Labour market institutions and business cycle dynamics, VAR analysis

Petteri Juvonen
Bank of Finland

November 16, 2017

Introduction

- do labour market institutions (LMIs) (level of unemployment benefits, employment protection, wage setting centralization) matter for business cycle fluctuations and on shock adjustment?
- policy guidance seems to be that more flexible labour market helps the economy to adjust on shocks, OECD Job Study (1994), OECD Jobs Strategy (2006), Pact for the Euro (2011), country reviews of IMF, European Commission, OECD

Introduction

- knowledge on the effects of LMIs is limited, OECD Employment Outlook (2012)
- relatively little research is done related to business cycle dynamics, more on the long term outcomes (e.g. on average unemployment rate)
- labour market reforms are advocated by their potential effects on macroeconomic dynamics

Introduction

- business cycle dynamics vary across countries, macro panel literature, e.g. Canova et al 2012
  - what causes the variation?
- much heterogeneity in labour market institutions across countries and some variation over time
- use this heterogeneity to identify the relation between LMIs and business cycle dynamics
- test empirically the predictions of DSGE models regarding epl and replacement rate
- try to provide quantitate evaluation on the importance of LMIs as causes for heterogenous dynamics
  - asses the scope that labour market reforms could result

This paper

Using VAR, study how labour market institutions matter for business cycle volatilities and correlations and shock adjustment

- estimate a VAR including wages, unemployment and gdp or gdp/employment for a panel of OECD countries
- allow VAR parameters to depend on LMI variables
- LMIs in this paper:
  - strictness of employment protection, EPL
  - unemployment benefit replacement rate, REP
  - wage setting coordination/centralization
- obtain business cycle statistics and impulse response functions from VAR parameters conditional on LMI variables

Findings

- LMI variables have explanatory power for business cycle heterogeneity
  - high wage setting coordination is linked to less volatile real wages, less responsive real wages on productivity shocks
  - high employment protection legislation is linked to less volatile wages, unemployment is less responsive on external demand shocks
  - wages and unemployment are more responsive on productivity shocks if replacement rate is high
- but quantitative importance seems limited
- inference is greatly affected by the assumption whether the relation between labour market institutions and business cycle dynamics is stochastic or deterministic

Some literature

- VAR studies Georgiadis (2014), Abritti and Weber (2010, 2017)
- Gnocchi et al (2015): rank correlation coefficient analysis for the relation between LMIs and business cycle statistics
- DSGE studies: Zanetti (2011), Campolmi and Faia (2011)
- OECD Employment Outlook (2015)..

Model

$$\mathbf{y}_{i,t} = \mathbf{X}_{i,t}\boldsymbol{\beta}_{\mathbf{i,t}} + \mathbf{e}_{i,t}, \qquad \mathbf{e}_{i,t} \sim \mathrm{N}(0, \boldsymbol{\Omega}_{i,t}) \tag{1}$$

$$\mathbf{A}_{i,t}\boldsymbol{\Omega}_{i,t}\mathbf{A}'_{i,t} = \boldsymbol{\Sigma}_{i,t}\boldsymbol{\Sigma}'_{i,t} \tag{2}$$

$$\begin{bmatrix} \boldsymbol{\beta}_{\mathbf{i,t}} \\ \mathbf{a}_{i,t} \\ log(\boldsymbol{\sigma}_{\mathbf{i,t}}) \end{bmatrix} = \mathbf{Z}_{i,t}\boldsymbol{\theta} + \boldsymbol{\eta}_{i,t} \tag{3}$$

- decompositions follow TVP-VAR literature, Primiceri (2005)
- similar formulation in Georgiadis (2014), Abritti and Weber (2010), Sa,Towbin, and Wiedladeck (2014)
- in some papers interaction terms of institutional and macro variables (e.g. Nunziata and Bowdler (2005))
- these papers don't allow for error term in (6), dependence is assumed to be deterministic
- Georgiadis (2014) restricts $a_{i,t}$ and $log(\boldsymbol{\sigma}_{\mathbf{i,t}})$ to be constant, A&W (2010) and STW(2014) $log(\boldsymbol{\sigma}_{\mathbf{i,t}})$ to be constant

Model

$$\begin{bmatrix} \boldsymbol{\beta_{i,t}} \\ \mathbf{a}_{i,t} \\ log(\boldsymbol{\sigma_{i,t}}) \end{bmatrix} = \mathbf{Z}_{i,t}\boldsymbol{\theta} + \boldsymbol{\eta}_{i,t} \tag{4}$$

- $\boldsymbol{\eta}_{i,t}$ captures the variation in the VAR parameters over time and countries that is not captured by LMI variables in $\mathbf{Z}_{i,t}$
- $\boldsymbol{\eta}_{i,t}$ should be both persistent and allow for permanent shifts
- assume that

$$\boldsymbol{\eta}_{i,t} = \boldsymbol{\eta}_{i,t-1} + \boldsymbol{\epsilon}_{i,t} \tag{5}$$

- if data doesn't support the dependence of VAR parameters on LMIs, TVP-VARs are estimated
- $\eta_{i,t}$ is divided into initial condition $\eta_{i,1}$ and $\eta_{i,t}$ for t=2,3..

Estimation

- although the VAR is small, the model contains lots of parameters and is certainly over parameterized
- to deal with curse of dimensionality, shrinkage priors, Bayesian Lasso as in Belmonte, Koop & Korobolis (2013) are used
- the model is estimated using Gibbs sampler, drawing repeatedly on the conditional distributions of parameters as in Primiceri (2005)

Estimation

- once the posterior distributions for $\boldsymbol{\theta}$ and $\boldsymbol{\eta}$ are simulated, VAR parameters are simulated conditional on different values of labour market institutions variables (20th and 80th percentile, median) using:

$$\begin{bmatrix} \boldsymbol{\beta} \\ \mathbf{a} \\ log(\boldsymbol{\sigma}) \end{bmatrix} = \mathbf{Z}\boldsymbol{\theta} + \boldsymbol{\eta} \tag{6}$$

- then from $[\beta \ a \ log(\sigma)]'$ business cycle statistics and impulse response functions are obtained

Data

- endogeneous variables: real wage, GDP, GDP/N in growth rates, unemployment rate
- exogeneous variable US GDP to control for common shocks
- LMI variables:
  - index for wage setting coordination/centralization (ICTWWS)
  - net unemployment benefits replacement rate (rep), (Vliet & Caminada (2012))
  - index for strictness of employment protection legislation (epl), (OECD)
- institutional control variables: Euro-dummy, openness to trade, ratio of government spending to GDP
- 23 OECD countries
- quarterly data, 1995-2013

Volatilities conditional on LMI variables

	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

Note: 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.

Cross-correlations conditional on LMI variables

	COORD			REP			EPL		
	Low	Intermed	High	Low	Intermed	High	Low	Intermed	High
cor(y,u)	-0,3 -0,6 0,0	-0,3' -0,4 -0,2	-0,2 -0,3 -0,0	-0,3 -0,4 -0,1	-0,2 -0,3 -0,1	-0,13 -0,2 0	-0,2 -0,3 -0,0	-0,2 -0,3 -0,1	-0,2 -0,3 -0,1
cor(y,w)	0,2 0 0,5	0,0 -0,1 0,2	0, -0,1 0,2	-0, -0,2 0,1	0,0 -0,1 0,1	0,0 -0,1 0,1	0,0 -0,1 0,2	0, -0,1 0,2	0, -0,0 0,2
cor(w,u)	-0,1 -0,5 0,3	-0,2 -0,4 -0,0	-0,1 -0,3 0,0	-0,2 -0,5 0,0	-0,1' -0,3 0,1	0,0 -0,2 0,2	-0,1 -0,4 0,1	-0,1 -0,3 0,1	-0,1 -0,3 0,1
cor(u,y/n)	-0,1 -0,5 0,2	-0,0 -0,1 0,1	0,1 -0,0 0,2	-0,0 -0,1 0,1	0,1 -0,1 0,1	0,1 -0,1 0,2	0,00 -0,1 0,2	-0,1 -0,1 0,1	-0,0 -0,1 0,1
cor(w,y/n)	0,2 -0,1 0,5	0,0 -0,1 0,2	0,1 -0,1 0,2	0,1 -0,1 0,2	0,1 -0,0 0,2	0,1 -0,0 0,2	0,1 -0,0 0,3	0,1 0 0,2	0,1 -0,0 0,2

Note: 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.

Auto-correlations conditional on LMI variables

	COORD			REP			EPL		
	Low	Intermed	High	Low	Intermed	High	Low	Intermed	High
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: 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.

Relative explanatory power of LMIs

- try to asses how much LMI variables explain the variability of business cycle statistics
- as the business cycle statics are calculated from the VAR parameters, they are functions LMI and control variables and $\eta_{i,t}$
- for a business cycle static G the importance of LMI variables is obtained as:

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

- repeat this for $Z_{i,t}^{controls}, \eta_{i,t}$

Relative explanatory power of LMIs

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

Comparison to literature

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

Zanetti(2011), Campolmi & Faia (2011) are DSGE studies
Gnocchi *et al.* (2015) and Abritti and Weber (2017) empirical studies

Deterministic vs stochastic relations

- Abbritti & Weber (2017) use similar approach but obtain more stronger results in terms of statistical significance
- the difference is that Abbritti & Weber (2017) assume deterministic, instead of stochastic relation for VAR parameters and LMIs

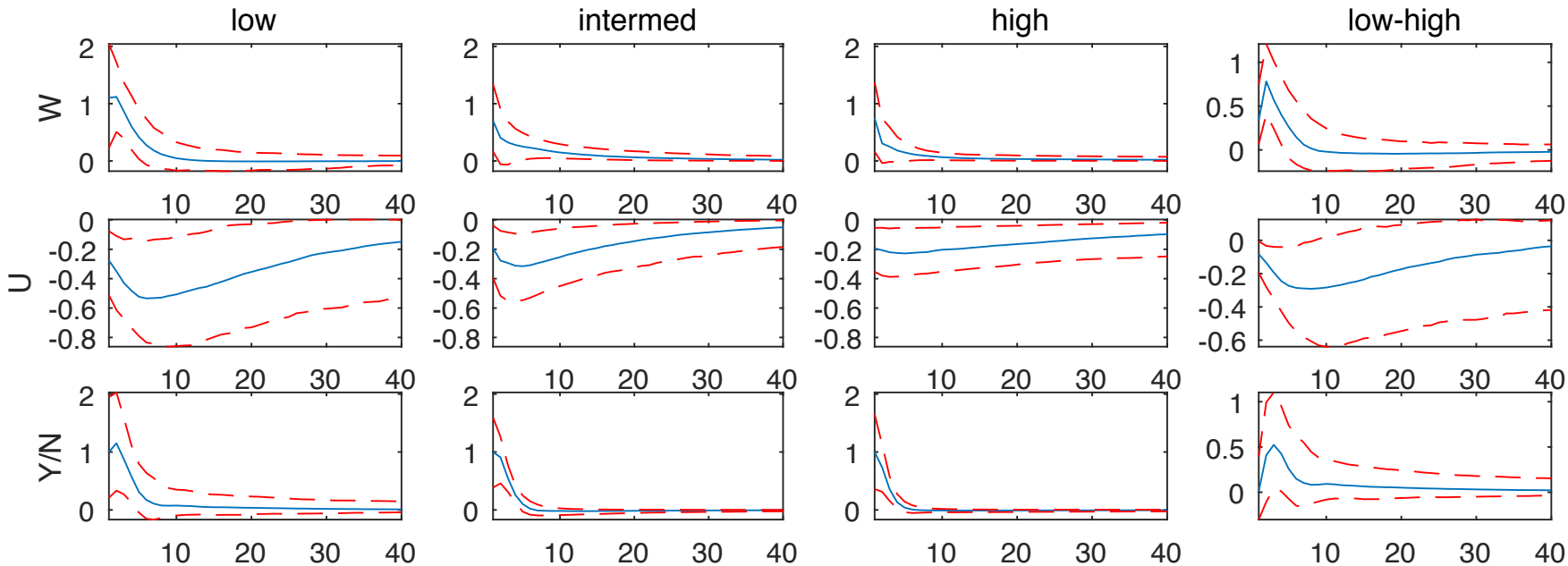
$$\begin{bmatrix} \boldsymbol{\beta_{i,t}} \\ \mathbf{a}_{i,t} \\ log(\boldsymbol{\sigma_{i,t}}) \end{bmatrix} = \mathbf{Z}_{i,t}\boldsymbol{\theta} \; (+ \; \boldsymbol{\eta}_{i,t}) \tag{7}$$

- when the analysis was conducted without the η error terms, the results showed more statistically significant and stronger results , e.g.
  - when assuming stochastic relation, var(u) not related statistically significantly to any of LMIs
  - when assuming deterministic relation, var(u) related statistically significantly to all LMIs
- Western (1998) and Wieladek (2016) show similar results

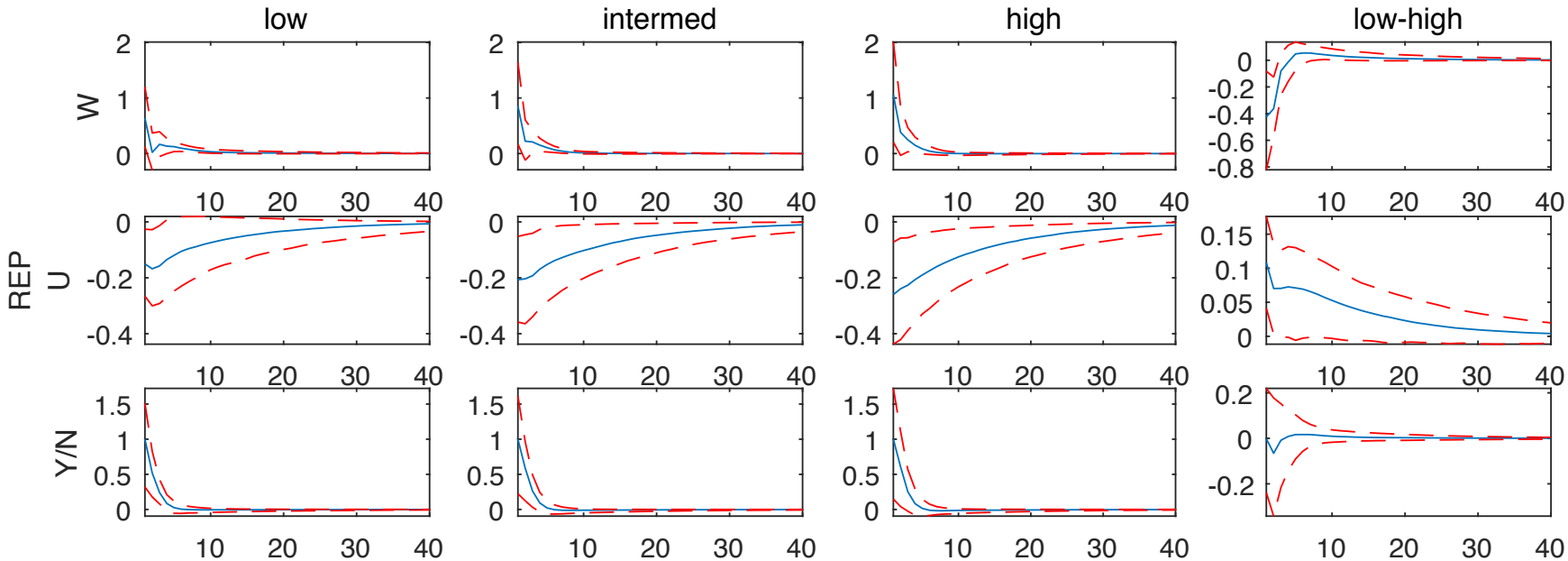
Conditional impulse response functions

- to obtain structurally more interpretable results impulse responses are calculated
- identification of productivity shock using sing restrictions
  - positive productivity shock (as in Mumtaz and Zanetti (2015), Y and Y/N respond positively, U negatively
- world demand shock, increase in US GDP growth rate
  - simple way to obtain a proxy for external demand shock

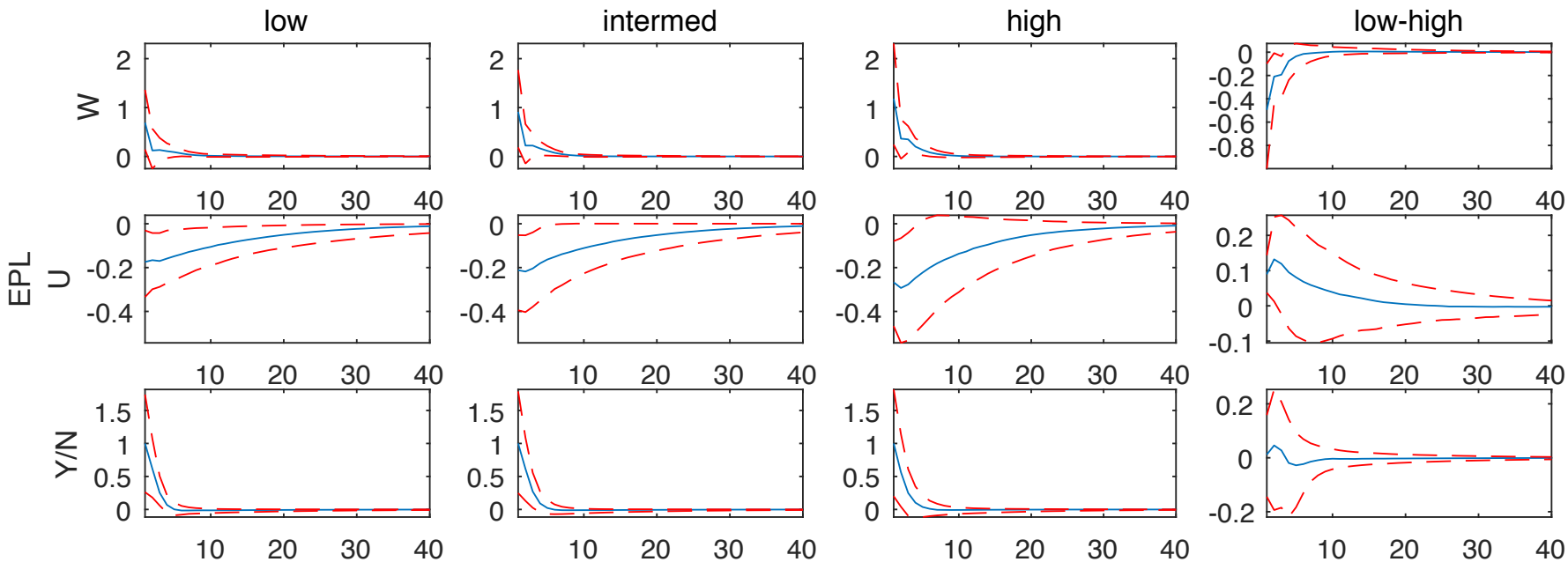
Productivity shock, conditional on three categories for coordination/centralization



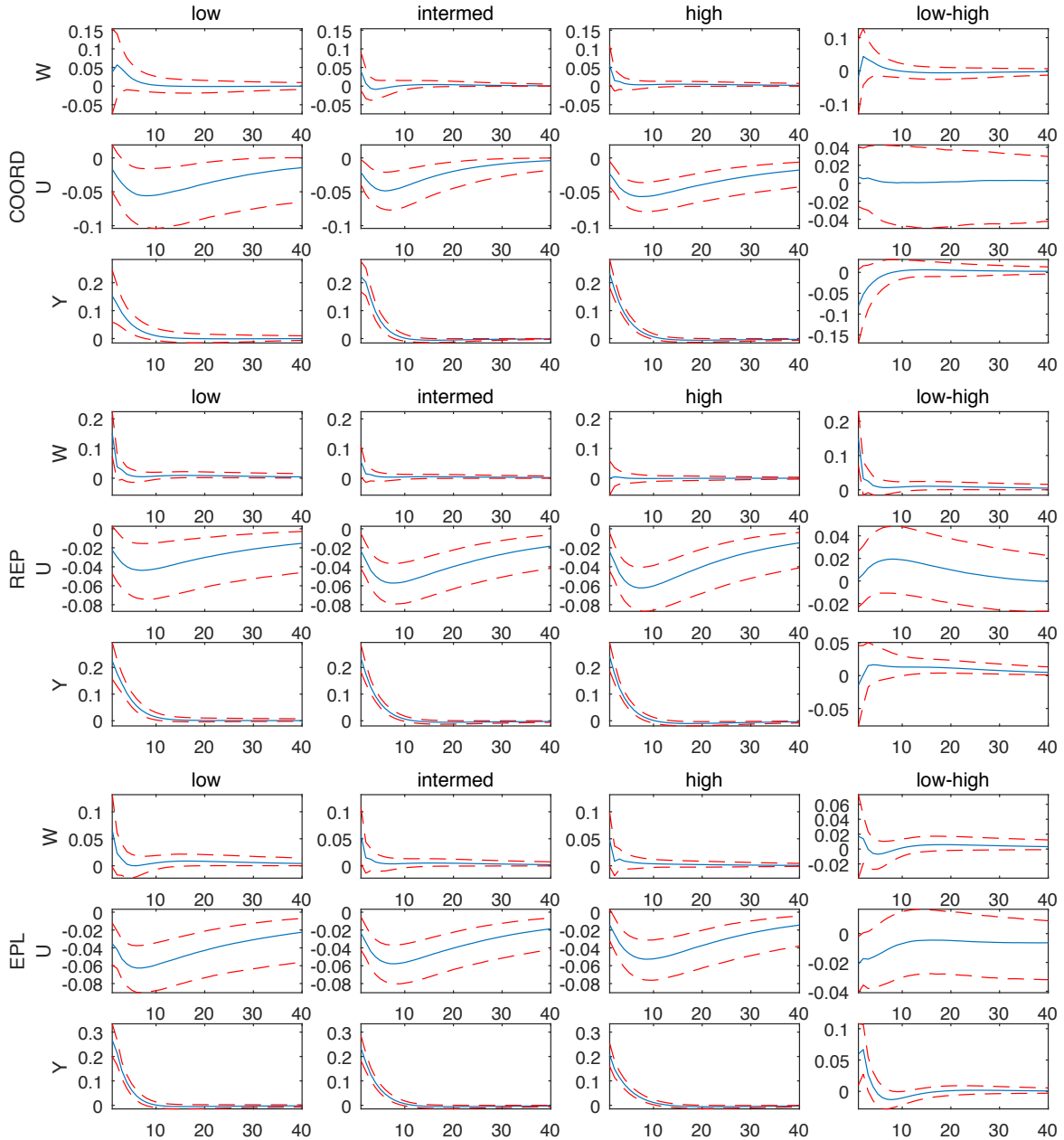
Productivity shock, conditional on replacement rate



Productivity shock, conditional on employment protection



Impulse responses on world demand shock



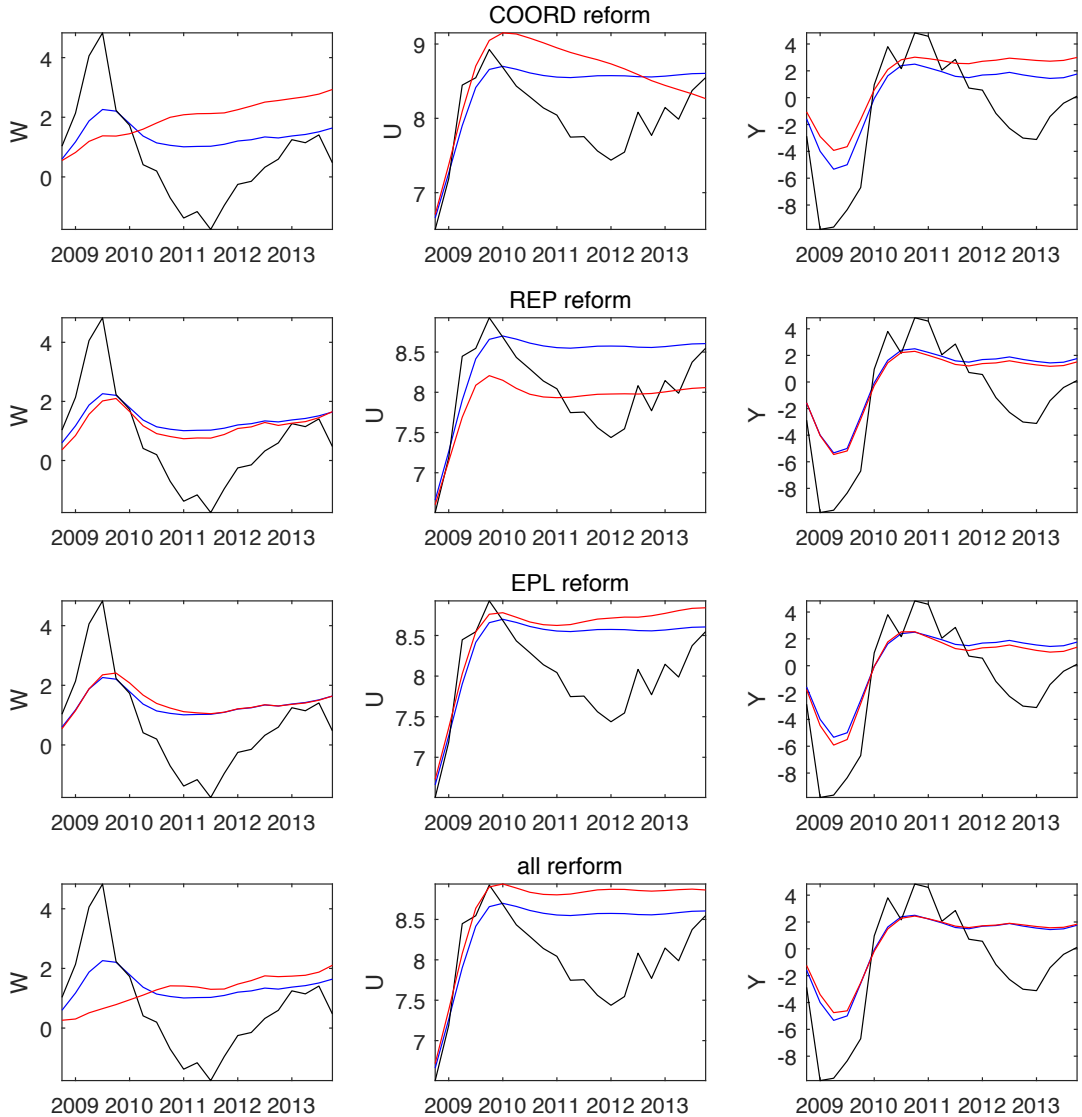
Reforms

- to get insight on how much labour market reforms could change the dynamics of an economy, following counterfactual analysis is conducted.
- 1. given a country (Finland, 2009-2013), using the VAR, run conditional forecast conditional on US GDP growth which is assumed to be exogenous variable
- 2. 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 counterfactual monetary policy rule.

Reforms

- wage setting reform, change fully centralized/coordinated wage setting to firm level wage setting
- drop replacement rate, from 42nd sample percentile to 22nd percentile
- drop employment protection indicator, from 50th sample percentile to 30th sample percentile

Reforms



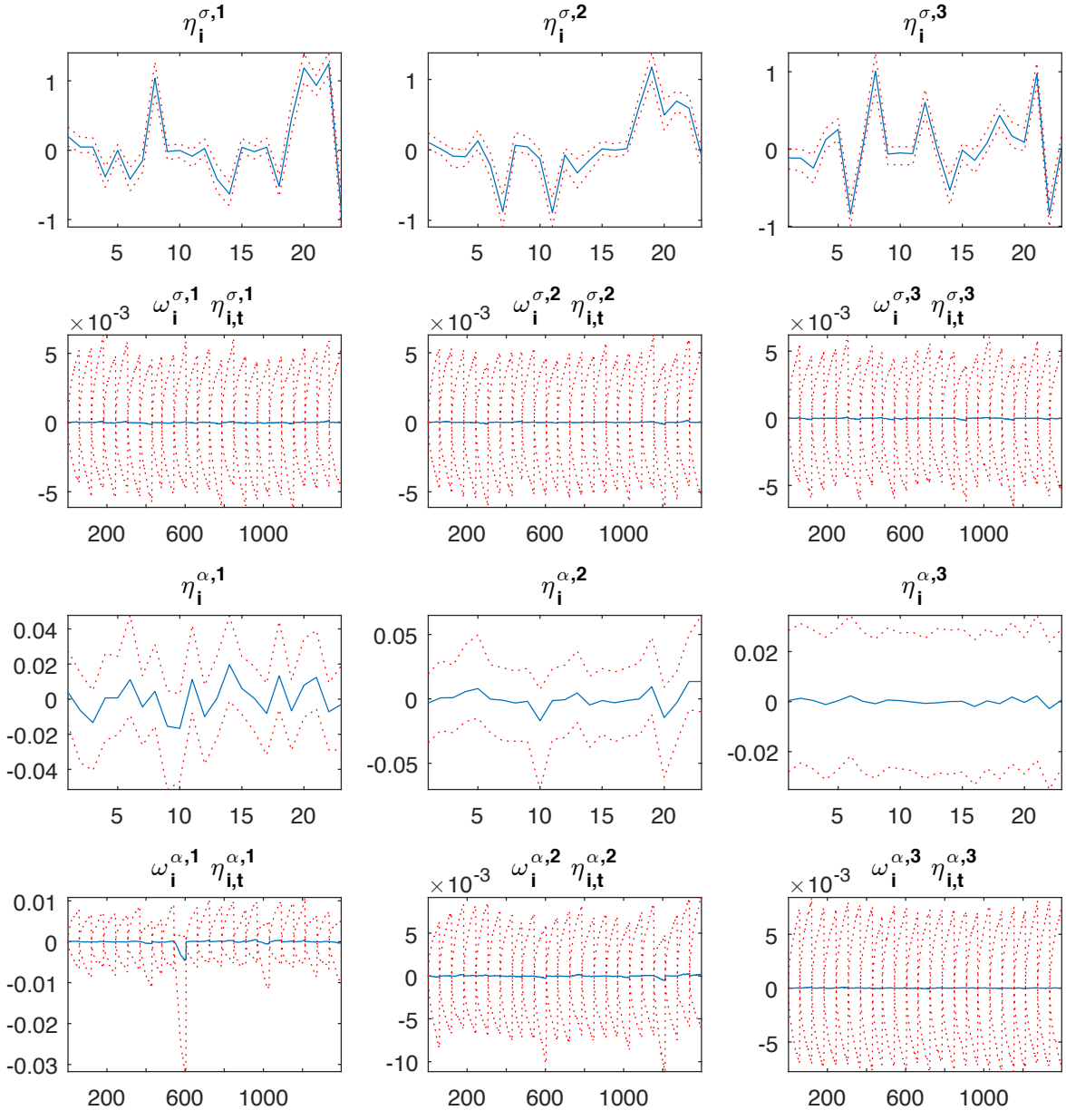
Black line, data. Blue line, conditional forecast. Red line, counterfactual conditional forecast.

Conclusions

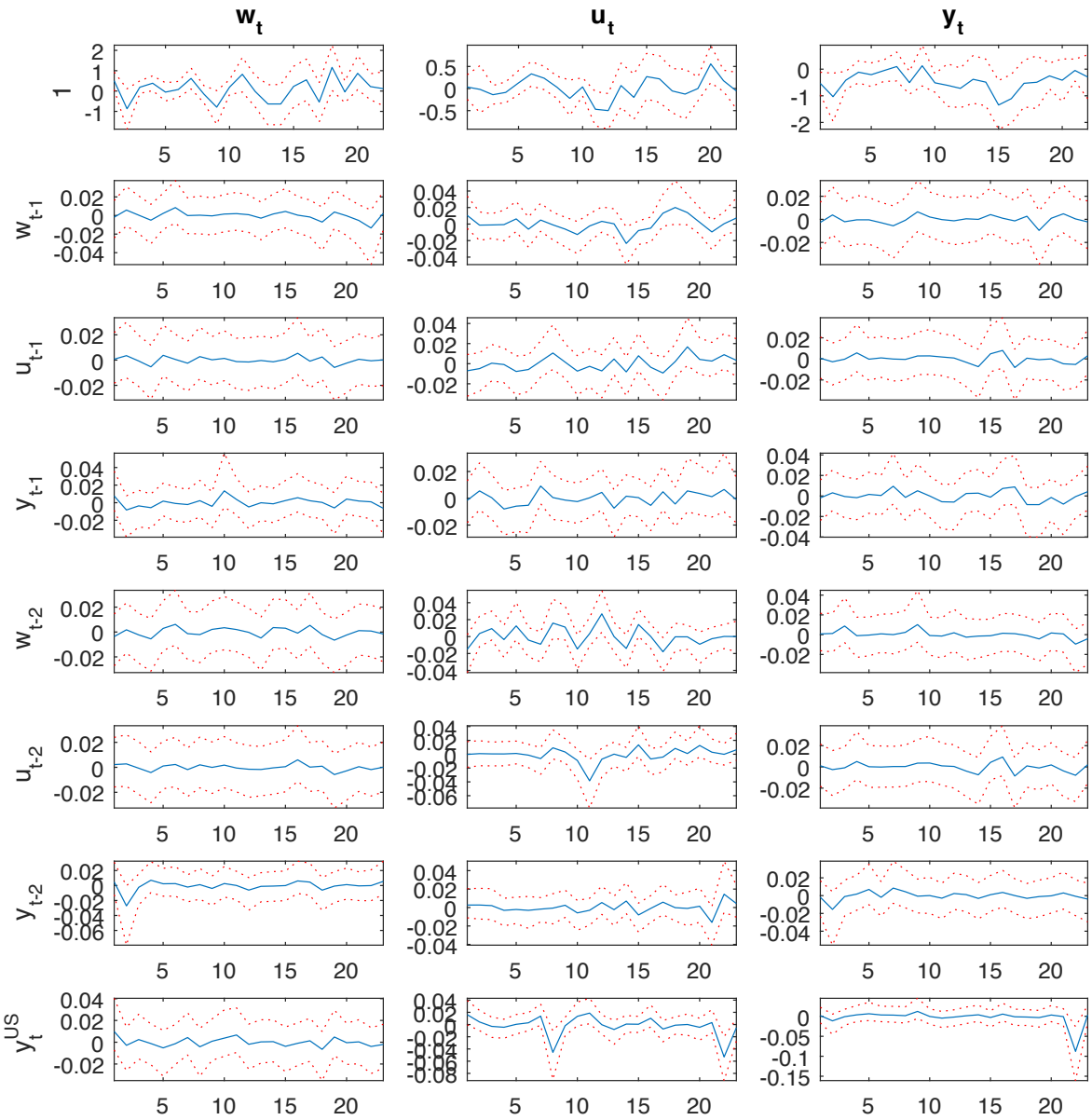
- strong LMIs seem to be associated with lower macroeconomic volatilities, contrary to results in Gnocchi *et al.* (2015)
- it seems that LMIs have explanatory power for the cross-country heterogeneity in business cycle dynamics and shock adjustment
- counterfactual analysis suggests only weak effects for labour market reforms on output dynamics, more on dynamics of wages and unemployment
- statistical inference is greatly affected by the assumption whether the relation between labour market institutions and business cycle dynamics is stochastic or deterministic
  - trade off between model misspecification and (over) complexity

Thanks!

Var-cov errors



Coefficient errors, country specific



Coefficien errors, country specific TVP