads to better performance.

To induce Lasso-type shrinkage following priors are assumed for the ω and η_i terms. The time-invariant unit specific η_i terms are distributed on prior as

$$\eta_i^k | \tau^2_{i,k} \sim N(0, diag(\tau^2_{i,k})) \tag{8}$$

where $k = (\beta, a, \sigma)$ Each term in vector $\tau_{i,k}$ is distributed on prior as

$$\tau_{k,i} | \lambda_k \sim exp\left(\frac{\lambda_k^2}{2}\right) \tag{9}$$

To induce shrinkage for time-varying error terms following prior for ω_i is used

$$\omega_{i,k} | \xi^2_{i,k} \sim N(0, diag(\xi^2_{i,k})) \tag{10}$$

where $k = (\beta, a, \sigma)$ Each term in vector $\xi_{k,i}$ is distributed on prior as

$$\xi_{k,i} | \kappa_k \sim exp\left(\frac{\kappa_k^2}{2}\right) \tag{11}$$

λ_k, κ_k require priors and non-informative priors as in Belmonte *et al.* (2014) are used.

For θ's independent Normal priors are assumed. θ's that are associated with the constants in Z give the average values of the VAR parameters over the sample. Prior means for these are obtained form training sample. For other terms in θ zero mean is assumed. Priors for θ's are relatively diffuse and hence these prior believes are dominated by the sample information.[9]

All model parameters have analytical conditional distributions and the model can be estimated using Gibbs sampler. The time varying terms $\tilde{\eta}_{i,t}$ are estimated using algorithm in Chan and Jeliazkov (2009) instead of Kalman simulation smoother algorithm, which is the standard in the TVP-VAR literature. The reason for this is the computational efficiency of Chan and Jeliazkov (2009) approach. Otherwise the estimation follows closely Primiceri (2005). A detailed description on the estimation is provided in the Appendix A.

The main methodological contribution over the existing studies that use institutional variables to explain parameter variation is that I allow also the elements of $\Sigma_{i,t}$ to be linked to institutional variables. This is important for the analysis of this paper, since one aim is to study if there is a relation between labour market institutions and business cycle moments that are obtained from the VAR parameters.

[9]Prior variances of θ's are set to 10.

Hence it is important that all the elements of the variance covariance matrix $\Omega_{i,t}$ are linked to institutional variables. This matters also for the impulse response analysis. Apart from the first cell in $\Omega_{i,t}$, its all other elements are functions of elements both in $A_{i,t}$ and $\Sigma_{i,t}$.

Another methodical contribution is to allow for η error terms in (3), call it second-stage relation. This is important since it increases the empirical performance of the model and is crucial for the inference. Allowing for error terms in (3) makes the relation between VAR parameters and institutional variables stochastic whereas without error terms it is deterministic. It should be highlighted, that the situation is very different from the usual econometric modeling, where the relations are always stochastic. Typically a researcher is interested on the relation between dependent and explanatory variables that are both observed whereas here the interest lies on the relation between unobserved dependent variables (VAR parameters) and observed explanatory variables (labour market institution and control variables). In standard regression analysis the relation is stochastic by construction, since the estimation would not be possible without allowing for error terms in the regression equation. When the interest is on the relation between regression parameters and observed institutional variables, as in this study, researcher has the possibility to decide whether the relation is stochastic or deterministic, since the dependent variables that are unobserved are constructed in the analysis.

One approach to model the effect of institutional variables to economic dynamics has been to simply augment a standard regression model with interaction terms of institutional variables and explanatory variables. Essentially the modeling procedure is the same as in this study, but the dependence between institutional variables and regression parameters is not modeled explicitly as in equation (3). Appendix A provides the details of the estimation and also in my approach the estimation proceeds by substituting equation (3) to equation (1). This gives a model with interaction terms of explanatory variables and institutional variables. In addition there is interaction terms of η error terms and explanatory variables which are typically neglected in the previous literature. This illustrates that if one uses interaction terms approach the maximum likelihood estimator is not standard ordinary least squares estimator, but generalized leas squares (GLS) type estimator because of the interaction terms between errors and explanatory variables. Canova (2008) shows the derivations for the GLS estimator in this context. However in Canova (2008) the error terms of the second stage relation are country specific constants. If the error terms are time-varying, like I have, the derivations would be more cumbersome.

Although it seems decisive whether one assumes the relation of institutional variables and model parameter to be deterministic or stochastic, fairly little research has been done on this. Wieladek (2016) illustrates that if one assumes deterministic relation for the VAR parameters and institutional variables, the distributions of impulse responses are significantly smaller than if stochastic relation was assumed. Further, according to Wieladek's (2016) results more institutions are found to be related to shock transmission statistically significantly when deterministic relation is assumed. Western (1998) finds that in the context of regression coefficients, the confidence bands are smaller when the relation to institutional variables is assumed to be deterministic. Similar results are obtained in this study and are discussed further in the next section.

A methodological contribution is also that Lasso type shrinkage is applied to TVP VAR. Belmonte *et al.*(2014) work with a single equation model and shrinkage is applied only on the coefficients of the model not on the variance.

Another approach to study the relation between institutional variables and dynamics, has been to estimate cross-section specific VARs, obtain impulse responses and group impulse responses according to a institutional variable. Calza, Monacelli & Stracca (2013) apply this methodology to study the relation of mortgage market characteristics on the transmission of monetary policy. This approach is robust and transparent but a limitation of this approach is that when the time dimension for the data is only modest, as is the case in my analysis, cross-sectionally estimated VARs can be poorly estimated. Grouping is also done one variable at a time, which in the case of labour market institutions would make comparisons difficult as labour market institution variables are highly correlated. Comparison would be less informative on the independent relations of each institutions on the business cycle dynamics and it would not be possible include additional control variables.

An appealing property of the methodology presented here is that is in line with the likelihood principle. The model is estimated under the hypothesis and prior belief that the institutional variables are linked to parameter variation of the VAR. Hence all the prior information is included to the estimation.

3 Data

The data set consists of 23 OECD countries.[10]The time period covers 1995-2013 and data is quarterly. For a subset of countries longer series exists and pre-1995 data of these countries are used as a training sample to get prior means for the terms in θ that are associated with the constants in Z. Previous studies have used longer data, but the advantage of using shorter data is that it allows to include more countries to the data set.[11]This is useful since most of the variation in labour market institutions is between countries and time variation within a country is relatively limited. Hence large N than large T is preferable. The majority of the countries that have long series are countries that have relatively strong labour market institutions. In turn, the countries that have shorter series are countries that have weaker labour market institutions than the majority of the old OECD countries. This further increases the heterogeneity in the labour market institutions compared to a data set that consists of long series of older OECD countries.

In addition, one difficulty in using long series is that although the variation in labour market institution is only modest, the time variation in business cycle statistics is large and even larger than the cross-country variation (see e.g. the figures in Canova, Ortega and Ciccarelli (2012)). In general the business cycle volatility has decreased in OECD countries from the 70's till the financial crisis of 2008. At the same the strictness of labour market institutions has slightly decreased in general. These common patterns might bring difficulties to the estimation.

[10] The countries are Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland,Italy, Japan, Netherlands, New Zealand,Norway, Sweden, Poland, Portugal, Slovakia, Spain, Switzerland and the UK.

[11]Czech Republic, Hungary, Poland and Slovakia have consistent data sets for both macro and labour market institution variables only from 1995 onwards.

Unbalanced panel estimation would efficiently use all the data available and would be technically feasible. Unbalanced panel estimation was not chosen since the countries with shorter series have weaker labour market institutions than the average in the sample. This could bring problems to the estimation, since countries with differing characteristics would have unequal weights in the sample.

The endogenous variables that enter the VAR are real wage growth, unemployment rate and GDP or labour productivity growth. Productivity is measured as GDP divided by employment, as in Amaral and Tasci (2016). GDP and productivity are included only in turns to keep the number of estimated parameters more compact. When results refer specifically to productivity, it is included in the VAR and otherwise GDP is included. Data for these variables is from the OECD Economic Outlook.[12]GDP growth was chosen since it is a proxy for economic activity. Unemployment and real wage growth were chosen since to these variables should labour market institutions have relatively direct relation. Productivity growth was chosen since Amaral and Tasci (2016) highlight the importance of the persistence of labour productivity for differing labour market variable volatilities.

USA is excluded from the sample since movements in US macro variables can potentially have large effects on other economies and cross-country correlations are not modeled in the estimation. Instead the US GDP is used as an exogenous variable to control for common shocks in the data. In order to control for common shocks the US GDP enters as a contemporaneous variable. Except unemployment rate all variables enter year-on-year growth rates. Lag length of two was chosen, but robustness of the results was studied with four lags.

The labour market institution variables that are considered are strictness of employment protection legislation, unemployment benefits replacement rate and wage setting coordination and centralization. An ample of other indicators also exists. These indicators were chosen since they constitute the minimum set to be able to test the predictions of DSGE model studies on the relation between labour market institutions and business cycle dynamics.

Employment protection variable is constructed as an average of the OECD indicators for the legislation related to dismissal of workers in regular contracts and the regulation on temporary contracts. Replacement rate data is from van Vliet and Caminada (2012) and it is the ratio of net unemployment benefits and net income for an average worker in the manufacturing sector.

For the wage setting two indicators are combined from the ICTWSS database.[13] The other indicator measures the centralization of the wage setting by defining the predominant level where wages are set (workplace, industry, national level or in between these levels) and the other measures the coordination in the wage setting process. Both indicators are on the scale from 1 to 5. These two variables are highly correlated and hence identifying their independent relations to macroeconomic dynamics in a relatively small sample is difficult. Although in the earlier literature wage setting coordination and centralization variables are treaded as continuous variables, it is not self evident that this would be the correct approach. Thinking about wage setting in a firm, sectorial or national level, it is difficult to see the

[12]Except for Swiss wage data, which is from the Swiss statistical authority.

[13]ICTWSS: Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts in 51 countries between 1960 and 2014, Visser (2016).

the differences as quantitative differences but mere qualitative or categorical differences. To circumvent these problems, high correlation between centralization and coordination variables and their categorical nature, I construct from these variables a singe categorical variable. This allows to combine information from both variables without expanding the parameter space and this takes into account the categorical nature of these variables. Also according to Calmfors and Driffill (1988) hypothesis the relation of wage setting centralization to macroeconomy is hump shaped, which can be captured with a three category variable. A three categorial variable is constructed as following: uncoordinated/decentralized if both indicators are less than two, intermediate if either indicator is greater than two but less than four, coordinated/centralized if either of the indicators is four or five. In what follows I refer to this variable as coordination for simplicity.

In addition to labour market institutions variables control variables are included to $Z_{\mathrm{i,t}}$. These are Euro dummy, openness to trade and the share of government spending of GDP. To model the global changes in business cycle dynamics during that sample period, volatility of US GDP growth as an explanatory variable in $Z_{i,t}$ is included.[14]

4 Results

4.1 Conditional business cycle statistics

This section studies the relation between labour market institutions and business cycle dynamics by calculating moments from the VAR parameters conditional on specific values for the labour market institution variables. Given the posterior distribution for θ's VAR parameters are obtained using equation (5). Using the formulas in the Appendix moments are easily calculated from the VAR parameters. Since moments are simulated using the distribution of θ's instead of point estimates of the mean, the exact small sample distributions are automatically generated. Moments are calculated conditional on each degree of coordination and conditional on 20th, 50th and 80th sample percentiles of replacement rate and employment protection. Each institution is studied in turn and other continuos variables in $Z_{i,t}$ are kept at a median value, coordination is kept at intermediate and euro dummy is set to equal one.

Table 1 shows the variances, cross-correlations and autocorrelations of real wage growth, unemployment, GDP and productivity growth conditional on labour market institution variables. Overall the medians of variances conditional on different values for labour market institution variables seem to be different even substantially but also confidence bands are large. In the case of coordination, volatilities of unemployment and wages are different between high and low coordination with 80 % confidence. (Meaning that 80% highest density region of differences between $var(w)_{high}$ and $var(w)_{low}$ does not include zero). Also the persistences of wages and labour productivity are higher if wage setting coordination is low.

Replacement rate of unemployment benefits seems to relatively weakly related on business cycle dynamics. According to table 1 only the correlation of wages and unemployment seems to be related to replacement rate. Employment protec-

[14]US GDP growth volatility is obtained from a TVP-AR(1) model with stochastic volatility

Table 1. Conditional business cycle statistics

	COORD			REP			EPL		
	Low	Intermed	High	Low	Intermed	High	Low	Intermed	High
var(w)	1,49’	1,36’	0,96	1,11	0,95	0,94	1,25*	0,96”	0,80
	1,02 2,64	1,03 1,87	0,77 1,23	0,81 1,64	0,76 1,21	0,75 1,21	0,92 1,81	0,77 1,22	0,65 0,99
var(u)	2,07	1,48	1,24	1,13	1,3	1,31	1,28	1,41	1,62
	0,8 10,59	0,87 3,04	0,7 2,89	0,52 4,09	0,72 2,85	0,74 2,94	0,61 4,25	0,77 3,04	0,92 3,55
var(y)	1,38	2,07’	1,55	2,07	1,73	1,59	1,84	1,91	2,02
	0,93 2,38	1,61 2,71	1,22 1,95	1,58 2,73	1,4 2,12	1,26 2,01	1,45 2,32	1,56 2,33	1,64 2,51
var(y/n)	2,02	1,35	1,30	1,76	1,47	1,37	1,63	1,58	1,59
	1,26 4,09	1,03 1,78	1,01 1,67	1,13 2,83	1,04 2,11	0,93 2,08	1,25 2,18	1,28 1,97	1,28 1,98
cor(y,u)	-0,27	-0,29’	-0,16	-0,25	-0,17	-0,13	-0,16	-0,18	-0,19
	-0,6 0,03	-0,38 -0,18	-0,26 -0,04	-0,38 -0,13	-0,27 -0,06	-0,24 0	-0,28 -0,02	-0,27 -0,07	-0,29 -0,07
cor(y,w)	0,24	0,03	0,05	-0,05	0,00	0,03	0,02	0,06	0,09
	0 0,48	-0,12 0,18	-0,05 0,15	-0,2 0,13	-0,11 0,1	-0,08 0,14	-0,12 0,16	-0,05 0,16	-0,01 0,2
cor(w,u)	-0,06	-0,21	-0,10	-0,17	-0,09’	0,00	-0,11	-0,1	-0,09
	-0,46 0,29	-0,41 -0,03	-0,28 0,04	-0,48 0,02	-0,26 0,06	-0,18 0,18	-0,39 0,08	-0,28 0,05	-0,28 0,06
cor(u,y/n)	-0,13	-0,01	0,07	-0,02	0,01	0,01	0,00	-0,01	-0,01
	-0,52 0,21	-0,13 0,14	-0,03 0,2	-0,14 0,12	-0,09 0,13	-0,11 0,16	-0,13 0,2	-0,1 0,12	-0,1 0,12
cor(w,y/n)	0,23	0,01	0,06	0,07	0,09	0,08	0,14	0,12	0,08
	-0,06 0,5	-0,14 0,17	-0,07 0,17	-0,09 0,22	-0,03 0,19	-0,03 0,19	-0,03 0,28	0 0,22	-0,02 0,18
acor(w)	0,74’	0,77*	0,62	0,66	0,62	0,61	0,65	0,62	0,6
	0,64 0,85	0,71 0,83	0,56 0,69	0,58 0,76	0,56 0,69	0,54 0,67	0,53 0,82	0,53 0,73	0,5 0,7
acor(u)	0,99	0,98	0,98	0,98	0,98	0,98	0,98	0,98	0,99
	0,97 1	0,96 0,99	0,97 0,99	0,96 0,99	0,97 0,99	0,97 0,99	0,96 0,99	0,97 0,99	0,98 0,99
acor(y)	0,79	0,77	0,71	0,7	0,71	0,72	0,7	0,72	0,73
	0,71 0,88	0,72 0,81	0,67 0,76	0,64 0,76	0,67 0,75	0,67 0,76	0,64 0,75	0,67 0,76	0,69 0,77
acor(y/n)	0,79*	0,65	0,59	0,55	0,59	0,62	0,59	0,60	0,61
	0,71 0,89	0,59 0,7	0,54 0,64	0,48 0,62	0,54 0,64	0,56 0,67	0,52 0,66	0,54 0,65	0,56 0,66

Note: Intervals refer to 80% confidence set. The distributions of low and intermediate regimes are compared to that of high.’ refer to zero is not included to 80 % highest density region of distribution for the difference.”, * ,** refer to 90, 95 and 99 highest density regions.COORD, wage setting coordination, REP, replacement rate of unemployment benefits, EPL, employment protection

Table 2. Relations, business cycle statistics and labour market institutions

Study			Relation with REP			
	var(w)	var(u)	var(y)	var(y/n)	cor(y,w)	cor(w,y/n)
Zanetti	-	+	+		-	
Campolmi & Faia	-					
Gnocchi *et al.*	+	+*	-	-		+
Abbritti & Weber		+*				
Juvonen	-	+	-	-	+*	+
			Relation with EPL			
	var(w)	var(u)	var(y)	var(y/n)	cor(y,w)	cor(w,y/n)
Zanetti	+	-	-		-	
Gnocchi *et al.*	+	+*	-	+		-*
Abbritti & Weber		-*				
Juvonen	-*	+	+	-	+	-
			Relation with Coordination			
	var(w)	var(u)	var(y)	var(y/n)	cor(y,w)	cor(w,y/n)
Gnocchi *et al.*	+*	+	+*	+*		-*
Abbritti & Weber		+*				
Juvonen	-*	-*	+	-	-*	-

Note: * refers to statistically significant relation. Campolmi & Faia (2011) and Zanetti (2011) are theoretical studies and results are obtained from simulations of DSGE models. REP, replacement rate, EPL, employment protection.

tion is related to wage dynamics implying higher volatility of wages if employment protection is low.

The persistence of labour productivity seems to related to the degree of wage setting coordination. It is difficult to reason what could be link from wage coordination to labour productivity since wage coordination should affect foremost wage dynamics. Table 5 presents results when η error terms are omitted. Then also replacement rate and employment protection are related to the persistence of labour productivity. Amaral and Tasci (2016) calibrate a search and matching model for a group of OECD countries and note that persistence in labour productivity has a significant impact on the model outcomes. The results here suggest that labour productivity persistence is related to labour market institutions. Hence obtaining better empirical fit for a search and matching model with cross-country data might require explicit modeling of labour market institutions.

The results of this paper with results from the earlier literature are compared in Table 2. Gnocchi *et al.* (2015) and Abbritti and Weber (2017) are empirical studies. Campolmi and Faia (2011) and Zanetti (2011) are theoretical studies and their results are obtained comparing simulations of DSGE models with changes in the values of parameters that can be interpreted to reflect the strictness of employment protection or replacement rate. Plus indicates that stricter employment protection or higher replacement rate implies greater value for the business cycle statistic.

Overall the evidence is mixed. The results of this paper and Gnocchi *et al.* (2015) indicate similar relation for only half of the cases and less than half of the implications of the theoretical papers are confirmed by empirical studies.

There seems to be statistically significant relation only for few business cycle statistics according to results in Table 1 and the statistically significant relations correspond to p-values of 0,05 or greater. This in contrast to Abbritti and Weber (2017) and Gnocchi *et al.* (2015). Abbritti and Weber (2017) find statistically significant relation for the majority of cases and Gnocchi *et al.* (2015) for roughly half of the cases. Both studies are able to report p-values smaller than 0,05. [15]

The difference between the statistical significance of the results of this paper and Gnocchi *et al.* (2015) and Abbritti and Weber (2017) is driven by the methodology. Table 5 in the Appendix displays the results when η error terms are omitted. There are much more statistically significant relations than in Table 1 and overall the statistical significance is stronger. When η's are omitted the dependence of VAR parameters on labour market institution and control variables is deterministic and the methodology corresponds closely to that in Abbritti and Weber (2017). Gnocchi *et al.* (2015) study the relation between estimated business cycle statistics and labour market institution and control variables. As is usual when employing two-step approaches, the estimated business cycle statistics are treated as observed when doing inference on the relationship between labour market institutions and business cycle statistics which limits the estimation uncertainty.

It is not self evident which approach should be preferred. Arguably the methodology I present here is closer to the data generating process than the model in Abbritti and Weber (2017). This is by construction since I allow for parameter variation in VAR that is not explained by labour market institutions and controls and the unexplained variation is captured by η's. On the other hand there is a risk that the model is overly complex and this could mitigate the statistical relationship between labour market institution variables and business cycle statistics as the model complexity increases estimation uncertainty. This could suggest that the criterion for the statistical significance should be viewed in relation to model complexity. However, no formal procedure exists for this.

To balance between model robustness and over parameterization I have used shrinkage priors for the η error terms as explained in Section 2. Figures 8-10 in the Appendix D plot the η error terms for VAR parameters. It seems that the time-varying part of η is less important than the constant, country specific part. Most important seems to be allowing η error terms for the σ's. Majority of the η's are shrunk to very close to zero which indicates that the used shrinkage procedure is working. This lessens the over parameterization concerns, since parameters that are shrunk tightly close to zero do not increase the overall estimation uncertainty. In this vein the weak statistical relationship between labour market institutions and business cycle dynamics does not seem to be artificially constructed by estimating an overly complex model but instead due to taking estimation uncertainty realistically into account.

Another aspect for the importance of labour market institutions for business cycle dynamics is how much do the differences in labour market institutions explain the variability of business cycle statistics. Besides Faccini *et al.* (2012) this has not been addressed in the literature. Faccini *et al.* (2012) regress labour market institution and control variables on estimated ratios of unemployment volatility to GDP volatility. By comparing the fit of models with and without labour market institution variables they conclude that labour market institutions explain roughly fourth of explained variability. Quantifying the explanatory power labour market institutions is of importance for the policy recommendations. Even if there existed statistically significant relation between labour market institutions and business cy-

[15] The comparison of frequentist p-values and Bayesian posterior distribution is not straight forward. However the comparison here is only illustrative.

Table 3. Measures of relative explanatory powers

	Z_{LMIs}	$Z_{controls}$	η
var(w)	0,29	0,54	0,58
var(u)	0,49	0,59	0,67
var(y)	0,27	0,28	0,41
var(y/n)	0,46	0,23	0,32
cor(y,u)	0,84	1,19	1,21
cor(y,w)	0,77	1,01	1,01
cor(w,u)	0,77	1,04	1,00
cor(u,y/n)	1,55	2,81	7,90
cor(w,y/n)	2,89	0,90	1,77
acor(w)	0,06	0,26	0,26
acor(u)	0,01	0,01	0,01
acor(y)	0,03	0,09	0,10
acor(y/n)	0,17	0,12	0,15

Note: Median relative errors for business cycle statistics when either labour market institution variables, control variables or parameter error terms are omitted.

cle statistics, but the explanatory power of labour market institutions was very little, then probably the efforts in structural reforms should focus to the other aspects of the economy than labour market institutions.

Let G be one of the business cycle statistics in Table 1. To analyze relative importance of the labour market institution variables as a source of explanation for the variability of G calculate

$$|[G(Z_{i,t}^{LMIs}, Z_{i,t}^{controls}, \eta_{i,t}, \theta) - G(0, Z_{i,t}^{controls}, \eta_{i,t}, \theta)]/G(Z_{i,t}^{LMIs}, Z_{i,t}^{controls}, \eta_{i,t}, \theta)|$$

for each data point. This gives relative predictive absolute errors for each data point when labour market institution (LMI) variables are omitted. Similar analysis is carried for the control variables in Z and for η error terms. Table 3 represents the sample medians of this summary statistic. The explanatory power of labour market institutions variables seems to be comparable to explanatory power of control variables. η's capture the parameter variation of the VAR that the labour market institutions and control variables cannot explain. According to Table 3 the relative explanatory power of η's for most of business cycle statistics is higher than explanatory power of labour market institution and control variables, but only to a limited degree.

The control variables include trade to GDP ratio, government consumption to GDP ratio and a euro dummy, which all capture important characteristics of macroeconomic environment. As the explanatory power of labour market institution variables is comparable to these variables this suggest that differences in labour market institutions are related to cross country business cycle variability. η error terms capture freely the unexplained variability in VAR parameters. As the explanatory power of η error terms is not much greater than that of labour market institution or control variables this suggests that the role of labour market institutions as drivers for business cycle heterogeneity is significant.

4.2 Conditional impulse responses

The results from the previous section suggests that there is a relation between business cycle heterogeneity and labour market institution variables. Still the interpretation of the results was not clear since business cycle statistics are reduced form statistics.To get more insight on how labour market institutions are related to shock adjustment, impulse responses conditional on labour market institution variables are calculated. A productivity shock is identified using sign restrictions and an external demand shock is generated by obtaining impulse responses to a positive unitary increase in US GDP growth. Additional details on the procedure are provided in the Appendix C.

Figure 1 displays impulse responses on productivity shock conditional on different categories for labour market institution variables. Identifying assumptions for productivity shock are that real wages (W) and labour productivity (Y/N) respond positively and unemployment U responds negatively. In principle this is a neutral technology shock and identifying assumptions are in line with those in Mumtaz and Zanetti (2015). Impulse responses are normalized to give a unitary increase in labour productivity on impact to get impulse responses across categories comparable. [16]

First three rows of impulse responses in figure 1 show the impulse responses to a productivity shock conditional on different degrees of wage setting coordination. Real wages seem to be more responsive in economies with firm level bargaining than in economies with high wage setting coordination. Also unemployment is more responsive if wage setting coordination is high. Interestingly adjustments through wages, a price, and unemployment, a quantity, do not seem to be substitutes. This could be rationalized by that more responsive wages to positive productivity shock create higher aggregate demand effect due to higher disposable income which in turn lowers the unemployment.

Impulse responses conditional on different values for replacement rate suggest that in economies with generous unemployment benefits real wages and unemployment rate are more responsive. Campolmi and Faia (2011) obtain in their DSGE model analysis that higher replacement increases the responses of unemployment and decreases the responses of real wages. Their argument for the responses of unemployment is that high replacement rate increases steady state wages and hence firm profits are smaller. For a given increase in productivity this results higher percentage increase in profits compared to an economy with lower replacement rate and hence in a high replacement rate economy firms have higher incentive two post new vacancies which then decreases unemployment. Contrary to Campolmi and Faia (2011) also real wages are more responsive when replacement rate is higher, which is difficult to rationalize. One explanation could that again it is due to general equilibrium effects. If unemployment is more responsive, more people move from unemployment to employment which increases their disposable income and through greater aggregate demand this increases the labour demand further and hence amplifies the response of the real wage.

Impulse responses conditional on different values for employment protection do not display significant differences in figure 1. Unemployment is slightly more responsive when employment protection is high, though the difference is not statistically significant. This suggests that in terms of productivity shock stricter employment protection does not create such a rigidity that limits the flows from unemployment

[16]The unnormalized impulse responses show only mild differences for labour productivity across categories for labour market institution variables and qualitative conclusions are the same with unnormalized impulse responses.

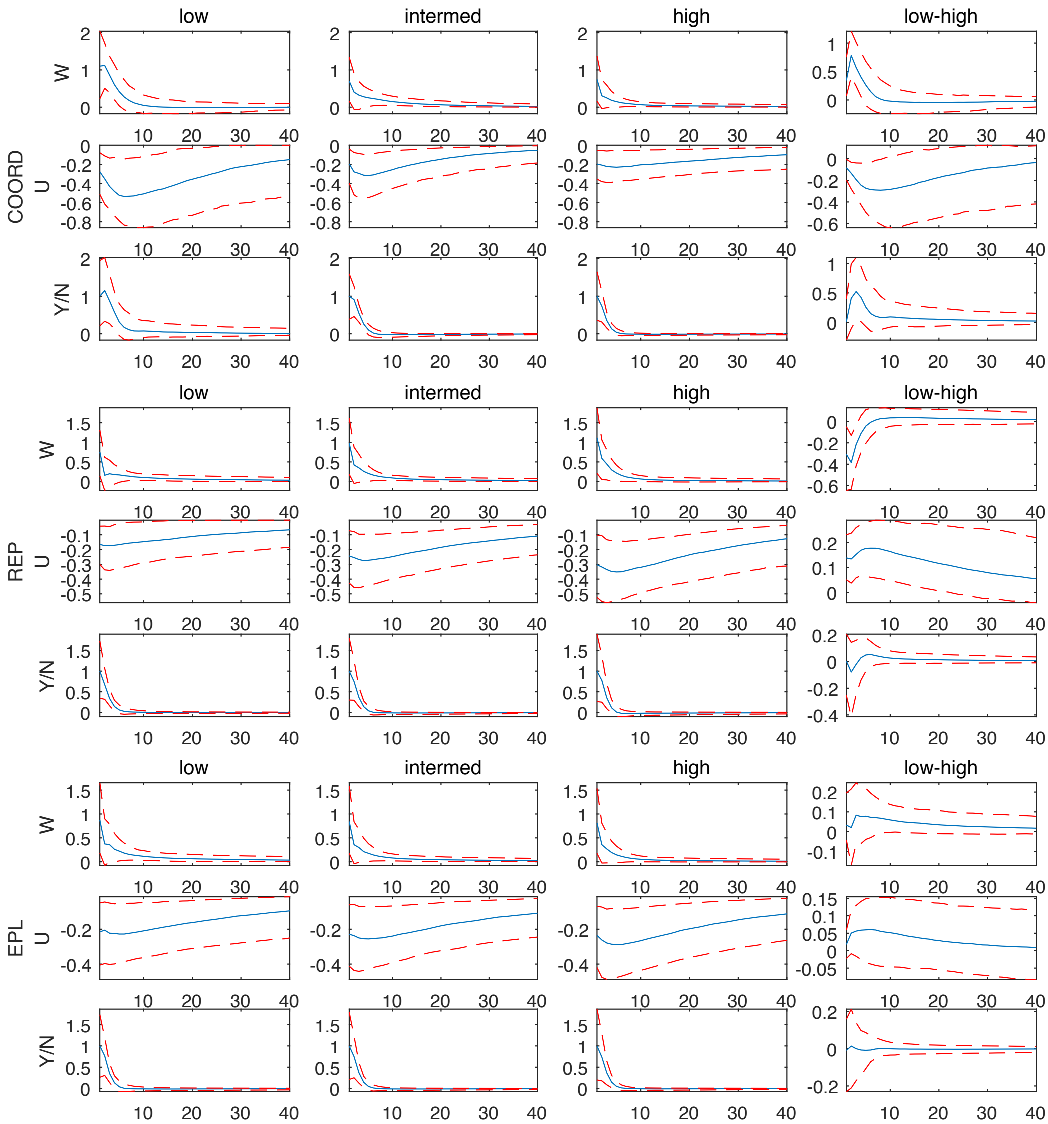

Figure 1. Impulse responses on productivity shock conditional on three categories for wage setting coordination (COORD), replacement rate (REP) and employment protection (EPL). 80% confidence bands that take into account both identification and parameter uncertainty. Impulse responses are normalized to give unitary response on impact for labour productivity Y/N.

to employment after a positive shock. On the other hand, it seems according to these results that given a negative productivity shock stricter employment protection legislation does not significantly reduce the ability of employers to adjust their labour demand and offers only limited degree of protection for the employees against firings.

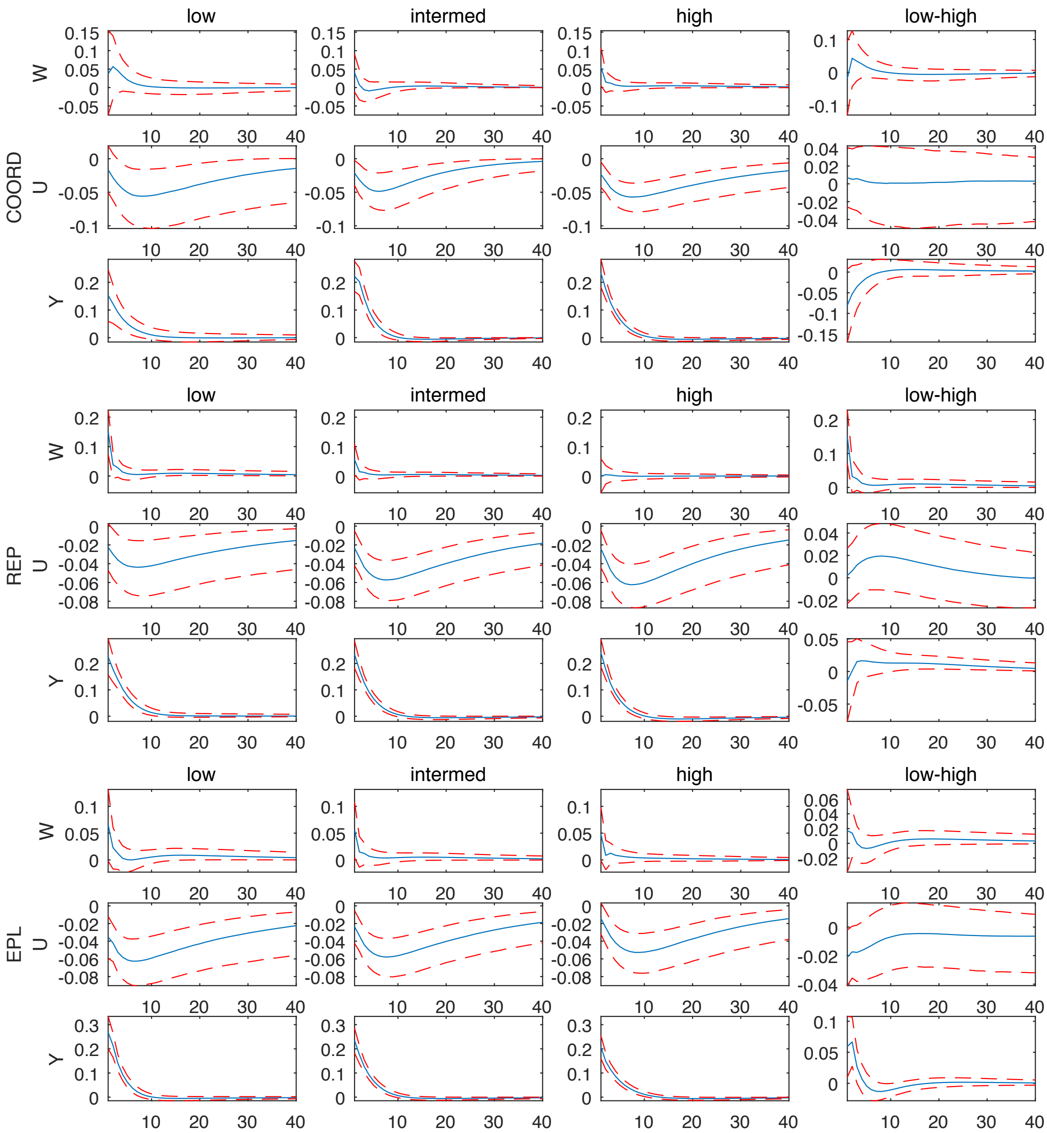

Figure 2. Impulse responses on temporary unit increase in US GDP growth conditional on three categories for wage setting coordination (COORD), replacement rate (REP) and employment protection (EPL). 80% confidence bands.

Analysis of impulse responses on productivity shock reveals how labour market institutions are related to adjustment on domestic shocks. To understand how labour market institutions are related to adjustment on external shocks I obtain impulse responses on a temporary increase in US GDP growth, which is assumed to be exogenous in the estimation. The identification is assumed to capture movements in external demand. Naturally US GDP growth can only capture a fraction of external demand faced by the countries in the sample. However this is a relatively transparent way of obtaining economically interpretable impulse responses and no additional identifying assumptions are required.

Figure 2 displays impulse responses on temporary unit increase in US GDP growth. In terms of coordination there are significant differences only with responses of output, which is more responsive if coordination is high. If anything wages are slightly more responsive if coordination is low as was with the responses to a productivity shock.

If the replacement rate is high the figure 2 shows that real wages are unresponsive to movements in US GSP growth whereas with low replacement real wages show a positive response. Low employment protection is associated with higher responses from unemployment on impact indicating that stricter employment protection does limit flow in and out of unemployment in the context of external demand shock. These results are in line with the results obtained in Abbritti and Weber (2017). They argue for a dichotomy that some labour market institutions restrict wages adjustment whereas others restrict unemployment adjustments. In their classification employment protection is related to unemployment rigidities and replacement rate is related wage rigidities, consistent to what impulse response analysis here implies.

Impulse response analysis suggests that differences in labour market institutions explain heterogeneity in shock adjustment. But again, quantifying the importance of labour market institutions on shock adjustment is difficult on the evidence provided by the impulse response analysis. Most importantly it is difficult to asses from the basis of impulse response analysis, whether labour market reforms are could be able to change the shock adjustment of an economy.

To get insight on how much labour market reforms could change the adjustment of an economy, following counterfactual analysis is conducted. Given a country, run conditional forecast conditional on US GDP growth which is assumed to be exogenous variable. Parameters of the VAR are obtained from the equations (5) and (6), conditionally on the institutional values for this country for this period. Then get another set of parameters for the VAR by changing the values of labour market institution variables in $Z_{i,t}$ and run a counterfactual conditional forecast with these VAR parameters. In the context of one country TVP VAR, Primiceri (2005) and Canova and Gambetti (2009) have employed counter factual analysis to simulate data under a counter factual monetary policy rule.

Figure 3 displays the actual data and conditional forecasts, which are based on actual path of data in $Z_{i,t}$ and variable values that contain a "reform". The country is Finland and the conditional forecasts start from 2008Q4. The time period starts from the beginning financial crisis. On 2019Q1 the Finnish GDP dropped 9 % on annual basis. At same time wage increases that were decided year before were implemented and real wages grew rapidly in 2009 despite the weakening economic conditions. This exercise tries to asses would the adjustment had been sounder if Finland had had different labour market institutions.

In the first panel the wage setting coordination variable is changed from high coordination to low coordination. In the second panel the value for replacement rate variable is changed. The actual value for Finland for replacement rate in 2009 corresponds to 42nd sample percentile, which is changed to 22nd percentile in the sample. In the third panel the value for employment protection is changed from the actual value which corresponds to 50th sample percentile to 30th sample percentile. In the fourth panel all these reforms are implemented.

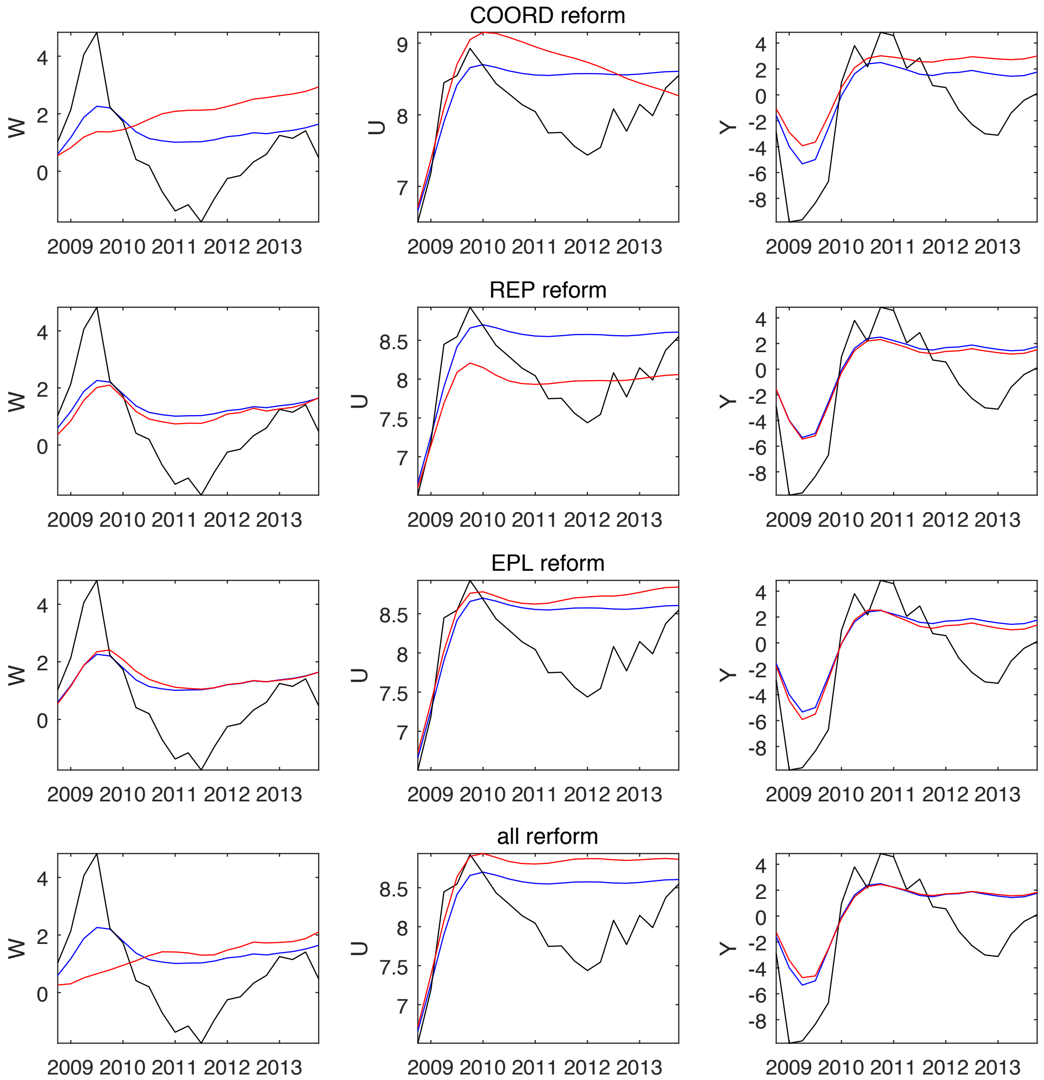

Figure 3. Conditional forecasts. Black line:data (Finland), blue line: conditional forecast, red line: conditional forecast with a reform. W:real wage growth, U:unemployment, Y: GDP growth

One difference to impulse response analysis is that now also the changes in intercepts matter. The unconditional means that VARs under different parameter values imply are different, which is behind the biggest level shifts. According to figure 3 it seems that employment protection reforms have fairly little to change the dynamics of an economy whereas wage setting coordination and unemployment benefit reforms have more scope. The results suggest that given a decentralized wage setting system, the initial impact of real wages would have been more favorable and GDP would have declined slightly less.

According to figure 3 the rise in unemployment would have been smaller if replacement rate had been lower. However this is not associated with a change in GDP developments. One explanation for this would be that given a lower replacement rate workers are willing to accept jobs with lower wages and lower productivity. This is beneficial for the unemployment but does not change much the GDP.

When all reforms are implemented, last row in figure 3, interesting result emerges. Real wages give a favorable adjustment in the beginning as was with a coordination reform only. However afterwards the real wage growth is more modest. This suggest that the interaction effects of labour market institutions are important. Move to a firm level wage setting in an economy where replacement rates are high could lead to high wage demands, since high replacement rate gives better outside option and hence increases the bargaining power of a worker.

One way of seeing figure 3 is that although the counterfactuals do seem to differ from the actual conditional forecasts, the differences are small compared to fluctuations that the data display. This suggest that labour market reforms can change the average dynamics of an economy over time, but offering labour market reforms as a cure for a crisis country is not backed by these results since the changes that reforms can potentially bring are small compared to the fluctuations that a country dwells in during a crisis time.

5 Conclusions

The relation of labour market institutions on business cycle dynamics was studied using a TVP VAR estimated on a panel of countries. Results suggest that labour market institutions have explanatory power for the heterogeneity in the volatilities of macroeconomic variables and in shock adjustment. In countries with high coordination in the wage bargaining wages are less volatile and respond less on productivity shocks. In countries with strict employment protection legislation wages are less volatile and unemployment is less responsive on external demand shocks. If unemployment benefits are generous unemployment and wages are more responsive to productivity shocks. The explanatory power of labour market institutions for business cycle heterogeneity seems to comparable to that of used control variables (trade to GDP, government consumption to GDP and Euro dummy). When trying to asses the scope that labour marker reforms could achieve in changing the shocks adjustment process of an economy, the results speak for only modest changes.

Growing number of papers studies the relation of institutions and macroeconomic characteristics on macroeconomic dynamics. For many countries the series for institutions and macroeconomic characteristics have not been before enough long for consistent estimation and hence better data availability in the near future might increase the attractiveness of this approach. In this paper of I have presented a Bayesian hierarchical estimation procedure that explicitly models the dependence of VAR parameters on institutional variables while allowing for unexplained parameter variation. Essentially, allowing for unexplained parameter variation makes the relation between institutional variables and VAR parameters stochastic whereas neglecting the unexplained parameter variation makes the relation deterministic. I have illustrated that assumption on deterministic or stochastic relations is crucial for the inference. Another distinction across studies is wether the comparison criteria, be it a business cycle statistic or a impulse response, is estimated first and then linked to institutional variables or as I have done, a (VAR) model is first estimated with a relation between model parameters and institutional variables and then comparison is made between model implied business cycle statistics and impulse responses conditional on institutional variables. Further research is needed to bring an established way of modeling heterogenous dynamics with institutional variables in order to make the results across studies more comparable and to understand the merits and pitfalls of different approaches.

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A Gibbs sampler algorithm for the restricted model

Model is given by

$$y_{\mathrm{i,t}} = X_{\mathrm{i,t}}\beta_{\mathrm{i,t}} + e_{\mathrm{i,t}}, \qquad e_{\mathrm{i,t}} \sim \mathrm{N}(0, \Omega_{\mathrm{i,t}}) \tag{12}$$

where $X_{i,t}$ includes lags of depended variables and a constant and exogenous variables. The variance-covariance matrix $\Omega_{\mathrm{i,t}}$ is decomposed with

$$A_{\mathrm{i,t}}\Omega_{\mathrm{i,t}}A'_{\mathrm{i,t}} = \Sigma_{\mathrm{i,t}}\Sigma'_{\mathrm{i,t}} \tag{13}$$

where $A_{\mathrm{i,t}}$ is a lower diagonal matrix with ones on the diagonal and $\Sigma_{\mathrm{i,t}}$ is a diagonal matrix. The evolution of the coefficients $\beta_{\mathrm{i,t}}$, and elements in $A_{\mathrm{i,t}}$ ($a_{i,t}$'s) and $\Sigma_{\mathrm{i,t}}$ ($\sigma_{\mathrm{i,t}}$'s) is given by the constants and the labour market institution variables in $Z_{i,t}$.

$$\begin{bmatrix} \beta_{\mathrm{i,t}} \\ a_{\mathrm{i,t}} \\ log(\sigma_{\mathrm{i,t}}) \end{bmatrix} = Z_{\mathrm{i,t}} \begin{bmatrix} \theta_\beta \\ \theta_a \\ \theta_\sigma \end{bmatrix} \tag{14}$$

A model that allows for error terms in (14) is introduced in section B.

In what follows, a stacked form of (12) is used in it is given as

$$Y = X\beta + E \qquad E \sim N(0, \Omega) \tag{15}$$

where $Y = \left[y'_{1,1}, y'_{1,2} \dots y'_{N,T}\right]'$, $\beta = \left[\beta'_{1,1}, \beta'_{1,2} \dots \beta'_{N,T}\right]$, $E = \left[e_{1,1}, e_{1,2} \dots e_{N,T}\right]$ and

$$X = \begin{bmatrix} X_{1,1} & & & \\ & X_{1,2} & & \\ & & \ddots & \\ & & & X_{N,T} \end{bmatrix}, \Omega = \begin{bmatrix} \Omega_{1,1} & & & \\ & \Omega_{1,2} & & \\ & & \ddots & \\ & & & \Omega_{N,T} \end{bmatrix}$$

Parameters in (14) do not have analytical joint distributions but conditional distributions can be derived following Primiceri (2005) and posterior sampling can be done using Gibbs sampler. Namely, the parameters are sampled block by block conditional on a draw of all other parameters. Rest of this section shows these steps.

A.1 Drawing θ_β

Substitute $\beta_{i,t} = Z_{i,t}\theta_\beta$ and with appropriately defined block diagonal matrices

$$Y = XZ\theta_\beta + E \tag{16}$$

(16) is essentially a normal linear regression model. Given Ω, the posterior distribution of θ_β is (see e.g.)

$$V_{\theta_\beta} = (D^{-1}_{\theta_\beta} + Z'X\Omega XZ)^{-1} \tag{17}$$

$$\bar{\theta}_\beta = V_{\theta_\beta}(D^{-1}_{\theta_\beta}\underline{\theta}_\beta + Z'X'\Omega y) \tag{18}$$

$$\theta_\beta| \sim N(\bar{\theta}_\beta, V_{\theta_\beta}) \tag{19}$$

D_{θ_β} is the prior variance-covariance matrix and $\underline{\theta}_\beta$ is the prior mean.

A.2 Drawing θ_a

Equations (12) and (13) can be combined to yield

$$y_{i,t} = X_{i,t}\beta_{i,t} + A_{i,t}^{-1}\Sigma_{i,t}\epsilon_{i,t} \tag{20}$$

where $\epsilon_{i,t} \sim N(0,1)$. Rearrange to get

$$A_{i,t}(y_{i,t} - X_{i,t}\beta_{i,t}) = A_{i,t}\hat{y}_{i,t} = \Sigma_{i,t}\epsilon_{i,t} \tag{21}$$

$A_{i,t}$ is lower diagonal matrix and (21) can be written as

$$\begin{bmatrix} 1 & 0 & 0 \\ a_{i,t}^1 & 1 & 0 \\ a_{i,t}^2 & a_{i,t}^3 & 1 \end{bmatrix} \begin{bmatrix} \hat{y}_{i,t}^1 \\ \hat{y}_{i,t}^2 \\ \hat{y}_{i,t}^3 \end{bmatrix} = \Sigma_{i,t}\epsilon_{i,t} \tag{22}$$

Omit the first equation from (22) and rewrite it as

$$\begin{bmatrix} \hat{y}_{i,t}^2 \\ \hat{y}_{i,t}^3 \end{bmatrix} = \begin{bmatrix} a_{i,t}^1 & 0 \\ a_{i,t}^2 & a_{i,t}^3 \end{bmatrix} \begin{bmatrix} -\hat{y}_{i,t}^1 \\ -\hat{y}_{i,t}^2 \end{bmatrix} + \begin{bmatrix} \sigma_{i,t}^2 & 0 \\ 0 & \sigma_{i,t}^3 \end{bmatrix} \begin{bmatrix} \epsilon_{i,t}^1 \\ \epsilon_{i,t}^2 \end{bmatrix} \tag{23}$$

And more compactly as

$$\ddot{y}_{i,t} = \tilde{A}_{i,t}\tilde{y}_{i,t} + \tilde{\Sigma}_{i,t}\tilde{\epsilon}_{i,t} \tag{24}$$

Conditionally on $\tilde{y}_{i,t}$ and $\tilde{\Sigma}_{i,t}$,the elements of $A_{i,t}$ can be sampled using results for normal linear regression. Although $\tilde{A}_{i,t}$ is a reduced matrix of $A_{i,t}$ it contains all the unknown elements of $A_{i,t}$. Substitute $\tilde{A}_{i,t} = Z_{i,t}\theta_a$ to (26) and with appropriately defined block diagonal matrices one gets

$$\ddot{Y} = \tilde{Y}Z\theta_a + \tilde{\Sigma}\tilde{\epsilon} \tag{25}$$

θ_a can be sampled with

$$V_{\theta_a} = (D_{\theta_a}^{-1} + Z'\tilde{Y}'\tilde{\Sigma}\tilde{\Sigma}\tilde{Y}Z)^{-1} \tag{26}$$

$$\bar{\theta}_a = V_{\theta_a}(D_{\theta_a}^{-1}\underline{\theta}_a + Z'\tilde{Y}'\tilde{\Sigma}\tilde{\Sigma}\ddot{y}) \tag{27}$$

$$\theta_a| \sim N(\bar{\theta}_a, V_{\theta_a}) \tag{28}$$

A.3 Drawing θ_σ

Given $A_{i,t}$

$$A_{i,t}(y_{i,t} - X_{i,t}\beta_{i,t}) = y_{i,t}^* = \Sigma_{i,t}\epsilon_{i,t} \tag{29}$$

Equation (29) is nonlinear but can be linearized by squaring and taking logs yielding

$$y_{i,t}^{**} = 2h_{i,t} + \epsilon_{i,t}^{**} \tag{30}$$

where $h_{i,t} = log(\sigma_{i,t})$; $\epsilon^{**}_{i,t} = log(\epsilon^2_{i,t})$; $y^{**}_{i,t} = log[(y^*_{i,t})^2 + \bar{c}]$. $\bar{c}$ is an offset constant to avoid numerical problems in the estimation since squared $y^*_{i,t}$ can be very small. (32) is linear but not Gaussian. $\epsilon_{i,t}$ is distributed Normally with unitary variance. Hence $\epsilon^{**}_{i,t}$ is distributed as a log $\chi^2(1)$. To transform (30) into Gaussian, a mixture of normals approximations of the log χ^2 is used, as is described Kim, Shepard and Chip (1998). Denote var($\epsilon^{**}_{i,t}$)= $S_{i,t}$ when the distribution of $\epsilon^{**}_{i,t}$ is approximated with a mixture of normal distributions.

Substitute $h_{i,t} = Z_{i,t}\theta_\sigma$ to (32) and with appropriately defined block diagonal matrices one gets[17]

$$Y^{**} = \mathbf{2}Z\theta_\sigma + \epsilon^{**} \tag{31}$$

θ_σ can be sampled with

$$V_{\theta_\sigma} = (D^{-1}_{\theta_\sigma} + Z'\mathbf{2}'S\mathbf{2}Z)^{-1} \tag{32}$$

$$\bar{\theta}_\sigma = V_{\theta_\sigma}(D^{-1}_{\theta_\sigma}\underline{\theta}_\sigma + Z'\mathbf{2}'SY^{**}) \tag{33}$$

$$\theta_\sigma| \sim N(\bar{\theta}_\sigma V_{\theta_\sigma}) \tag{34}$$

5.1 A.4 Summary

B Gibbs sampler algorithm for the general model

This section specifies Gibbs sampler algorithm for a model which allows for unit specific and time varying error terms in the VAR parameters. VAR model is given in (12) and (13) but instead of (14), VAR parameters are assumed to follow

$$\begin{bmatrix} \beta_{\mathrm{i,t}} \\ a_{\mathrm{i,t}} \\ log(\sigma_{\mathrm{i,t}}) \end{bmatrix} = Z_{\mathrm{i,t}} \begin{bmatrix} \theta_\beta \\ \theta_a \\ \theta_\sigma \end{bmatrix} + \omega_{\mathrm{i}}\tilde{\eta}_{\mathrm{i,t}} + \eta_{\mathrm{i}} \tag{35}$$

$$\tilde{\eta}_{i,t} = \tilde{\eta}_{i,t-1} + u_{i,t}, u_{i,t} \sim N(0, I) \tag{36}$$

$$\tilde{\eta}_{i,0} = 0 \tag{37}$$

Start by substituting (37) to (12) and obtain

$$y_{i,t} = X_{i,t}Z_{i,t}\theta_\beta + X_{i,t}\omega^\beta_i\tilde{\eta}^\beta_{i,t} + X_{i,t}\eta^\beta_i + e_{i,t} \tag{38}$$

In what follows, β subscripts are omitted to simplify the notation.
Conditional on $\omega_i\eta_{i,t}, \eta_i$ and $\Omega_{i,t}$ posterior for θ is given by

$$\bar{\theta} = V_\theta(D^{-1}_\theta\underline{\theta} + Z'X'\Omega(y - X\omega\tilde{\eta} - X\eta)) \tag{39}$$

$$\theta| \sim N(\bar{\theta}, V_\theta) \tag{40}$$

[17] $\mathbf{2}$ refers to a diagonal matrix with diagonal entries equaling 2.

The posterior of η can be sampled with

$$V_\eta = (D_\eta^{-1} + X'\Omega X)^{-1} \tag{41}$$

$$\bar{\eta} = V_\eta(D_\eta^{-1}\underline{\eta} + X'\Omega(y - X\omega\tilde{\eta} - XZ\theta)) \tag{42}$$

$$\eta| \sim N(\bar{\eta}, V_\eta) \tag{43}$$

Conditional on ω, η, θ and Ω the simulation of $\tilde{\eta}$ could be carried out using the standard procedure in TVP-model literature, which uses Kalman filtering. However, when working with a macro panel data, this results that the Kalman filtering loops are not of size T but of size NT, which increases the computation time. Hence I use alternative simulation approach by Chan and Jeliazkov (2009), which simulates the latent states of a TVP model without the need for loops and with one step.

The law of motion for $\tilde{\eta}$ in (36) and (37) can be written compactly as

$$H\tilde{\eta} = u, \qquad u \sim N(0, S_u) \tag{44}$$

where

$$H = \begin{bmatrix} I & & & & \\ -I & I & & & \\ & -I & I & & \\ & & \ddots & \ddots & \\ & & & -I & I \end{bmatrix}, S_u = \begin{bmatrix} 0 & & & & \\ & 1 & & & \\ & & 1 & & \\ & & & \ddots & \\ & & & & 1 \end{bmatrix} \tag{45}$$

(45) implies that prior for η is $\tilde{\eta} \sim N(0, K^{-1})$ where $K = H'S_u^{-1}H$

The posterior simulation of η uses again the fact that conditional on other parameters (40) is simply a normal linear regression model.

$$V_\eta = (K + X'\omega'\Omega X\omega) \tag{46}$$

$$\bar{\bar{\eta}} = V_\eta^{-1}(\omega'\Omega(y - XZ\theta - X\eta_i)) \tag{47}$$

$$\eta \sim N(\bar{\bar{\eta}}, V_\eta^{-1}) \tag{48}$$

The merit of the approach by Chan and Jeliazkov (2009) is that instead of inverting the very large matrix V_η , the simulation can be implemented using only Cholesky factors of V_η.[18] This is efficient since V_η is sparse matrix, containing non-zero elements only close to diagonal.

Given $\eta, \eta, \theta, \Omega$ ω can be sampled with

$$V_\omega = (K + X'\tilde{\eta}'\Omega X\tilde{\eta}) \tag{49}$$

$$\bar{\omega} = V_\omega^{-1}(\tilde{\eta}'\Omega(y - XZ\theta - X\eta)) \tag{50}$$

$$\omega \sim N(\bar{\omega}, V_\omega^{-1}) \tag{51}$$

[18] The columns and rows of V_η are of length NT times the number of coefficients, over 30 000 in the application of this study.

B.2 Update prior variances

The prior variance for η_i is a diagonal matrix, D_η and each element is distributed individually as

$$\tau_i^2 \sim exp\left(\frac{\lambda^2}{2}\right) \tag{52}$$

and the posterior is given by inverse Gaussian:

$$\tau_i^2 \sim IG\left(\sqrt{\frac{\lambda^2}{\eta_i^2}}, \lambda^2\right) \tag{53}$$

and λ is updated with

$$\lambda \sim Gamma\big(n_\eta + a_1, \frac{1}{2}\sum_{j=1}^{n_\eta} \tau_j + a_2\big) \tag{54}$$

where n_η is the length of η vector.

The prior variance for ω_i is a diagonal matrix, D_ω and each element is distributed individually as

$$\xi_i^2 \sim exp\left(\frac{\kappa^2}{2}\right) \tag{55}$$

and the posterior is given by inverse Gaussian:

$$\xi^2 \sim IG\left(\sqrt{\frac{\kappa^2}{\omega_i^2}}, \kappa^2\right) \tag{56}$$

and κ is updated with

$$\kappa \sim Gamma\big(n_\omega + b_1, \frac{1}{2}\sum_{j=1}^{n_{\beta_i}} \xi_j + b_2\big) \tag{57}$$

This section has presented how to simulate conditional posterior distributions for the parameters related to VAR coefficients. Similar logic applies to the posterior simulation of parameters related to $a_{i,t}$'s and $\sigma_{i,t}$'s. Hence these steps are not reported here but are available upon a request.

C Conditional business cycle statistics and impulse responses

This section explains how business cycle statistics and impulse responses are obtained conditional on institutional variables. Given distributions for θ's and η's VAR parameters can be simulated using equations (35) after specific values are given for variables in $Z_{i,t}$.

After VAR parameters are obtained, moments from the VAR can be computed according to following formulas. Omit the intercepts, separate endogenous and exogenous variables (US GDP) and rewrite the VAR in companion form as

$$Y_{i,t} = B_y Y_{i,t-1} + B_x X_{i,t} + E_{i,t} \qquad E_{i,t} \sim N(0, \Sigma_{E_{i,t}})) \tag{58}$$

where $Y_{i,t} = \begin{bmatrix} y_{i,t} & y_{i,t-1} & \dots & y_{t-q+1} \end{bmatrix}$.

The unconditional variances and covariances of $Y_{i,t}$ are given by

$$\begin{aligned} &E[(Y_{i,t} - E(Y_{i,t}))(Y_{i,t} - E(Y_{i,t}))] \\ = &E[((B_y Y_{i,t-1} + B_x X_{i,t} + E_{i,t}) - E(B_y Y_{i,t-1} + B_x X_{i,t})) \\ &\times((B_y Y_{i,t-1} + B_x X_{i,t} + E_{i,t}) - E(B_y Y_{i,t-1} + B_x X_{i,t}))] \end{aligned} \tag{59}$$

Given fixed values in Z and η, VAR parameters are constant and covariance stationarity can be safely assumed. Together with assuming the exogeneity of $X_{i,t}$, $cov(Y_{i,t-1}, X_{i,t}) = 0$,(59) leads to

$$\Sigma_y = B_y \Sigma_y B_y' + B_x \Sigma_x B_x' + \Sigma_E \tag{60}$$

Σ_y can be solved with formula (see Canova (2007) for closer details):

$$vec(\Sigma_Y) = [I - B_y \otimes B_y]^{-1} vec(B_x \Sigma_x B_x' + \Sigma_E) \tag{61}$$

Auto covariances can be obtained with $ACF(\tau) = B_y^{\tau} \Sigma_Y$

The sign-identified impulse responses are obtained as in Rubio-Ramírez, Waggoner and Zha (2010). Given variance-covariance matrix of the residuals, Ω obtain Cholesky decomposition $PP' = \Omega$. Draw N times N matrix J, from N(0,1) distribution. Take QR decomposition for J, that is J=QR. A candidate impact matrix is given as $M = PQ$. If this satisfies the restrictions, it is stored. In the application of this study there is always three Ω's, corresponding to three regimes, high, intermediate and low. It is required that all $P_{high}Q, P_{intermed}Q$ and $P_{low}Q$ satisfy the sign-restrictions.

D Additional tables and figures

Table 4. Conditional business cycle statistics, pre-2009 data

	COORD			REP			EPL		
	Low	Intermed	High	Low	Intermed	High	Low	Intermed	High
var(w)	1,9''	1,05	0,97	1,07	0,98	0,98	1,11	0,97	0,91
	1 4,27	0,74 1,61	0,7 1,35	0,77 1,57	0,77 1,26	0,74 1,32	0,78 1,62	0,77 1,25	0,71 1,19
var(u)	1,56	1,02	0,98	1,42	1,1	1,01	1,04	1,13	1,32
	0,63 7,54	0,61 2,02	0,59 2,06	0,69 4,74	0,66 2,15	0,59 2,23	0,53 3,45	0,67 2,23	0,81 2,42
var(y)	1,45	1,12	1,12	1,59	1,42	1,38	1,31	1,42'	1,66
	0,84 2,92	0,85 1,51	0,85 1,45	1,12 2,37	1,05 1,95	0,97 2,03	0,98 1,74	1,13 1,8	1,31 2,14
var(y/n)	3,21*	1,13	1,14	1,51	1,28	1,24	1,22	1,33'	1,55
	1,62 8,84	0,88 1,48	0,88 1,49	0,84 2,95	0,78 2,17	0,69 2,37	0,92 1,66	1,04 1,7	1,23 1,99
cor(y,u)	-0,15	-0,19''	-0,03	-0,07	-0,06	-0,07	-0,07	-0,06	-0,05
	-0,53 0,21	-0,31 -0,06	-0,15 0,1	-0,2 0,11	-0,18 0,06	-0,19 0,07	-0,21 0,1	-0,17 0,06	-0,17 0,08
cor(y,w)	-0,11	-0,01	-0,04	-0,05	-0,07	-0,08	-0,08	-0,05	0
	-0,41 0,19	-0,18 0,15	-0,15 0,07	-0,2 0,11	-0,18 0,04	-0,2 0,04	-0,24 0,09	-0,16 0,07	-0,11 0,11
cor(w,u)	0	-0,05	0,01	-0,05	0,02	0,05	0,02	0,01	-0,01
	-0,33 0,29	-0,25 0,14	-0,16 0,16	-0,34 0,16	-0,15 0,18	-0,14 0,22	-0,25 0,24	-0,16 0,17	-0,18 0,16
cor(u,y/n)	-0,16	-0,11''	0,05	-0,05	-0,02	0,02	-0,07'	-0,02'	0,05
	-0,53 0,19	-0,21 0	-0,06 0,16	-0,17 0,07	-0,13 0,1	-0,11 0,17	-0,21 0,07	-0,13 0,09	-0,06 0,17
cor(w,y/n)	-0,06	-0,02	0,04	0,1	0,05	0,01	0,1	0,07	0,01
	-0,49 0,33	-0,17 0,12	-0,07 0,15	-0,03 0,25	-0,05 0,16	-0,11 0,13	-0,05 0,25	-0,04 0,18	-0,1 0,11
acor(w)	0,66'	0,67''	0,54	0,55	0,55	0,55	0,57	0,54	0,53
	0,53 0,83	0,56 0,77	0,44 0,64	0,44 0,67	0,47 0,62	0,47 0,63	0,47 0,68	0,47 0,62	0,45 0,61
acor(u)	0,97	0,97	0,97	0,98	0,97	0,97	0,97	0,97	0,98
	0,94 0,99	0,96 0,98	0,95 0,99	0,96 0,99	0,96 0,99	0,95 0,99	0,95 0,99	0,96 0,99	0,97 0,99
acor(y)	0,79''	0,69	0,67	0,61'	0,67''	0,7	0,65	0,67	0,7
	0,7 0,89	0,62 0,75	0,62 0,72	0,54 0,69	0,62 0,72	0,65 0,76	0,58 0,72	0,62 0,72	0,64 0,75
acor(y/n)	0,83**	0,58	0,6	0,54'	0,6'	0,64	0,58	0,6'	0,64
	0,68 0,98	0,47 0,69	0,52 0,69	0 0	0 0	0 0	0,51 0,65	0,55 0,66	0,59 0,7

Note: Intervals refer to 80% confidence set. The distributions of low and intermediate regimes are compared to that of high.' refer to zero is not included to 80 % highest density region of distribution for the difference.", * ,** refer to 90, 95 and 99 highest density regions.

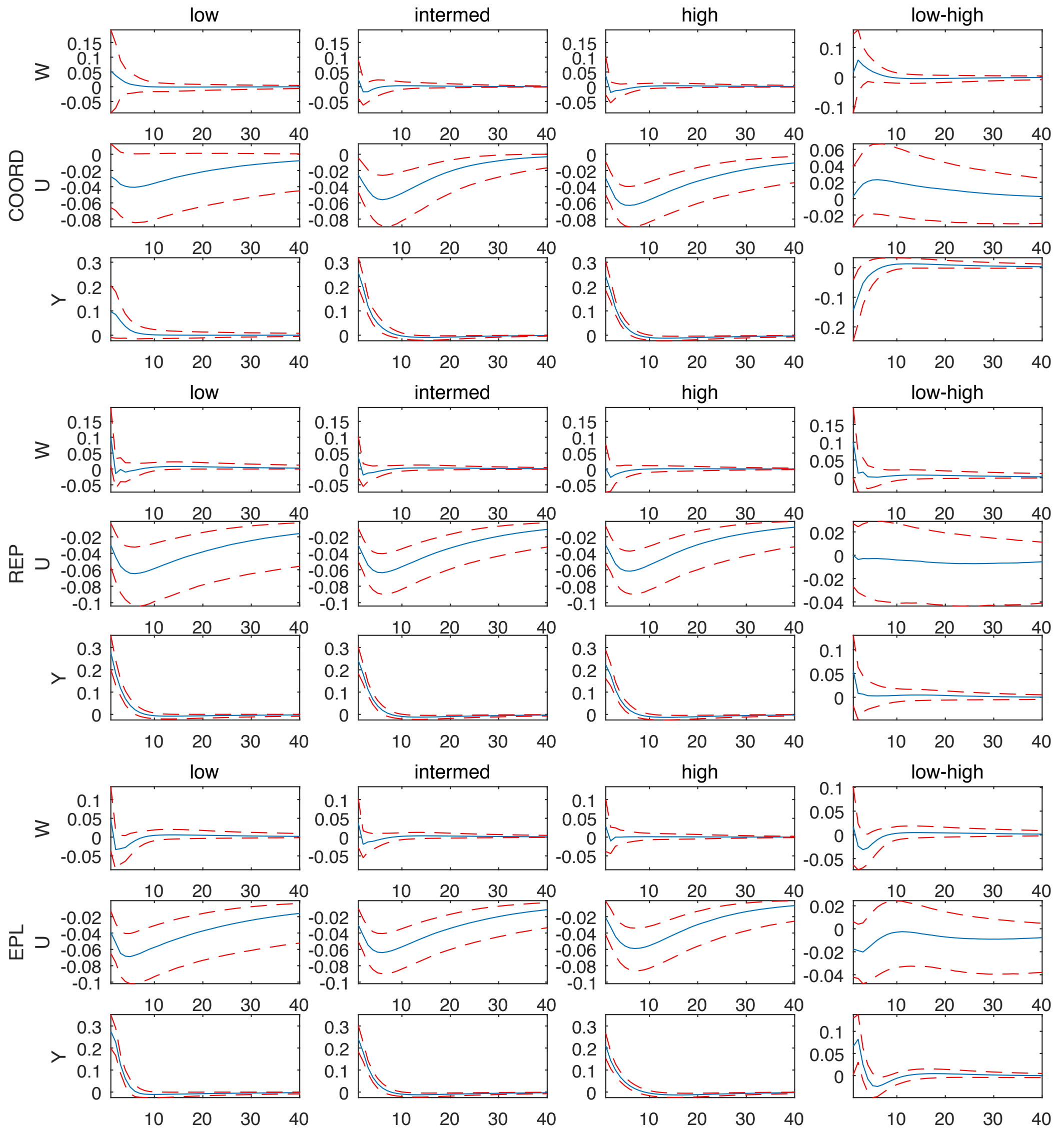

Figure 4. Impulse responses on temporary unit increase in US GDP growth conditional on three categories for wage setting coordination (COORD), replacement rate (REP) and employment protection (EPL), pre-2009 data. 80% confidence bands.

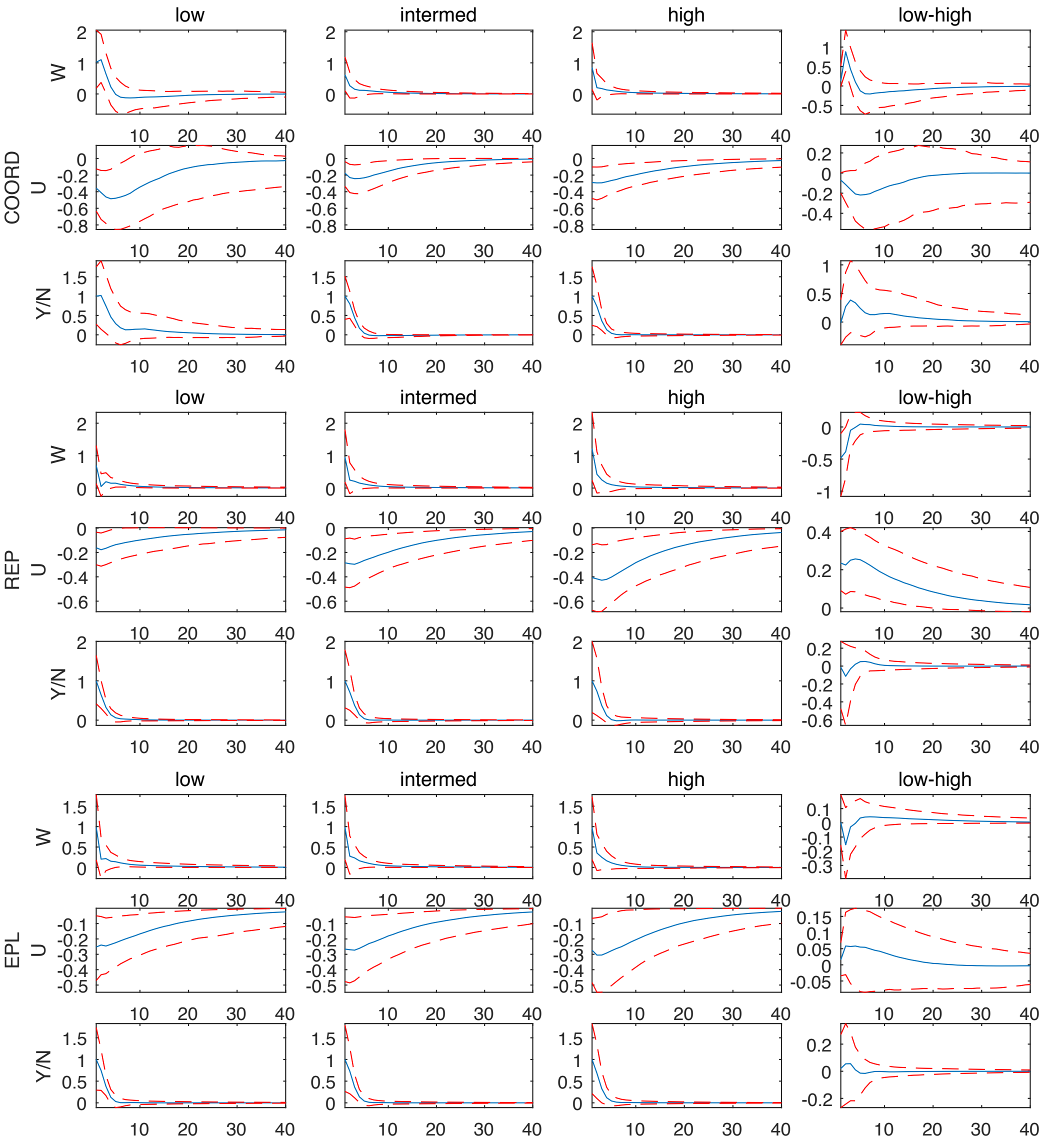

Figure 5. Impulse responses on productivity shock conditional on three categories for wage setting coordination (COORD), replacement rate (REP) and employment protection (EPL),pre-2009 data. 80% confidence bands that take into account both identification and parameter uncertainty. Impulse responses are normalized to give unitary response on impact for labour productivity Y/N.

Table 5. Conditional business cycle statistics, pre-2009 data, model without error terms for the VAR parameters

	COORD			REP			EPL		
	Low	Intermed	High	Low	Intermed	High	Low	Intermed	High
var(w)	2,07**	1,42''	1,02	1,39**	1,03*	0,92	0,73**	1,03**	1,55
	1,53 2,98	1,1 1,92	0,9 1,18	1,04 1,92	0,84 1,29	0,74 1,16	0,6 0,92	0,9 1,19	1,37 1,79
var(u)	1,28''	1,04	0,46	1,21**	0,55**	0,38	0,39*	0,56**	0,85
	0,46 16,62	0,61 2,14	0,32 0,79	0,84 1,99	0,41 0,77	0,28 0,55	0,22 0,86	0,36 0,98	0,56 1,49
var(y)	0,92	1,21	1,16	2,43**	1,51*	1,25	1,48'	1,59''	1,8
	0,58 1,65	0,97 1,52	0,99 1,39	1,91 3,18	1,17 2	0,88 1,81	1,14 1,98	1,24 2,09	1,37 2,45
var(y/n)	0,91	1,2	1,08	2,11**	1,35**	1,11	1,35	1,41'	1,58
	0,58 1,79	0,99 1,47	0,92 1,29	1,62 2,8	1,03 1,81	0,78 1,62	1,12 1,63	1,19 1,68	1,28 1,95
cor(y,u)	0	-0,13''	0	-0,01	-0,06	-0,09	-0,09	-0,07	-0,04
	-0,32 0,4	-0,22 -0,03	-0,08 0,09	-0,11 0,09	-0,14 0,03	-0,18 0	-0,17 0	-0,15 0,02	-0,14 0,07
cor(y,w)	-0,38''	0,08	-0,06	-0,1	-0,07	-0,06	-0,12	-0,07	-0,03
	-0,6 -0,14	-0,08 0,23	-0,16 0,03	-0,25 0,04	-0,2 0,06	-0,21 0,08	-0,26 0,03	-0,18 0,03	-0,12 0,07
cor(w,u)	-0,03	0,05	0,1	0,08	0,12	0,11	0,18	0,12	0,06
	-0,28 0,18	-0,13 0,21	0,02 0,19	-0,07 0,21	0,02 0,21	0,02 0,21	0,04 0,31	0,02 0,21	-0,03 0,15
cor(u,y/n)	-0,12	-0,08*	0,13	0,04	0,01	0	-0,06*	0,00*	0,11
	-0,45 0,26	-0,19 0,04	0,03 0,23	-0,07 0,16	-0,09 0,12	-0,12 0,12	-0,16 0,05	-0,1 0,11	-0,01 0,23
cor(w,y/n)	-0,19	0,01	0,01	0,05	0,05	0,03	-0,02	0,03	0,05
	-0,65 0,27	-0,21 0,23	-0,14 0,17	-0,07 0,18	-0,06 0,15	-0,09 0,14	-0,17 0,12	-0,08 0,14	-0,06 0,15
acor(w)	0,64**	0,69**	0,45	0,46	0,45	0,44	0,54*	0,45*	0,37
	0,45 0,9	0,51 0,86	0,31 0,58	0,25 0,66	0,3 0,58	0,3 0,58	0,36 0,72	0,3 0,58	0,22 0,51
acor(u)	0,97	0,97''	0,95	0,97*	0,96''	0,95	0,95	0,96	0,96
	0,94' 1	0,95 0,98	0,93 0,97	0,94 0,99	0,93 0,98	0,91 0,98	0,91 0,97	0,94 0,97	0,94 0,98
acor(y)	0,77*	0,64	0,61	0,52*	0,62*	0,66	0,6	0,62	0,64
	0,67 0,87	0,57 0,7	0,55 0,67	0,32 0,68	0,5 0,72	0,54 0,78	0,53 0,65	0,56 0,67	0,58 0,7
acor(y/n)	0,75*	0,56	0,57	0,51*	0,57*	0,6	0,53'	0,57''	0,61
	0,64 0,87	0,48 0,63	0,5 0,63	0,34 0,66	0,44 0,69	0,45 0,73	0,46 0,6	0,5 0,62	0,54 0,68

Note: Intervals refer to 80% confidence set. The distributions of low and intermediate regimes are compared to that of high.' refer to zero is not included to 80 % highest density region of distribution for the difference.", * ,** refer to 90, 95 and 99 highest density regions.

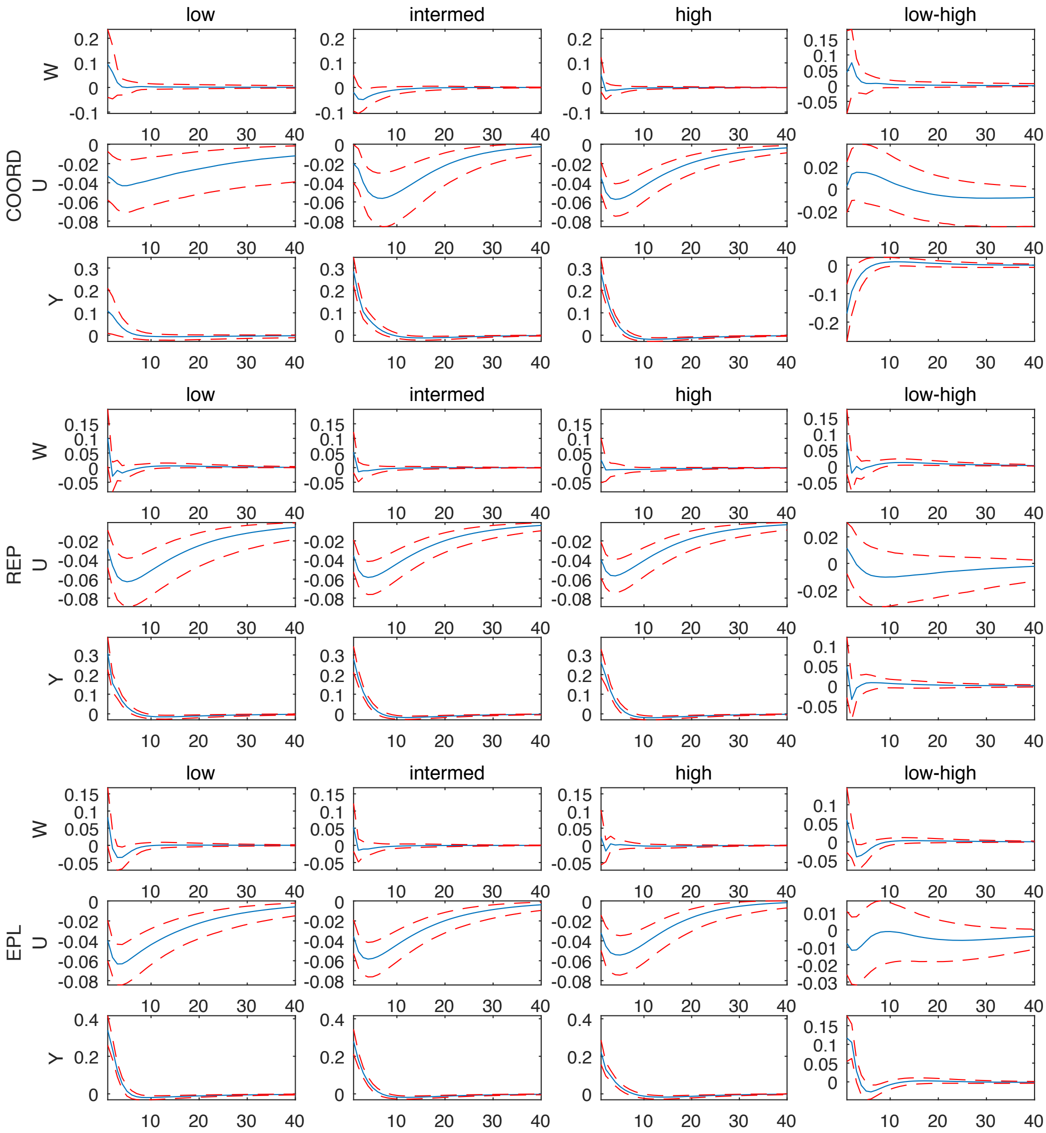

Figure 6. Impulse responses on temporary unit increase in US GDP growth conditional on three categories for wage setting coordination (COORD), replacement rate (REP) and employment protection (EPL), pre-2009 data, model without error terms for the VAR parameters. 80% confidence bands.

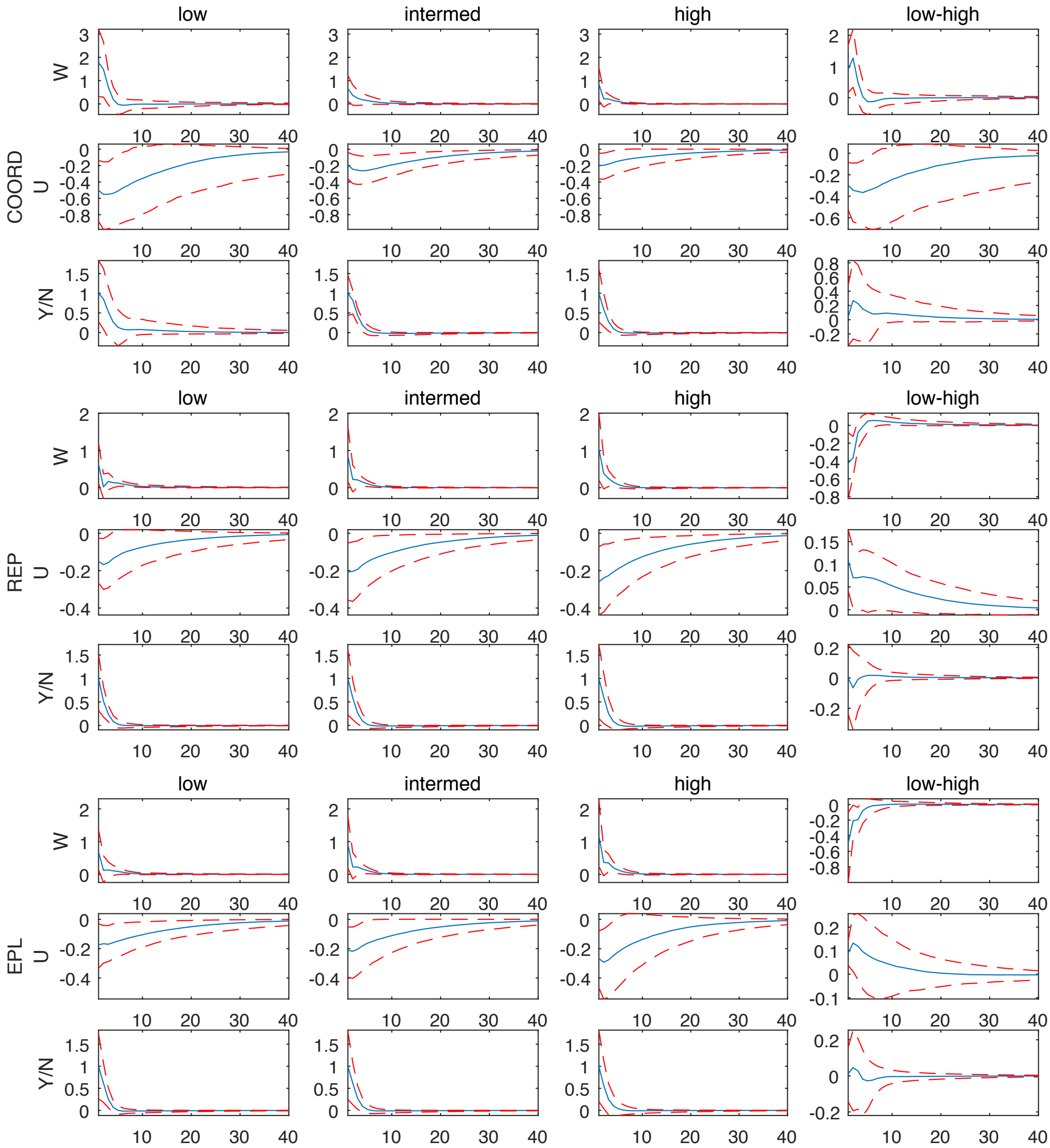

Figure 7. Impulse responses on productivity shock conditional on three categories for wage setting coordination (COORD), replacement rate (REP) and employment protection (EPL), pre-2009 data, model without error terms for the VAR parameters. 80% confidence bands that take into account both identification and parameter uncertainty. Impulse responses are normalized to give unitary response on impact for labour productivity Y/N.

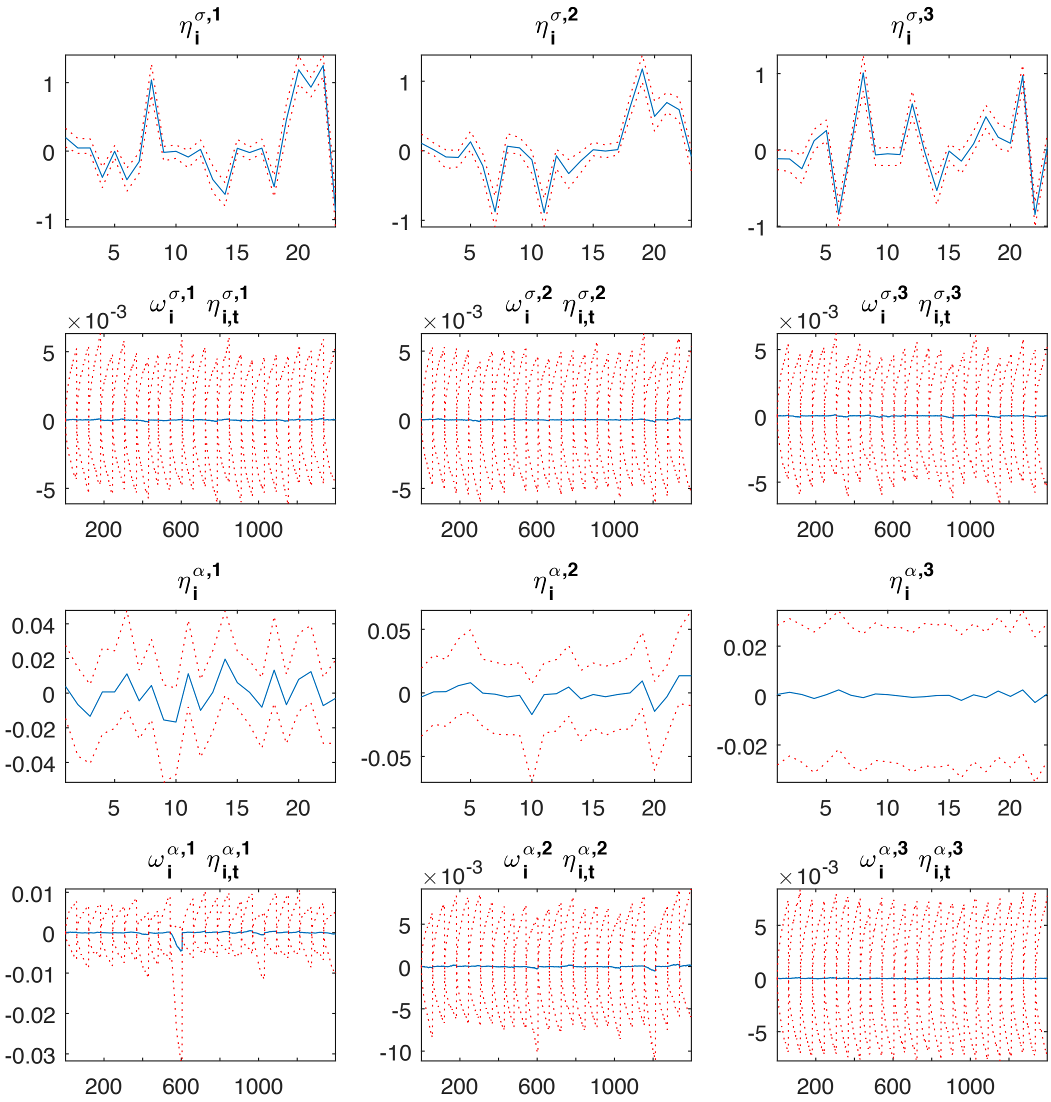

Figure 8. Error terms for the parameters of variance covariance matrix, $\Omega_{i,t}$. First two rows of plots show error terms for $log(\sigma)$'s. Ordering of the variables in the VAR is real wage growth, unemployment and GDP growth. Last two rows of plots show error terms for the elements in $A_{i,t}$. a_1 corresponds to (2,1) cell in A, a_2 to (3,1) cell and a_3 to (3,2) cell. The $\eta_i$terms are country specific initial conditions. The $\omega_{i,t}\eta_{i,t}$terms are the country specific time-varying error process and are stacked country by country.

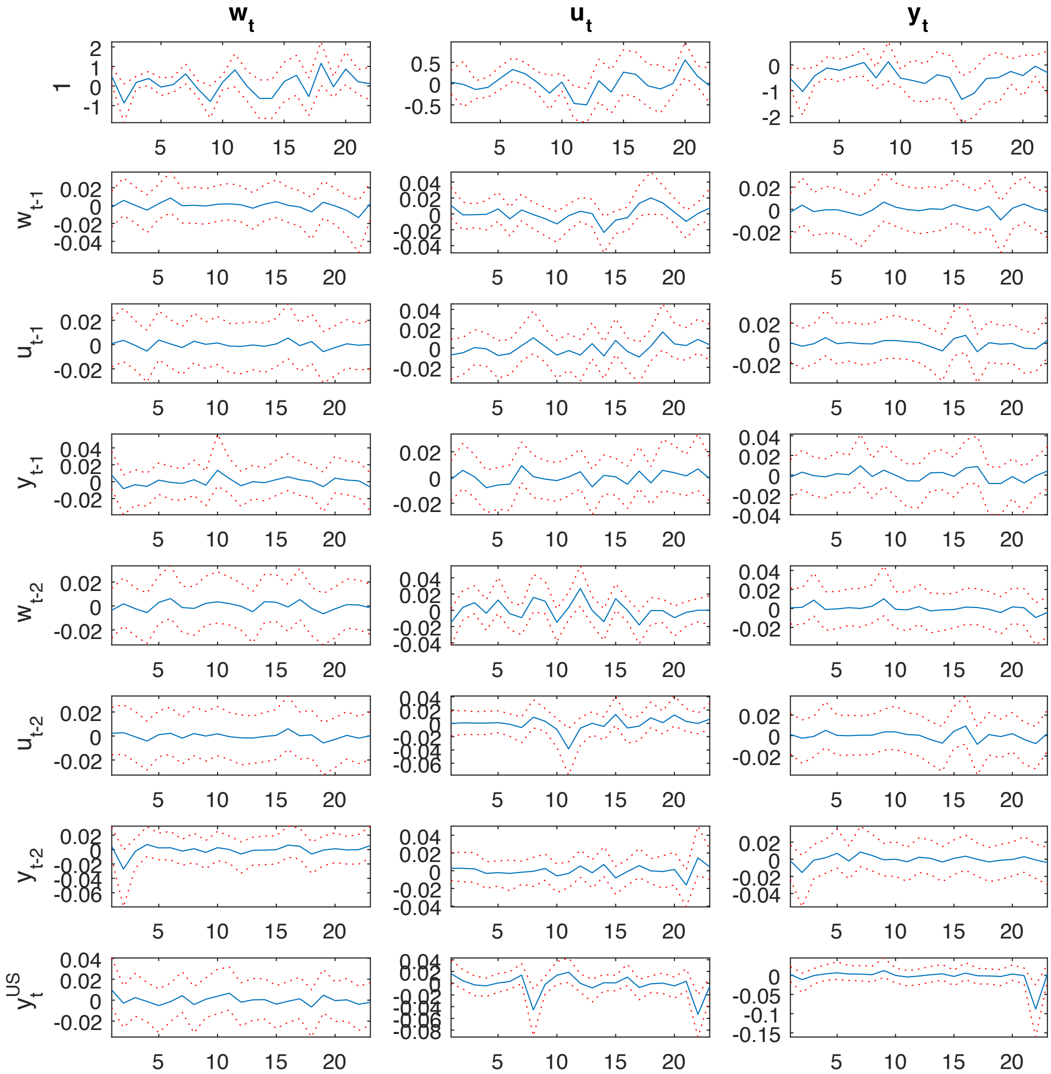

Figure 9. Error terms for the VAR coefficients, unit (country) specific initial conditions, η^{β}. Intercepts (first row of plots) are estimated without shrinkage.

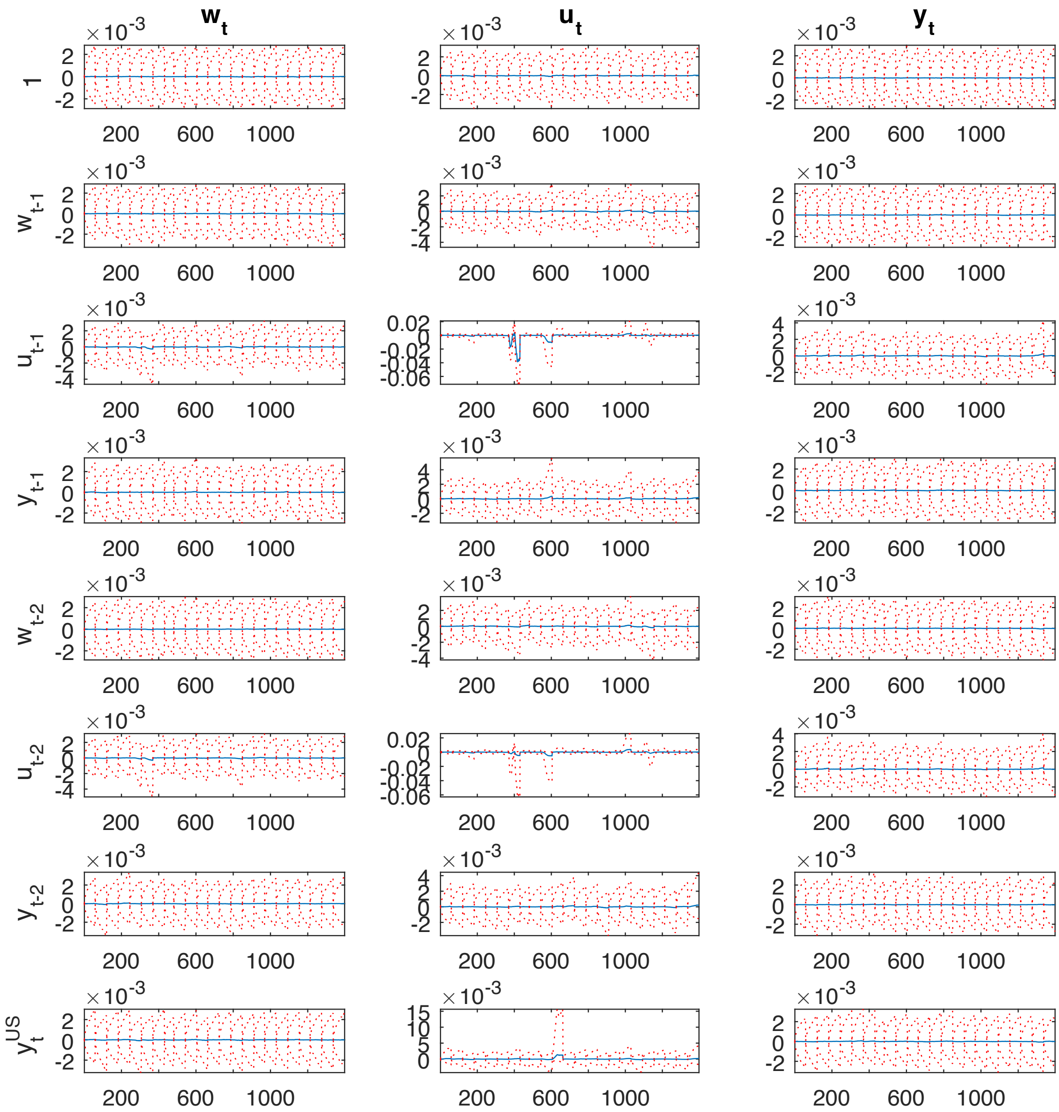

Figure 10. Error terms for the coefficients, country spesific time varying part. Terms are stacked country by country.