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A comparison of pre- and post-crisis efficiency of OECD countries: evidence from a model with temporal heterogeneity in time and unobservable individual effects

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Abstract

The purpose of this article is to estimate and compare shifts in (technical) efficiency across OECD countries, caused by the global financial crises and heterogeneity. Technical efficiency of OECD countries is estimated by applying the panel model with arbitrary temporal heterogeneity in time and factor structures (a model with unobservable individual effects) that fits the stochastic frontier analysis. Because of missing values in observations, the bootstrapping-based algorithm allowing for trends in data across observations within a cross-sectional unit is applied for imputations. The parameters are estimated in a semi-parametric way. The proposed estimation derives sufficient results regardless of any assumption on the temporal pattern of country individual effects and contributes to the development of a tool for better understanding of unobserved factors that drive fluctuations in OECD countries.

JEL Classification: E01, F15, C23, O52

Keywords: Efficiency, Stochastic Distance Frontier, Heterogeneity in Time, Unobserved Factors, Principal Component Analysis, Comparative Economics

1. Introduction

The importance of taking measures of efficiency and productivity, as well as their further benchmarking to improve the performance of any economic system, is recognised. These measures are success indicators and performance metrics (Fred *et al.,* 2008, p.7-15). In general, to estimate efficiency one can compare observed performance (values) to some optimal values, or to some maximum potential output obtained from the available input. Optimum values can be defined in terms of the production possibilities of countries. Although "true" potential is unknown, it is possible to observe best practice, its evolution over time and its variation among countries. Thus, it refers to an operation on a best-practice "frontier" that leads to the identification of countries with the best performance, and further benchmarking performance of the rest against those of the best. Efficiency in this case is derived as the evaluation of observed outputs as compared to maximum potential outputs obtainable from the given inputs. This defines efficiency as technical efficiency.

Technical efficiency, or its opposite term – inefficiency, is a heterogeneous phenomenon and varies both over time and across countries. According to Kose

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et al. (2008), heterogeneity across countries matters, despite the common evolution of business cycles. Macro factors largely drive heterogeneities since they define initial conditions for business and ways in which economies absorb shocks. Nowadays, economies are increasingly interconnected and integrated in all areas of economic activity. The literature has already highlighted the role of heterogeneity and interdependency in economic development (e.g., Chaserant and Harnay, 2013; Tamborini, 2014). The significant role of interdependency was also demonstrated during the recent global financial crisis (e.g. Dallago, 2013; Vollmer and Bebenroth, 2012). It is possible to assume that an estimation of efficiency on a macro level is sensitive to heterogeneity. Ignoring heterogeneity on a macro level may cause estimates to become highly biased which may lead to misinterpretations. This, therefore, is the motivation behind a study of technical efficiency on a macro level with respect to heterogeneity in various dimensions.

Classical approaches to heterogeneity are based on panel models, which try to account for heterogeneity, including unobserved heterogeneity, by using dummy variables or structural assumptions on an error term (Baltagi, 2005; among others). Nevertheless, this approach has limitations, because unobserved heterogeneity is assumed to be constant over specified time. Extending classical models with a factor structure is one of the effective ways to deal with unobserved time-varying heterogeneity. This approach can provide a parsimonious specification which identifies the effects of unobserved heterogeneity on the outcomes of interest, allowing for access to time-varying technical efficiency.

This paper focuses mainly on shifts in technical efficiency of OECD countries that are caused by the global financial crises, heterogeneity and interdependencies. The motivation for this is instigated by the great variety in the initial economic conditions and development of OECD countries on the one hand, and their high integratability, on the other hand. In this study OECD countries are analyzed as production units. Their outputs are real GDP and export of goods and services. Whilst inputs are limited to labor (the number of employed), capital (gross fixed capital formation) and import of goods and services. Thus, a dataset is formed for 34 OECD countries[1], including the abovementioned 2 outputs, 3 inputs, and covering the 2000Q1-2014Q4 period.

This paper contributes to previous literature by computing and comparing technical efficiency in terms of productivity growth for each OECD country taking into consideration an arbitrary temporal heterogeneity through time to minimize bias and improve inference. For this purpose, the estimation of parameters and residuals of the panel model that has temporal heterogeneity

[1] Countries: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States; source: OECD.

through a time and factor structure (a model with unobservable individual effects) is based on a novel semi-parametric approach developed by Bai (2009) and Kneip *et al.* (2012). Another issue that is addressed in this paper is the one of missing values, which is the endemic problem for researchers working with economic indicators for a set of countries. Since the dataset should be balanced for heterogeneity estimation, a bootstrapping-based algorithm in the spirit of King *et al.* 2001, Honaker and King 2010 - allowing for trends in time series across observations within cross-sectional units - is applied for multiple imputations. This keeps all OECD countries within the analysis.

The results received help to shed light on current issues that have gained growing attention from researchers and practices in terms of comparative studies of different economies, and they contribute to the attempt to develop tools for better understanding of unobserved factors that drive fluctuation in economic development across countries, including OECD countries.

The plan of the paper is as follows. In second chapter a theoretical framework of the research is described. Attention is paid to a radial stochastic frontier, a Cobb-Douglas production function, and an arbitrary temporal heterogeneity in time panel model. The third chapter introduces empirical results and discussion. The fourth chapter contains a summary and concluding remarks.

2. Theoretical framework and model set-up

In the last decade, a number of research projects have been developed to estimate and benchmark performance measures on a macro level by applying various approaches, e.g., Cherchye *et al.* (2004), Despotis (2005), Ravallion (2005), Yörük and Zaim (2005), etc. Within the framework of the current study, methods which are well-established in the field of production theory are used. There are two fundamental ways to deal with efficiency estimation: the frontier approach that was introduced by Farrell (1957) and the non-frontier approach, initially developed by Solow (1957) and Griliches and Jorgenson (1966). As the main idea of this study is to compare the productivity growth across OECD nations the stochastic frontier approach, proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van cave Broeck (1977), and further developed by Schmidt and Sickles (1984), is chosen as a starting point. Furthermore, these models are particularly suitable when countries cannot entirely control their deviations from a production frontier due to external influences, e.g. crises. Thus, this study is based on the properties of the traditional micro-economic theory of production. A radial stochastic frontier and a Cobb-Douglas production function are used as back-bone models. Detailed reviews of these models are provided by Førsund *et al.* (1980), Kumbhakar and Lovell (2000), Kumbhakar (2006), and Greene (2008), among others. The application of these methods is done in the similar way, as in Matkovskyy (2015a, 2015b).

Two main types of estimation techniques are discussed in the literature on technical efficiency analysis. The first one includes econometric techniques that represent a stochastic approach. The second one is mathematical programming techniques that are nonparametric methods of the estimation. Econometric techniques allow for incorporating statistical noise, which is an advantage in comparison to mathematical programming, which does not naturally produce these estimates. Therefore, in this paper econometric techniques are used in a semi-parametric way, which allows for arbitrary temporal heterogeneity in time with a factor structure.

2.1. Stochastic Frontier Model

Let us denote a vector of output as Y, and an input requirement set as X. Thus, a production process can be formalized as

$$L(Y) = \{X: (Y, X) is\ producible\}.$$

The production function can be defined in terms of the efficient subset as an isoquant $(Y) = \{X: X \in L(Y)\}$.

Broadly speaking, productivity can be defined as the ratio of output to input. Efficiency means a comparison between observed and optimal values of its output and input. Thus, the optimum is defined in terms of production possibilities and efficiency is technical and can be estimated as a comparison between the observed output and maximum potential output obtainable from the given input.

According to Debreu (1951) and Farrell (1957), a production function can be formalized as $Y \leq f(X)$. Since a country uses several inputs to produce several outputs, both the outputs and the inputs should be aggregated in some economically sensible way. Adams *et al.* (1999) proposed a persuasive *m*-output and *n*-input deterministic distance function for efficiency estimation, D(Y, X)≤1, that estimates a radial measure of technical efficiency in the following way:

$$\frac{\Pi_j^m Y_j^{\gamma_j}}{\Pi_k^q X_k^{\delta_k}} \leq 1, \tag{1}$$

where Y is an aggregated output, X is a given input, γ_j and δ_k are weights of outputs and inputs that describe a country's technology, respectively.

A stochastic frontier model can be specified as the Cobb-Douglas production function:

$$Y_{it} = f(X_{it}) - u_{it} + \epsilon_{it}, \tag{2}$$

where $(-u_{it}+\epsilon_{it})$ represents a composed error term, where ϵ_{it} is statistical noise, and u_{it} is a country's specific level of radial technological efficiency. Then, according to Lovell *et al.* (1994), Equation (1) can be rewritten as

$$0 = \sum_{j=1}^{m} \gamma_j \ln y_{j,it} - \sum_{k=1}^{q} \delta_k \ln x_{k,it} + v_{it} + \epsilon_{it}, \tag{3}$$

then

$$\ln y_{J,it} = \sum_{j=1}^{m} \gamma_j (-\ln \hat{y}_{j,it}) - \sum_{k=1}^{q} \delta_k \big(-\ln x_{k,it}\big) - v_i(t) + \epsilon_{it}, \tag{4}$$

where $y_{J,it}$ is the normalized output, and $\hat{y}_{j,it} = {}^{y_{j,it}}/_{y_{J,it}}$, $j=1,\ldots,m, j\neq J$.

Denoting the variables from Equation (4) as

$$Y_{it} = \ln y_{J,it},$$
$$X_{it} = (-\ln \hat{y}_{j,it}, -\ln x_{k,it}),$$
$$\beta = (\gamma_j', \delta_k'),$$
$$v_i(t) = -u_i(t) - \beta_0(t),$$

where $\beta_0(t) \coloneqq \frac{1}{n}\sum_{i=1}^{n} -u_i(t)$, Equation (4) can be presented as the panel model with arbitrary temporal heterogeneity in time, which fits a frontier model of the type described in Aigner *et al.* (1977), Meeusen and Van den Broeck (1977), Schmidt and Sickles (1984) and Cornwell *et al.* (1990):

$$Y_{it} = \beta_0(t) + X_{it}'\beta + v_i(t) + \epsilon_{it}, \tag{5}$$

where Y_{it} is the dependent variable for each country i at time t; $\beta_0(t)$ is the general average function, that requires to have x_{itj}, $j=1,..p$, varying over time, t; X_{it} includes explanatory variables, $x_{it} \in \mathbb{R}^P$; $v_i(t)$ are time-varying individual effects (or individual differences) of country i at time $t \in \{1,\ldots,T\}$, $v_i(t) = \sum_{l=1}^{d} \lambda_{il} f_l(t), v_i(t) \in \mathbb{R}$, generated by d common time-varying factors, where $f_l(t)$ are unobserved common factors for all countries, λ_{il} are heterogeneous impacts of common factors on a country i; and ϵ_{it} is the idiosyncratic error term.

Then, following Schmidt and Sickles (1984), technical efficiency, $TE_i(t)$, of a country i at time t is calculated in the same way as for standard time-invariant fixed effects and random effects models:

$$TE_i(t) = \exp\{v_i(t) - max_{j=1,\ldots,n}(v_j(t))\}. \tag{6}$$

2.2. Testing dimensionality

The following tests help to determine the presence of heterogeneity and define the maximum number of factors, *d*.

The test of sufficiency of classical additive effects (Bai, 2009) can derive the preliminary result, whether the factor dimension, *d*, in a model is superior to 2. Consequently, its first role is to advise whether there is a need for further dimensionality identification. It can be calculated by applying the Hausman test to the following hypotheses:

$H_0: v_{it} = a_i + \theta_t;$
$H_1: v_{it} = \sum_{l=1}^{2} \lambda_{il} f_l(t).$

where $f_l(t)$ are unobserved common factors for all countries, λ_{il} are heterogeneous impacts of common factors upon a country *i*. The application of the Hausman test is as follows[2]:

$$J_B = nT(\hat{\beta} - \hat{\beta}_{within})\Delta^{-1}(\hat{\beta} - \hat{\beta}_{within}) \overset{a}{\sim} \mathcal{X}_P^2 \tag{7}$$

where $\hat{\beta}_{within}$ is the classical within OLS estimation, Δ is the asymptotic variance of $\sqrt{nT(\hat{\beta} - \hat{\beta}_{within})}$, P is the vector-dimension of β, $\mathcal{X}_P^2$ is the $\mathcal{X}^2$distribution with P degrees of freedom. Thus, the null hypothesis can be rejected in a case when $J_B > \mathcal{X}_{P,1-\alpha}^2$, where $\mathcal{X}_{P,1-\alpha}^2$ is the $(1-\alpha)$-quantile of the $\mathcal{X}^2$distribution with P degrees of freedom.

The next test for the existence of common factors is applied to determine which model specification is more appropriate to fit the data. It determines the presence of interactive effects, or in other words, the existence of common factors, beyond the possible presence of classical "individual", "time", or "twoway" effects in the model. Kneip *et al.* (2012) propose to test the following hypothesis

$H_0: d = 0;$
$H_1: d > 0.$

by applying the next statistic:

[2] Refer to Bai (2009) for detailed technical discussion.

$$J = \frac{n\, tr\,(\hat{\Sigma}_W) - (n-1)(T-1)\hat{\sigma}^2}{\sqrt{2n}(T-1)\hat{\sigma}^2} \overset{a}{\sim} N(0,1) \tag{8}$$

where $\hat{\Sigma}_w$ is the covariance matrix of the within residuals, $\hat{\sigma}^2$ is defined as

$$\hat{\sigma}^2 = \frac{1}{nT-(n+T)\hat{d}-P+1} \sum_{i=1}^{n} \sum_{t=1}^{T} (y_{it} - x_{it}^T \hat{\beta} - \sum_{l=1}^{\hat{d}} \hat{\lambda}_{il} \hat{f}_{lt})^2 \tag{9}$$

where $\hat{d}$ is the maximum number of dimensions. This test returns the *J*-statistic with a significance level of α=0.01. If $J > z_{1-a}$, where z_{1-a} is the (1-*a*) – quantile of the standard normal distribution the null hypothesis H_0 can be rejected.

To identify a maximum number of unobserved factors in a model, the following tests are applied:

- *KSS.C* dimensionality criterion (Kneip *et al.* 2012) that tests if KSS.C(0) ≤ z_{1-a} , z_{1-a} is the (1-*a*) – quantile of the standard normal distribution, H_0 : *d*=0, 1, …, *m* until H_0 cannot be rejected[3] (Appendix 1);
- *IC(l)* (*IC1, IC2, IC3)* and *PC (PC1, PC2, PC3, BIC3)* criteria which vary in penalty terms, developed by Bai and Ng (2002) (Appendix 2);
- *ABC.IC1* and *ABC.IC2* developed by Alessi *et al.* (2010). These are Bai and Ng (2002) criteria improved by introducing a tuning multiplicative constant in the penalty, that was proposed by Hallin and Liška (2007);
- Eigenvalue Ratio (*ER*) and Growth Ratio (*GR*) proposed by Ahn and Horenstein (2013) (Appendix 3);
- *IPC1*, *IPC2* and *IPC3* panel criteria suggested by Bai (2004) (Appendix 4); and
- The Threshold Approach developed by Onatski (2010) (Appendix 5).

2.3. Parameter estimation

To incorporate heterogeneity in time into a model, residuals should be allowed to have a variation in time. One of the conceivable approaches to gauge unobserved time-varying heterogeneity is to augment panel models with a factor structure that provides a parsimonious specification to detect unobserved heterogeneity effects.

Factor models in the context of time-variability have been extensively studied by, e.g., Stock and Watson (2002), Forni *et al.* (2000), Bai and Ng (2002),

[3] This criterion has a tendency to ignore weakly auto-correlated factors; therefore, its values can be underestimated (Bada and Liebl, 2014).

Ahn, Lee and Schmidt (2005), Bai (2009), etc. In this paper, the algorithm proposed by Kneip *et al.* (2012) is used to derive estimates of the panel model with temporal heterogeneity in time and unobserved individual effects, specified by Equation 5. This algorithm derives a small number of common functions by means of principal component analysis and natural splines with no explicit restrictions on a temporal pattern of country effects. Factor loadings and factors are treated as parameters of a model. Since differences can eliminate some share of information, provided by data, the goal is to keep this information and use it for an analysis. Another advantage of this method is that it allows factors to be non-stationary.

In general, parameter estimation of Equation 5 includes the next two steps: (i) a semi-parametric calculation of β_j and $v_i(t)$, and (ii) estimation of unobserved factors by means of the functional principal component analysis[4].

In the first step, β_j and $v_i(t)$ are calculated by minimizing

$$\sum_{i=1}^{n}\frac{1}{T}\sum_{t=1}^{T}\left(Y_{it}-\sum_{j=1}^{P}\beta_j X_{itj}-v_i(t)\right)^2+\sum_{i=1}^{n}k\frac{1}{T}\int_1^T(\,v_i{}^{(m)}(s))^2 ds. \tag{10}$$

where $v_i{}^{(m)}$ is the *m*-th derivative of v_i. Minimization is performed over all possible values of β and *m*-time continuously differentiable functions $v_1,\dots,v_n$ on [1; T].

Equation (10) can be rewritten in a matrix notation:

$$\sum_{i=1}^{n}(\|Y_i-X_i\beta-Z\xi_i\|^2+\kappa\xi_i' A\xi_i), \tag{11}$$

where $\bar{Y}_{it}=\frac{1}{n}\sum_{i=1}^{n}Y_{it}$, $Y_i=(Y_{i1},\dots,Y_{iT})'$, $X_{ij}=(X_{i1j},\dots,X_{iTj})'$, $\bar{X}_{it}=\frac{1}{n}\sum_{i=1}^{n}X_{itj}$, $v_i{}^{(m)}$ – m-th derivative of v_i; $\|\cdot\|$ is the usual Euclidean norm in $\mathbb{R}^T$, κ is a preselected smoothing parameter; $\xi_i=(\xi_{i1},\dots,\xi_{iT})'$, are natural spline bases, where $\hat{v}_i(t)=\sum_{j=1}^{T}\hat{\xi}_{ji}z_j(t)$, z_j.

The optimal number of a smoothing parameter κ can be derived by applying cross-validation criterion such as:

$$CV(\kappa)=\sum_{i=1}^{n}\left\|Y_i-X_i\hat{\beta}_{-i}-\sum_{l=1}^{d}\hat{\lambda}_{-i,l}\hat{f}_{-i,l}\right\|^2, \tag{12}$$

[4] Refer to Kneip et al. (2012) and Bada and Liebl (2014) for all technical details.

where $\hat{\beta}_{-i}$, $\hat{\lambda}_{-i,l}$, and $\hat{f}_{-i,l}$ are estimates of β, λ and f, respectively, $-i$ is a number of observations.

Then, the semiparametric solutions are the following:

$$\hat{\beta} = (\sum_{i=1}^{N} X_T' (I - Z_\kappa) X_i)^{-1} (\sum_{i=1}^{N} X_T' (I - Z_\kappa) Y_i), \tag{13}$$

$$\hat{\xi}_i = (Z'Z + \kappa R)^{-1} Z'(Y_i - X_i \hat{\beta}), \tag{14}$$

$$\hat{v}_i = Z_\kappa (Y_i - X_i \hat{\beta}), \tag{15}$$

where $Z_\kappa = Z(Z'Z + \kappa R)^{-1} Z'$ and it is a positive semi-definite symmetric matrix with eigenvalues [0, 1].

Unobserved factors can be estimated as follows:

$$\hat{f}_l(t) = \sqrt{T} \hat{\gamma}_{lt}, \text{ for all } l \in \{1, \dots, d\}, \tag{16}$$

where $\sqrt{T}$ is the scaling factor, $\hat{\gamma}_{lt}$ are the first d eigenvectors that correspond to the largest eigenvalues of the covariance matrix:

$$\hat{\Sigma} = \frac{1}{n} \sum_{i=1}^{n} \hat{v}_i \hat{v}_i'. \tag{17}$$

Individual loading parameters are calculated as

$$\hat{\boldsymbol{\lambda}}_{il} = \frac{1}{T} \boldsymbol{f}_l'(\boldsymbol{t})(\boldsymbol{Y}_i - \boldsymbol{X}_i \hat{\boldsymbol{\beta}}). \tag{18}$$

And the variance is estimated in the following way:

$$\hat{\sigma}^2 = \frac{1}{(n-1)T} \sum_{i=1}^{T} \left\| Y_i - X_i \hat{\beta} - \sum_{l=1}^{d} \hat{\lambda}_{il} \hat{f}_l(t) \right\|^2. \tag{19}$$

3. Empirical results

For the empirical estimation a panel data set that covers the 2000Q1-2014Q4 period of time for 34 OECD countries is formed. The data contains the following input and output categories[5]:

[5] Source: OECD

- real GDP (in US dollars, fixed PPPs and seasonally adjusted);
- export of goods and services (in US dollars, fixed PPPs and seasonally adjusted);
- gross fixed capital formation, that can explain how much of the new value added to the economy is invested rather than consumed (in US dollars, fixed by PPPs and seasonally adjusted);
- import of goods and services (in US dollars, fixed by PPPs and seasonally adjusted); and
- the number of employed persons (thousands of persons).

The final data are taken as changes in their values. Thus, the Cobb-Douglas stochastic distance frontier with multiple inputs/multiple outputs includes the following variables: Y=ln(real GDP), Y^*=-ln(export of goods and services/real GDP), X=(-ln(gross fixed capital formation), -ln(number of employed persons), -ln(import of goods and services)). This is in keeping with a classical application of the Cobb-Douglas stochastic distance frontier.

3.1. Missing values imputation

The dataset formed includes missing values that makes it unbalanced. The missing values are in the employment time-series, mainly at the beginning of the series (see Table 1 and Fig. A1 in Appendix):

Table 1: The number of missing values in the employment variable

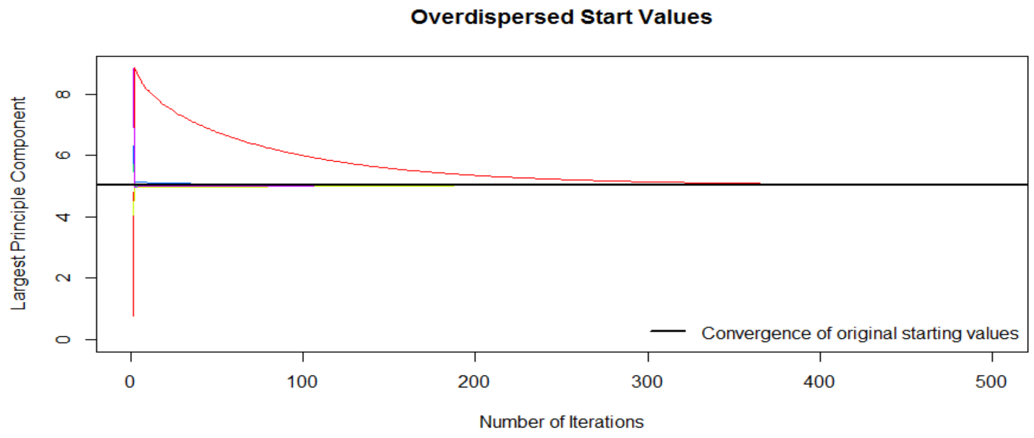
Country	Number of missed values
Canada	1
Chile	1
Iceland	9
Mexico	1
Poland	1
Slovenia	1

Since taking heterogeneity into consideration requires a dataset to be balanced, for this purpose a multiple imputation approach is applied.

Multiple imputation of missing data has become popular since its formal introduction by Rubin (1978). There are a variety of imputation methods applied nowadays, e.g., Schafer (1997), Van Buuren and Oudshoom (2000) and Raghunathan *et al.* (2001), etc. In this study, a bootstrapping-based algorithm (King *et al.,* 2001; Honaker and King, 2010) is utilized. This algorithm allows for trends in time series across observations within a cross-sectional unit, as well as priors. Its application generates results of a similar quality as the standard imputations or expectation-maximization approaches, but it is faster. The general description of the algorithm logic is provided in Appendix 6[6].

Figure 1 below proves that there are no significant problems with finding the global maximum of the likelihood surface due to different starting values that can affect imputations.

Figure 1: Converging of EM chains



Source: Author's calculation

In Figure 1, the *y*-axis of this figure denotes a number of principal components and represents a movement in the high dimensional parameter space. The other axis represents the number of iterations of a chain. It is possible to observe that the likelihood is well behaved and all expectation-maximization chains converge to the same value of the global maximum, regardless of starting values.

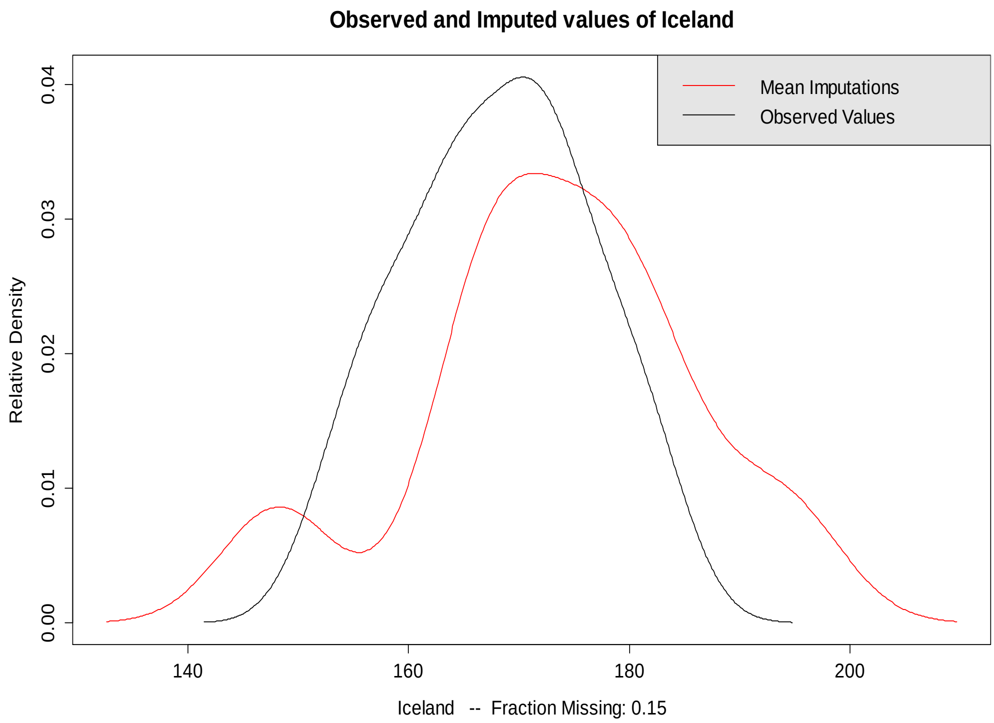
A comparison of the distribution of imputed values with the distribution of observed values is performed as proposed by Abayomi *et al.* (2008). It is obvious, that these distributions *a priori* cannot be identical, since the missing values might vary systematically. The comparison shows that the differences in distributions of employment data are not significant (Figure 2a). Although, the presence of differences does not inevitably indicate problems with the imputations since these missing values are missing in a random manner.

Honaker *et al.* (2011) proposed an overimputation diagnostic that implicates treating each of the observed values in a sequential way as if they had actually

[6] The calculations were done by means of R package Amelia II.

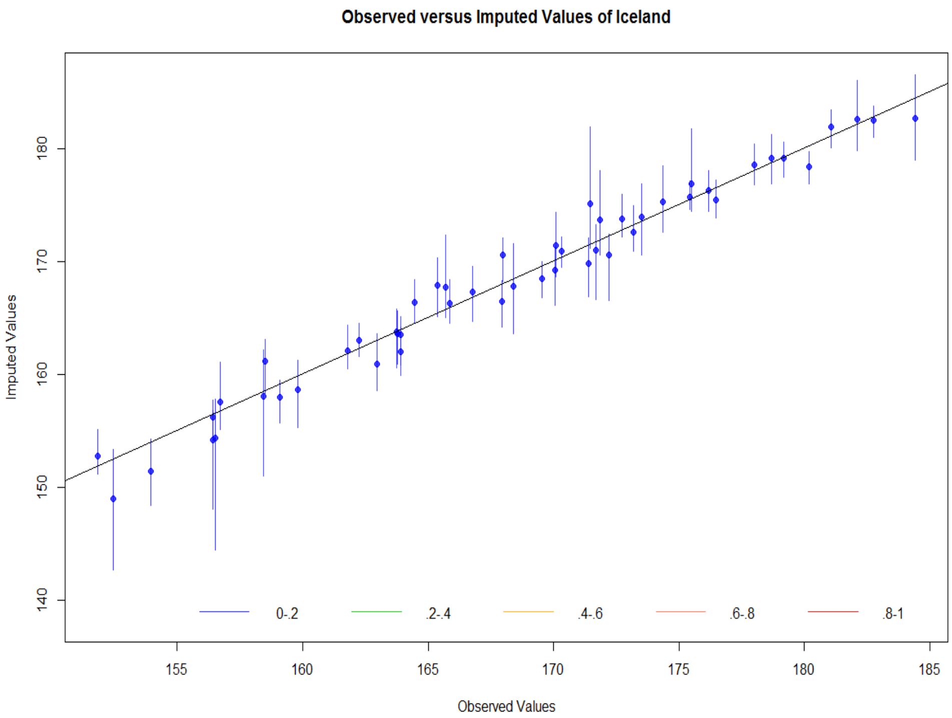
been missing. A $y = x$ line in Figure 2b is the line of perfect agreement. Imputations perfectly correspond to true values if they fall on this line in the similar way, as we mainly have in our case.

Figure 2a: Comparison of the distributions of imputed and observed values



Source: Author's calculation

Figure 2b: Overimputation diagnostic results of Iceland employment variables



Source: Author's calculation

3.2. Technical Efficiency Estimation

A heterogeneous in time panel model with additive and interactive unobserved effects is specified as:

$$Y_{it} = \theta_t + X'_{it}\beta + v_i(t) + \epsilon_{it}, \quad (20)$$

where Y= ln(*real GDP*), X=(-ln(*Export of goods and services/real GDP*), -ln(*Gross Fixed Capital Formation*), -ln(*Import of goods and services*), -ln(*Employment*)), θ_t are time effects, and $v_i(t)$ are interactive unobserved effects, which are derived as

$$v_i(t) = \sum_{l=1}^{d} \lambda_{il} f_l(t), \quad (21)$$

where $f_l(t)$ are unobserved common factors for all countries, λ_{il} are heterogeneous impacts of common factors on a country *i*.

3.2.1. Dimensionality estimation

The test of the sufficiency of classical additive effects (Equation 7) investigates the factor dimension, *d* in the first place. It returns the negative value of J_B due to the negative definiteness of Δ. It means that there is insufficiency of classical additive effects and the factor dimension in the model is larger than 2.

The test for the existence of common factors (Equation 8) returns the following results (Table 2):

Table 2: Test results for the existence of common factors

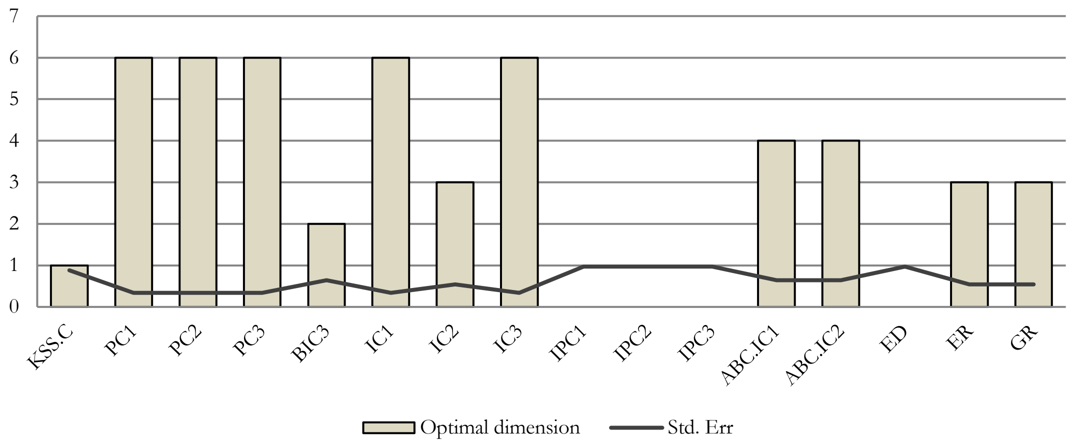
Test-Statistic	*p*-value	crit.-value	sig.-level
38.51	0.00	2.33	0.01

Source: Author's calculation

It means that the null hypothesis[7] can be rejected at the significance level a=0.01.

The results of the next 6 tests are summarized and presented in Figure 3 below.

Figure 3: Dimensionality for the OECD countries' model



Source: Author's calculation

Performed empirical and graphical analyses show, that the better results are derived by the most robust *PC(l)* criteria with various penalty terms. Thus, according to Figure 3, the PC1, PC2, PC3, IC1, and IC3 criteria tell us that *d*

[7] H0 : the factor dimension is equal to 0

should be equal to 6. ABC.IC1 and ABC.IC2 estimate *d* at the level of 4 factors, IC2, ER and GR advocate 3 factors. BIC3 proposes 2 factors, estimation of KSS.C criterion derives 1 factor, and IPC1, IPC2, IPC3 and ED do not distinguish any factors. The standard errors have their lowest values with 6 factors. The tests also indicate that 6 factors explain more than 65% of the variance. Therefore, it is possible to assume that the maximum number of the unobserved factors, *d*, is 6.

3.2.2. Parameters estimation results

The estimates of the slope coefficients are provided in Table 3. The estimate of the "import" variable is not statistically significant in the model. It allows for the assumption that the real GDP of OECD countries does not depend on these countries imports. The insignificance of (Export/real GDP) is not important since it is a second output variable.

Table 3: Slope coefficients

Variable	Estimate / Std. Err.	*z*.value	Pr(>*z*)
l.Export_GDP	-0.00684/0.00918	-0.746	0.45600
l.GFCF	-0.07770 /0.00642	-12.100	<2e-16
l.Import	-0.00265 /0.00919	-0.289	0.77300
l.Employment	-0.04970 /0.01670	-3.270	0.00106

Note: Residual standard error=0.000128; Unobserved factors=6; R^2*=0.377.*

Source: Author's calculation

Additive time effects impact OECD countries in a common way. In Figure 4 the dynamics of the additive time parameter, θ_t, is presented.

Figure 4: Additive time effects, $\boldsymbol{\theta_t}$

Source: author's calculation

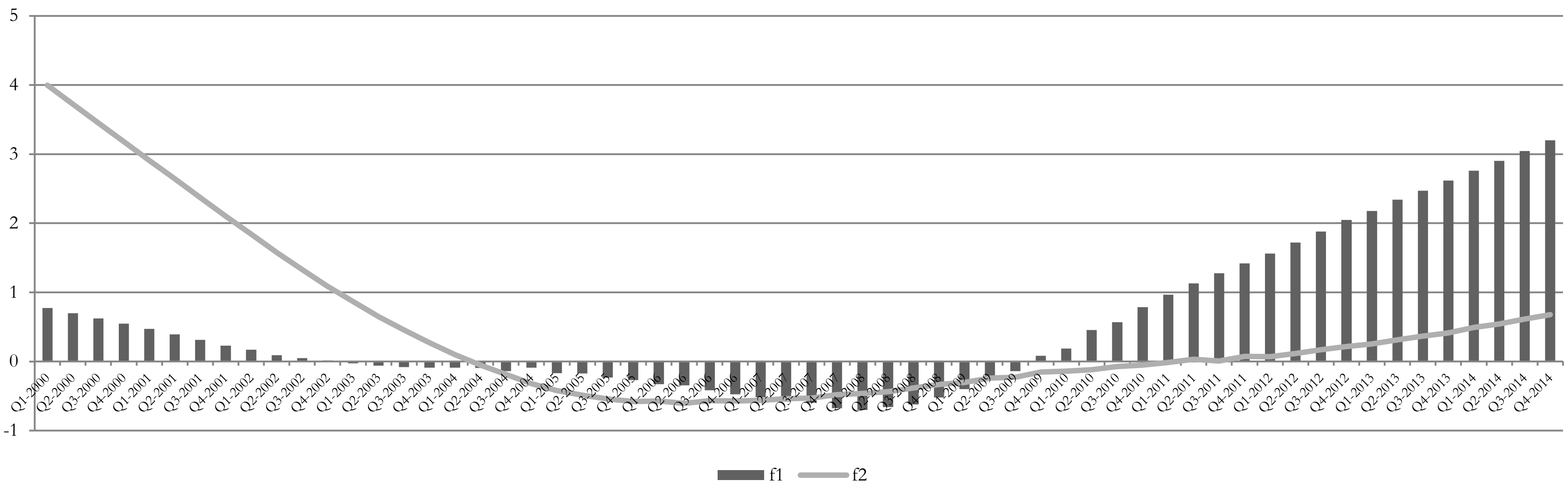
We can observe that a rapid decrease starts in 2007Q2 which corresponds to the beginning of the global financial crisis. The lower values of θ_t are found in the 2008Q4-2009Q1 period, and then θ_t increases until 2010Q3. The next negative tendency of the additive time parameter behavior that relates to the beginning of the global economic crisis begins in 2010Q4. Despite the different GDP growth rates[8] in OECD countries, the effect of the additive time parameter is similar in 2001-2002 and 2014. Thus, observing θ_t can help to identify crises common to a set of countries.

The dynamics of normalized common unobserved factors, $f_l(t)$, shows the influence of common shocks on outputs. According to the performed tests, the model includes 6 common factors. The first two common factors explain together more than 95% of the total variance of the time-varying individual effects $v_i(t)$. The calculation of the variance shares of common factors represents slightly antagonistic results if compared to the dimensionality test results (Figure A2). It can be assumed, that theoretically the variance can be explained by more than 6 unobserved factors due to a high heterogeneity of OECD countries.

To give some economic meaning, $f_l(t)$ values are rotated by applying the VARIMAX method. Since the common unobserved factors were normalized during their estimation, VARIMAX rotation is performed without the Kaiser normalization phase. The results are presented in Figure 4 below and in Figure A3 in the Appendix.

[8] During 2001, 2002, and 2014 the OECD growth rate was approximately 0.7, 1.7, and 0.6, respectively. The output growth varies across OECD countries, e.g. in 2000 the output growth in the USA was higher than in the Euro Area or Japan.

Figure 5: Dynamics of the common *f₁(t)* and *f₂(t)* unobserved factors, (*d*=6), VARIMAX rotated

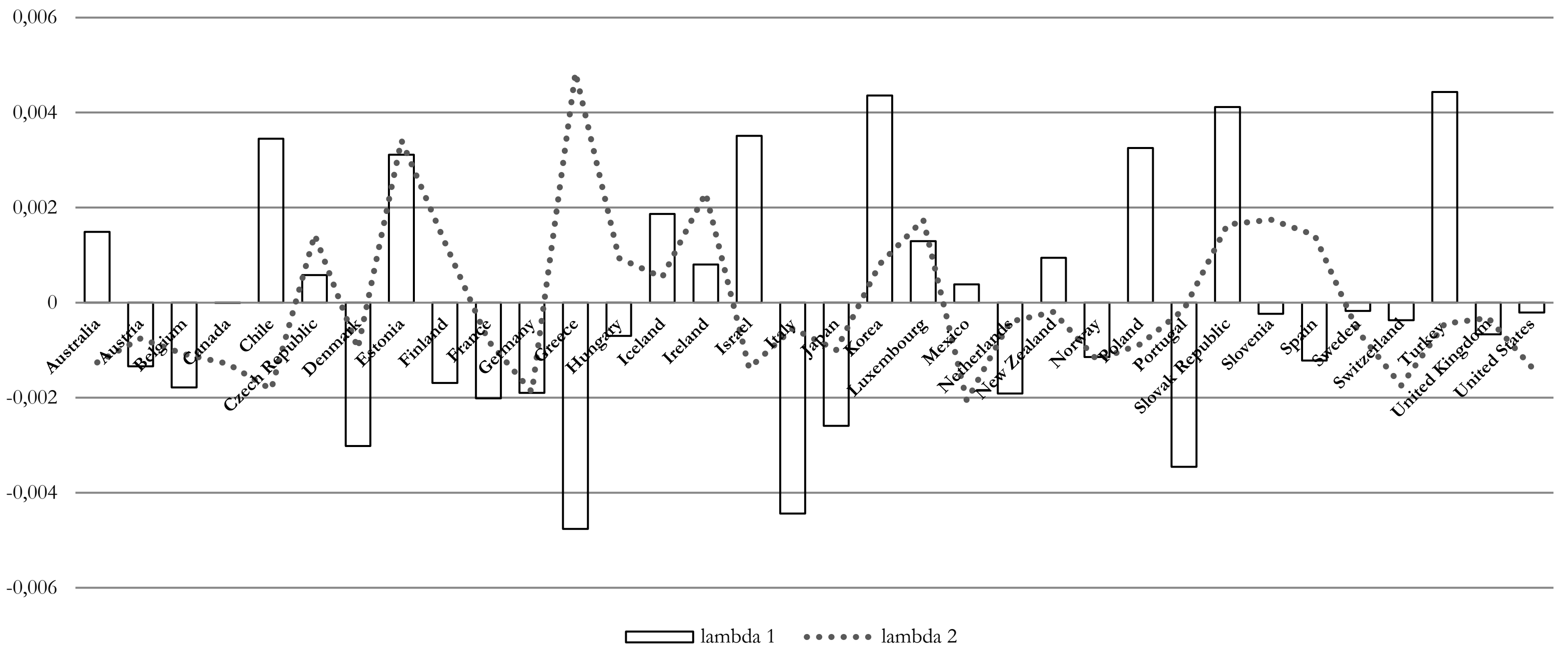


Source: author's calculation

It is obvious that the common unobserved factors have cyclical dynamics (Figure 5 and Figure A3). The average cycle length of OECD countries is equal to 6 years. The negative values of the two first factors during the 2003Q3-2009Q3 period correspond to the general economic decline observed in world markets (late-2000s recession).

Individual factor loadings, λ_{il}, are presented in Figure 6. They explain the heterogeneous impact of unobserved common shocks, $f_l(t)$, on a country *i*.

Figure 6: The dynamics of the unobserved individual factors loadings, λ_{il} (d=6)

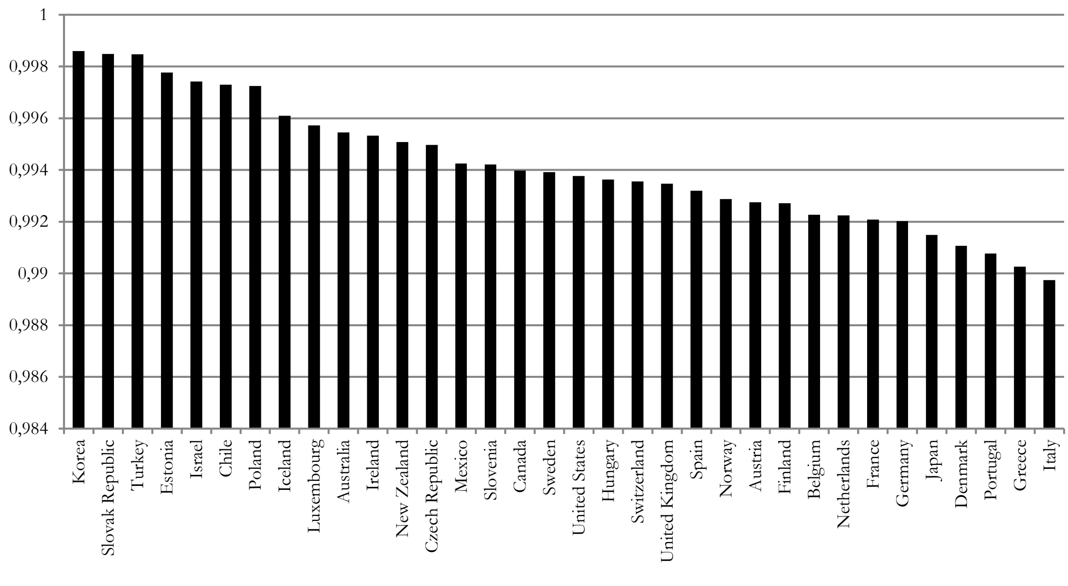


Source: author's calculation

The unobserved individual factor loadings with values close to zero show the neutral response of a specific country's output to the unobserved common shocks, $f_l(t)$. Positive values of these loadings can be interpreted as the amplifiers of the impacts of unobserved common shocks. Negative values demonstrate some resistance of a country to shocks. In our case (Figure 6), the most resistant to shocks in terms of productivity growth are the following economies: Austria, Belgium, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain (but the second factor is strongly positive), Switzerland and the United Kingdom. The influence of negative shocks was amplified by the value of λ_{il} in Australia, Chile, Czech Republic, Estonia, Greece (the second factor), Iceland, Ireland, Israel, Korea, Luxemburg, Mexico, New Zeeland, Poland, the Slovak Republic, Slovenia (second factor), Spain (second factor) and Turkey. The productivity growth in such countries as Canada, Sweden and the United States was not considerably affected.

The technical efficiency of the analyzed economies is calculated by means of Equation (6). The average technical efficiency during the 2000Q2-2014Q4 period and the average technical efficiency across countries are presented in Figure 7 and Figure 8, respectively.

Figure 7: Average technical efficiency of countries during the 2000Q2-2014Q4 period



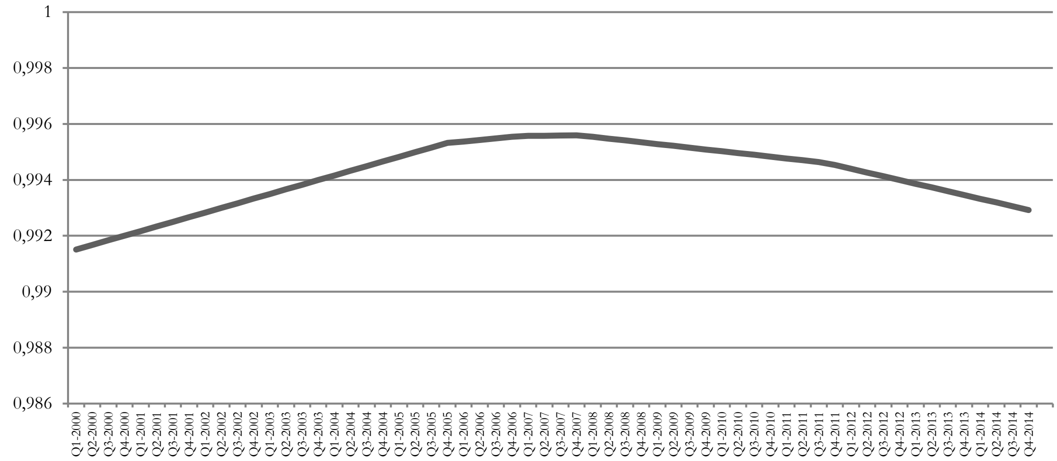
Source: author's calculation

Figure 7 shows, that during the 2000Q2-2014Q4 period the lowest average level of technical efficiency was observed in Italy, Greece, Portugal, and

Denmark. Countries such as Korea, the Slovak Republic and Turkey are at the closest distance to the boundaries of their average possibilities.

According to Figure 8, average technical efficiency was growing until around 2006Q4. Starting from 2008Q1 the level of technical efficiency constantly decreases. Thus, the approximate delay between the beginning of the crisis and the decline in the technical efficiency of OECD countries is approximately 4 quarters. The current level of technical efficiency of OECD countries is at the level of 2001.

Figure 8: Average technical efficiency across OECD countries

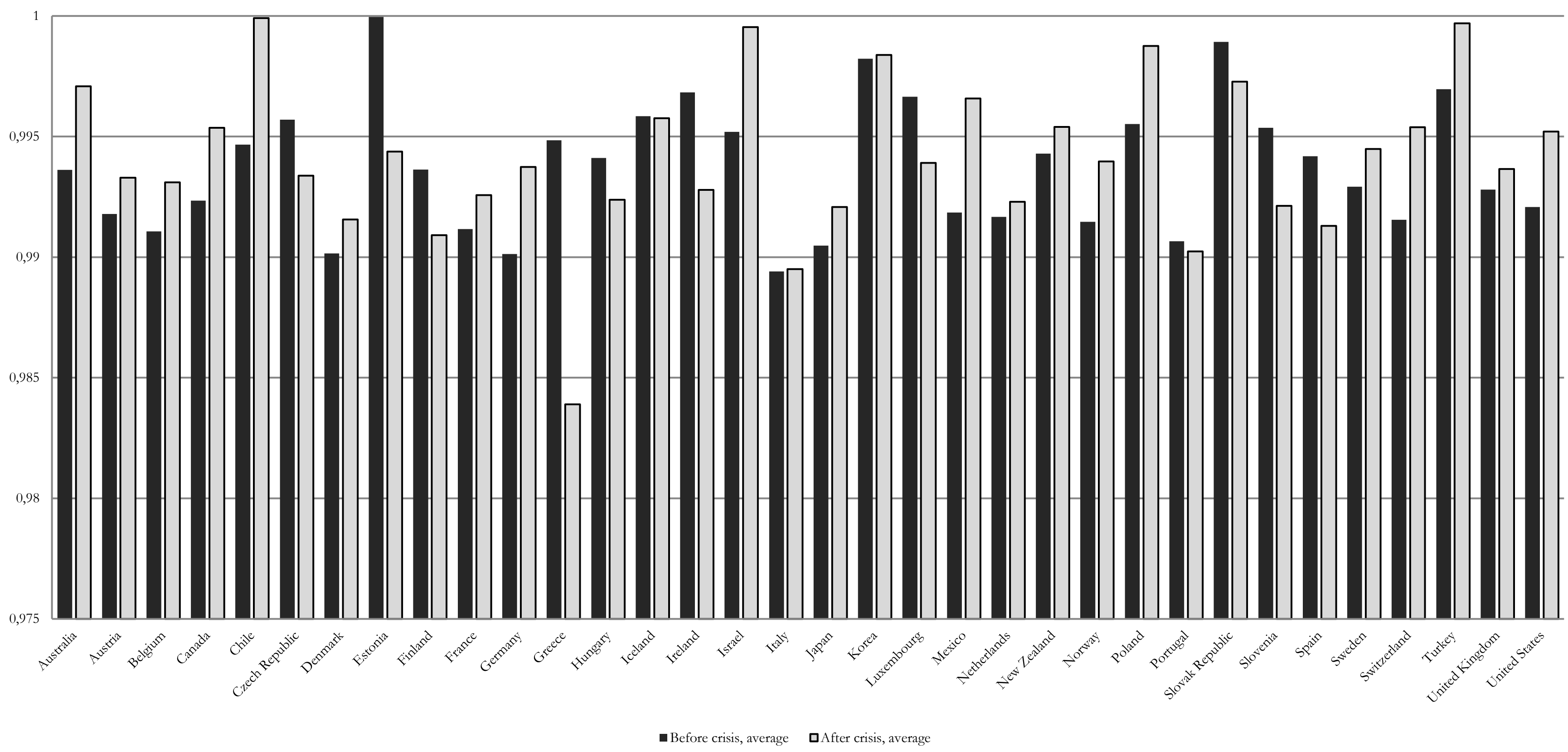


Source: author's calculation

Comparison of the pre-crisis period (2000-2006) to the post-crisis period (2010-2014) in terms of average technical efficiency shows that countries mainly increase their efficiency after the crisis (Figure 9).

The most noticeable growth is observed in Australia, Austria, Belgium, Canada, Chile, Denmark, France, Germany, Israel, Japan, Mexico, New Zeeland, Norway, Poland, Swede, Switzerland, Turkey and the United States. The exceptions are the following countries: the Czech Republic, Estonia, Finland, Greece (the greatest lag between pre- and post- crisis period of time), Hungary, Ireland, Luxemburg, the Slovak Republic, Slovenia, and Spain, which have their technical efficiency decreased. The minimum changes in efficiency are observed in Iceland, Italy, Korea, the Netherlands, Portugal, and the United Kingdom. Comparison of the countries also shows that if values of the country's unobserved individual factor loadings, λ_{il}, are either negative or close to zero, this country's technical efficiency increases after the crisis.

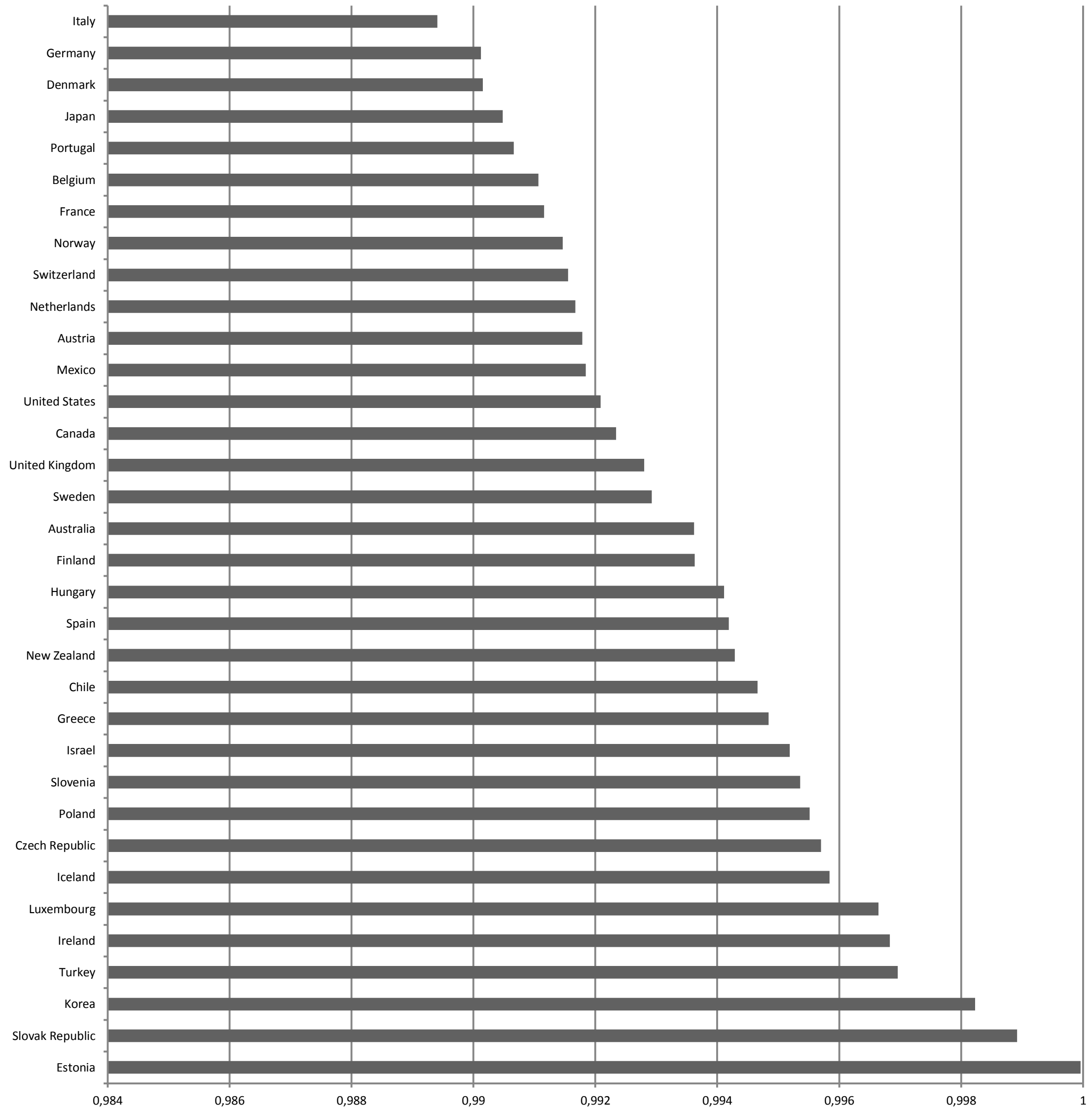
Figure 9: Comparison of the technical efficiency of OECD countries before 2007 and after 2009



Source: author's calculation

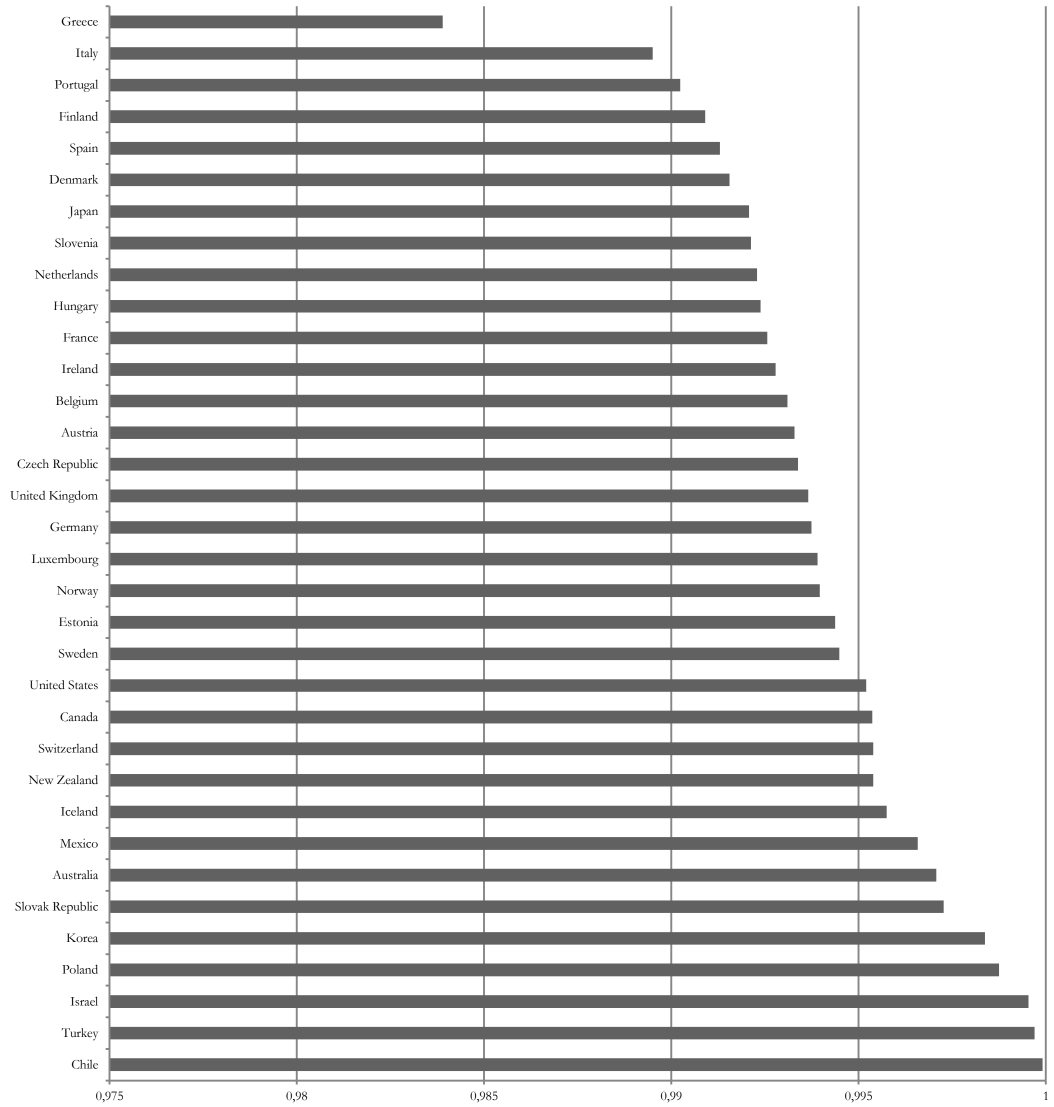
There is also another difference between these two periods of time. Thus, according to Figure 10a and Figure 10b, during the 2000-2006 period OECD countries were more highly differentiated in terms of their technical efficiency. After the crisis, the variation across countries in their technical efficiency is less.

Figure 10a: The average technical efficiency of countries before the crisis (2000-2006)



Source: author's calculation

Figure 10b: The average technical efficiency of countries after the crisis (2010-2014)



Source: author's calculation

4. Conclusions

Using the dataset of 34 OECD countries over the 2000-2014 time period the panel model with arbitrary temporal heterogeneity in time and factor structure (a model with unobservable individual effects) is fit to the multiple inputs/multiple outputs stochastic distance frontier.

Imputations of the missing values were carried out by means of a bootstrapping-based algorithm (King *et al.*, 2001; Honaker and King, 2010) allowing for trends in time series across observations within a cross-sectional unit. The statistical characteristics of the imputations prove the appropriateness of the chosen method.

The parameters of the models are estimated in the semi-parametric way. The received results suggest that the approach proposed by Kneip *et al.* (2012) yields reasonable estimates regardless of the assumption on the temporal pattern of countries' individual effects. Based on the dimensionality test results, a 6-factor model was built and analyzed. Time-varying individual effects catch differences among the analyzed countries over time and significantly extend the classical model by explaining the heterogeneous impact of unobserved common shocks on the productivity growth of the countries. It is obvious that heterogeneity over time and across OECD countries matters.

Model coefficient interpretations might be of interest to policy makers, because action taken to boost productivity performance requires a precise attribution of observed performance to its components and factors. Thus, observing θ_t can help to identify common crises for a set of countries. Normalized common unobserved factors, $f_l(t)$, define the evolution of the crisis influence on countries over time. Individual factor loadings, λ_{il}, explain the heterogeneous impact of unobserved common shocks, $f_l(t)$, on a country, and therefore can help to identify a country's resistance to negative shocks.

- The empirical results divulge the differences in technical efficiency across OECD countries in both pre- and post-crisis periods of time:
- approximately 53% of OECD countries increase their efficiency after the crisis, around 30% of the countries decrease their efficiency, and nearly 17% of OECD countries have the minimum changes in their efficiency after the crisis;
- the average length of common shocks cycles that influence outputs of OECD countries is equal to 6 years;
- the approximate delay between the beginning of the crisis and the decline in the technical efficiency of OECD countries is 4 quarters;
- the most resistant to shocks in terms of productivity growth are approximately 38% of OECD countries, namely: Austria, Belgium, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Switzerland and the United Kingdom;
- the influence of negative shocks was amplified by the value of λ_{il} in 50 % of OECD countries, namely: Australia, Chile, the Czech Republic, Estonia, Greece (the second factor), Iceland, Ireland, Israel, Korea, Luxemburg, Mexico, New Zeeland, Poland, the Slovak Republic, Slovenia (second factor), Spain (second factor) and Turkey;

- productivity growth in the countries such as Canada, Sweden and the United States - that is approximately 9% of OECD countries - was not considerably affected;
- the current average level of technical efficiency of OECD countries is at the level of 2001;
- variation in technical efficiency across countries decreased after the crisis.

These results can help to track how OECD countries develop over time in terms of their technical efficiency, as well as highlight some shortcomings in regulation of OECD countries co-operation process, which is in line with OECD Regulatory Policy 2015 (OECD, 2015).

Acknowledgement

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Appendix

Appendix 1: *KSS.C* dimensionality criterion

KSS.C dimensionality criterion is the sequential testing procedure which follows (see Kneip et al. 2012 for all technical details):

$$KSS.C = \frac{n\sum_{r=d+1}^{T}\hat{\rho}_r-(n-1)\hat{\sigma}^2 tr(Z_k\hat{P}_d Z_k)}{\hat{\sigma}^2\sqrt{2N\cdot tr((Z_k\hat{P}_d Z_k)^2)}} \overset{d}{\sim} N(0,1) \tag{A.1}$$

where k is a smoothing parameter, estimated as in Equation (12); Z_κ is a positive semi-definite symmetric matrix with eigenvalues [0, 1]; $\hat{\rho}_r$ are the resulting eigenvalues of the empirical covariance matrix $\hat{\Sigma} = \frac{1}{n}\sum_{i=1}^{n}\hat{v}_i\hat{v}_i'$; $\hat{P}_d$ is the projection matrix projecting into the (n–d) dimensional linear space orthogonal to *span* $\{Z_{kg1}, \dots, Z_{kgd}\}$ and is derived as

$$\hat{P}_d = I - \frac{1}{T}\sum_{l=1}^{d} f_l f_l' \text{ with } f_l = (f_l(1), \dots, f_l(T))' \tag{A.2}$$

and $\hat{\sigma}^2$ is calculated as

$$\hat{\sigma}^2 = \frac{1}{(n-1)tr((I-Z_k)^2)}\sum_{i=1}^{n}\left\|(I-Z_k)(Y_i - X_i\hat{\beta})\right\|^2 \tag{A.3}$$

This estimator may have a tendency to overestimate $\hat{\sigma}^2$, but according to Kneip et al. (2012) and Bada and Liebl (2014) it is suitable for dimension selection.

Appendix 2: *IC(l)* and *PC* criteria

In *IC(l)* (*IC1, IC2, IC3*) and *PC (PC1, PC2, PC3, BIC3)* criteria d is derived from minimizing the following (see Bai and Ng (2002) and Bada and Liebl (2014) for technical details):

$$IC(l) = \log\left(\frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}(y_{it} + \hat{y}_{it}(l))^2\right) + l g_{nT} \tag{A.4}$$

where l is a given factor dimension $l \in \{1, 2, 3, \dots\}$, g_{nT} is a penalty term that is estimated in the one of the following ways:

$$g_{nT}^{(IC1)} = \frac{(n+T)}{nT}\log(\frac{nT}{n+T}) \quad (A.5)$$

$$g_{nT}^{(IC2)} = \frac{(n+T)}{nT}\log(\min\{n,T\}) \quad (A.6)$$

$$g_{nT}^{(IC3)} = \frac{\log(\min\{n,T\})}{\min\{n,T\}} \quad (A.7)$$

$$PC(l) = \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}(y_{it} + \hat{y}_{it}(l))^2 + lg_{nT} \quad (A.8)$$

where $\hat{y}_{it}(l)$ are the fitted values for a given factor dimension $l \in \{1, 2, 3, \dots\}$, g_{nT} can be specified by one of the following penalty terms:

$$g_{nT}^{(PC1)} = \hat{\sigma}^2\frac{(n+T)}{nT}\log(\frac{nT}{n+T}), \quad (A.9)$$

$$g_{nT}^{(PC2)} = \hat{\sigma}^2\frac{(n+T)}{nT}\log(\min\{n,T\}), \quad (A.10)$$

$$g_{nT}^{(PC3)} = \hat{\sigma}^2\frac{\log(\min\{n,T\})}{\min\{n,T\}}, \quad (A.11)$$

$$g_{nT}^{(BIC3)} = \hat{\sigma}^2\frac{(n+T-l)}{nT}\log(nT) \quad (A.12)$$

where $\hat{\sigma}^2$ is the sample variance of the residuals

$$\hat{\sigma}^2 = \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}(y_{it} - \hat{y}_{it}(d_{max}))^2 \quad (A.13)$$

Appendix 3: Eigenvalue Ratio and Growth Ratio

See Ahn and Horenstein (2013) for the technical details.

Eigenvalue Ratio (*ER*):

$$ER = \arg\max_{l \le d_{max}} \frac{\hat{\rho}_l}{\hat{\rho}_{l+1}} \quad (A.14)$$

where $\widehat{\rho}_l$ and $\widehat{\rho}_{l+1}$ are the *l*-th and (*l*+1)-th largest eigenvalues of the sample covariance matrix. The threshold values are estimated from the empirical distribution of the eigenvalues and the maximum value factors.

Another way to derive the number of factors is to maximize the ratio of the growth rates (*GR*):

$$GR = \frac{\ln\left(\sum_{r=l}^{T}\widehat{\rho}_r \Big/ \sum_{r=l+1}^{T}\widehat{\rho}_r\right)}{\ln\left(\sum_{r=l+1}^{T}\widehat{\rho}_r \Big/ \sum_{r=l+2}^{T}\widehat{\rho}_r\right)} \qquad \text{(A.15)}$$

In a similar way as in (A.14) a GR function (A.15) is nearly symmetric around the true number of factors.

Appendix 4: ***IPC1***, ***IPC2*** and ***IPC3*** panel criteria

IPC1, *IPC2* and *IPC3* panel criteria suggested by Bai (2004):

$$IPC(l) = \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}(y_{it} + \hat{y}_{it}(l))^2 + l g_{nT} \qquad \text{(A.16)}$$

where

$$g_{nT}^{(IPC1)} = \hat{\sigma}^2 \frac{\log(\log(T))}{T}\frac{(n+T)}{nT}\log(\frac{nT}{n+T}), \qquad \text{(A.17)}$$

$$g_{nT}^{(IPC2)} = \hat{\sigma}^2 \frac{\log(\log(T))}{T}\frac{(n+T)}{nT}\log(\min\{n,T\}), \qquad \text{(A.18)}$$

$$g_{nT}^{(IPC3)} = \hat{\sigma}^2 \frac{\log(\log(T))}{T}\frac{(n+T-l)}{nT}\log(nT) \qquad \text{(A.19)}$$

Appendix 5: Eigenvalue Differences (threshold approach)

Eigenvalue Differences by Onatski (2010) are based on the fact that for the data with *l* latent common factors, the largest *l* eigenvalues of the second-moment matrix of the data grow without limit with *n*. Thus, a threshold value is derived from the empirical distribution of the eigenvalues to differentiate the diverging ones from the bounded ones:

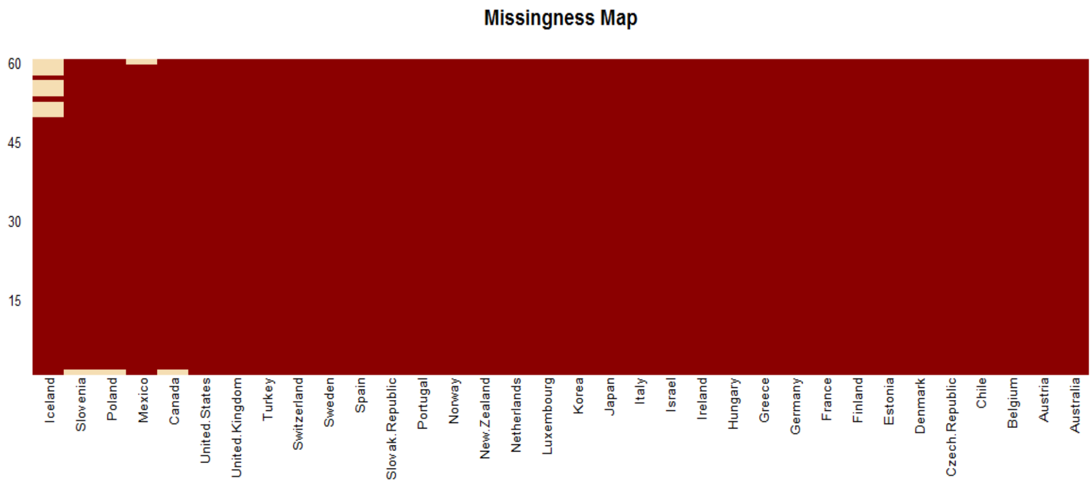
$$\hat{d} = \max\{l \leq d_{max} : \hat{\rho}_l - \hat{\rho}_{l-1} \geq \delta\} \quad \text{(A.20)}$$

where $\hat{\rho}_l$ and $\hat{\rho}_{l-1}$ are eigenvalues, δ is a positive threshold estimated iteratively from the raw data.

Appendix 6: Missingness imputations

6A. Missing values

Figure A1: Missingness map of the variable "Employment"



6B. The general algorithm of missing values imputations

It is assumed that the panel dataset of OECD countries, D, ($n \times t$), has a multivariate normal distribution with a mean vector μ and a covariance matrix Σ, $D \sim \mathcal{N}_k(\mu, \Sigma)$, and includes both observations (D^{obs}) and missing values (D^{mis}). Another assumption is that missingness depends on the observed data. It implies that missing values are missing at random (MAR) and do not depend on the complete-data parameters, that are in the line of the most of multiple imputation methods.

Thus, the likelihood of observed data is

$$p(D^{obs}, M|\theta) = p(M|D^{obs})p(D^{obs}|\theta), \quad \text{(A.21)}$$

where $\theta = (\mu, \Sigma)$ are the complete-data parameters, M is the missingness matrix. Since the main interest is in inference on the complete-data parameters, the likelihood can be rewritten as (see King *et al.,* 2001; Honaker and King, 2010; and Honaker *et al.,* 2011 for technical details):

$$L(\theta|D^{obs}) \propto p(D^{obs}|\theta) = \int p(D|\theta)dD^{mis}. \tag{A.22}$$

Then, imputations are derived by drawing missing values from their distributions, conditional on D^{obs} and the draws of θ.

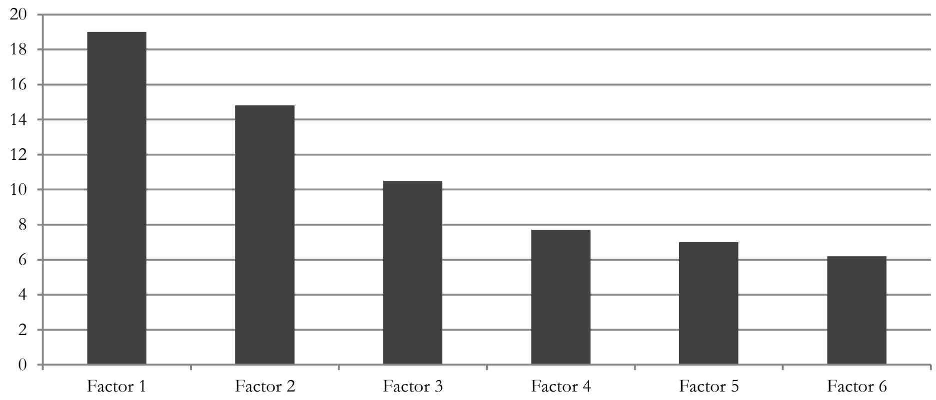
Alternatively to King *et al.* (2000), after simulations of imputation sets, e.g., *m*=5…1000, the model results are combined by averaging of estimated inputs, q, over all separate estimates, *m (*Honaker *et al.,* 2011):

$$\bar{q} = \frac{1}{m}\sum_{j=1}^{m} q_j \tag{A.22}$$

where $\bar{q}$ is the average of estimated inputs q_j.

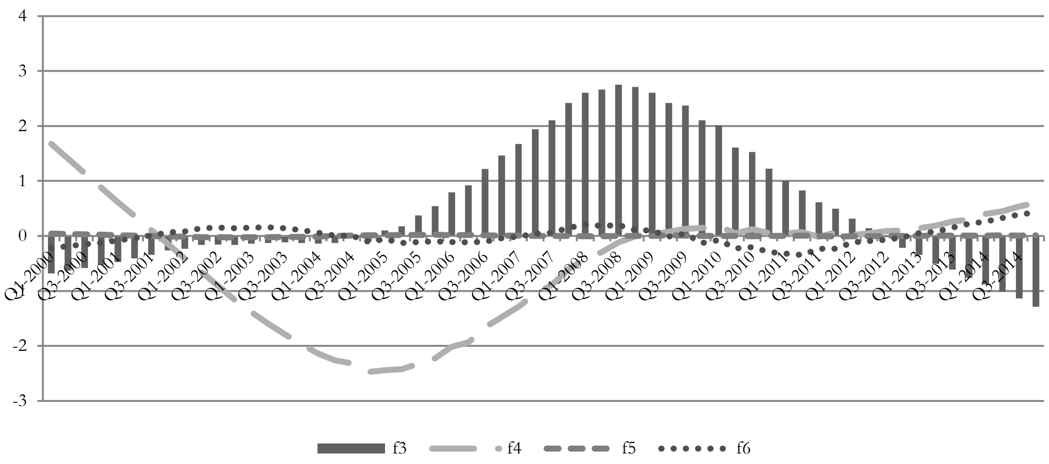
Appendix 7. Unobserved factors

Figure A2: Proportion of variance explained by the factors, % (pre-estimation from the tests)



Source: Author's calculation

Figure A3: Dynamics of common $f_3(t)$-$f_6(t)$ unobserved factors, (*d*=6), VARIMAX rotated



Source: Author's calculation

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