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Brůha, Jan; Polanský, Jiří

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Reviewed by: Martyna Marczak (University of Hohenheim)
Stephen Millard (Bank of England)
Jan Šolc (Czech National Bank)

Project Coordinator: Jan Babecký

Empirical Analysis of Labor Markets over Business Cycles: An International Comparison

Jan Brůha and Jiří Polanský *

Abstract

The goal of this paper is to document and summarize the main cyclical features of labor market macroeconomic data in advanced countries. We report the second moments (correlations, coherences and volatility) of labor market variables for various data transformations (growth rates and cycles). Then we use dynamic factor models to inquire about the number of orthogonal shocks that drives labor market data dynamics. We also investigate the time-varying nature of these features: we ask whether they are stable over time, especially at times of severe crises such as the Great Recession. Finally, we compare these features across countries to see whether there are groups of countries characterized by similar features, such as labor market institutions. We find that certain features are stable over time and across countries (such as Okun's Law), while others are not. We also confirm that labor market institutions influence selected characteristics, but to a limited degree only. We find that one or at most two orthogonal shocks seem to drive the cyclical dynamics of labor market variables in most countries. The paper concludes with our interpretation of these findings for structural macroeconomic models.

Abstrakt

Cílem tohoto článku je zdokumentovat a shrnout hlavní cyklické charakteristiky makroekonomických dat trhu práce ve vyspělých ekonomikách. V článku uvádíme druhé momenty (korelaci, volatilitu a koherenci) těchto dat pro různé transformace (tempa růstu a cyklické složky). Používáme také dynamické faktorové modely, abychom odhalili počet fundamentálních šoků, které ovlivňují dynamiku veličin trhu práce. Zkoumáme, zda se tyto charakteristiky mění v čase, zejména v obdobích závažných krizí jako např. Velká recese. Nakonec zkoumáme, zda existují skupiny zemí, které jsou charakterizovány společnými rysy, např. institucemi na trhu práce. Ukazujeme, že některé vlastnosti jsou společné v čase a v různých zemích (např. Okunův zákon). Naopak jiné charakteristiky se mezi zeměmi liší. Instituce trhu práce vybrané vlastnosti ovlivňují, ale pouze málo. Zjišťujeme, že cyklickou dynamiku veličin trhu práce ve většině zkoumaných zemí zřejmě vysvětluje jeden, nebo nejvýše dva šoky. Článek uzavíráme interpretací těchto závěrů pro strukturální makroekonomické modely.

JEL Codes: E24, J21, J30.
Keywords: Dynamic factor models, Great Recession, labor market institutions, Okun's Law.

* Jan Brůha, Czech National Bank; jan.bruha@cnb.cz
Jiří Polanský, Czech National Bank (formerly); Česká spořitelna, a.s. (currently); jpolansky@csas.cz
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Nontechnical Summary

In this research, we ask what (if any) are the stable cyclical features of labor market data in advanced countries. We are interested in features that are robust across time and space. We are also interested in the implications of the findings for structural macroeconomic modeling. To fulfill this task, we collect labor market data for more than 30 countries and apply a set of empirical methods. First, we compute the second moments (correlations, coherence, and volatility) of labor market variables for various data transformations (growth rates and cycles). We find that at business cycle frequencies there are stable and robust relationships, Okun's Law being the prominent example. We also show that the relationship is visible especially in cycles, and less so in growth rates. The reason is that growth rate transformation amplifies high-frequency noise in the data, noise that can obscure the relations between variables.

We do not find evidence for trade-offs between the volatilities of the variables investigated. Higher volatility of the output cycle is associated with higher volatility of cycles in labor market variables. Moreover, we find that the volatilities of the cycles of labor market variables are also positively related. A similar conclusion holds for the volatilities of growth rates.

We then use dynamic factor models to inquire about the number of orthogonal shocks that drive labor market data dynamics. We find that for the countries in our sample, the major part of the business cycle dynamics of labor market variables is explained by just one or two dynamic factors, i.e., at most two orthogonal shocks are needed to explain the data. We argue that this finding has an implication for structural models in that two structural shocks should be dominant in explaining the cyclical dynamics of labor markets.

Then we ask whether the differences across countries can be explained by labor market institutions, especially by employment protection legislation. Consistently with previous studies, we find that employment protection legislation does systematically influence the second moments of the data, but that its effect is limited: it explains about one-third of the variability.

Finally, we also investigate the time-varying nature of these features: we ask whether they are stable over time, especially at times of severe crisis such as the Great Recession. We find that in most countries the cyclical relationship between output and unemployment (i.e., Okun's Law) is not affected by the Great Recession.

1. Introduction

This paper asks what are the robust cyclical features of the main labor market data in advanced countries: we are interested in various margins of labor quantities (employment, hours worked, and the unemployment rate) and in the price of labor (the wage bill and wages). We try to characterize those features which seem to be stable over time and across countries and distinguish them from country- or episode-specific features. Such an analysis may be useful for various reasons. First, one may be interested to know which data features are robust across countries and which depend on countries' characteristics, such as culture or labor market regulation. Second, our results can be used to build a set of empirical checks when constructing structural models with explicit labor market blocks. Prominent examples of such structural models include dynamic stochastic general equilibrium (DSGE) models with labor market frictions. Third, our empirical results can shed some light on the labor market developments observed recently in advanced countries.

The paper is empirical. We employ several empirical methods and techniques to reveal possible comovement patterns and properties of labor market variables in a large set of developed countries. First, we report the second moments (correlations, relative volatilities, and coherence) for various frequencies and data transformations (growth rates and cycles). We then use factor models (factor-augmented vector autoregressions estimated in the time domain and non-parametric dynamic principal component analysis estimated using frequency-domain techniques) to inquire about the number of primitive shocks that drive labor market data dynamics. Finally, we ask whether the features we identify are stable over time, especially at times of severe crisis such as the Great Recession.

There are alternatives, of course. Structural Vector Autoregression (SVAR) is a popular tool for establishing facts that can be confronted with structural models. This approach is usually based on comparison of the impulse responses of a structural model with those based on SVAR or a related technique (such as time-varying or Bayesian SVAR models). Although useful, SVARs have been challenged from multiple directions. Theoretical economists are skeptical due to the lack of credible identification[1], but even the estimation of the reduced form of VARs can be challenging; for example, the data transformation assumed proves crucial.[2]

Structural estimated macroeconomic models (nowadays prominently DSGE models) are also a popular tool for analyzing and/or comparing labor markets across time and space. The implied properties of these models, however, depend on the structure assumed, and the conclusions may be misleading if the model is misspecified. Our analysis instead proposes a number of facts, robust across time and space, that can be used to check the model specification. In particular, the stability of the relationship between output and unemployment has significant implications for structural macroeconomic models, implications that in our view are not always taken seriously.

We appreciate the usefulness of SVAR and DSGE models for the analysis of labor market data and for cross-country comparisons. Nevertheless, as these types of models rely on a set of assumptions (about identification and the appropriate reduced-form structure in the case of SVARs, and about economic structure in the case of DSGE models), it is also useful to employ empirical models to establish the set of robust statistical features and facts.

[1] In certain cases, identification is not possible at all – see, for example, Fernández-Villaverde et al. (2007).

[2] See, for example, the 'heated' discussion between Chari et al. (2008) and Christiano (2008). Moreover, Andrle and Brůha (2014) show that the reduced forms of many monetary SVARs applied to inflation-targeting countries are misspecified in that they do not respect the institutional framework or stylized facts.

From a certain perspective, our paper is related to the index model by Sargent and Sims (1977). Nevertheless, we concentrate on labor market variables and our sample consists of data on more than 30 countries. The country dimension is important for our purposes. If we find that a certain feature holds in all or most countries, this increases the confidence that such feature is really a 'fact.' In other words, the cross-country dimension lowers type I errors of accepting a false statistical feature as genuine.

We show that there are robust relations between some variables across countries and time at business cycle frequency. The cyclical comovement between real output and selected labor market indicators (mostly employment, unemployment, and hours worked) is strong and these cyclical features hold not only in normal times, but also during the period of the Great Recession and the latest debt crisis. Moreover, we show that these patterns are much clearer at business cycle frequencies than at lower or higher frequencies. We also show that the stability does not hold for other variables, the cyclicality of wages being the prominent example. We also ask whether the characteristics are influenced by the country's institutional features. Finally, we show that in most countries, there are just one or two driving forces behind the set of labor market variables, and we discuss the implications for macroeconomic modeling. Finally, we ask about the stability of selected relationships over time, especially during the Great Recession.

The paper is organized as follows. The next section 2 is devoted to an overview of related literature. In the following section 3, we briefly describe the dataset used. Section 4 presents an analysis of second moments. A dynamic factor models analysis is employed in Section 5. Section 6 asks whether labor market institutions can explain cross-country differences in business cycle characteristics. Section 7 investigates the stability of the features identified during and after the Great Recession. The last section 8 concludes the paper with our interpretation of selected – in our view the most interesting – findings for structural macroeconomic models. Appendices contain additional materials.

2. Related Literature

For this literature review, we selected topics that seem especially relevant to our analysis, although we appreciate that there may be many more studies covering similar themes. First, we review recent evidence on Okun's Law. We chose this law because it started to be questioned at the onset of the Great Recession (all the buzz about a 'jobless recovery') and because we can use Okun's Law to illustrate some important methodological issues about data transformation. Our reading of recent literature as well as our own work in this paper demonstrate that appropriate data transformation **is** crucial for uncovering stable economic relationships.

Next, we review the literature on the cyclicality of wages. This is, in a sense, the polar opposite of Okun's Law. While Okun's Law is one of the most robust features across time and space, the same cannot be said for the cyclical behavior of wages: there is much, especially cross-country, heterogeneity. Finally, as we ask in the paper whether the cross-country differences can be explained by institutions, we also review recent literature on this issue.

By selecting these three areas, we necessarily neglect some other interesting papers. We comment on such papers and contrast our findings through the paper.

2.1 Okun's Law

One of the most famous 'laws' of macroeconomics concerns the relationship between unemployment and output. The origins of this law date back to 1962, when Arthur Okun reported an empirical regularity in the shape of a negative short-run relationship between unemployment and output. His article was rooted in neo-Keynesian synthesis. Although the original motivation was normative, this regularity was soon reinterpreted as a stylized fact and prior to the Great Recession it was rarely questioned.

In the original paper, Okun (1962) proposes two ways of representing his law. One possibility is to relate the gaps of the two variables:

$$U_t - U^* = \alpha + \beta(Y_t - Y_t^*) + \varepsilon_t, \tag{1}$$

where U_t is actual unemployment, U^* is its equilibrium value (set to 3.72% in the original paper), Y_t is actual output, Y_t^* is potential output, ε_t is the residual, and β is the coefficient of interest (henceforth called *Okun's coefficient*). Okun suggested measuring potential output by fitting a suitable deterministic trend to the data on real output.

The obvious generalization of (1) is to consider a time-varying equilibrium unemployment rate, i.e., to allow for the possibility that the equilibrium unemployment rate varies due to exogenous forces unrelated to business cycles, such as tastes, social norms, or incentives (taxes):

$$U_t - U_t^* = \alpha + \beta(Y_t - Y_t^*) + \varepsilon_t, \tag{2}$$

The second possibility outlined in the original paper is to consider output in percentage changes and unemployment in changes in percentage points:

$$U_t - U_{t-1} = \alpha + \beta(\log Y_t - \log Y_{t-1}) + \varepsilon_t, \tag{3}$$

If the equilibrium rate of unemployment is constant and the equilibrium rate of output grows at a constant exponential rate (both conditions seemed reasonable for the sample used in the original article), then there is not much difference as regards which of these formulations is used to recover Okun's coefficient.

However, if the equilibrium rate of unemployment or the equilibrium growth rate is not constant, these formulations can yield quite different conclusions about Okun's Law and its stability over time. The problem is that the equilibrium quantities in (2) are not directly observable and have to be estimated.[3] The need to estimate the equilibrium quantities in (2) probably explains why some studies prefer to employ the formulation (3). However, as put by Ball et al. (2013) this is equivalent to ignoring the problem, not solving it.[4]

Our reading of recently published studies (we concentrate on those which cover the Great Recession) yields an interesting message: studies that confirm the stability of Okun's Law (including during the period of the Great Recession) are those based on the formulation (2), i.e., with possibly time-varying gaps in both unemployment and output. On the other hand, studies which use growth rates tend to reject stability of Okun's Law over time. This is in line with our own work presented in this paper.

[3] See Lee (2000) for a comparison of different techniques that can be used to isolate the frequencies of interest.
[4] In Appendix A, we discuss this issue from the statistical perspective.

On the one hand, Ball et al. (2013) use formulation (2), where the equilibrium quantities are identified using the HP filter. They find on U.S. data that Okun's Law fits the data well (the R^2 of regression (2) is about 0.8) and is robust in that it holds for various time periods and for both quarterly and annual data. Based on a sample of advanced countries, they find that Okun's coefficient varies across countries, but it is stable within a given country and that it is not related to employment protection legislation in a transparent way. Moreover, they do not find evidence for non-linearity in the sense that the adjustment of unemployment during recoveries is slower than the adjustment during booms.

On the other hand, there are studies that use the formulation with growth rates (3), possibly including more lags of U_t or $\log Y_t$ in the regression. The representative studies include IMF (2010), Cazes et al. (2011), Chinn et al. (2013), and Cheng et al. (2015). Although these studies differ in the econometric methodologies used, they find an increase (in the absolute value) of Okun's coefficient after 2008, i.e., an increase in the responsiveness of unemployment to output. In other words, these studies find that unemployment rose more than expected after the output decline after 2008.

To conclude, reduced-form studies suggest that the comovement between the series is strong at cyclical frequencies, but the relationship between the growth rates of the two variables is less strong and unstable over time.

2.2 Cyclicality of Wages

The cyclicality of wages is, in a sense, the polar opposite of Okun's Law. The classic survey article Abraham and Haltiwanger (1995) concludes that based on U.S. data it is difficult to draw any firm conclusion about wage cyclicality, as the results depend on the time period analyzed and on the deflator used to construct real wages, and their literature review shows the importance of the composition effect.[5]

The difficulty in establishing the cyclicality of wages is confirmed by the cross-country study by Messina et al. (2009). These authors gathered data on a sample of OECD countries and looked at the factors explaining the cyclicality of wages in manufacturing. They conclude that the approach matters: real wages deflated using the PPI are systematically less cyclical than when other deflators are used (the same finding as by Abraham and Haltiwanger (1995)). They find that openness matters (more open countries tend to have less cyclical wages) and that labor market institutions may matter: union coverage is a factor that reduces wage cyclicality. Like us, they find that wage cyclicality is positively correlated with employment cyclicality.

Hart et al. (2001) use the frequency domain and find real wage cyclicality on U.S. data. Contrary to other studies, they do not find that the cyclicality of the real wage depends on the deflator used.

Country-based studies tend to confirm the findings of aggregate studies about the importance of the deflator used for construction of the real wage. For example, Marczak and Beissinger (2013) find, using several methods, that real wages in Germany are cyclical over business cycle frequencies and lag behind the business cycle. Higher procyclicality is found for consumer price-deflated real wages

[5] The composition effect captures the observed tendency of employment losses during economic downturns to occur disproportionately for workers with lower than average wages. Thus, the composition effect can obscure the true relationship between wages and economic conditions. Micro studies tend to find that when composition bias is controlled for, wages are highly procyclical – see, for example, the decomposition for the UK by Devereux and Hart (2005) and that for the U.S. by Daly et al. (2011). Brůha et al. (2013) describe the effect of the composition effect on forecasts with a structural macroeconomic model.

than for PPI-deflated series. Miyamoto (2015) confirms for Japan that real wages constructed using the CPI and GDP deflator are procyclical while PPI-deflated wages are not.

To conclude, the cyclicality of real wages depends on the country investigated, the sample period, the methods used (time-domain versus frequency-domain), and the deflator used to construct real wages. The composition effect seems to be important. It is therefore difficult to make a robust conclusion.

2.3 Labor Market Institutions

Economists have long been interested in the effect of labor market institutions and policies on the labor market. Most studies deal with the effect on long-run values, i.e., they ask how institutions and policies influence, for example, long-run equilibrium unemployment. Recently, however, there has also been interest in how labor market institutions and policies influence the second moments of labor market variables, i.e., their volatility and cross-correlations. In this part of the paper we review important studies in this field, and in Section 6 we provide own our analysis.

One of the earliest studies in this field is the paper by Houseman and Abraham (1993), who use case studies to investigate the responses of three European labor markets to shocks and compare them with the U.S. market. They do not find that employment protection necessarily inhibits labor market flexibility. In contrast to the case study by Houseman and Abraham (1993), recent studies tend to rely on large panel data for advanced economies.

Nunziata (2003) after having presented a theoretical model uses a panel of OECD countries to inquire about the effect of employment protection legislation on the output elasticity of employment. He concludes that – in line with the theoretical analysis – employment protection legislation reduces the employment elasticity of output. Similarly, Faccini and Rosazza Bondibene (2012) find that unemployment benefits, taxation, and employment protection appear to reduce the volatility of unemployment rates.

Abbritti and Weber (2010) construct a DSGE model to inquire about the effect of various labor market imperfections on inflation and unemployment. On a panel of OECD countries, they then estimate a VAR model (with varying coefficients that reflect various forms of imperfections) to check the predictions of theoretical models. They find that economies with rigid labor and flexible wages exhibit a strong reaction of inflation and a weak reaction of unemployment to a negative supply or external demand shock, while the opposite is true for economies with flexible labor and rigid wages.

Rumler and Scharler (2011) find that countries characterized by high union density tend to experience more volatile movements in output, whereas the degree of coordination of the wage bargaining system and the strictness of employment protection legislation appear to play a limited role in output volatility.

Hirata (2012) finds that in a DSGE model with search-and-matching frictions in labor markets, employment protection increases the standard deviation of real wages to the standard deviation of unemployment. He uses a dataset for OECD countries to show that this feature also holds in the data.

Jump (2014) proposes an interesting semi-structural model of unemployment. He finds – both in the model and in an OECD country panel – that an increase in the replacement rate increases the volatility of hours worked and reduces the volatility of real wages.

Gnocchi et al. (2015) use a set of empirical methods on a panel of OECD countries and find that more flexible institutions are associated with lower business cycle volatility. Reforms reducing replacement rates make labor productivity more procyclical. Wage bargaining reforms increase the correlation of the real wage with labor productivity and the volatility of unemployment. Employment protection reforms increase the volatility of employment and reduce the correlation of the real wage with labor productivity.

All in all, institutions appear to be important for the cyclical features of data. Nevertheless, as Faccini and Rosazza Bondibene (2012) note, although institutions are important, they explain only a part of the differences in cyclical behavior across countries.

3. Data

We gather data from 37 countries. Our objective is to cover a majority of developed countries. On the other hand, we deliberately refrain from using data from developing countries due to the poor nature or non-availability of some of the time series.[6] We collected data on these countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Turkey, the United Kingdom, and the United States.[7]

In most of this paper, we focus on patterns acquired by aggregating and comparing mechanically applied statistics based on each country's data . Because of the purpose of this paper, we prefer such automation, since any departure for a particular country could be understood as purpose-built. For each country we use as long a series as we were able to collect. We try to harmonize our data across countries as much as possible.[8] If we find that some feature is present in most countries regardless of their degree of development and regardless of the time span of the available data, such a feature should be judged as important even if it would be difficult to identify in a single given country.

We are interested in main the labor market variables and their comovement with GDP or among themselves. We work with quarterly, seasonally adjusted data.[9] Namely, we collect nominal GDP (denoted as $nGDP_t$ throughout the paper), real GDP (GDP_t), the GDP deflator ($pGDP_t$), nominal and real household consumption (nC_t and C_t), total hours worked (H_t), total compensation of employees (denoted as the wage bill throughout the paper, WB_t), gross wages and salaries (W_t), total employed persons (EMP_t), the unemployment rate (UNR_t), and the participation rate (PR_t). From these time series, we compute additional data: the labor share, defined as the wage bill divided by nominal

[6] The shadow economy can be significant in these countries, implying possible bias in some officially published labor market time series (e.g. employment and wages).

[7] The data come from the Australian Bureau of Statistics, the Cabinet Office of Japan, Eurostat, FRED, Statistics Canada, Statistics Korea, Statistics New Zealand, the Turkish Statistical Institute, and the (U.S.) Bureau of Labor Statistics.

[8] That is why for European countries we rely mainly on Eurostat data.

[9] Monthly data are transformed into quarterly units. We prefer official seasonal adjustment performed by statistical offices. In cases where seasonally adjusted data were not available, we used the x12 to filter out seasonal components. The x12 filter is currently available as a component of the IRIS Toolbox Beneš (2013), which is also used for several other computations.

GDP (LS_t), average nominal wages, defined as the total wage volume divided by the number of employed persons (aWE_t) or by hours worked (aWH_t), their real-terms counterparts ($raWE_t$ and $raWH_t$), and also similar time series for the wage bill ($raWBE_t$ and $raWBH_t$).

We consider three ways of deflating the nominal variables: using the GDP deflator $raWE_t$, $raWH_t$ using the consumption deflator $raWE2_t$, $raWB2_t$, and using the CPI $raWE3_t$, $raWB3_t$.

For isolating cyclical frequencies, our preferred approach is the Christiano-Fitzgerald band-pass filter Christiano and Fitzgerald (2003), which is applied at the corresponding frequencies (6–32 quarters for gaps and 33 or more quarters for trends). We prefer this method to other univariate filters, as it can easily be set to different frequencies.[10] As we are aware of the possible poor performance of univariate filters at the tails of time series, we do not use the first three and the last three observations in the gap series for the analysis. For robustness, we check the results using the Hodrick-Prescott filter Hodrick and Prescott (1997) with the usual smoothing parameter value for quarterly frequency $\lambda = 1,600$. The results are similar and can be found in Appendix B.

For the analysis of cyclical frequencies in the time domain, we filter *all* the time series, including the unemployment rate, in order to filter out some structural changes in the labor market. Except for rates and shares (the unemployment and participation rates and the labor share) the variables are logged before filtering. For simplicity, the cyclical parts obtained using statistical filters are referred to as '*cycles*' or '*gaps*,' although we are aware that these terms can have different meanings in macroeconomics. In this paper, these terms simply mean the cyclical components obtained using the univariate statistical filter. Growth rates are computed as first differences from their logged values, except for rates and shares, for which 'growth rates' are computed as first differences.

4. Analysis of Second Moments

4.1 Sample Correlations

This subsection presents a correlation analysis for selected variables at the -6 to 6 leads-lags interval and for various data transformations. We do not show higher leads (or lags), as these could be affected by the *next* cycle. We show the results for the band-pass (BP) gaps and the quarter-on-quarter (q/q) growth rates.[11] We also show histograms depicting the lag/lead with the strongest correlation between the series. Figures summarize the results only for countries with more than 40 observations.

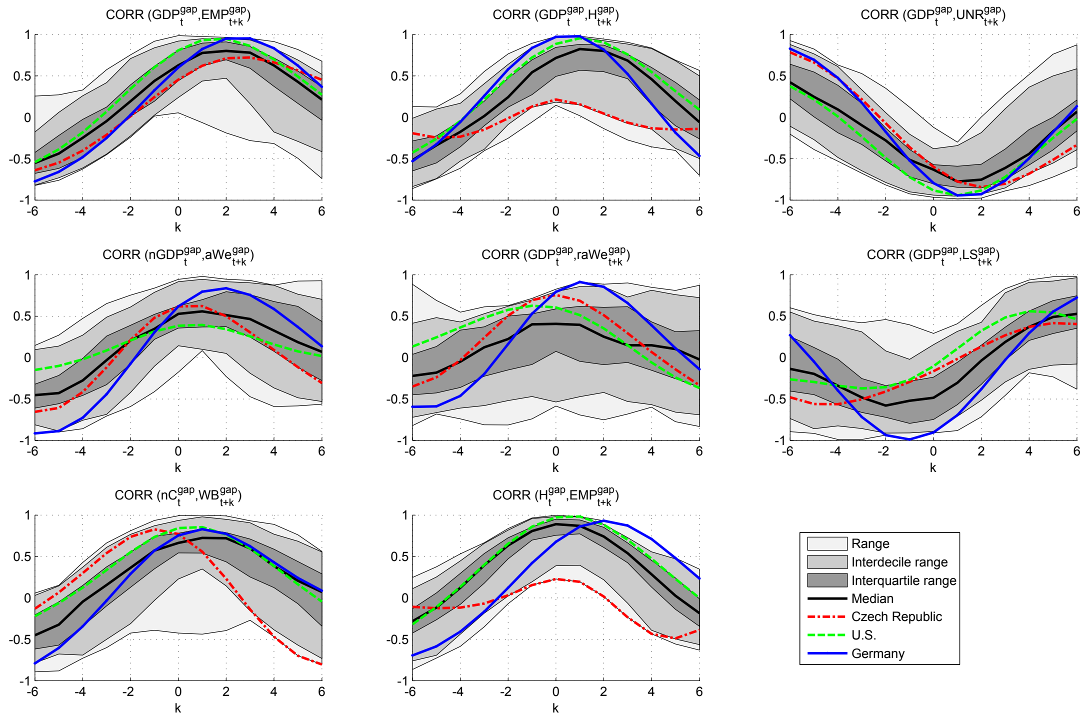
The figures in this section are organized as follows. The median is shown as a bold line with quantile ranges around it: the dark shadow area is the interquartile range (25th–75th percentiles), the mid-shadow area denotes the interdecile range (10th–90th percentiles), and the light shadow area is the overall range based on all available countries. We select these ranges in order to get a sense of how robust the results are across countries. For example, if the shadow areas are thin, it means that the underlying pattern is very similar for a majority of countries in the sample. We also use colors to denote three countries: the Czech Republic (green line), the U.S. (red line), and Germany (blue line).

[10] The HP gap filter keeps some high-frequency components in the gap series. Moreover, King and Rebelo (1993) show that using the HP filter for detrending removes data components that are regarded as parts of business cycles.
[11] Figures based on the HP filter are shown in Appendix B.

Figures 1 and 2 present the correlations between real GDP and certain labor market variables at business cycle frequencies. They indicate robust relations between real output and hours worked, total employment, and the unemployment rate. Hours worked and employment are cyclical variables. Unemployment is a strongly countercyclical variable. The cycles of these variables typically lag behind the output cycle by 1 or 2 quarters. The labor share is a countercyclical variable that in most countries leads the cycle by 1 quarter. The countercyclicality of the labor share is a manifestation of the Shimer puzzle Shimer (2009) for the canonical search-and-matching models.[12]

Finally, real wages are cyclical in some countries, but acyclical or even countercyclical in others, which is well in line with the literature (see Section 2).

Figure 1: Correlations of Cyclical Components of Labor Market Variables with Output Cycle (Band-pass Filter)

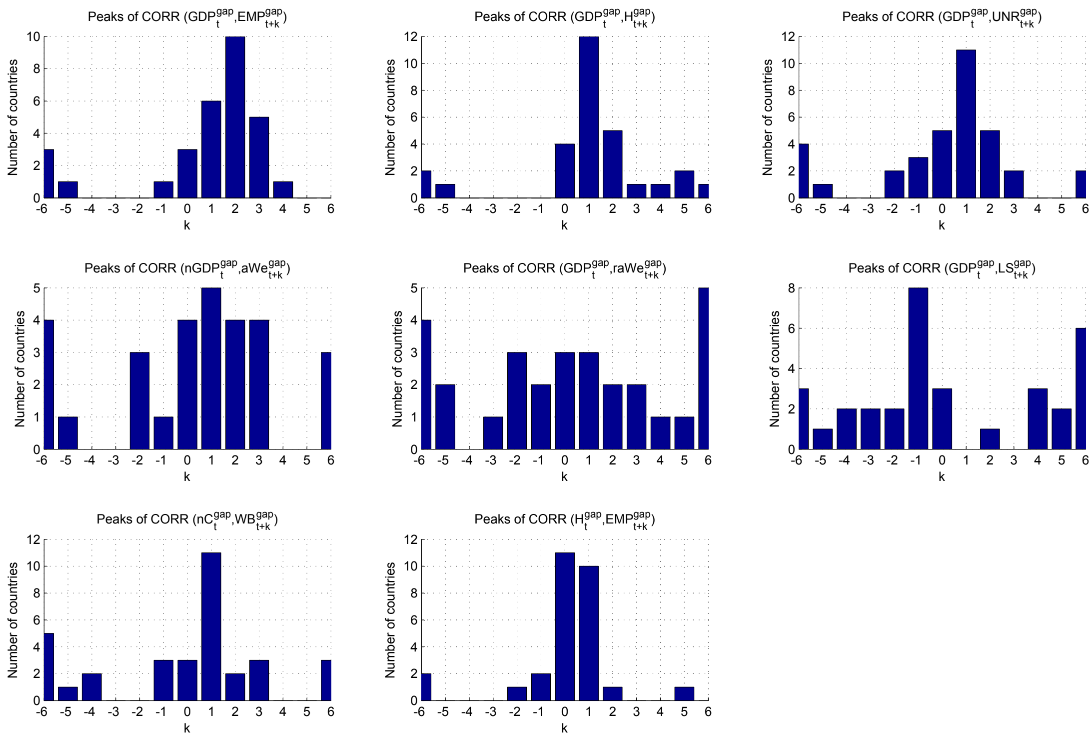


Curiously, Ohanian and Raffo (2012) find a zero correlation between the cycles of employment and hours worked in post-1984 European data. We do not confirm this finding: both labor input margins seem to be procyclical for most of the countries in our sample.

All in all, the correlation between the output cycle and the cycles in labor market variables seems to be stronger than the correlation between labor market variables themselves. The cycles isolated using the HP filter exhibit similar patterns to the analysis using the band-pass filter; see Appendix B.

[12] In the standard framework, the labor share is related to the labor wedge (i.e., the difference between the marginal product of labor and the marginal rate of substitution), which is a symptom of inefficiency on the labor market. Shimer (2009) noted that the countercyclical labor share presents problems for standard search-and-matching labor market models. In recessions, searching frictions should be small, but the countercyclical labor share makes the labor market wedge particularly severe for recessions. See also Karabarbounis (2014) for further elaboration of this issue.

Figure 2: Distribution of Strongest Correlations of Cyclical Components with Output Cycles (Band-pass Filter)



Figures 3–4 present the same type of figures for the quarter-on-quarter (q/q) growth rates. In general, there are several interesting findings. First, the majority of relations are much weaker for this data transformation. Most other correlations do not get significantly (if at all) over 0.5. Thus, the median correlations do not have such high values (in absolute terms) as for cyclical frequencies, although some comovement patterns (e.g. Okun's law) are presented in growth rates as well. Second, some of the correlations are characterized not by a rather smooth pattern, but by a significant contemporaneous peak.

When one analyzes the yearly growth rates (instead of the quarterly growth rates), the correlation profiles are smoother and stronger than the q/q growth rates, but still weaker than for the cycles. The year-on-year growth rates suppress high-frequency noise (being a moving-average of the q/q growth rates) and induce phase shifts (both effects should increase the strength of the correlations), but still do not necessarily eliminate low-frequency components that can lower the correlation patterns (see Appendix A for a discussion).

We performed a number of sensitivity analyses. Two of them are worth mentioning. First, we looked at various other measures of real average wages using various price deflators and alternative indices (full-time equivalent wages rather than wages based on the national accounts) to see whether other wages are more cyclical. This was not confirmed (see Appendix C). Second, using a subsample of European countries, we tried to adjust real wages for the composition effect on the sector level (see Appendix D). We found that adjustment of real wages using sector-level data does not help make wages more cyclical. We therefore conclude that the composition effect probably operates on the individual level rather than on the sector level.

Figure 3: Correlations of Growth Rates with Real Output Growth

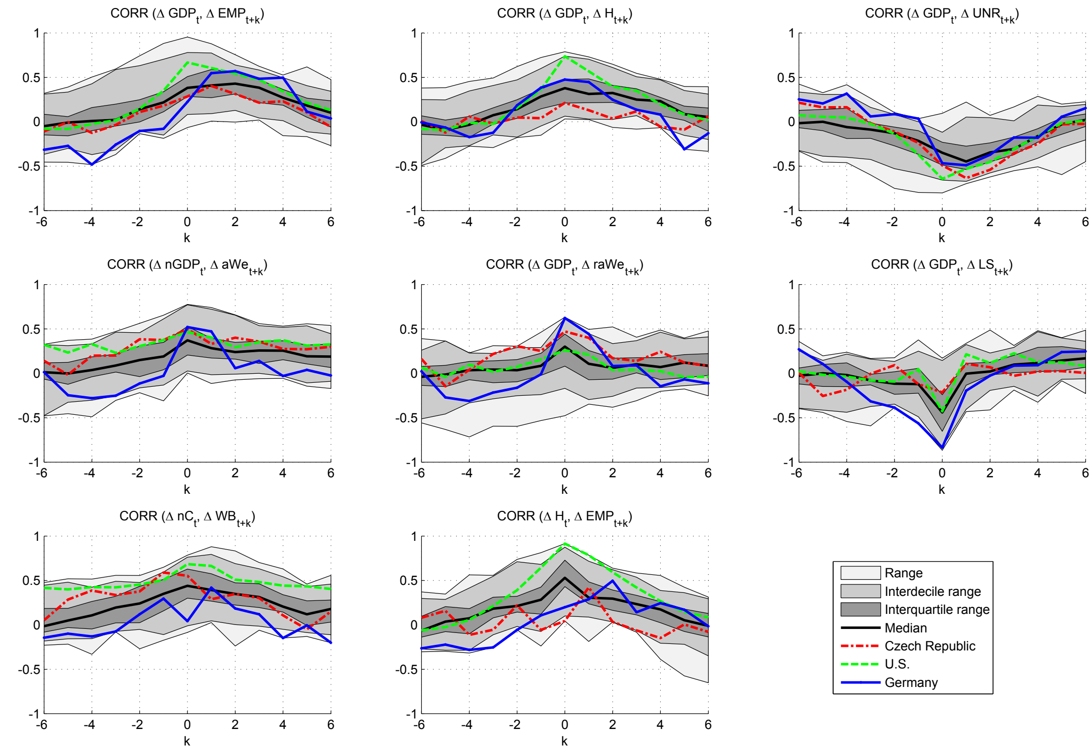
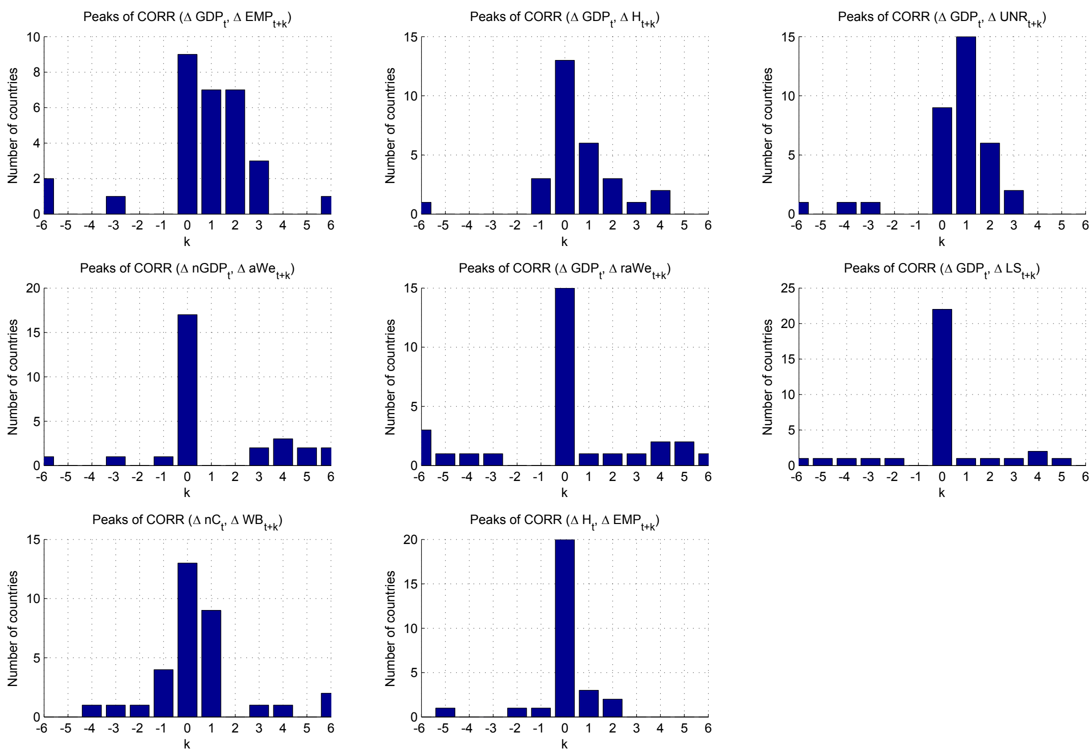


Figure 4: Distribution of Strongest Correlations of Growth Rates of Labor Market Variables with Real Output



4.2 Relative Volatilities

This subsection deals with the volatility of labor market variables. Figure 5 plots the boxplots[13] of the (base 10) logarithm of the standard deviations of the cycles in the variables relative to the standard deviations of output $\varsigma_x^{rel} = \log_{10}\left(\frac{\sigma_x^{gap}}{\sigma_{GDP}^{gap}}\right)$, where σ_x^{gap} are the sample standard deviations of the cyclical part of the time series x. Logarithmic transformation was chosen for better readability of the figure. Obviously, $\varsigma_x^{rel} < 0$ means that the gap in the respective variable is less volatile than the output gap, while $\varsigma_x^{rel} > 0$ means the opposite. If $\varsigma_x^{rel} \cong 1$, the cycle in the variable x is about ten times more volatile than the output cycle.

Similarly to the previous subsection, some patterns emerge. The cycles in total employment and hours worked are typically slightly less volatile than the output cycle.[14] The median statistics of real wages are also negative, but their third quartiles are near to, or slightly above, zero. The wage bill (in nominal terms) is more volatile than (real) GDP and its volatility resembles that of nominal GDP and nominal consumption. The other nominal variables in our selection – average wages with respect to total employment and hours worked – have volatilities slightly lower than, or approximately the same as, GDP. Variables denominated as rates (the unemployment rate, the labor share, and the participation rate) are much less volatile than GDP. This is due to units and it is appropriate to compare the volatilities of these variables among each other rather than to compare them with gaps based on levels.

Moreover, the distribution of relative volatilities for wages (real as well as nominal) and the wage bill is much more diverse compared to employment or hours worked.

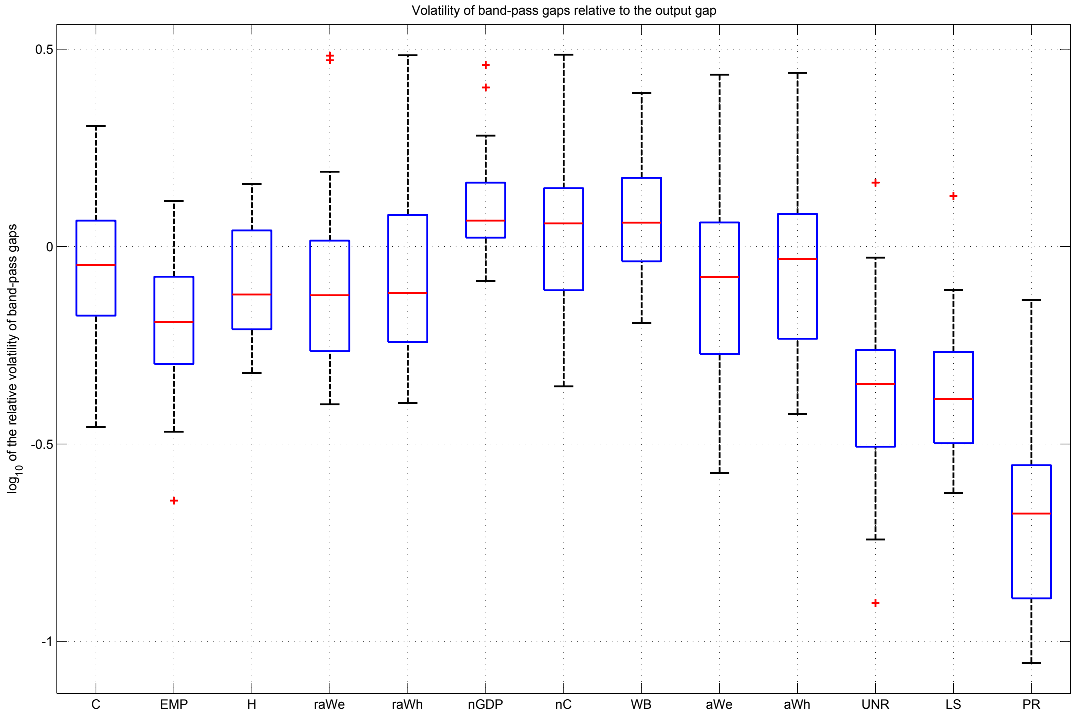
Figure 6 compares the volatilities of the cyclical components of the labor market variables against the volatility in the output cycle. In each panel, the dots denote data (countries) and the dashed line is the nonparametric fit performed by the local linear model Li and Racine (2006), with the smoothing parameter determined by the usual least-square cross validation. Obviously, countries that exhibit more volatile output cycles also have more volatile other labor market variables. There is no systematic trade-off between volatility in output and volatility in other variables at cyclical frequencies. The same conclusion holds if we compare the volatility of growth rates.

Figure 7 shows the relations between the pairs of relative volatilities among countries. The first panel shows that the higher is the relative volatility of employment, the higher is the relative volatility of hours worked. This can be broadly interpreted as meaning that in countries, the adjustment of economies to shocks goes through both the intensive and extensive margins. The volatilities of the two productivity measures and of the two average wages (per worker and per hours worked) are also positively related. The volatility of productivity and employment is almost unrelated, while the volatilities of employment and the average wage and of employment and consumption are both positively related. Therefore, the data do not support the notion that there is a trade-off between wage and employment adjustments to shocks. The volatility of hours worked seems to be unrelated to the volatility of the average real wage or productivity. There is a weak positive relationship between the volatilities of the cycles in hours and in consumption.

[13] The boxplots are organized using the Matlab default settings: in each box, the central red mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points considered not to be outliers, and the outliers are plotted individually by red crosses. Outliers are defined as observations larger than $P_{75} + 1.5(P_{75} - P_{25})$ or smaller than $P_{25} - 1.5(P_{75} - P_{25})$, where P_{25} and P_{75} are the 25th and 75th percentiles, respectively.

[14] Ohanian and Raffo (2012) also find that hours worked are slightly less volatile than output, with the exception of Norway. We do not, however, confirm their result: Norway is not an outlier in our dataset.

Figure 5: Relative Volatilities of Cyclical Components (Cycles: Band-pass Filter)



Figures 8 and 9 present the analogous graphs for quarterly growth rates. There are several notable results. First, the dispersion (the size of the box) is higher for several variables (e.g. employment and hours worked). Second, there are more outliers. And third, several boxplots are 'shifted' upwards, i.e., the variables are typically more volatile than real GDP. An important exception is employment, whose relative volatility falls at lower frequencies. The relationships between relative volatilities are qualitatively similar to the case of cyclical volatilities, with the exception of hours worked, where there is now a positive relationship between relative volatility in hours worked and relative volatility in the average wage.

Figure 6: Volatilities of Cyclical Components of Labor Market Variables Against Volatility in Output Cycle (Cycles: Band-pass Filter)

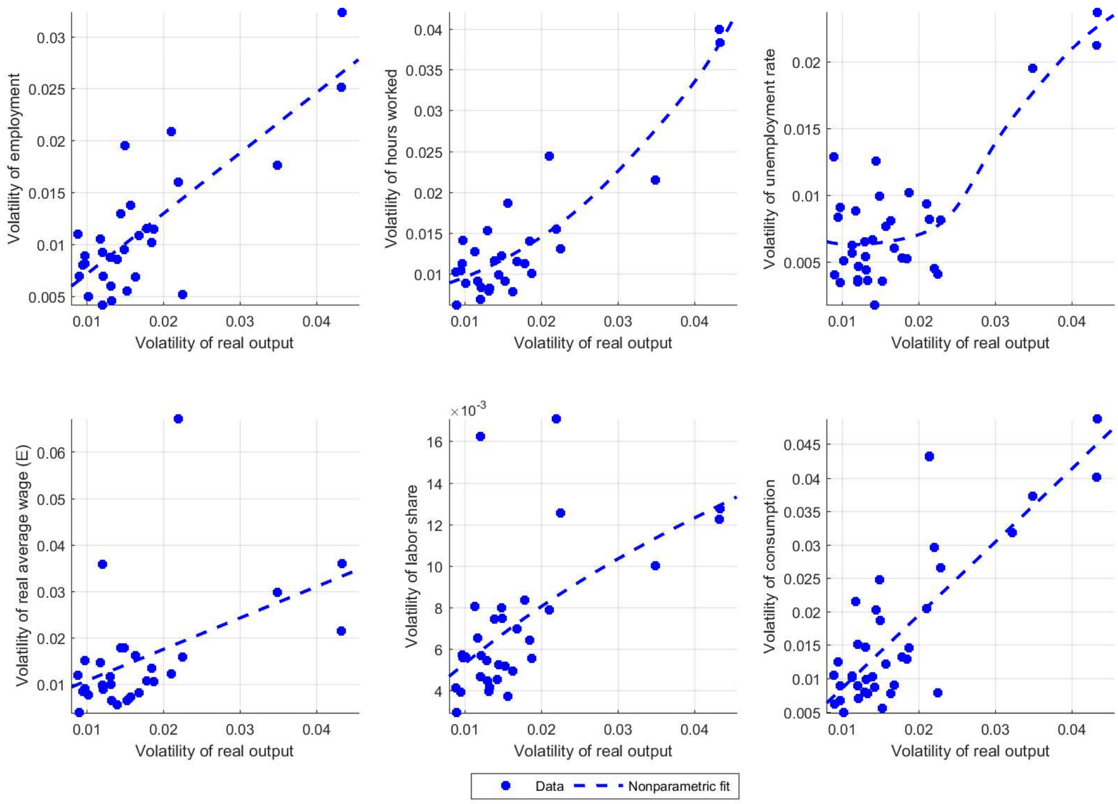


Figure 7: Relative Volatilities – Data and Nonparametric Fit (Cycles: Band-pass Filter)

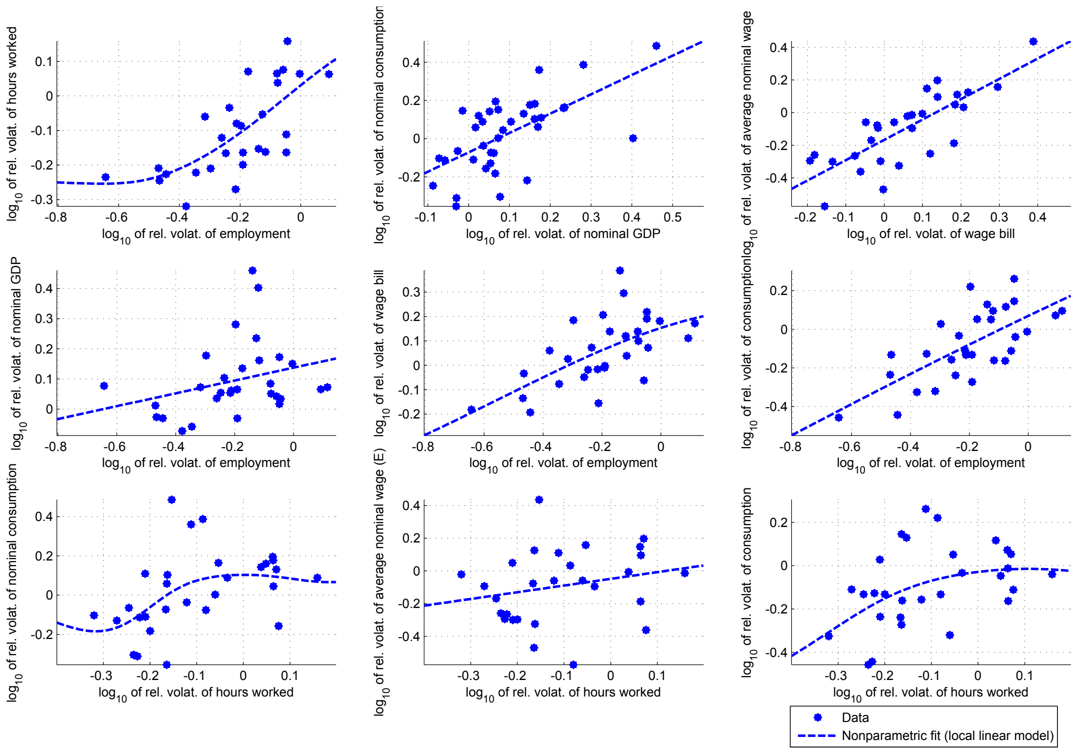


Figure 8: Relative Volatilities of Quarterly Growth Rates

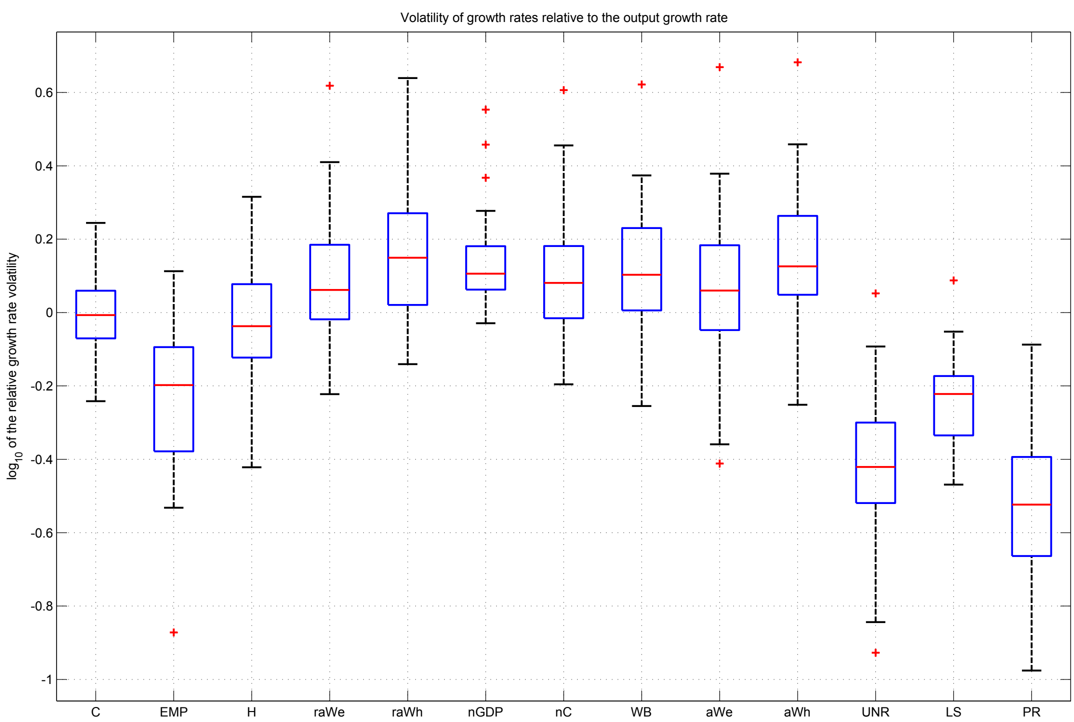
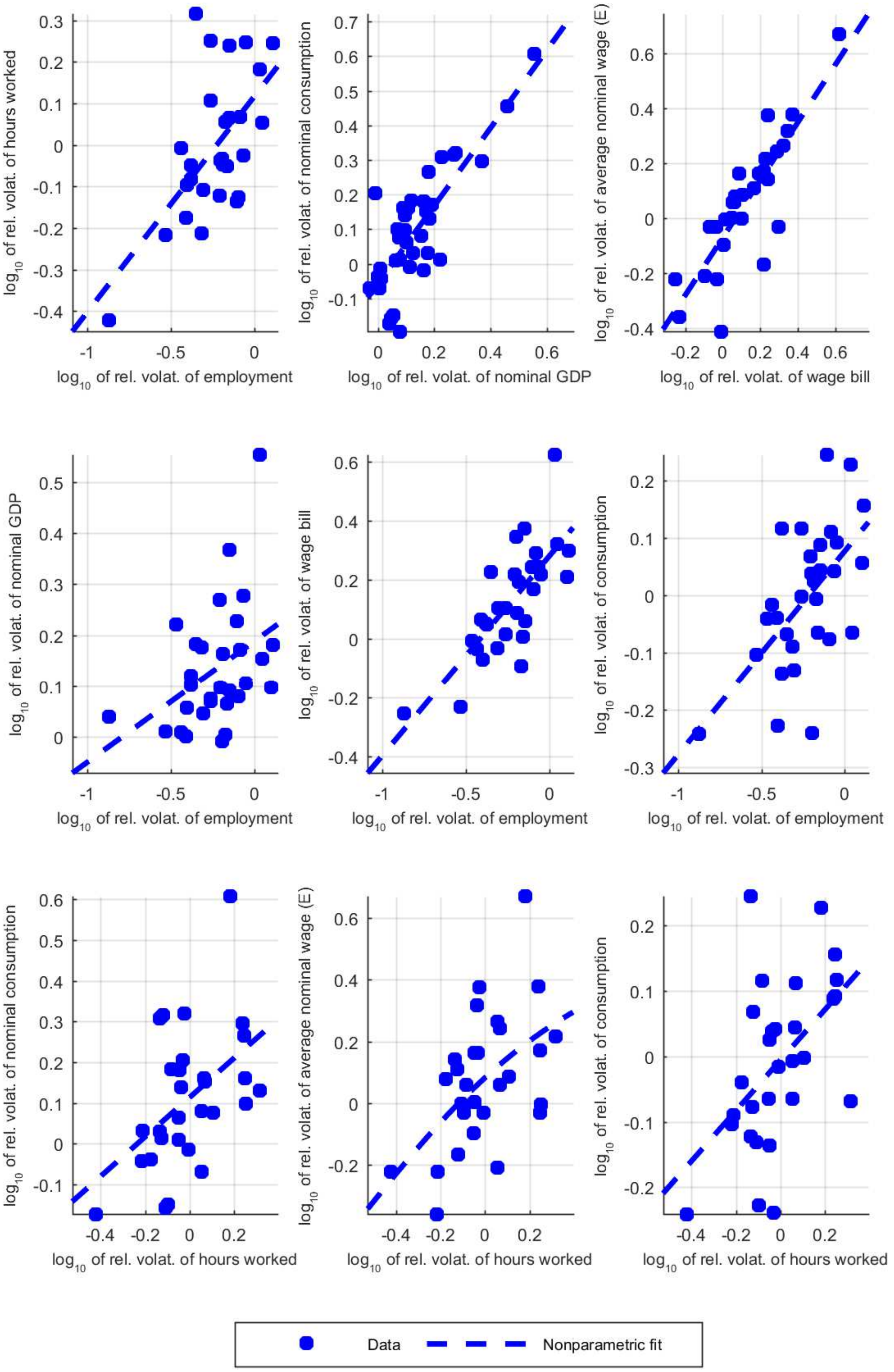


Figure 9: Relative Volatilities – Data and Nonparametric Fit (Quarterly Growth Rates)



4.3 Coherence Analysis

As discussed in Section 2, there are different views on the appropriate transformation of the time series investigated (growth rates versus band-pass filters). An obvious alternative is to use frequency-domain techniques: one can look at the frequencies of interest without the need to prefilter data in the time domain. A useful tool is coherence, which is the frequency-specific analogue of the square of correlation. Coherence describes the strength of the linear association between time series over frequencies. The dependence between the series is not limited to simultaneous values, but also captures leads and lags. Its value lies between 0 and 1.

Formally, the coherence between two time series x and y is defined as

$$\rho^2_{x,y}(\omega) = \frac{|S_{x,y}(\omega)|^2}{S_x(\omega)S_y(\omega)} \in [0,1] \qquad \text{for } 0 \leq \omega \leq 2\pi,$$

where S_x is the spectrum of time series x at frequency ω, and $S_{x,y}$ denotes the cross-spectrum of x and y.

There is a subtle issue: for non-stationary series, the spectrum is not defined at 0 and, moreover, the usual approaches for estimating spectra require stationarity of time series. To deal with this issue, we utilize the coherence-invariance property:[15]

$$\rho^2_{x,y}(\omega) = \rho^2_{\Delta x,y}(\omega),$$

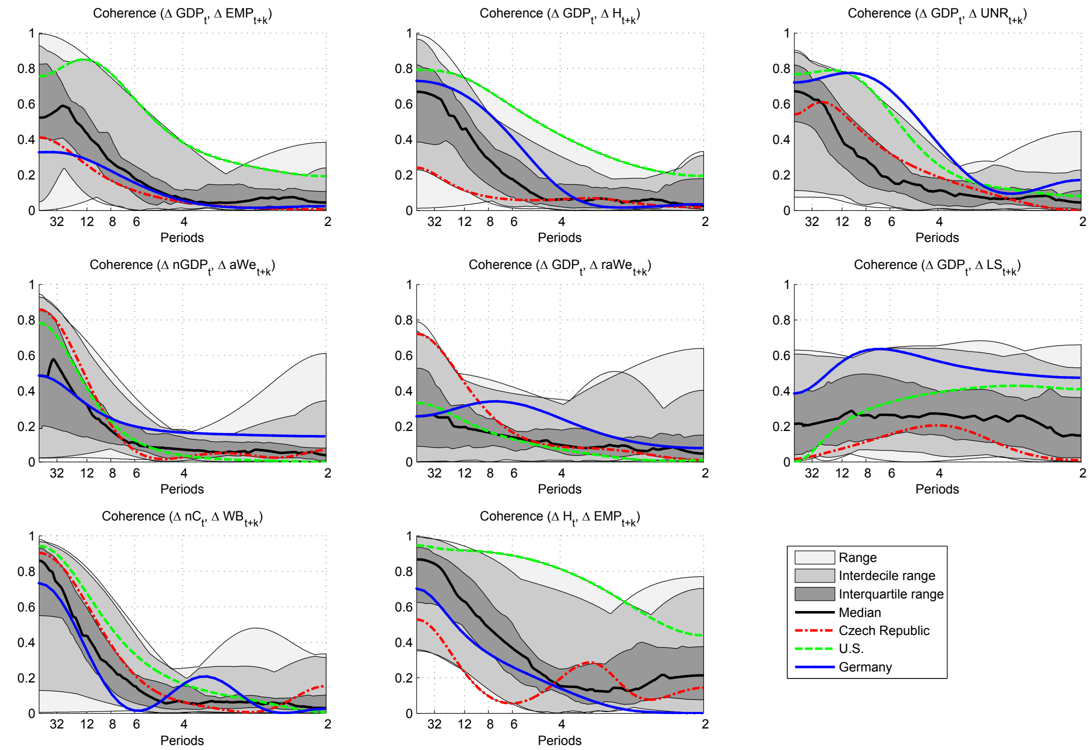
for ω such that both sides are defined (i.e., $\omega \neq k2\pi$ for $k \in \mathbb{N} \cup 0$). Therefore, when computing spectra, we work with growth rates.[16]

There are several results (see Figure 10): first, the sample of point estimates of coherence is relatively wide, as are the standard errors for the coherence for individual countries. Nevertheless, the coherence between labor inputs (employment and hours worked) and output are high for a typical country at business cycle frequencies and for some countries even at low frequencies (32 or more quarters). The same applies to the coherence between unemployment and output, where it typically peaks in the band of 8–32 quarters. Interestingly, for some countries, the output-unemployment coherence is high even at low frequencies (32 or more quarters) – this is the case, for example, for the U.S.[17] There is also strong business cycle synchronization between output, consumption, and the wage bill.

The rest of the sample coherence exhibits a great diversity of cross-country patterns. This may be due to the high sampling variability of the coherence estimates.[18]

[15] See, for example, Koopman (1974), p. 149. Andrle et al. (2013) use the same approach.
[16] The invariance property can generalized for a general linear time-invariant filter. In large samples, the same coherence should be obtained if the series are stationarized by another suitable filter. There are, however, finite sample issues and our Monte Carlo experiments indicate that growth rates work reasonably well.
[17] Lafourcade, P. et al. (2015) confirm this finding using a different dataset of yearly data that spans more than 50 years.
[18] There are various approaches to estimating coherence Hamilton (1994). We looked at two of them: (i) the parametric approach, which first estimates a VAR model and then derives the coherence, and (ii) the non-parametric Bartlett approach. The two approaches seem to have comparable sampling uncertainty. Our reported results are based on the parametric approach, where the lag of the estimated VAR was chosen by the AIC.

Figure 10: Coherence of Labor Market Variables with Real Output



5. Dynamic Factor Models

In this section, we apply a dimension-reduction technique involving dynamic factor models (DFMs). Our motivation is to inquire how 'factors' (i.e., orthogonal shocks) can explain the business cycle dynamics of our labor market data. Andrle et al. (2016) argue that the number of important 'factors' (i.e., factors that explain the major share of the time series) is revealing about the number of shocks that drive the dynamics of the series under investigation. Structural models (such as DSGE models) tend to rely on a high number of shocks (relative to the number of observable variables),[19] and it is interesting to know whether this is supported by the data.

There are various formulations of DFMs. For the sake of robustness of our results, we apply two of them: in the first subsection we employ the factor-augmented VAR model in the time domain, and in the second subsection we analyze the results based on dynamic principal component analysis in the frequency domain.

The list of variables entering all our DFM exercises is the following: real GDP, real consumption, hours worked, the unemployment rate, employment (in persons), and the real wage. For obvious reasons, we do not include those time series which are linear combinations of other time series (such as the labor share, which is derivable from GDP and the wage bill). We include in the analysis only those countries which have at least 15 years of data available for all these variables.

5.1 Factor-Augmented VAR

The factor-augmented VAR (FAVAR) is formulated in the time domain using a state-space representation:

$$y_t = \sum_j \Lambda_j f_{t-j} + \varepsilon_t,$$

where $\sum_j \Lambda_j f_{t-j}$ is the common component based on unobserved factors f_t and ε_t are idiosyncratic components. To estimate this model, we follow the approach described in Troy Matheson's tutorial on FAVAR modeling within the IRIS Toolbox, which is available on the IRIS website.

Figure 11 shows the cumulative variance explained by k factors acquired from the model (normalized) singular values, which represents the proportion of the variance explained by the k-th factor. The first panel depicts the results for time series prefiltered using the band-pass filter, and the third and fourth panels show the results for q/q and y/y growth rates. The second panel presents results based on q/q growth rates acquired from the HP-filtered data with a low smoothing parameter ($\lambda = 1$). We analyze this option because standard q/q growth rates sometimes contain higher-frequency noise and HP-filtering with low λ should filter out the noise component without destroying the fundamental information presented in the data.

There are three notable results. First, when one works with cycles, the dominant factor typically explains almost 60% and two factors more than 90% of the variance in the data for most countries.[20]

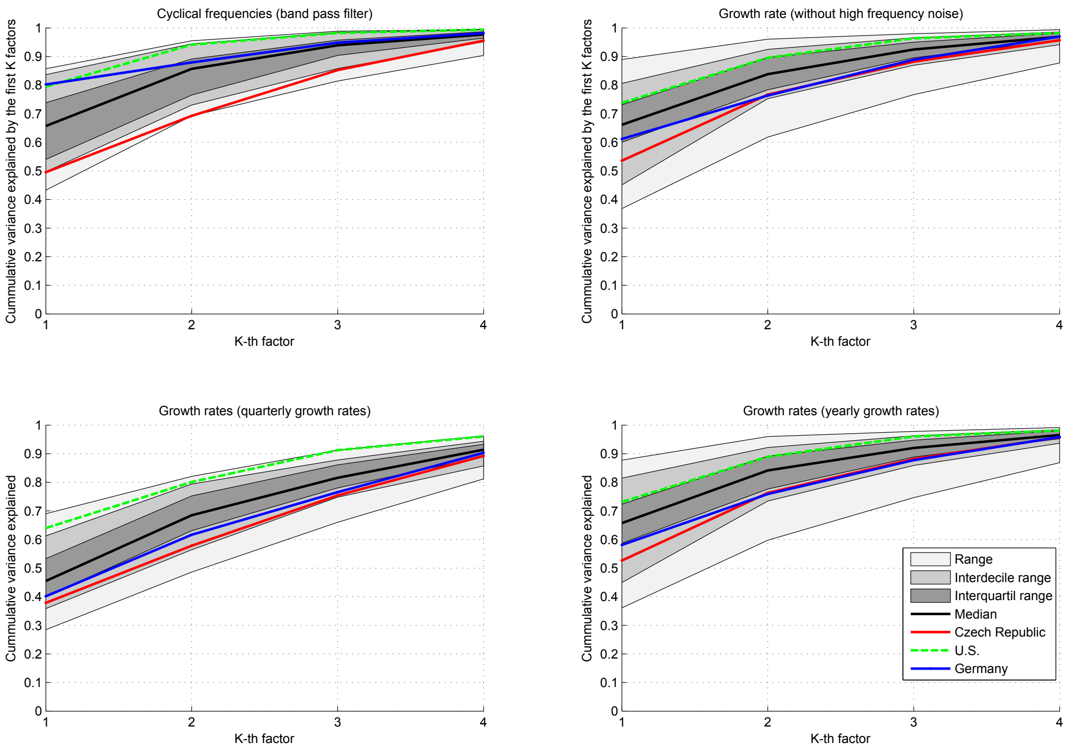
[19] Andrle et al. (2016) propose a test for structural models based on the number of shocks. If the number of 'important' shocks in a structural model is higher than the number of factors, this can be considered a sign of model misspecification.

[20] Our list only contains real variables. If we incorporate some nominal variable into our list (e.g. nominal wages) the results change in such a way that the first factor would typically explain less than 60% but the variance explained by the second factor would be similar. These results could mean that the second factor is necessary for explaining the adaptation of an economy to shocks through prices.

Second, the median-based q/q growth rates are moved downward compared with the band-pass cycles. Thus, similarly to correlation analysis, there are weaker relationships between the variables at lower frequencies. And third, the median lines for the smooth q/q growth rates and y/y growth rates are not far from each other.

In the case of the Czech Republic, the first dynamic factor explains one of the lowest shares of the variance: about half. This is because consumption is not well synchronized with real output in the Czech Republic. This feature makes the Czech Republic an outlier.[21] For the rest of the countries, real wages are typically the variable that reduces the variance explained by the first factor.

Figure 11: Factor-Augmented VAR: Cumulative Explained Variance



We then report the results for each variable separately, i.e., we report the percentage of each variable explained by the factors using the standard $\Re^2$ measure of fit:

$$\Re^2 = 1 - \frac{\sum_{t=1}^{T}(x_t - \hat{x}_t)^2}{\sum_{t=1}^{T}(x_t - \bar{x})},$$

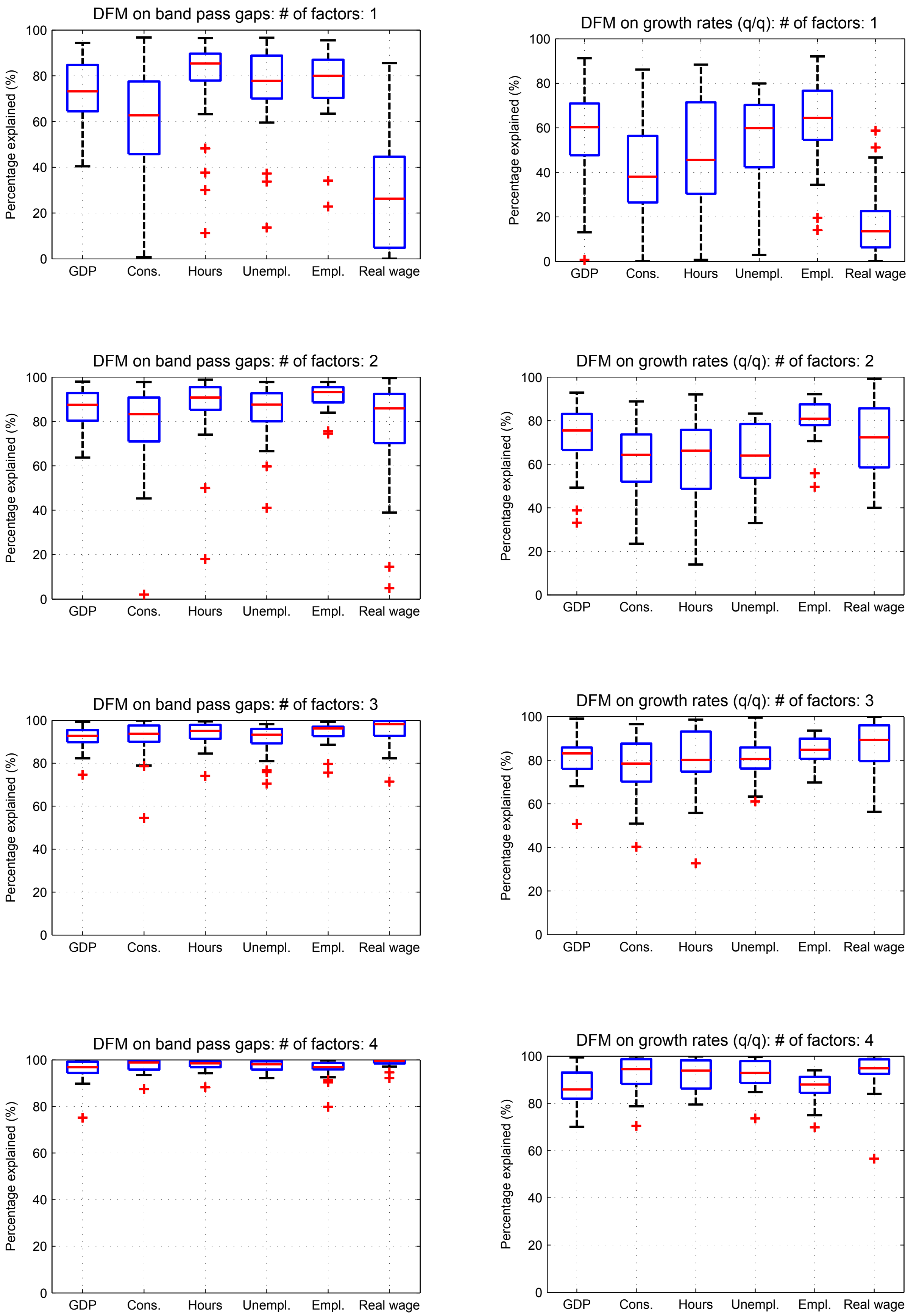
where x_t is the actual series (in a given transformation), $\bar{x}$ is the mean of the series, and $\hat{x}_t$ is the filtered common component $\hat{x}_t = \sum_j \Lambda_j f_{t-j}$.

The results are presented in Figure 12. The first factor typically explains approximately 70%–80% of the variance of the cyclical parts of output and of labor market quantities (employment, hours

[21] The dynamics of consumption during 2010–2014 are responsible for this result. In 2010, optimism (as measured by the usual confidence indicators) prevailed among Czech households and consumption was relatively high. However, subsequent economic developments did not confirm this optimism. On the other hand, households' expectations in 2013 and 2014 were less optimistic than justified by subsequent economic developments. This contributed to a decoupling of the consumption cycle from the output cycle.

worked, and unemployment rate), about 60% of the variance in consumption, and less than 50% of the cyclical variance of the real wage. However, there are exceptions: there are countries where consumption is less cyclical (the Czech Republic) and countries where wages are cyclical (for example, the U.S.). The first two factors explain approximately 90% of the cyclical variance. Qualitatively, the same pattern holds for the growth rates, but the percentage of the variance explained is typically somewhat less than for the cycles. The lower fit is mainly due to high-frequency noise. If the exercise is done on yearly growth rates, the explanation is almost identical to the band-pass cycles.

Figure 12: Percentage of Variables Explained



5.2 Dynamic Principal Component Analysis

As an alternative, we use dynamic principal component analysis (DPCA) in the frequency domain. This approach is based on the seminal work of Brillinger (1964), which was introduced into empirical macroeconomics by Forni et al. (2000). The approach is essentially based on eigenvalue decomposition of the spectral density. It can be reverted back to the time domain, resulting in a two-sided filter that can be used to filter the common component.

Rather more formally, DPCA is based on the following representation:

$$x_t = \chi_t + \xi_t,$$

where x_t is the observed series, χ_t is the low-dimensional common component, and ξ_t is idiosyncratic noise, which is uncorrelated with the common component χ_t and only 'weak' correlation among the elements of ξ_t is allowed. Frequency-domain DPCA starts with estimation of the multivariate spectral density of the observed process x_t, from which the spectral density of the common component χ_t is obtained by selecting dominant eigenvalues of the multivariate spectral density of x_t. This is essentially a frequency-domain filter. That frequency-domain filter can be inverted back into the time domain to obtain a two-sided filter that relates the observed series to the common component:

$$\chi_t = \sum_{k=-K}^{K} \Lambda_k x_{t+k}, \tag{4}$$

where $\{\Lambda_k\}_{k=-K}^{K}$ are the weights of the time-domain filter. The choice of $K > 0$ implies that DPCA can easily account for the lead-lag relationship among the variables (such as unemployment and output).[22]

We present the results for DPCA in both the time and frequency domain. As said earlier, frequency-domain representation is centered on the multivariate spectral density, denoted henceforth as $\Sigma(\omega)$. Let $\{\lambda_{(i)}(\omega)\}_{i=1}^{n}$ be ordered eigenvalues of $\Sigma(\omega)$ at frequency ω. Since $\Sigma(\omega)$ is positive semi-definite for each frequency ω, all eigenvalues are non-negative. Therefore, for a stationary time series Y, we consider the following statistics:

$$\sigma_Y(\omega,k) \equiv \frac{\sum_{i=1}^{k} \lambda_{(i)}(\omega)}{\sum_{i=1}^{n} \lambda_{(i)}(\omega)},$$

which intuitively tells us the percentage of the variability explained by the k principal components at frequency ω.

A nice property of this statistic is its invariance to the difference filter (similarly to the case of coherence). Indeed, it holds that:

$$\sigma_Y(\omega,k) = \sigma_{(1-L)Y}(\omega,k), \tag{5}$$

[22] The choice of $K > 0$ means that the common component cannot easily be estimated at the beginning and the end of the sample. However, the two-sided nature of the filter is not an issue for us since we are interested not in real-time forecasting but in ex-post analysis of the data. For replication purposes, we use exactly the same approach in estimating the multivariate spectral matrix (the Bartlett non-parametric approach with the same setting for the smoothing window) as described by Forni et al. (2000).

for all ω, such that both sides are defined. Again, as in the case of coherence, this means that for non-stationary $I(1)$ time series, the statistics (5) can be estimated only for first differences for frequencies away from $\omega \neq 2k\pi$.

Figure 13 shows the fit in the frequency domain using the first dynamic component (i.e., $\sigma_{\Delta Y}(\omega, 1)$ in 5) in the frequency domain. Apparently, just the first principal component for frequencies lower than 6 quarters explains about two-thirds of the dynamics in a typical country. That means that at business cycle frequencies, just one shock typically explains about two-thirds of the dynamics.

Figure 13: DFM Fit in Frequency Domain

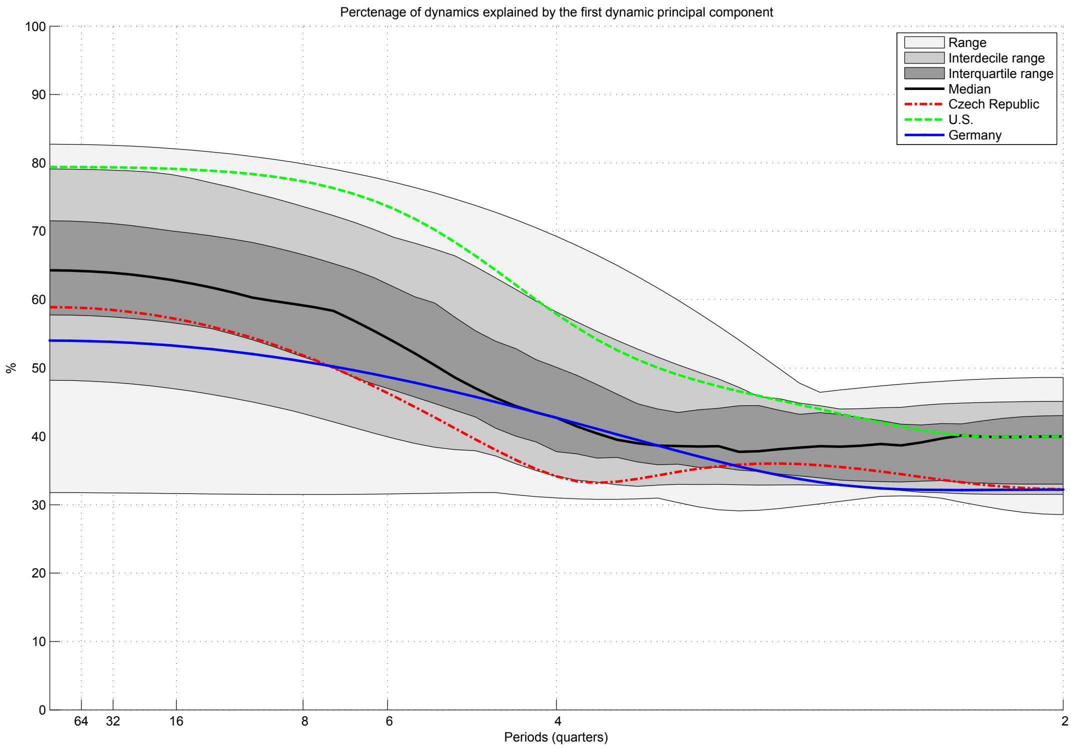


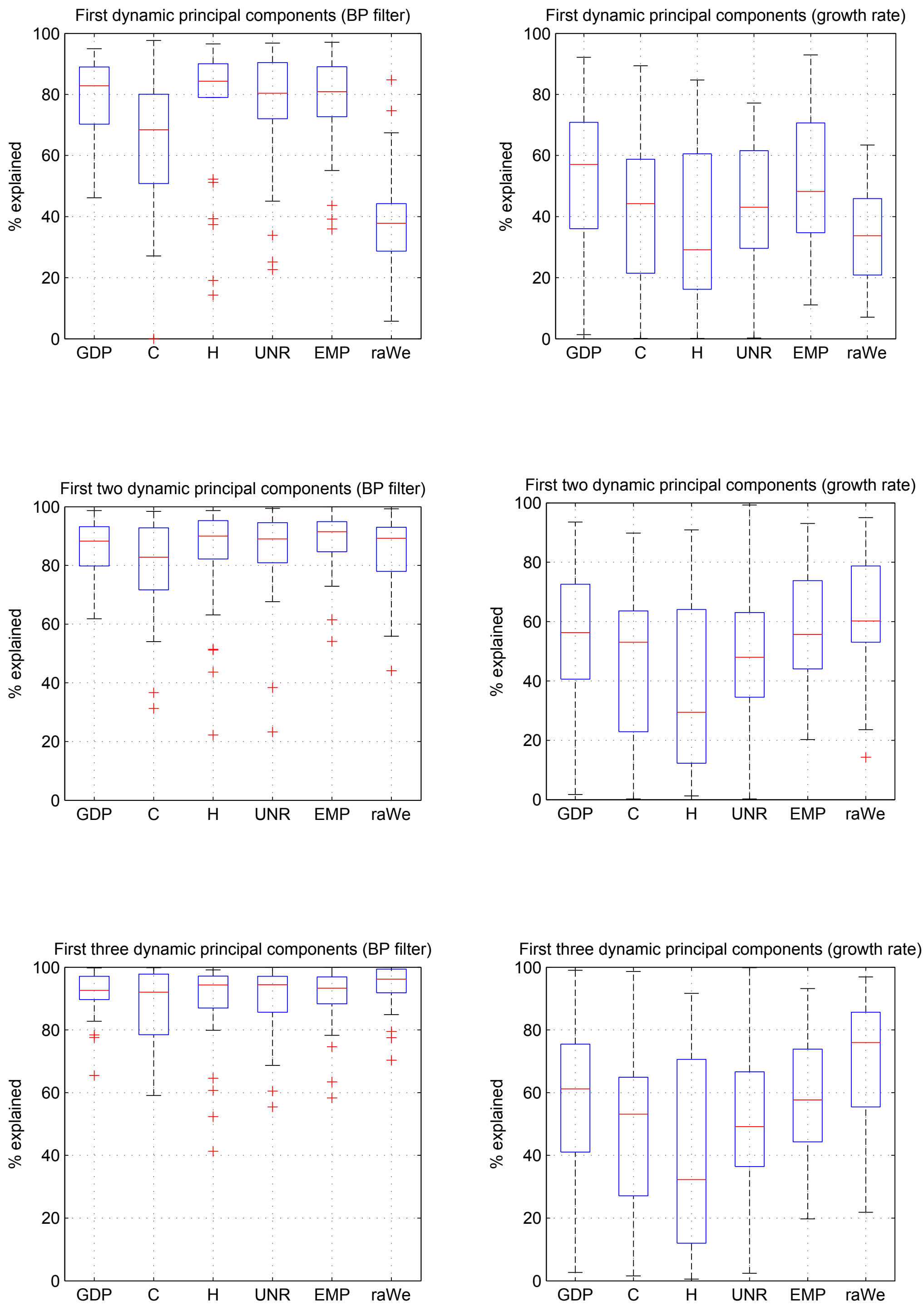
Figure 14 shows the fit of the time series based on filter (4) in the time domain for two data transformations (band-pass cycles and growth rates). Again, we use the R^2 statistic to measure comovements. Let χ_{it}^k be the common component for the series x_{it} estimated using k first dynamic principal components. Our preferred statistic is the analogue of the R^2 statistic for linear regression:

$$\Re^2(k) = 1 - \frac{\sum_{t=1}^{T}(x_{it} - \chi_{it}^k)^2}{\sum_{t=1}^{T}(x_{it} - \bar{x}_i)^2},$$

where $\bar{x}_i$ is the sample mean of x_{it}.

The results roughly confirm those based on the FAVAR model. GDP, unemployment, and labor market inputs strongly comove, while consumption comoves less. In a typical country, the comovement between the real wage and the rest of the variables is low, and the second factor is typically needed to span the space of all variables, including real wages.

Figure 14: DFM Fit in Time Domain



6. Institutions: The Case of Employment Protection Legislation

In this part of the paper, we investigate whether there is a robust statistical association between employment protection legislation (EPL) and the labor market characteristics analyzed in the preceding sections. We use EPL indicators composed by the OECD.[23] The OECD reports a set of 8 EPL indicators that capture various aspects and various types of contracts. For each country, we use the mean value of each indicator for the time period when the indicator is available. It is would be difficult to analyze the effects of individual indicators, especially because they are correlated across countries. We therefore opt instead – as in Gnocchi et al. (2015) – for principal component analysis.

It turns out that there are two main principal components that explain the variability of the EPL indicators across countries. The first principal component explains more than 67% and the first two principal components more than 90% of the variability in the indicators. The first principal component explains most of the variability in EPL for permanent contracts, while the second principal component is needed to explain the variability in the strictness of EPL for temporary contracts (above the portion already explained by the first component). Hence, we look at the explanatory power of the first two principal components.

First, we look at the impact of institutions on the relative volatilities of labor market variables. The first principal component[24] of the EPL indicators reduces the volatility of the cyclical components of hours worked, employment, and unemployment, but increases the cyclical volatility of wages and productivity. This is quite intuitive: more rigid labor markets seem to adjust more through prices than through quantities, and the finding is consistent with Nunziata (2003), Faccini and Rosazza Bondibene (2012), and Gnocchi et al. (2015). The second principal component (which is associated with more rigid temporary contracts above the first component) increases the cyclical volatility of hours worked, but reduces the cyclical volatility of employment, which means that countries with more rigid regulation of temporary contracts adjust through hours worked rather than through employment of persons. These conclusions also tend to hold for growth rates, although the relationships are much weaker.

Figures 16 and 17 display the relationship between the first principal component of EPL and the correlation among the variables. Apparently, stricter EPL reduces the cyclicality of labor inputs (employment, unemployment, and hours worked), while the cyclicality of the real wage increases. This conclusion survives for growth rates, although is weaker. This is consistent with the findings of Nunziata (2003), Hirata (2012), and Gnocchi et al. (2015).

The R^2 of the simple OLS regression of the cyclical correlations of the first two principal components is less than 0.2 in all cases. This means that although institutions influence the cyclical features of the data, their influence is limited and should not be overstated. This is consistent with the findings of Nunziata (2003) and Messina et al. (2009).

[23] The OECD indicators measure the procedures and costs involved in dismissing individuals or groups of workers and the procedures involved in hiring workers on fixed-term or temporary work agency contracts. The data are available at www.oecd.org/employment/protection.

[24] Principal components can be arbitrarily normalized. We use the normalization that positive values of the first principal component are associated with stricter EPL.

Figure 15: Relative Volatilities of Cyclical Components Versus EPL

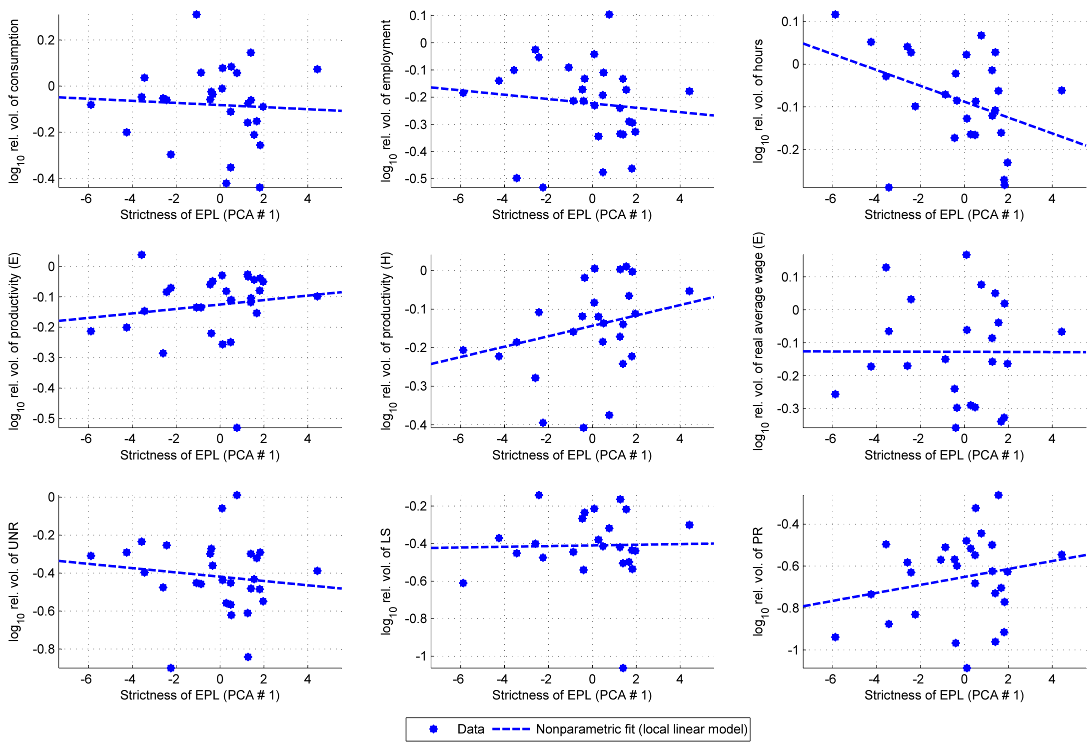


Figure 16: Cyclical Correlations Versus EPL

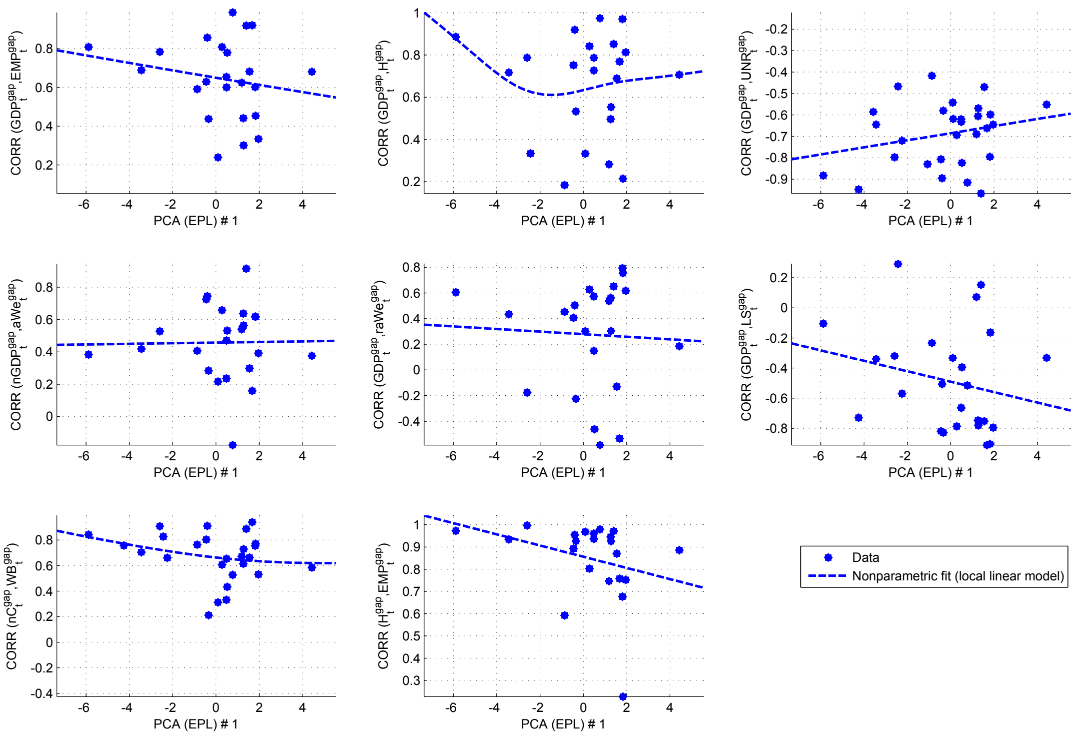
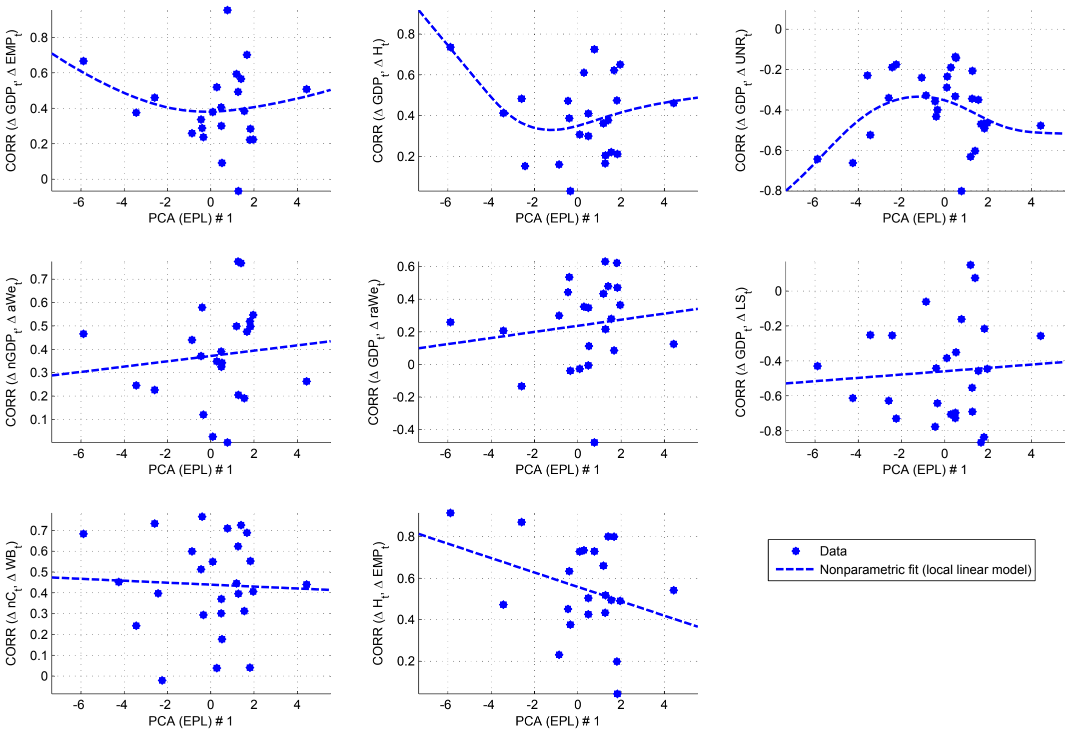


Figure 17: Correlations of Growth Rates Versus EPL



7. Is This Time Different?

In this section, we ask whether the Great Recession changed the comovement among the variables. Our exercise with the estimated FAVAR indicates that – at least for selected countries (the U.S. and the Czech Republic) – it probably did not change it much.

In Figures 18–23, we depict the cycles in output versus the cycles in selected labor market variables and ask whether the relationship between the two variables changed after 2008. We estimate the regression line on the pre-2008 sample of GDP_t^{gap} on X_{t+k}^{gap}, where X_t^{gap} is the cycle in variable X and k is the lead/lag for which the correlation between the two variables is the strongest. If the linear relationship between the two variables has not changed, we would expect the post-2008 observations to lie near this regression line. To get a sense of how much is 'near', we construct a 95% confidence interval along the line. Formally, one would have to expect 95% of the red crosses to lie between these confidence intervals.

For most countries, the post-2008 conditional distribution of the unemployment cycle is consistent with the behavior before 2008 (Figure 18). There are just a few exceptions: Germany, Slovakia, and Slovenia exhibit a smaller rise in cyclical unemployment during the crisis compared to the pre-crisis norm. On the other hand, Ireland and Japan seem to exhibit a stronger reaction of the unemployment cycle to output than before the crisis. Finally, the correlation of the cycles in unemployment and output in Bulgaria seems puzzling before 2008 and returns to normal after 2008.

The relationship between the output cycle and the cycle in hours worked also seems stable in most countries (Figure 19). Notable exceptions are Bulgaria, the Czech Republic, Slovakia, and Luxembourg, where the pre-2008 period witnessed little correlation between the two cycles, but after 2008 it seems that the two cycles started to be positively related.

The relationship between the cycles in output and employment is stable in most countries (Figure 20). With the exception of Denmark, Lithuania, Poland, and the UK (where the employment cycle seems to be more sensitive to the output cycle in the post-2008 period), the relationship seems stable. The data for Turkey are puzzling in the period before 2008, but behave normally after 2008.

To conclude, the cyclicality of labor inputs (employment and hours worked) did not change much in most countries after 2008, and where changes are detected the labor inputs seem to *increase the comovement with output* in most cases. The only exception to this rule is unemployment in three countries (Germany, Slovakia, and Slovenia), where it seems that the unemployment rate has reacted *less* than was the norm before the crisis.

When looking at the cyclicality of wages (Figures 21 and 22), our test detects that about half of the countries seem to witness a change in the elasticity of wages to output. There are countries where the relationship still holds (the Czech Republic, Germany, and the U.S., for example). Therefore, the correlation of wages with output not only is variable across countries, but also can vary over time.

Based on these findings, we do not have evidence that the flexibility of the labor market changed much in most countries.

Figure 18: Output – Unemployment Before and After 2008

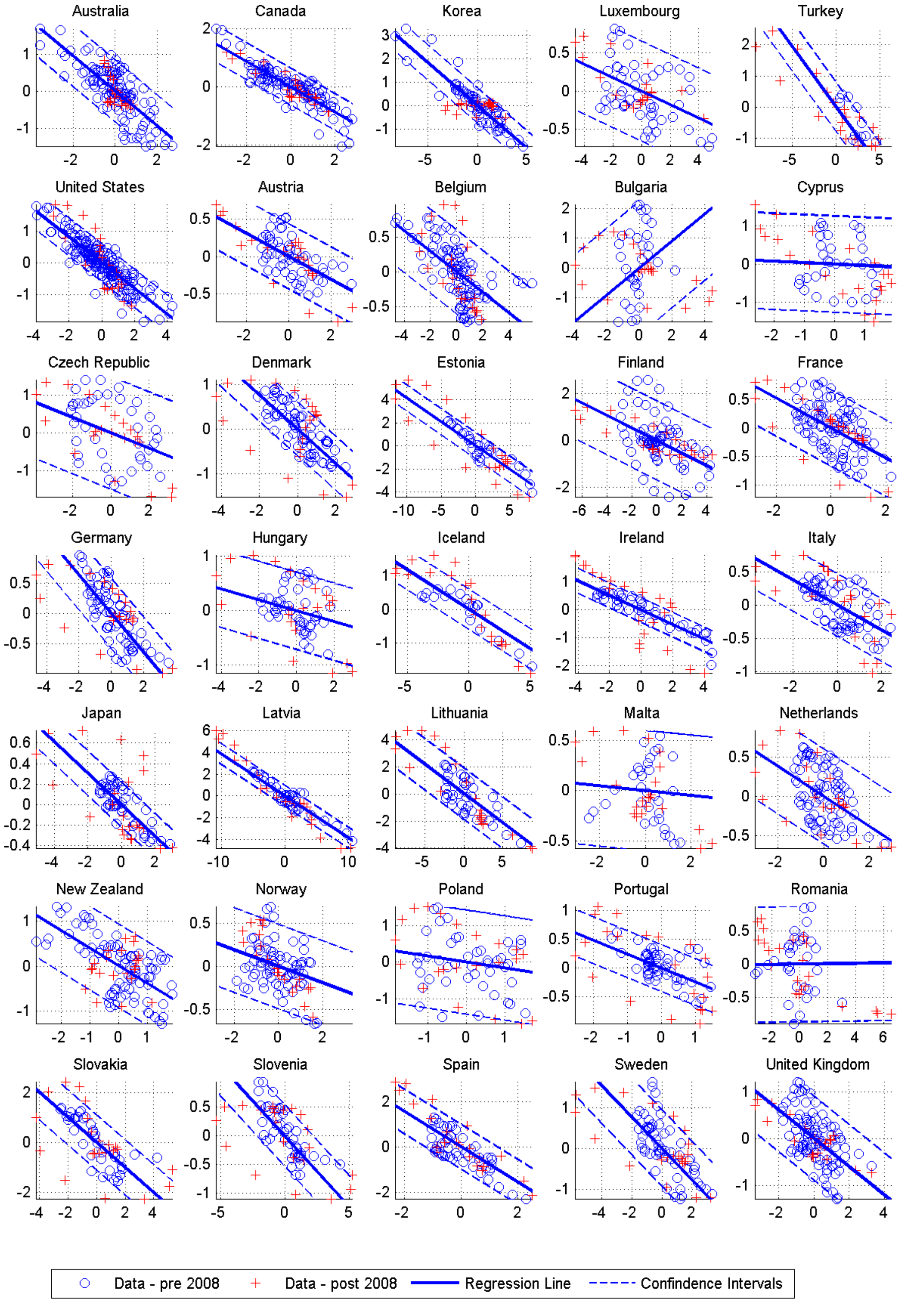


Figure 19: Output – Hours Worked Before and After 2008

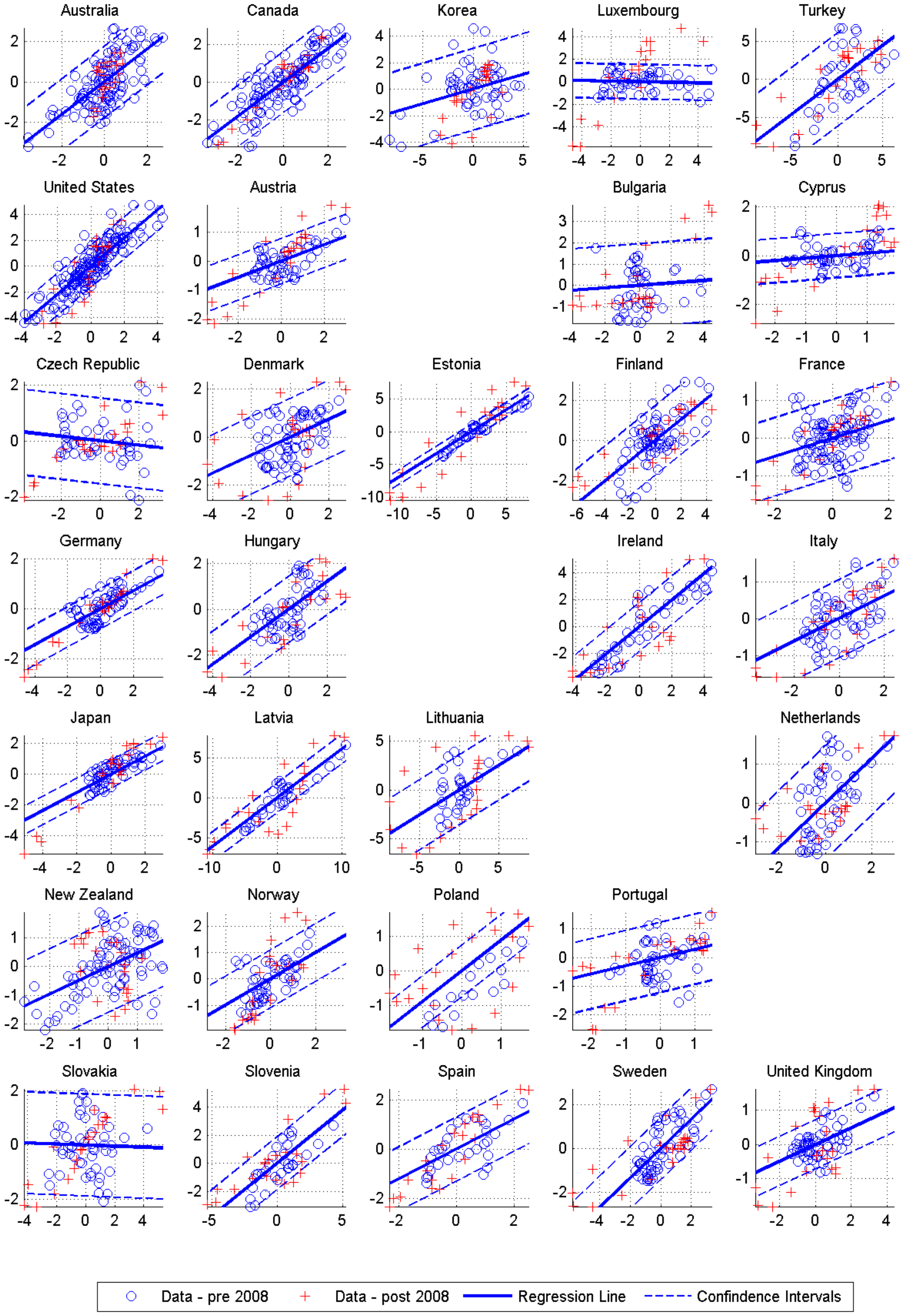


Figure 20: Output – Employment Before and After 2008

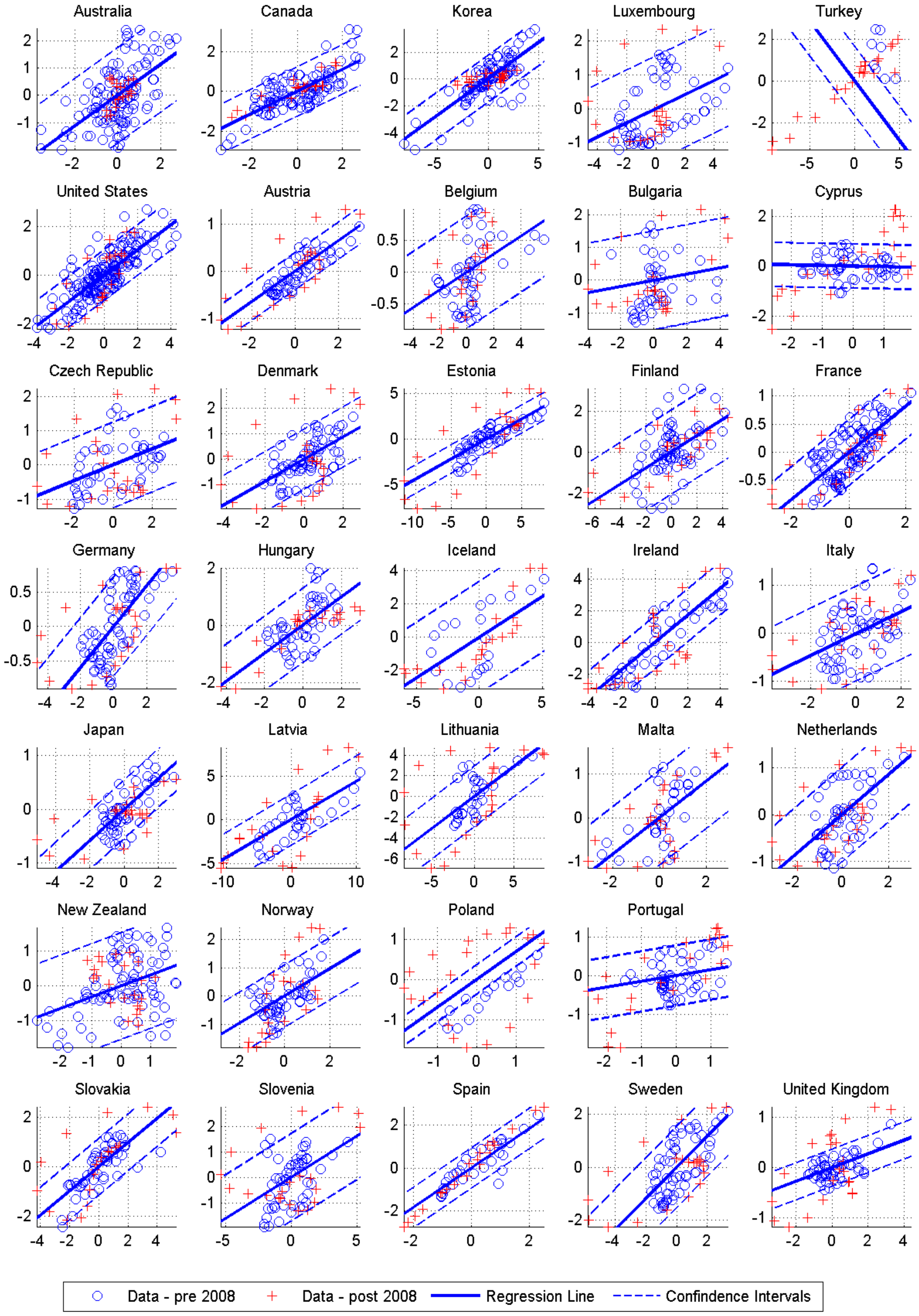


Figure 21: Output – Real Wage (raWE) Before and After 2008

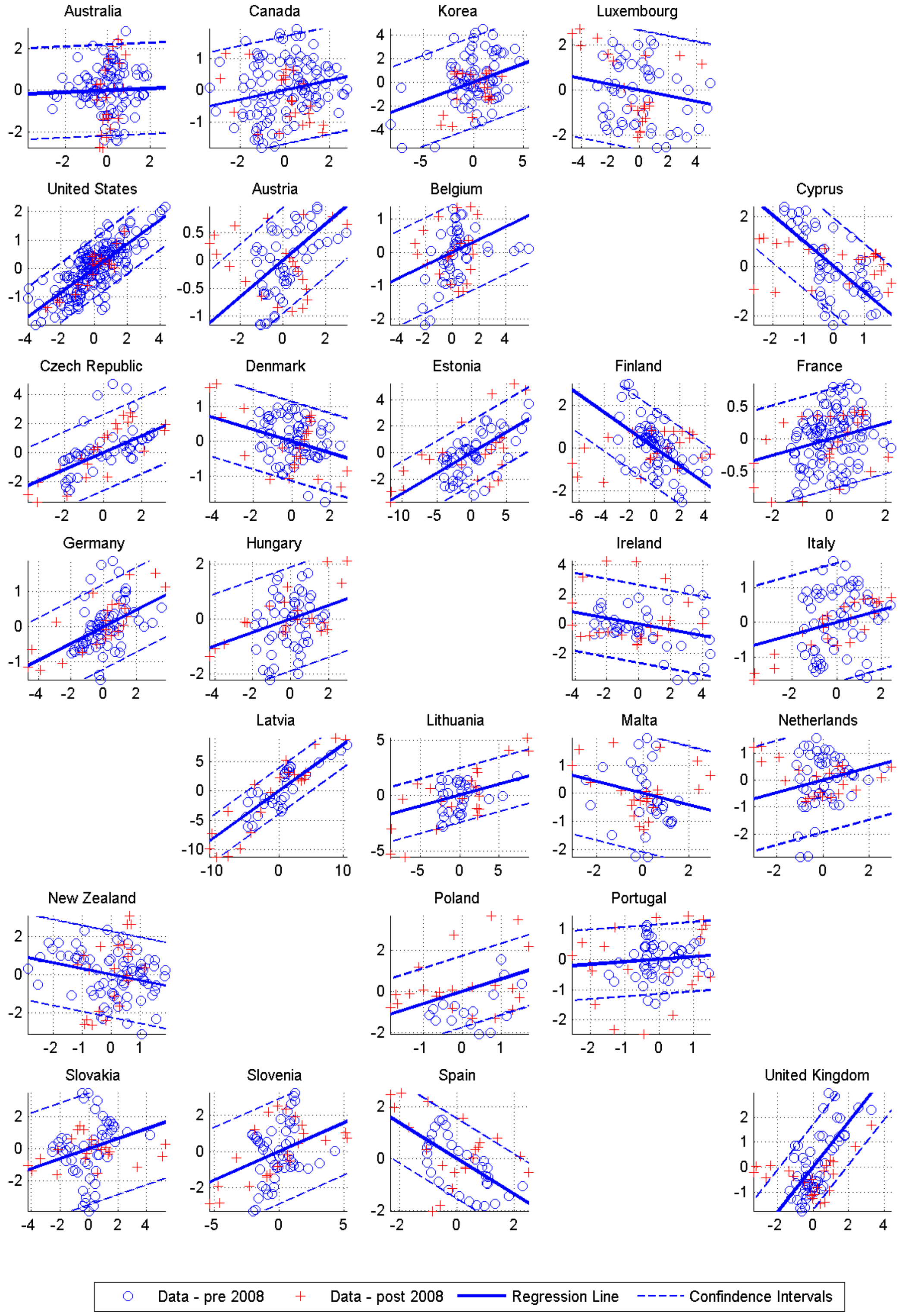


Figure 22: Output – Real Wage (raWH) Before and After 2008

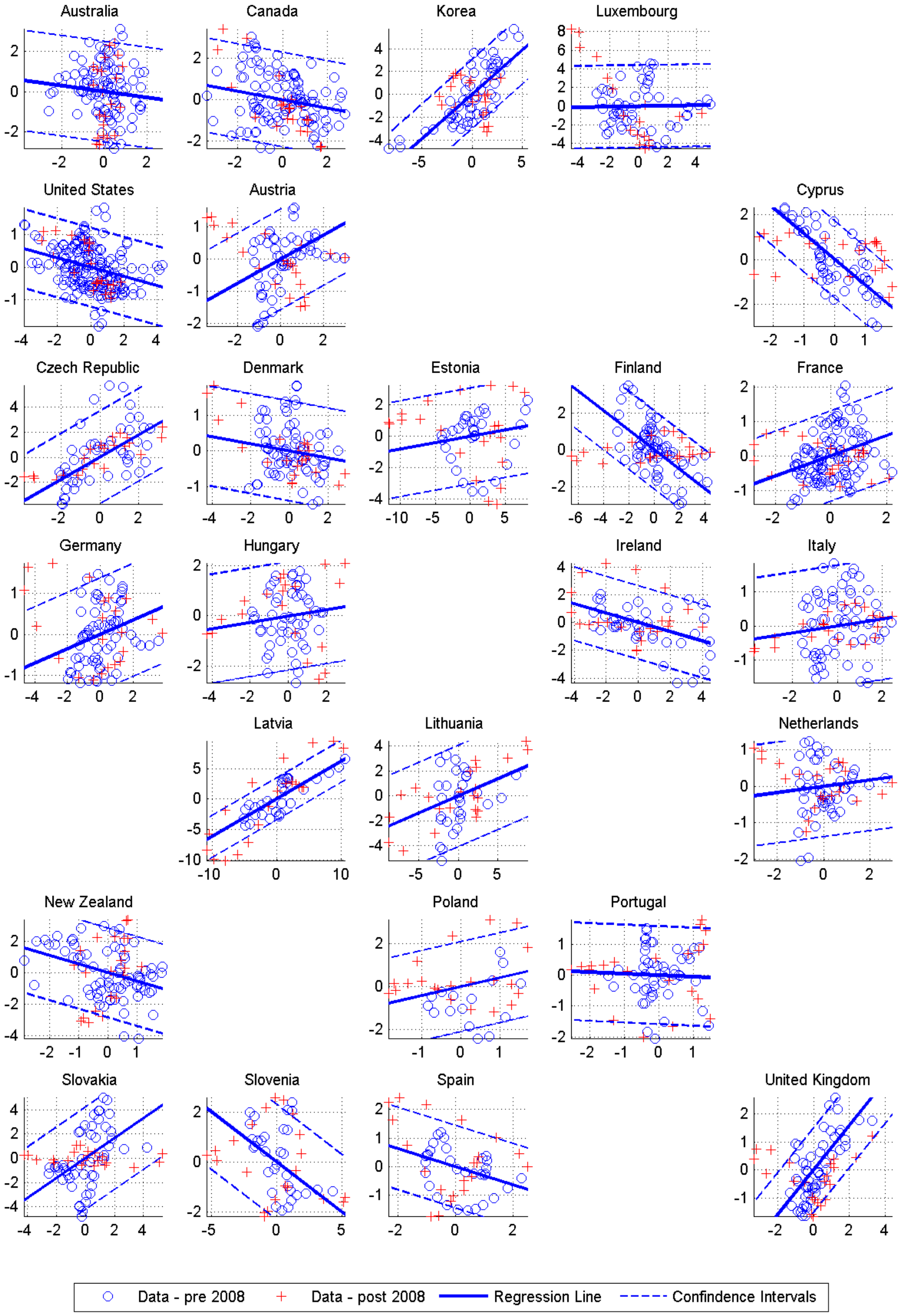
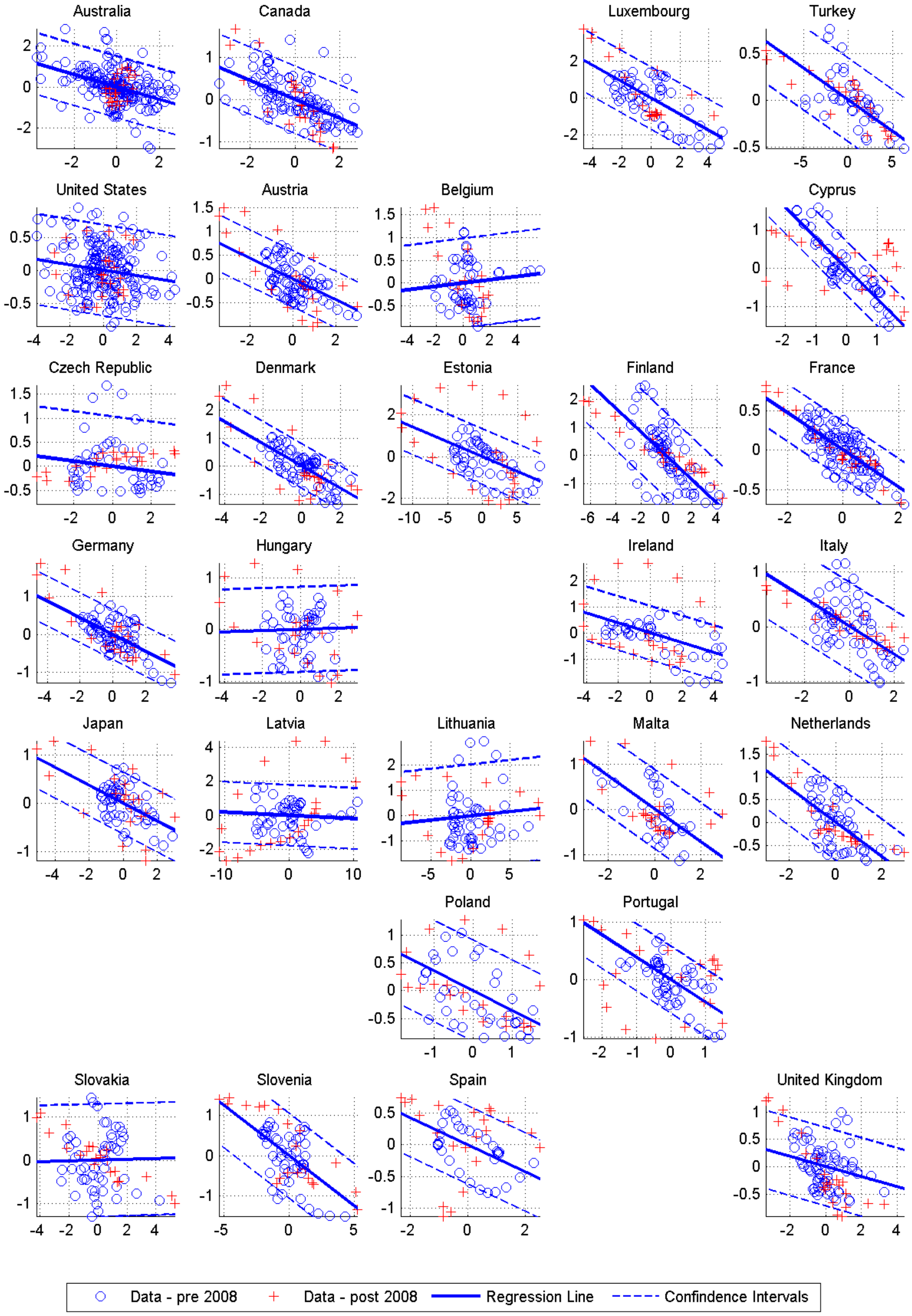


Figure 23: Output – Labor Share Before and After 2008



8. Conclusions and Implications

In this paper, we documented several interesting findings on labor market variables across time and space both with a literature survey and with our own empirical work. To conclude our paper, we outline our interpretation of these findings and the implications for structural macroeconomic models featuring a labor market. In this section, we comment on two *selected findings* that seem the most interesting to us.

8.1 Okun's Law

First, we present evidence for a strong and stable relationship between output and unemployment at cyclical frequencies. We document this with a literature survey and with our own work. While the relationship is stable and robust for cycles, it appears less stable when one analyzes growth rates: most studies using formulation (3) to test Okun's Law find a change in the relationship during the Great Recession. On the other hand, the cyclical comovement survives the inclusion of the Great Recession in the sample. This strong comovement can be used to test structural macroeconomic models with unemployment: structural macroeconomic models should replicate the significant correlation between the two variables at cyclical frequencies (frequency-specific moments can be derived analytically from the reduced form of the model).

It seems that capturing the negative correlation between the output and unemployment cycles is much more important than capturing the moments among other pairs of variables. Given its stability across countries and over time, it is extremely unlikely that this is due to sampling errors. This contrasts with some other moments (such as the cyclicality of wages), which might be country- or episode-specific.

The stability of Okun's Law also implies that the cyclical parts of the two variables should be explained by the same shocks (up to the sign, of course). It is highly unlikely that different sets of shocks explain output and unemployment, since this would destroy the stability of the cyclical relationship over time.

Second, the fact that studies using growth rates tend to reject the stability of Okun's Law means that interesting things happen at other frequencies, such as persistent changes in the equilibrium level of unemployment (i.e., for trends). Owyang and Sekhposyan (2012) provide evidence that the changes happen especially during and after recessions (and the recent Great Recession is a typical recession from that perspective). This implies that not only business cycles, but also trend components are important for the overall dynamics of labor market variables. However, to understand the long-run changes we would probably need other types of structural models than New Keynesian DSGE models, as DSGE models were developed *to explain cyclical fluctuations during normal times* and any trends are purely exogenous processes in DSGE models. One example of a model that can be used for understanding the recent changes in labor markets is the one by Jaimovich and Siu (2012), which proposes an explanation for long-run structural changes in labor markets.

It should be stressed that in this research we are not interested in making cross-country comparisons of the absolute values of Okun's coefficient. However, there are differences between countries in this respect. The values of this coefficient reflect the relative volatility of the unemployment cycle with respect to the output cycle rather than a deep economic relationship. What we see as important for structural macroeconomic models is the almost miraculous stability of the coefficient in individual countries.

8.2 Number of Shocks

Our analysis of labor market data using a dimension-reduction technique suggests that at business cycle frequencies, one shock typically explains about two-thirds of the dynamics. Two orthogonal shocks seem to explain most of the cyclical dynamics. This has strong implications for structural models. Typically, nowadays, structural macroeconomic models exhibit a ‘rich’ shock decomposition in the sense that a relatively high number of shocks contribute to *non-trivial* dynamics. Our analysis indicates that there are one or two key factors (fundamental shocks) in an economy that explain the behavior of key labor market variables, pointing to possible misspecification of structural models featuring labor markets.

Of course, more shocks are needed to capture the overall dynamics of labor markets. However, outside the two dominant business cycle shocks, they should be either short-lived shocks that capture the high-frequency dynamics of the data (such as measurement errors, non-fundamental movements due to ephemeral idiosyncratic factors, or noise in the data due to changes in methodology) or long-run trends that explain slowly moving changes spanning several business cycles (such as declines in the labor share or in the participation rate due to institutions or incentives).

8.3 Conclusion

In this paper, we put together a large dataset on labor market variables from advanced countries and we inquired about stable and robust patterns. We find that certain features are stable over time and across countries (such as Okun’s Law), while others are not (real wages are cyclical in some countries but acyclical or even countercyclical in others). We also confirm that labor market institutions influence selected characteristics, but to a limited degree only. Finally, the Great Recession does not seem to change the cyclical characteristics in most countries to a significant extent, at least those which are robust.

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Appendix A: To Filter or Not To Filter? This Is NOT the Question

As we have described (Section 2), there is a debate about the correct specification and estimation of Okun's Law (and similar specifications): should it be done in first differences or using 'gaps'? Formulation (3) has the seeming advantage of only requiring data, while Formulation (2) requires us to estimate the unobserved quantities U^* and Y^*. In the literature, one can find two main objections to statistical filters: (i) the output gap must be estimated and the estimation is uncertain and subject to errors, (ii) the two-sided nature of statistical filters means that it is difficult to estimate the gap near the beginning and the end of the sample, and even if the gap can be estimated on the whole sample, some statistical filters (such as the HP filter) have a tendency to make significant revisions at the end of the sample ('end-point bias').

We find the first objection (i.e., the notion that the first-difference approach is preferable since it does not require 'prefiltration') to be fundamentally confused. The difference operator (as in 3) is also a filter: basically a difference filter, which has its own transfer function and frequency-domain properties. The transfer function of the difference filter increases monotonically from 0 at frequency 0 to 2 at frequency π; in other words, the difference filter amplifies the short-run fluctuations at high frequencies, which may obscure the identification of the cyclical pattern.

Let us illustrate the argument using a simple example: let X_t be a time series of interest composed of trend, cyclical, and noise components ($X_t = T_t + C_t + e_t$). Then, after the application of the difference filter:

$$(1-L)X_t = T_t - T_{t-1} + C_t - C_{t-1} + e_t - e_{t-1}.$$

First, if the trend is a random walk process (possibly with a constant drift), the difference filter eliminates the trend component, which is fine. However, if the trend process T_t has more complicated dynamics than a simple random walk, the difference filter will not eliminate it completely. This would be the case if the trend was a random walk with a drift, where the drift follows another random walk, as in the specification proposed by Harvey and Jaeger (1993). In such a situation, the difference operator would not eliminate the total trend component.

If the original noise component is (approximately) white noise, then the noise component in the difference series will have an MA structure, with a variance twice as big as the variance of the original noise (only if the original e_t were negatively correlated would the MA term reduce the variance).

Finally, even if the trend component is eliminated and the increase in the variance due to the MA term is negligible, the correlation of the cyclical parts of the two series is not the same as the correlation of the first differences of the cyclical parts of these series. To summarize, the first difference filter is not a suitable tool for treating the relationships that operate in business cycles. Although the various statistical band-pass filters can yield imprecise results, the situation with the difference filter is not necessarily better.

The second objection is that common statistical filters that isolate frequencies of interest do not behave nicely near the beginning or the end of the sample and are subject to frequent revisions. First, this is not too problematic if one is interested in ex-post analysis rather than forecasting. If the main interest is forecasting, there is an alternative in using implicit filters based on explicit state-space representations (see Section II.B in Andrle (2013) for an example).

Appendix B: Results Based on the HP Filter

Figure B1: Correlations of Cyclical Components – Real Output (HP Filter)

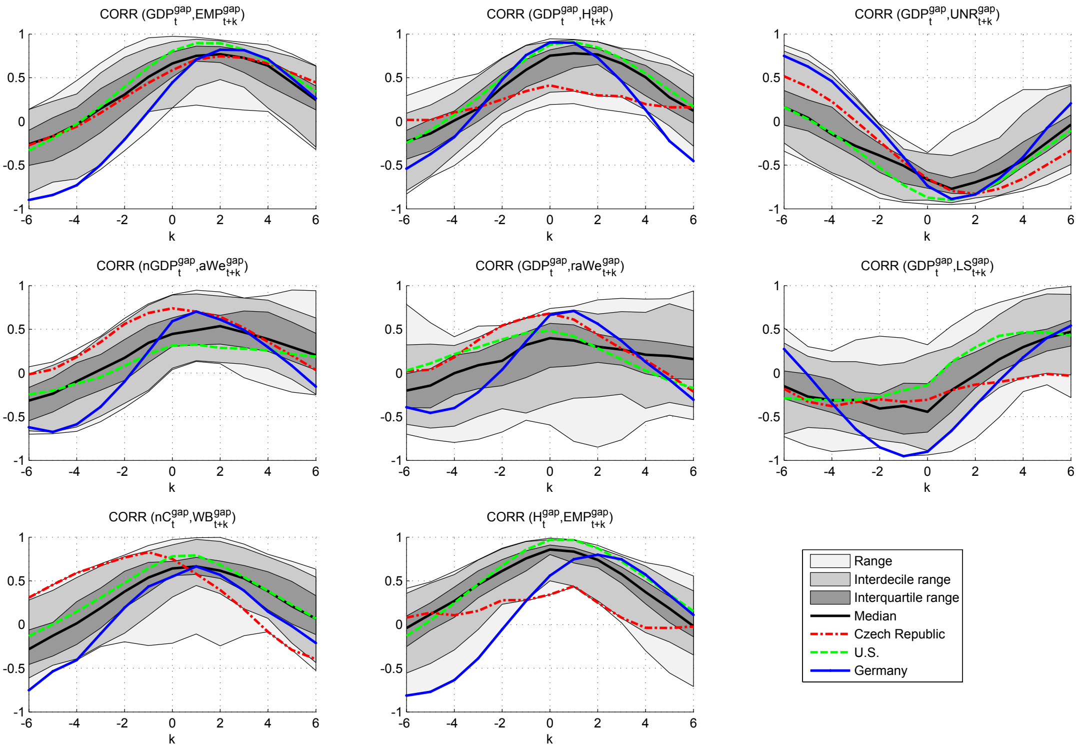


Figure B2: Peaks of Correlations of Cyclical Components – Real Output (HP Filter)

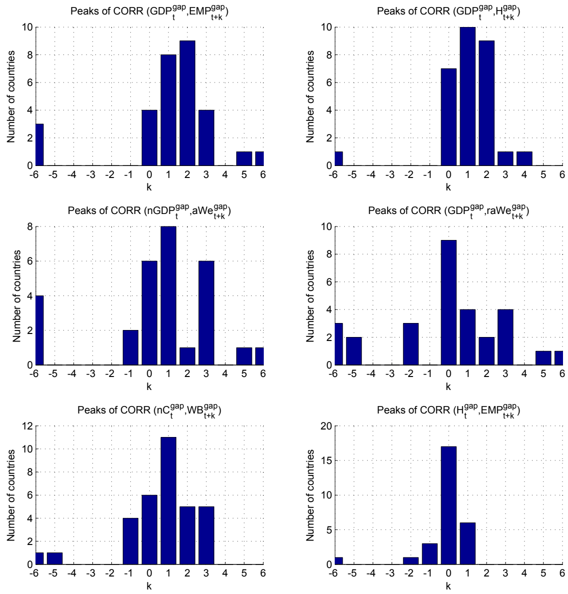
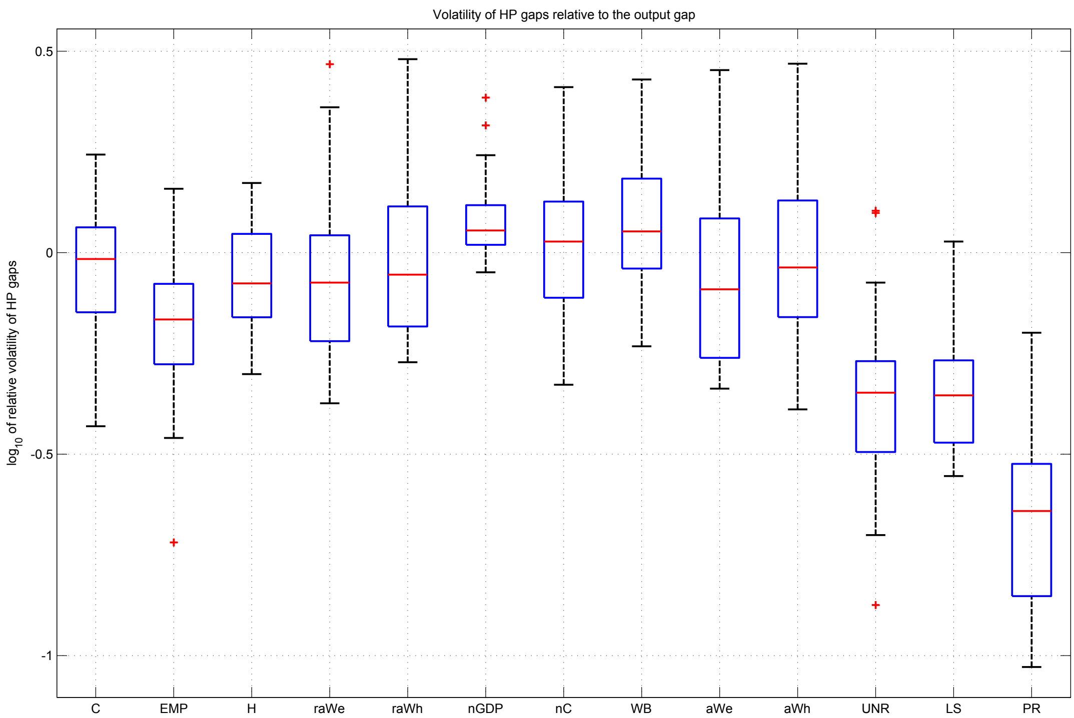


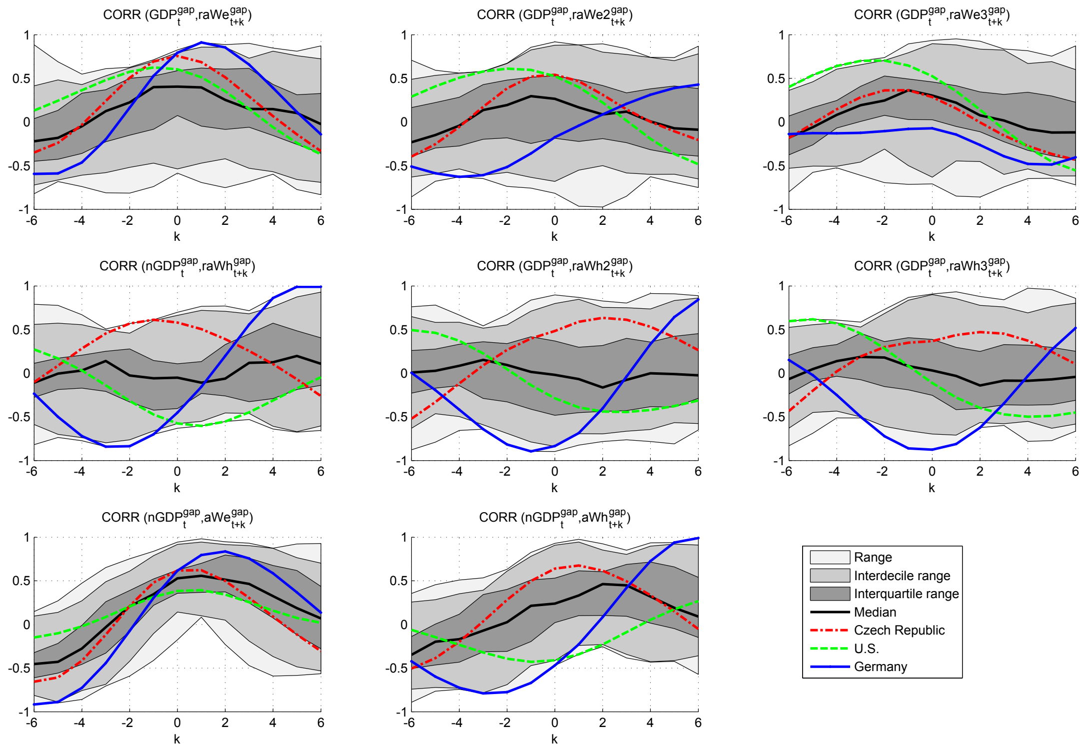
Figure B3: Relative Volatilities of Cyclical Components (Cycles: HP filter)



Appendix C: Sensitivity Analysis of the Cyclicality of Wages

The following figure shows the correlation of GDP with various types of wages. The first row shows the correlation of the real wage per employee with real GDP. The variable $raWE1$ is the real wage computed using the GDP deflator, $raWE2$ is the real wage computed using the consumption deflator, and $raWE3$ is the real wage computed using the CPI. The second row shows the correlation of the real wage per hour with real GDP, again computed using the three deflators. The last row shows the correlation of nominal GDP with nominal wages per employee aWE and per hour aWH.

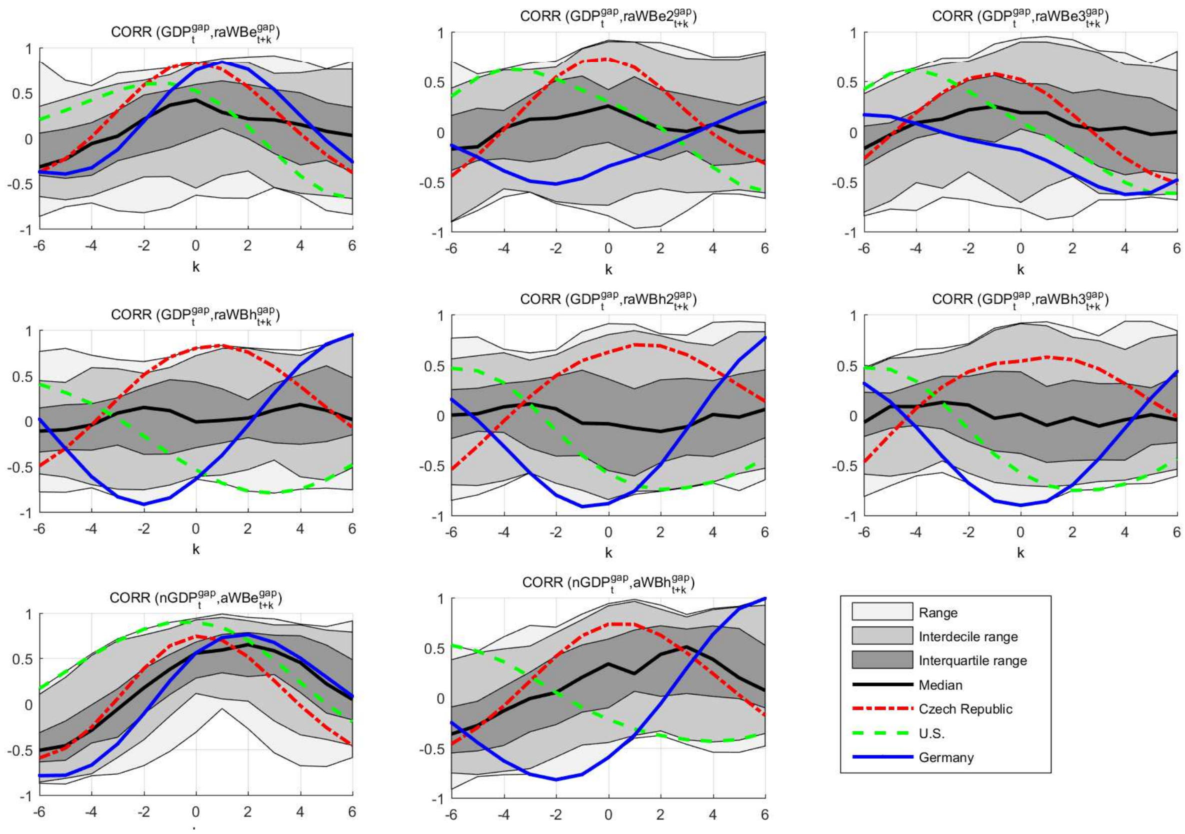
Figure C1: Correlations of Various Wages with GDP (Band-pass Filter)



For nominal variables, there is a correlation between output and wages, but not for all countries. For real variables, the correlation is much weaker regardless of the type of the deflator used to calculate real wages.

As an additional sensitivity analysis, we also used full-time equivalent wages for industry (we were unable to find a series for the whole economy). Using FTE wages, we repeated the analysis. We do not find a particularly strong pattern of cyclical wages for these wages either. Although there are countries with cyclical FTE wages (e.g., the Czech Republic), there are other countries for which they are not cyclical.

Figure C2: Correlations of Wages (FTE Equivalents) with GDP (Band-pass Filter)



Appendix D: Composition Effect and the Cyclicality of Wages

As we discussed in the literature overview, one of the popular explanations of why wages need not be cyclical is the composition effect – see Devereux and Hart (2005) or Daly et al. (2011). It is impossible to test the composition effect with our macro database.

Nevertheless, with sector-level data, it is possible to test for the composition effect on the sector level. Some sectors may be hurt more than other sectors in a recession, and given that the average wage is different across sectors, this effect may also obscure the relationship between wages and output.

To explore this possibility, we used data for nine selected European countries and – following Brůha et al. (2013) – we performed an index decomposition analysis (IDA).

The IDA was applied to the following identity:

$$W_t/Y_t = \sum_i s_{it} l_{it} \varpi_{it}, \tag{D1}$$

where $s_{it} = Y_{it}/Y_t$ are nominal shares, $l_{it} = L_{it}(1+d_t)/Y_{it}$ is the labor intensity, $\varpi_{it} = W_{it}/(1+d_t)L_{it}$ is the average 'real' wage in sector i (deflated using the **GDP deflator** d_t), and L_{it} is employment in sector i. The IDA applied to (D1) decomposes the labor share into:

Composition effect , which is related to changes in the structure of current-year GDP, s_{it}, i.e., when labor-intensive sectors increase their shares, then *ceteris paribus* we may expect an increase in W_t/Y_t.

Labor intensity effect , which is related to changes in labor used to produce a unit of output in a given sector (note that output is deflated not by sectoral deflators, but by the GDP deflator). This corresponds to the inverse of labor productivity.

Wage effect , which is the weighted average of the wage growth in individual sectors (the weights are given by the output and labor intensity shares).

Therefore, we can isolate the composition effect and construct an *adjusted* wage series that represents the hypothetical wage that would prevail in the economy if there were no composition effect. The results for the nine European economies are given in Figure (D1).

Figure (D2) then shows the sample correlation of real wages (both actual and adjusted) with real output. Apparently, the composition effect on the sector level does not help make wages more cyclical: for some countries, this goes in the counterintuitive direction. Therefore, we conclude that if the composition effect is important for explaining why wages need not be cyclical, it works on the firm or worker level, not on the sector level.

Figure D1: Actual and Adjusted Wage Growth in Selected European Economies (Annualized Quarterly Growth Rates)

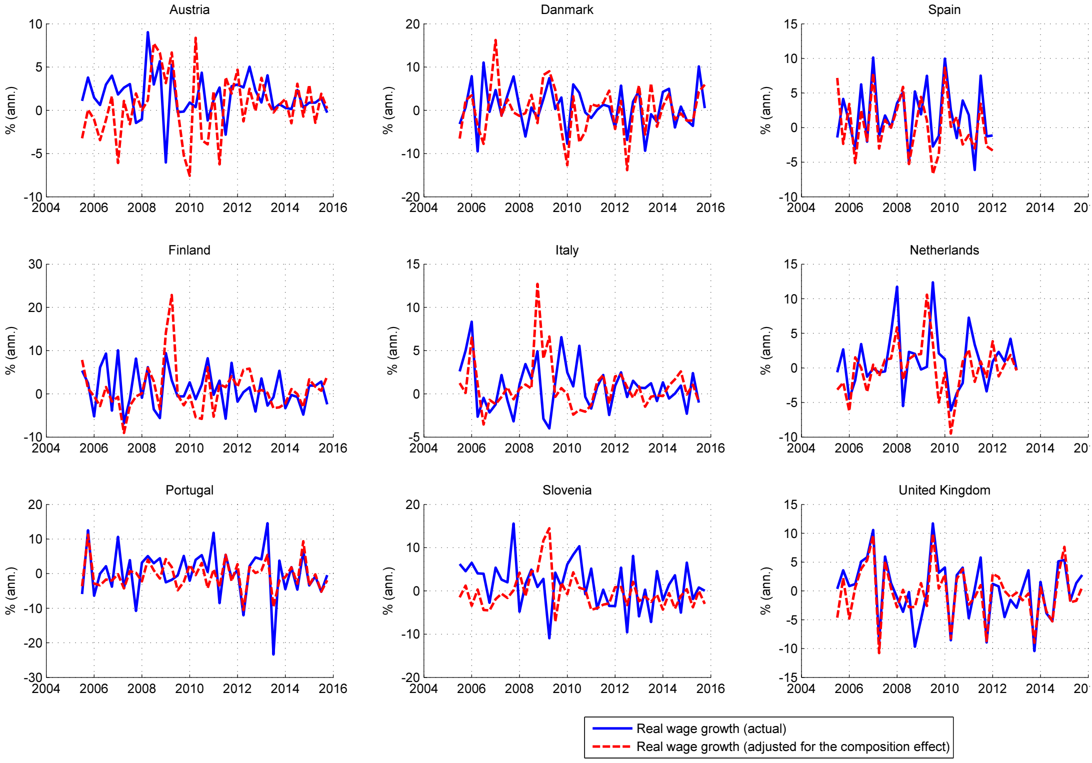
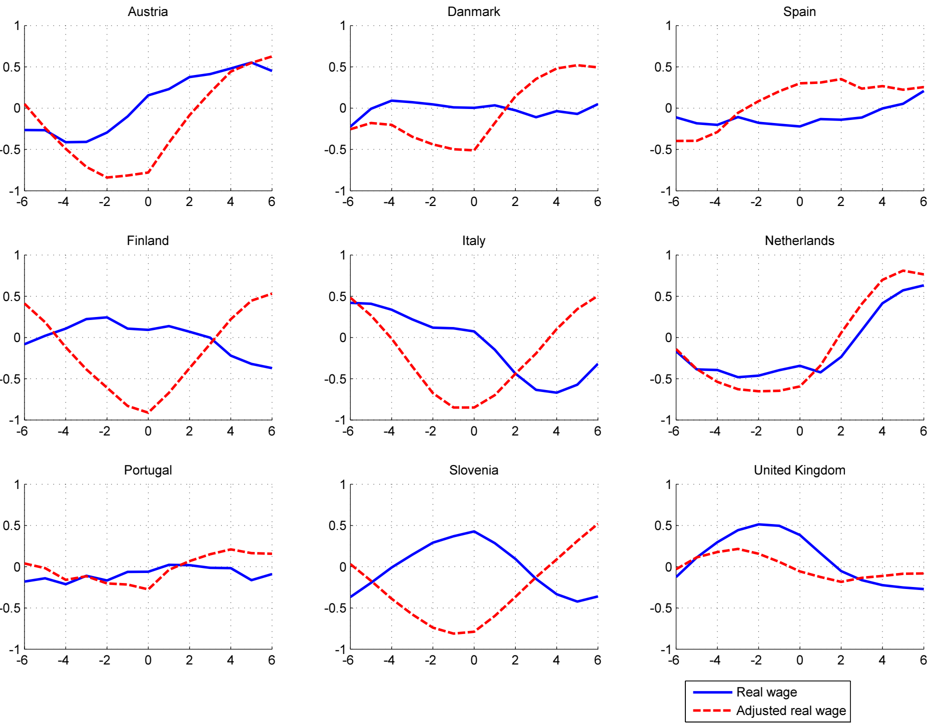


Figure D2: Correlation of Real Wage and Output: Actual and Adjusted Wages



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Economic Research Department
Na Příkopě 28, 115 03 Praha 1
Czech Republic
phone: +420 2 244 12 321
fax: +420 2 244 14 278
http://www.cnb.cz
e-mail: research@cnb.cz
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