Austria's Competitiveness and its Determinants

Concepts, Developments, Relative Performance and Policy Options

— Final Report —

OeNB Anniversary Fund. Project No. 17686

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Abstract: Austria's rather poor development in international competitiveness rankings gave rise to questions about the economic concept of competitiveness and about the determinants and policies that can make an economy thrive again. The three modules of this research project aim at finding answers to these questions. They analyze labor costs, labor productivity, total factor productivity (TFP) and economic potential using a wide range of methods including shift-share analysis, panel econometrics, Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). The authors gratefully acknowledge the financial support by the Anniversary Fund ("Jubiläumsfonds") of the Oesterreichische Nationalbank (OeNB).

Keywords: Competitiveness, TFP, Labour Productivity, Potential, Austria, Data Envelopment Analysis, Stochastic Frontier Analysis

JEL classification: C23, E24, O47

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Introduction

When we applied for OeNB funding in spring 2017, we motivated the need for our research by deploring Austria's all-time low in the World Economic Forum's (WEF) global competitiveness ranking (23^{rd} of 137 countries) that it had hit two years before. Since then, Austria had managed to crawl up to rank 18 in 2018, but then eventually dropped back to 21^{st} (of 141 countries) in the most recent ranking before the WEF paused country rankings due to COVID-19. Hence, it still seems worthwhile to identify and investigate country characteristics that determine an economy's competitiveness. We, therefore, thank the Oesterreichische Nationalbank (OeNB) for its generous financial support and are happy to hereby provide our final report. It consists of the three modules lined out in the initial exposé:

Module A – conducted by principal investigator Klaus Weyerstraß – sets the stage for the analyses that will follow. It provides the descriptive foundation and deals with labor costs, labor productivity, the resulting *unit* labor costs (ULC) and total factor productivity (TFP). It also gives first insights into what drives differences in labor productivity and TFP by means of shift-share analysis and panel regressions.

Module B picks up where the preceding module has ended and dives deeper into the investigation of TFP growth. It aims at identifying relevant indicators for TFP growth in EU countries during the recovery phase following the 2008/09 economic crisis. It proceeds in three steps: First, TFP growth is estimated by means of Stochastic Frontier Analysis (SFA). Second, a TFP growth decomposition exercise is performed in order to get measures for changes in technical progress (CTP), technical efficiency (CTE), scale efficiency (CSC) and allocative efficiency (CAE). And third, BART – a non-parametric Bayesian technique from the realm of statistical learning – is applied in order to identify relevant predictors of TFP growth and its components from the Global Competitiveness Reports. We find that indicators that characterize technological readiness, such as broadband internet access, are outstandingly important in order to push technical progress while issues that describe innovation seem only to speed up CTP in higher income economies.

The work in this module has been conducted by Jan Kluge together with Sarah Lappöhn and Kerstin Plank. The version presented in the final report at hand is a shortened version of the one being available as IHS Working Paper.[1] It is currently under review in *Empirical Economics*.

Finally, module C investigates the economic potential of Austria and all other 26 EU member states (and the United Kingdom) and the deviations of these countries from their potentials between 2000 and 2014. Both a static and an intertemporal analysis are carried out, whereas the latter allows to distinguish between different causes for productivity changes, utilizing data envelopment analysis, input-output analysis, Malmquist productivity index and Luenberger productivity indicator. In the static analysis, we find that roughly half of the EU countries remain at a fairly low inefficiency level, including Austria. In the intertemporal analysis we find that technical change is the main driver of productivity. Moreover, the majority of analyzed countries experienced an overall positive development of productivity throughout the period in question. Although the financial crisis is clearly visible, the respective paths to recovery differ substantially. In a next step, the static analysis is extended by including additional restrictions in the model, which focus on greenhouse gas emissions and corresponding abatement activities in the individual countries. Even though there are several data issues concerning the environmental analysis, we find for a subset of countries that all of them could reach collectively agreed climate goals if they channeled all their unused production potential towards abatement activities. In a final step, we allow workers to change their educational level both in the static and in the intertemporal framework. We find that allowing for changes in qualifications increases the potential of an economy.

The work in this module was conducted by Alexander Schnabl in cooperation with Kerstin Plank, Lorenz Wimmer and Hannes Zenz. It is going to be publicly available in the IHS Working Paper Series. The results will also be submitted to a renowned journal (yet to be determined; e. g. *European Journal of Operational Research*, *Economic Systems Research* or the *Journal of Productivity Analysis*).

[1] https://irihs.ihs.ac.at/id/eprint/5455

Main Findings and Policy Conclusions

Module A analyzes the developments of labor productivity and of total factor productivity in an international comparison. Labor productivity measures output per labor input, where labor can be measured via the number of employees or the number of hours worked. Total factor productivity (TFP) or multifactor productivity is defined as that part of the change in output that is not caused by changes in labor or capital input. It, hence, captures factors such as management practices or technical progress. The main findings of module A can be summarized as follows:

- In almost all industrialized countries, productivity growth has slowed down considerably during the past decades.
- While before the Great Financial Crisis of 2008/2009, labor productivity growth in the EU was higher than in the U.S., since then then EU fell behind.
- Within the EU, the Central and Eastern European Countries (CEECs) experienced a high productivity growth due to their catching-up process to the income level of the Western economies. Productivity growth within sectors was positive in the EU, the U.S., and Japan. On the other hand, in particular after 2009, structural change contributed positively only in the CEECs to the labor productivity development, while it contributed negatively in the other regions. This is due to the ongoing shift of economic activities from industry towards services.

Insofar as the slowdown of the growth rate of labor productivity is caused by a sectoral shift towards services which are more labor intensive, this might not be considered problematic. However, in order to remain internationally competitive, this requires also slower wage growth, and it might lead to a larger spread in wage increases between industry with high productivity growth and services with lower productivity advancements. An analysis of unit labor costs shows that within the Euro area, countries at the southern periphery experienced a real appreciation due to higher (wage) inflation as compared to the core of the Euro area. After the outbreak of the Great Financial Crisis, this erosion of competitiveness had to be sharply corrected by very low and in some cases even negative wage growth. In a global context, the EU fell behind the U.S. in terms of labor productivity growth after the Financial Crisis. Furthermore, the U.S. experiences higher TFP growth. This could lead to a further loss of competitiveness of the EU vis-à-vis the U.S. Reasons for the slower TFP growth of the EU might be that the EU is lagging behind in widespread use of new technologies. This in turn might be due to a lack in venture capital or in the spin-off of start-up firms from university. Several studies have shown that the EU is good in basic research, but lags behind in the widespread application and marketing of innovations.

Module B aims at identifying relevant predictors of TFP growth in EU countries during the recovery phase after the 2008/09 economic crisis. The approach consists of three steps: First, TFP growth is estimated using Stochastic Frontier Analysis (SFA). Second, a TFP growth decomposition is performed in order to get measures for changes in technical progress (CTP), technical efficiency (CTE), scale efficiency (CSC) and allocative efficiency (CAE). And third, BART – a non-parametric Bayesian statistical learning technique – is deployed in order to identify relevant predictors from the Global Competitiveness Reports.

The findings can be summarized as follows:

- Only a handful of indicators from the Global Competitiveness Reports prove to be relevant predictors for TFP growth.
- The most robust predictor is "Technological readiness" which – unlike "Innovation" – does not cover actual R&D activities but mostly the preconditions for understanding, using and only eventually enhancing existing technologies. Hence, technological readiness includes variables like broadband internet access and internet usage. Such indicators are positive predictors for changes in technical progress (CTP) in all EU countries.
- "Innovation" joins the list of relevant predictors only when the most developed EU countries are considered. Hence, only those very close to the frontier benefit from R&D in order to push the frontier further out. Those countries further away, however, can speed-up their catch-up process by increasing technological readiness. Providing high-speed internet access for them seems more crucial than engaging in sophisticated R&D programs.

- An interesting but puzzling result is that “Financial market efficiency” yields negative effects on changes in allocative efficiency (CAE). This might be attributed to “zombie” companies keeping up with inefficient production set-ups when their access to loans is too easy.

Module C investigates the economic potentials of the 27 EU member states (and the United Kingdom) and their deviations from these potentials during the years 2000 to 2014. The analysis is carried out for the 56 industries defined in the World Input-Output Database (WIOD). We use three models of data envelopment analysis (DEA): a classical radial DEA, directional distance function (DDF) DEA as well as a slacks-based measure (SBM) DEA model. As input factors we use intermediate (domestic) consumption, capital stock as well as labor. Our outputs are the deliveries to final demand.

The module contains an economic, an environmental and a social analysis, comprising of a static and an intertemporal analysis for each. The economic model serves as the basis for the environmental and the social model, in which we introduce greenhouse gas emissions reduction goals and allow for workers to change their qualification levels.

Our main findings can be summarized as follows:

- Roughly half of the EU countries remain at a fairly low inefficiency level.
- Technical change is the main driver of productivity, while changes in efficiency contribute to a lesser extent.
- A subset of countries could reach their climate goals if they channeled all unused production potential towards greenhouse gas emissions abatement activities.
- Allowing for changes of qualification levels in the model increases the production potential of the countries.

Part I.

Module A: (Total Factor and Labor) Productivity Developments

1. Introduction

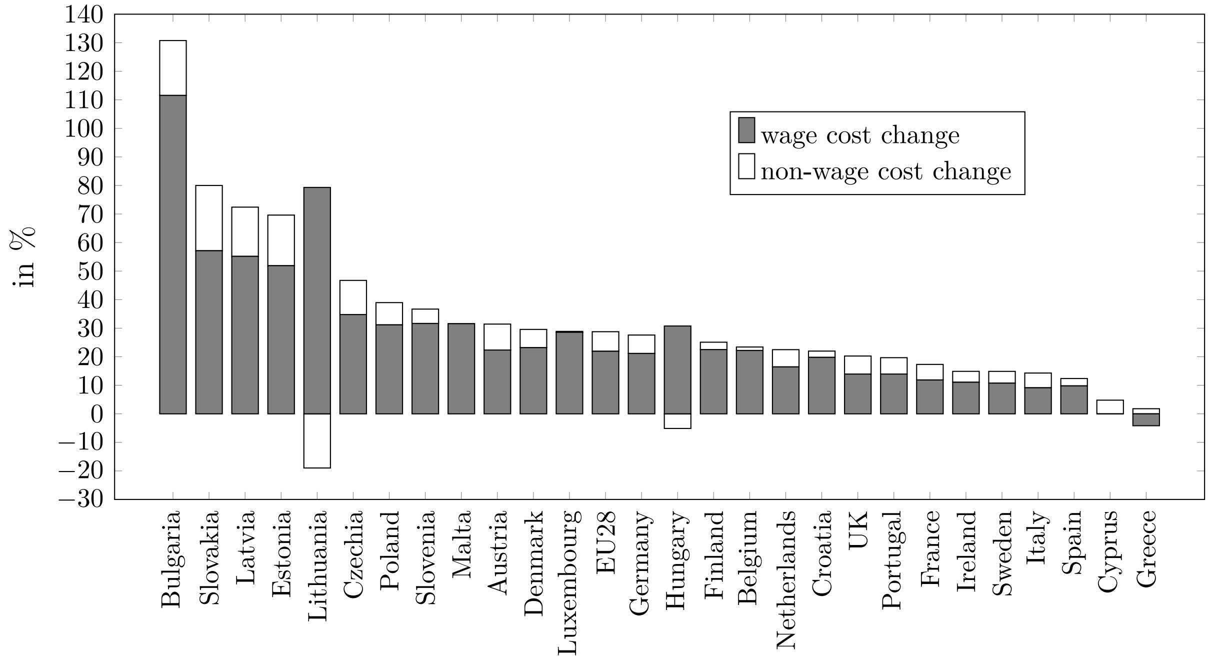
A good starting point for any analysis of competitiveness is to look at different measures of productivity and compare them between countries. The two most important indicators in this context are wage costs (or, more general, *labor* costs) which measure how much is to be paid for one unit of labor, and labor productivity which captures how much can be produced with one unit of labor. Both measures combined result in *unit labor costs* (ULC) which give a first hint about how competitive a country is compared to its trade partners. While labor cost is a simple measure which usually does not get much academic attention, labor productivity developments are more crucial and are therefore analyzed in more detail in section 3 of this module. Finally, when capital or other production factors are added to the equation, the module will shift its focus away from labor and will look at *total factor productivity* (TFP) and its determinants in section 4.

2. (Unit) labor costs

Labor costs are usually measured by monthly or hourly compensations of employees (gross wages plus employers' social security contributions). Hence, it is decomposed into direct wages and salaries as well as non-wage costs. The former are in most cases determined by the market and/or in negotiations between trade unions and employers' associations. Governments have only very limited impact on this part of labor costs (they might impose statutory minimum wages). However, a large part of non-wage costs, e. g. social security contributions, are under direct control by public authorities.

Figure 1 shows how labor costs have developed in European countries since the Great Financial Crisis (GFC) of 2008/09. In accordance with expectations, countries with initially rather low labor costs have seen considerable increases during the last decade. This

Figure 1
Labor cost growth rates (2008-2019; Industry, construction and services (except public administration, defense, compulsory social security))



Source: Eurostat – *Labour cost levels by NACE Rev. 2 activity [lc_lci_lev]*, author's calculations and illustration. (Romania not shown due to missing data.)

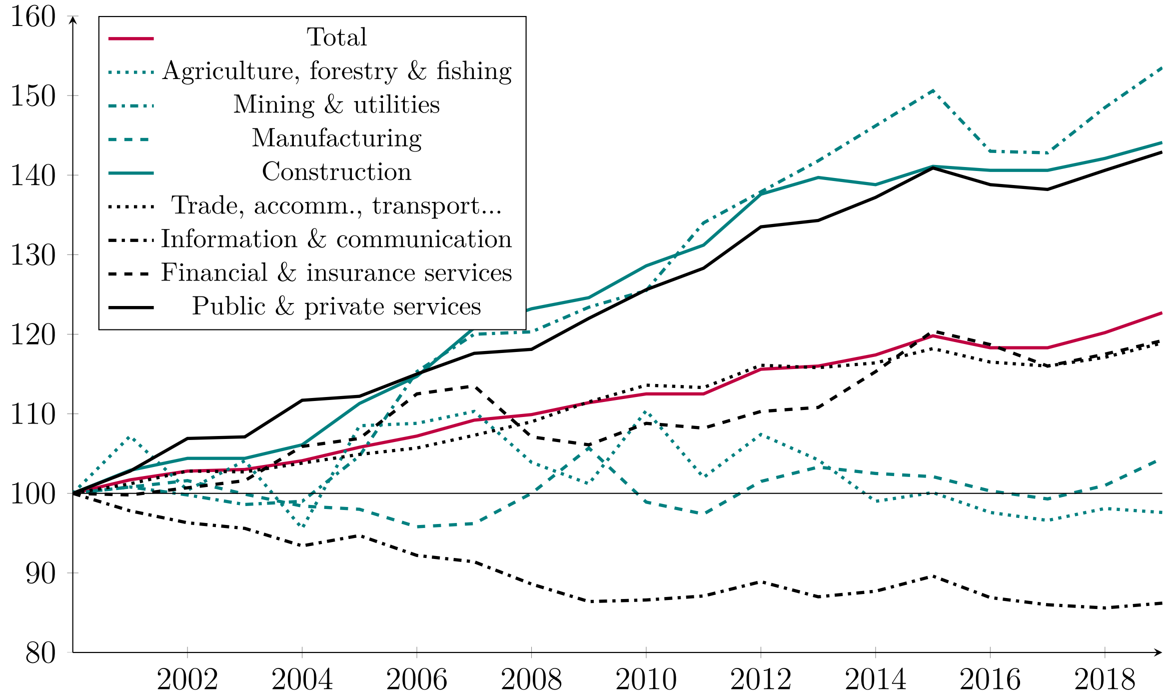
increase was primarily driven by rising wages and only to a smaller extent by increases in non-wage labor costs. Two countries even took measures to dampen wage rises by decreasing non-wage costs (Lithuania and Hungary). Greece was the only country that experienced decreasing labor costs, driven by – which is even more unusual – decreasing wages. This development was triggered by the sharp rise of wage costs prior to the GFC. Austria ranks in midfield but is slightly above the EU 28 average. While the Austrian wage increase was moderate, the increase in non-wage costs of about 9 % was among the highest in the EU.

The analysis of labor costs only gives a blurred picture of how competitive a country really is as high labor costs (wage or non-wage) can be offset by higher productivity. It is therefore more interesting – and a first step towards actual productivity analyses – to look at *unit* labor costs (ULC). They are usually defined as the ratio of total labor compensation to output per labor input. Labor input may be measured via the number of employees or the number of hours worked. While internationally more data are available for the number of employed persons, hours worked give a more accurate picture. In particular during a sharp recession such as the one following the GFC or the Corona pandemic, companies try to hoard labor so as to be prepared for the subsequent upswing. Often, this is supported by public subsidies for short-time programs. In this case, employment is adjusted via the number of hours worked per employee, while the number of employees is reduced to a much lesser extent. Unit labor costs would rise if wages (and/or non-wage labor costs) increase without being accompanied by a similar increase in labor productivity. Hence, countries that allow increases in ULC over longer periods of time are likely to fall behind in terms of competitiveness.

Figure 2 shows that unit labor costs in the EU have increased overall and in most industries over the last 20 years. The overall increase was about 23 %. Unit labor costs in *mining and utilities* were even more than 50 % higher in 2019 than they were in 2000. Hence, wage growth was way ahead of productivity growth over the entire observation period. Only *agriculture, forestry & fishing* and *manufacturing* stayed fairly constant. The *information and communication* industry was the only one that experienced considerably negative ULC growth as it benefited from enormous productivity gains that wages did not keep up with.

Figure 2

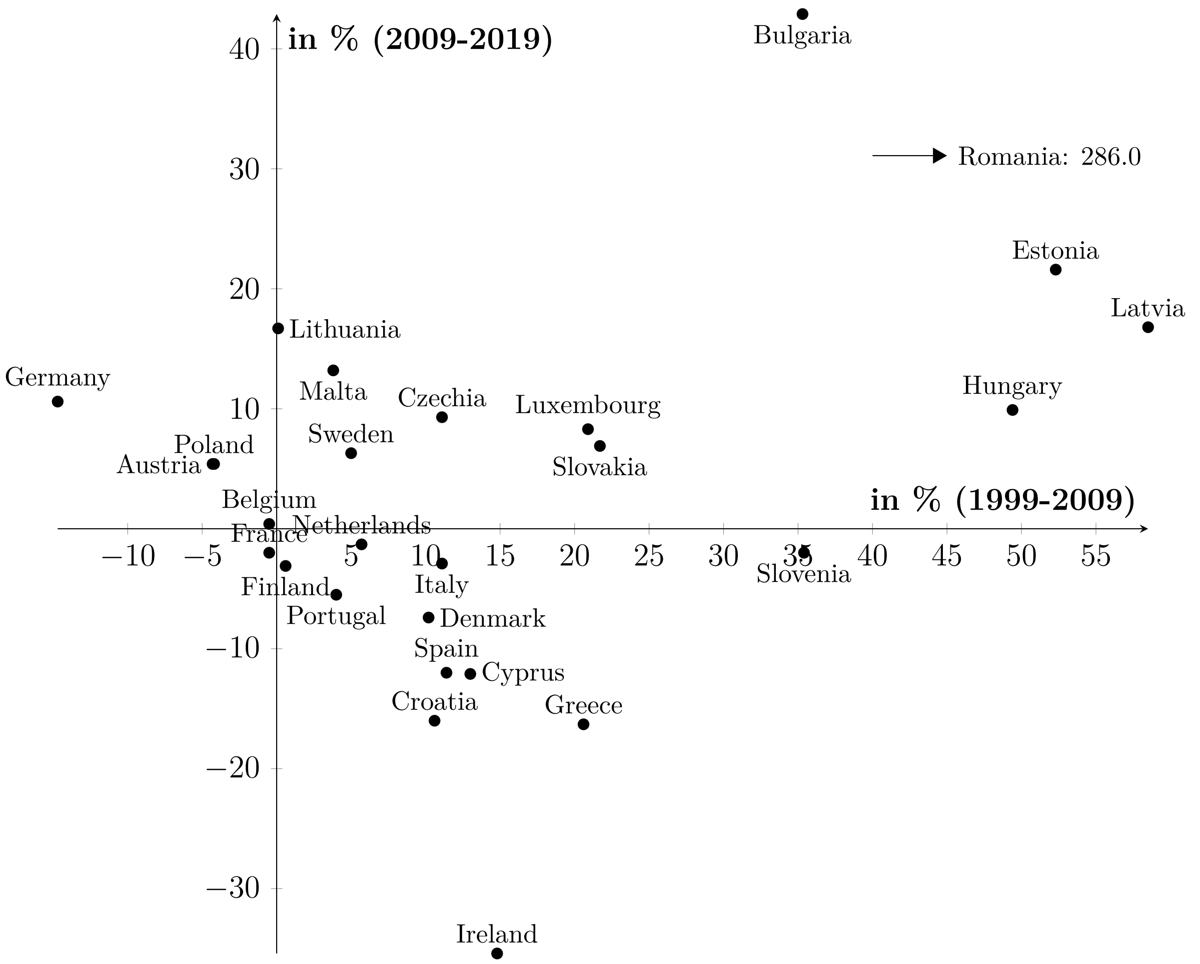
Unit labor cost growth in the EU28 (2000-2019, Index: 2000=100)



Source: OECD.Stat – *Productivity and ULC by main economic activity (ISIC Rev. 4)*; author's calculations and illustration.

As unit labor costs determine a country's competitiveness, it makes sense to benchmark them against one another. Figure 3 displays how selected European countries have performed in terms of unit labor costs compared to the Euro area average by showing 10-year ULC growth rates.

Figure 3
Unit labor cost development in relation to the Euro area



Source: Eurostat – *Unit labour cost performance related to the euro area - annual data [TIPSLM50]*; author's calculations and illustration.

Roughly three groups of countries can be identified: countries with below average ULC growth in the decade preceding the GFC allowed for stronger growth in the decade after (e. g. Germany and Austria). The second group started with low ULC *levels* and – after joining the EU – were able to converge towards the Euro area average (mostly countries from Central and Eastern Europe ("CEEC")). The third group of countries allowed for high ULC growth before the crisis and had to undergo difficult adjustment processes during and after the GFC leading to below average ULC growth rates (e. g. Greece, Spain, Portugal etc.). France was the only member of a hypothetical fourth group: It reported ULC growth rates slightly below average both before and after the GFC.

3. Labor productivity trends

As outlined above, labor costs (i. e. the numerator of unit labor costs) can to a certain degree be controlled by governments. Any political decision, however, has to take into account how labor productivity (i. e. the denominator of unit labor costs) develops around the world and across industries. Due to the higher potential to substitute capital for labor, productivity usually increases faster in industry than in services. This pattern can be observed in the international comparison depicted in Figure 4. It shows labor productivity growth in the EU, the U.S., and Japan over the period 2000 to 2017 (until 2015 in Japan). In addition to analyzing the entire period, the period is also divided into the sub-periods before and after the Great Financial Crisis, respectively.

Figure 4
Development of labor productivity

Source: EUKLEMS, author's calculations and illustration.

Since countries from Central and Eastern Europe are still undergoing a faster structural change than the "old" EU member states, the EU panel was divided into the countries that formed the EU before 2004 (but excluding the UK (i. e. "EU14")), and 11 countries from Central and Eastern Europe ("CEEC") that joined the EU in 2004, 2007, and 2013, respectively (without Malta and Croatia due to missing data).

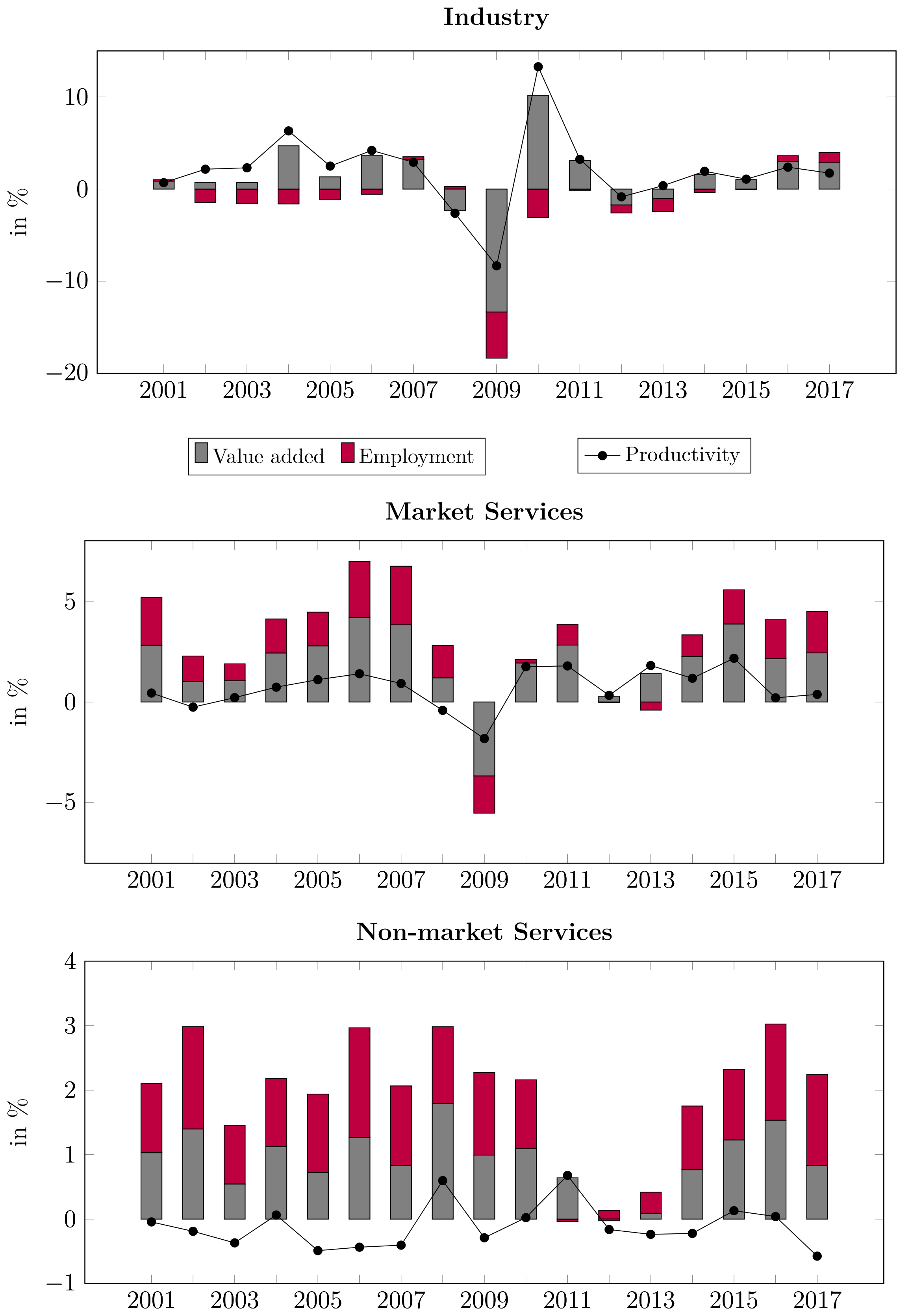
Over the entire period (but especially before the GFC), the countries from Central and Eastern Europe experienced very high labor productivity growth rates. Due to their lower starting points, this catching-up process was to be expected. Interestingly, before the GFC, the U.S. experienced way higher labor productivity growth than the "old" EU member countries and Japan, but after the GFC, those differences have more or less disappeared.

Figures 5 and 6 show the contributions of the growth rates of value added and of employment to the development of labor productivity (Figures 7 and 8 show the same information for the U.S. and Japan). Labor productivity growth is defined as the difference between the growth rates of value added and of employment. Hence, labor productivity growth is positive only if the growth rate of value added outpaces employment growth.

Regarding the sectoral decomposition, it is evident that industry exhibits a much faster productivity growth than services. Among the services sectors, market services achieve a higher growth of labor productivity than non-market services, where labor productivity merely stagnated or, in the case of Japan, even declined. Market services here comprise trade, repair of vehicles, but also financial and business services. Particularly financial services are more and more automatized, and hence labor productivity grows in this industry. In contrast, non-market services such as health care, public administration and household services require much more physical labor and can only to a small extent be replaced by robots or online services.

Figure 5

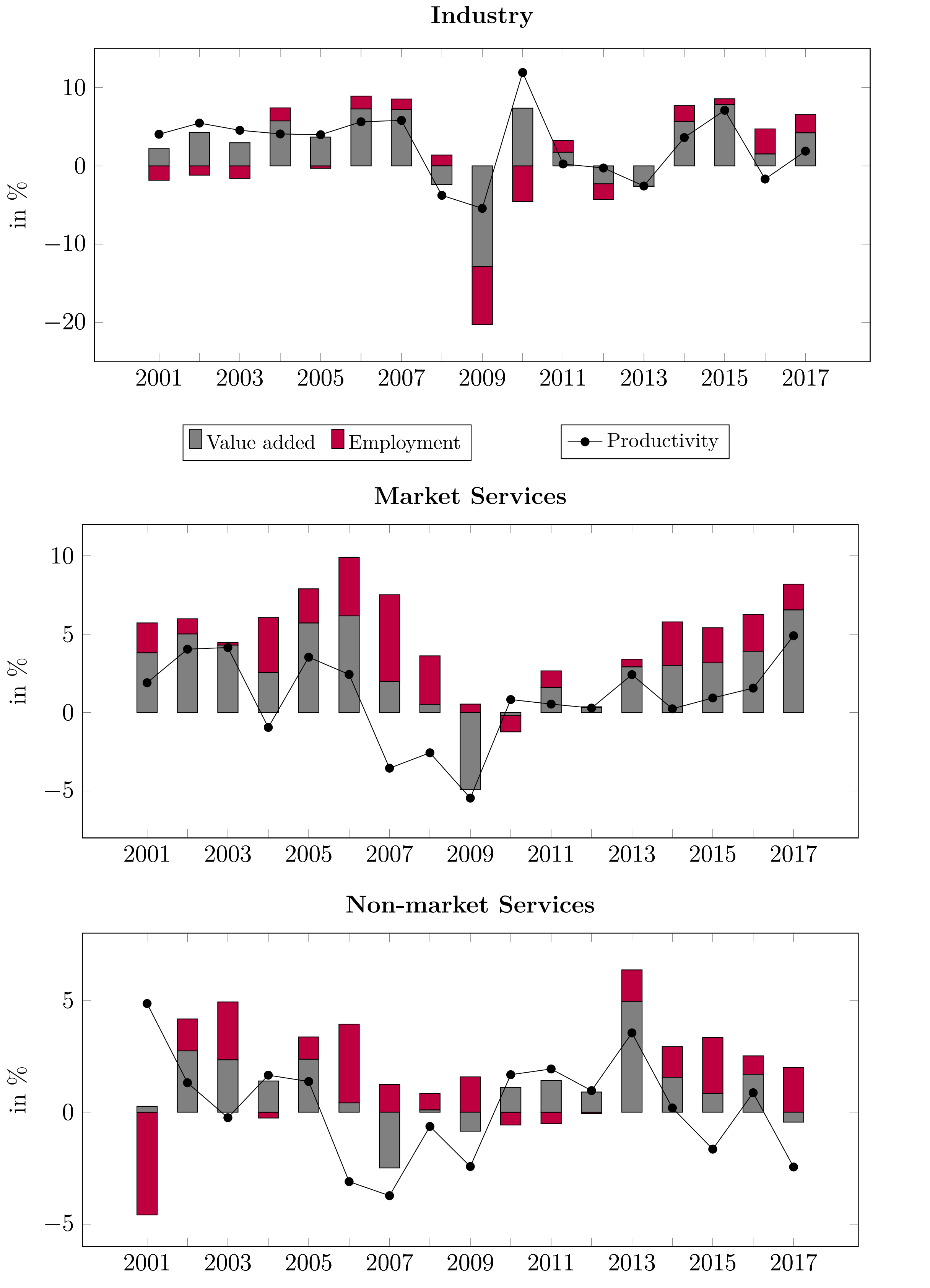
Decomposition of labor productivity growth in the EU14



Source: EUKLEMS, author's calculations and illustration. EU14: Austria, Belgium, Denmark, Germany, Greece, Finland, France, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden.

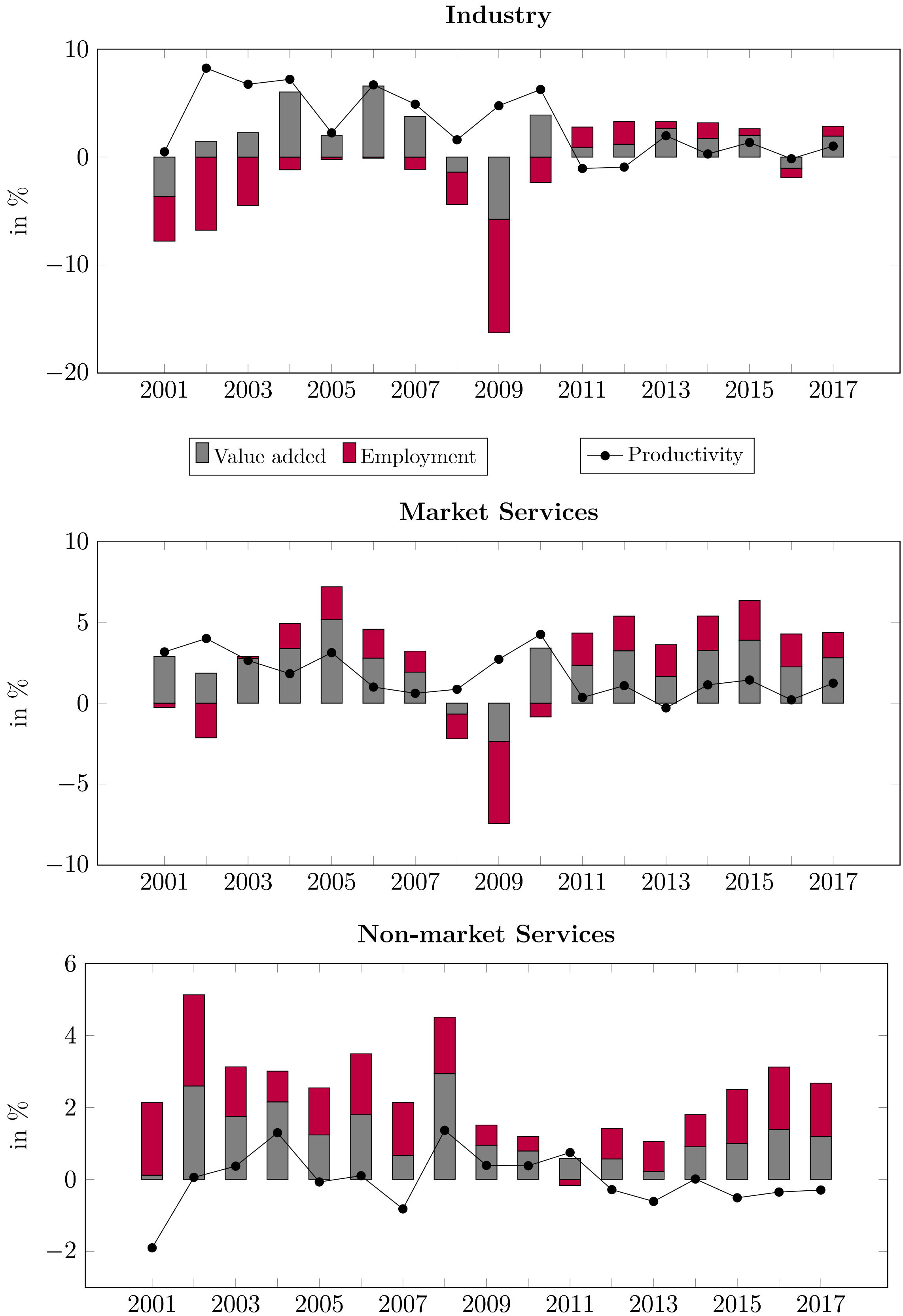
Figure 6

Decomposition of labor productivity growth in the CEECs



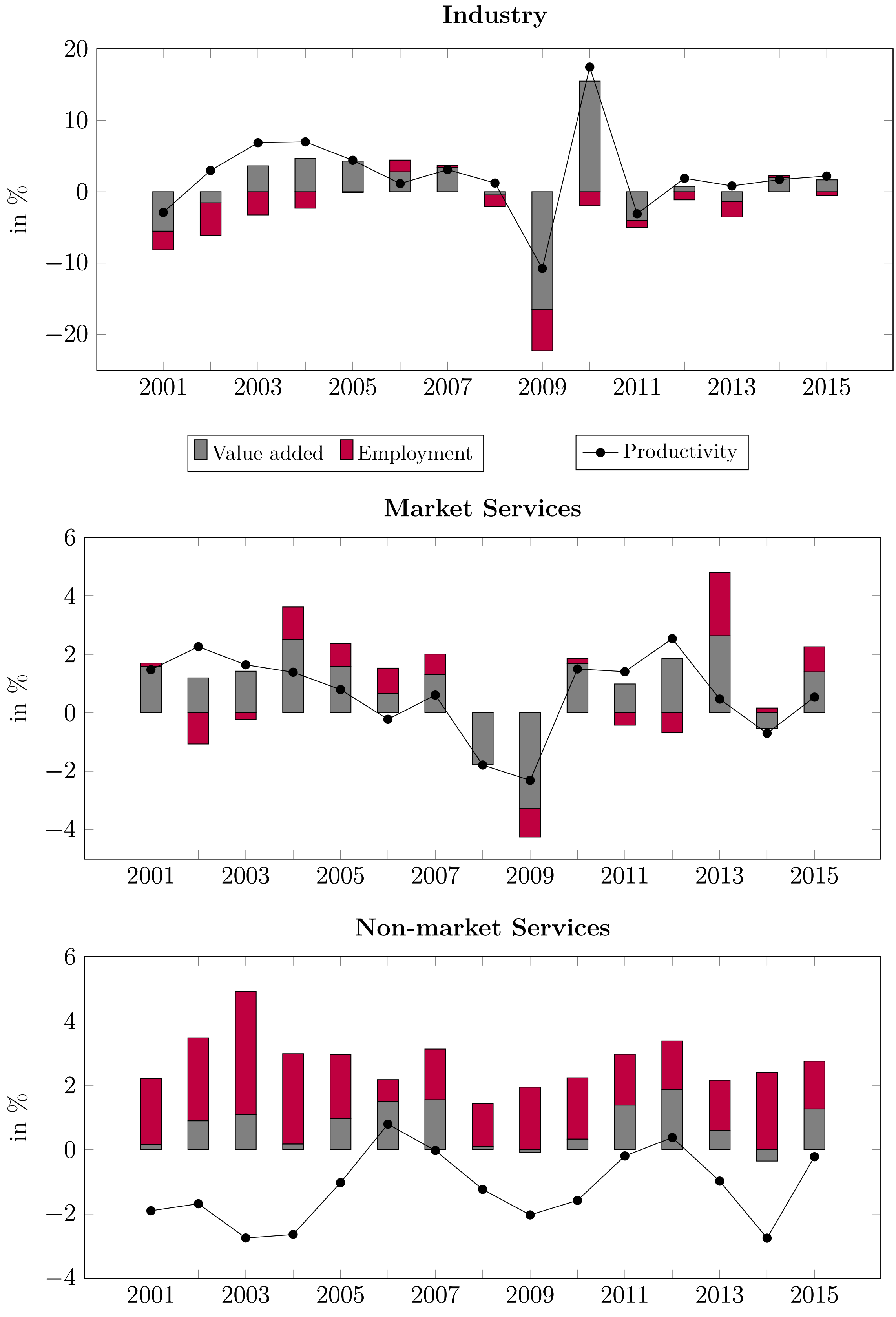
Source: EUKLEMS, author's calculations and illustration. CEECs: Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland Romania, Slovakia, Slovenia.

Figure 7
Decomposition of labor productivity growth in the U.S.



Source: EUKLEMS, author’s calculations and illustration.

Figure 8
Decomposition of labor productivity growth in Japan



Source: EUKLEMS, author's calculations and illustration.

3.1. Methodology: Shift-share analysis

As the previous analysis has shown, labor productivity growth varies greatly across industries. Hence, the development of productivity growth is driven both by the growth of productivity within industries and by changes in the sectoral composition of the economy. The evolution of economy-wide labor productivity can thus be decomposed into productivity growth in each industry and the change in the sectoral composition of the economy. The traditional form of the shift-share analysis was developed by Creamer (1943), and was later formalized by Dunn Jr (1960). Stevens and Moore (1980) provide a critical review of the literature. The technique was applied to analyze the development of labor productivity in Switzerland (Altun and Ley (2015)), as well as in the EU in comparison to the U.S. (Denis *et al.* (2004)).

For i sectors and l time periods, the shift-share analysis is based on the following formula (Altun and Ley (2015)):

$$\dot{P}_t = \sum_{i=1}^{n} \left(\dot{p}_t^i \cdot \frac{v_{t-l}^i}{V_{t-l}} + r_{t-1}^i \cdot \Delta s_t^i + \dot{p}_t^i \cdot r_{t-l}^i \cdot \Delta s_t^i \right) \tag{1}$$

where $\dot{P}_t$ is the aggregate labor productivity growth and $\dot{p}_t^i$ denotes labor productivity growth in sector i. The aggregate gross value added is the sum of sectoral value added and captured by $V = \sum_i v_i$. The variable s_t^i captures employment in sector i as a share of total employment; $r_t^i = \frac{p_t^i}{P_t}$ is the relative labor productivity of sector i.

According to the formula above, economy-wide labor productivity growth is the sum of three effects:

- $\dot{p}_t^i \cdot \frac{v_{t-1}^i}{V_{t-1}}$: The *growth* effect shows the contribution of the individual industries i to overall productivity growth, assuming constant employment shares of the industries. This effect is also called the direct productivity effect. If productivity of an industry increases, its growth effect is positive.

- $r_{t-1}^i \cdot \Delta s_t^i$: The *structural* change effect represents the contribution that can be attributed to a decrease or increase in the share of employment between the sectors with low or high average productivity, assuming constant productivity levels in the sectors. A positive structural change effect means that there has been a shift in employees from sectors with lower to those with high average productivity.

- $\dot{p}_t^i \cdot r_{t-1}^i \cdot \Delta s_t^i$: The *interaction* effect is a residual and cannot be clearly assigned to one of the two other phenomena. However, it can be viewed as an effect resulting from the interaction between changes in employment and productivity. The interaction effect is positive if the employment share of sectors increases with increasing productivity. The interaction effect measures correlations between productivity and employment changes, with positive (negative) efficiency changes interacting with the expansion (contraction) of specific industries. The interaction term is positive when the first two effects (i. e. the intra-industry plus the "structural" effects) are complementary (i. e. productivity growth is positive in expanding industries and negative in contracting industries). Hence, the interaction effect is negative when the first two effects are substitutes, i. e. productivity growth is positive in contracting industries and negative in expanding industries (Denis *et al.* (2004)).

3.2. Data

The shift-share analysis has been applied to analyze the determinants of the labor productivity development in the EU, the U.S., and Japan. Data on real value added and the number of employees was taken from the EU KLEMS database, 2019 Release.[2] It contains data for the EU countries that were part of the EU already before 2004 for the period 1995 to 2017. For the countries of the EU enlargement rounds since 2004, data usually start in 2000. For Japan, the time series end in 2015.

As mentioned above, to account for the differences in productivity growth between "old" and "new" member states, the EU panel was divided into the countries that formed the EU before 2004, but excluding the UK ("EU14"), and 11 countries from the "CEECs" that joined the EU in 2004, 2007, or 2013 (excluding Malta and Croatia due to missing data).

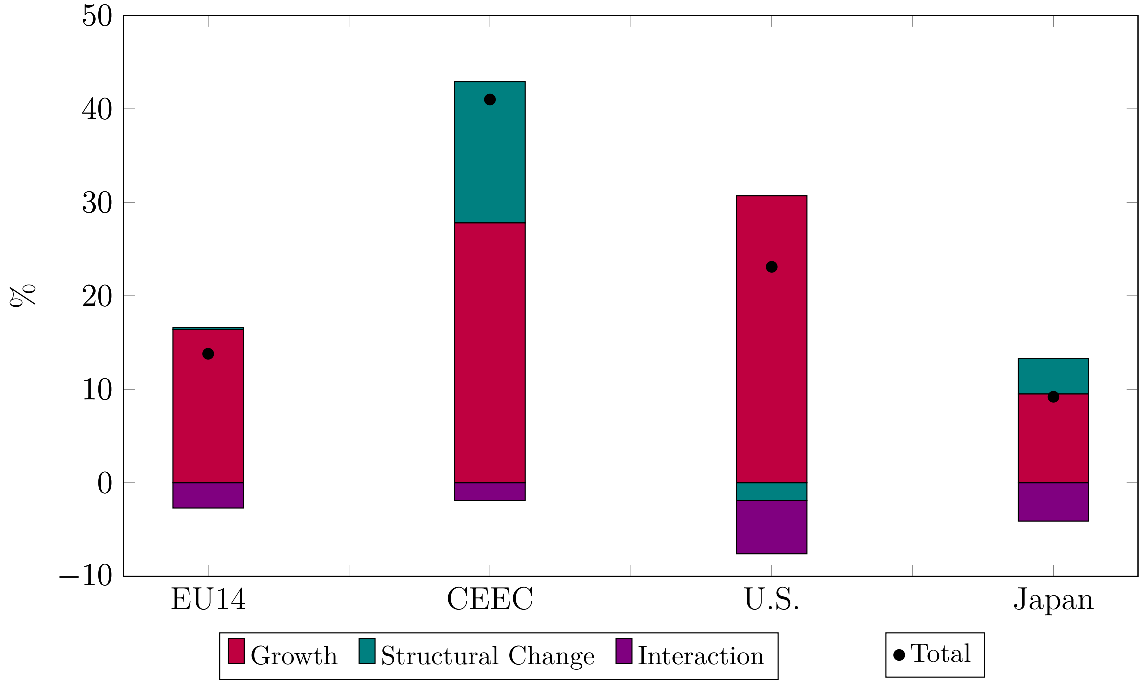
3.3. Results

This subsection discusses the shift-share analysis results. Figure 9 shows the results for the entire period 2000 to 2017 (Japan: until 2015), while Figures 10 and 11 contain the results for the sub-periods before and after the Great Financial Crisis (GFC) of 2008/2009, respectively.

[2] https://euklems.eu/

Figure 9

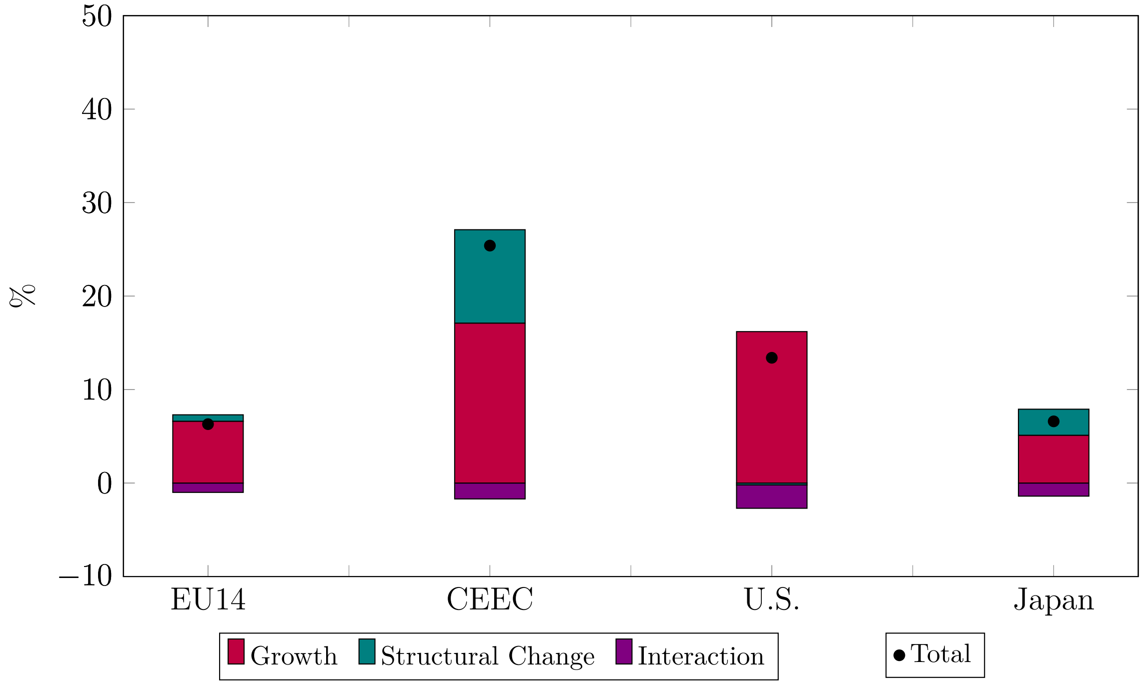
Decomposition of labor productivity growth 2000 to 2017 (Japan till 2015)



Source: EUKLEMS, author's calculations and illustration.

Figure 10

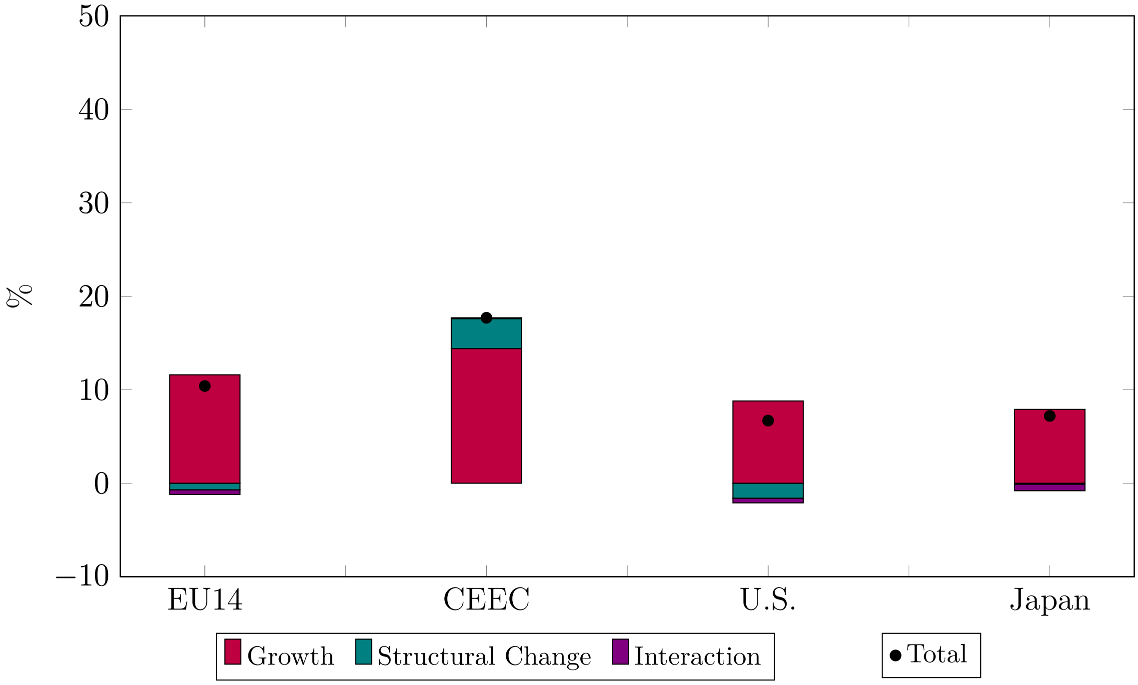
Decomposition of labor productivity growth 2000 to 2008



Source: EUKLEMS, author's calculations and illustration.

Figure 11

Decomposition of labor productivity growth 2009 to 2017 (Japan till 2015)



Source: EUKLEMS, author's calculations and illustration.

Turning to the detailed results of the shift-share analysis, the high productivity growth in the CEECs was driven both by the growth effect and by structural change from industries with lower to industries with higher productivity growth. For the "old" EU countries, the structural change effect was positive before and negative after the GFC. For Japan, structural change was conducive to productivity growth before and neutral after the financial crisis. Finally, the U.S. structural change contributed slightly negatively to productivity growth before 2009, and this negative contribution increased in the second sub-period.

The shift-share analysis shows that in all industrialized countries there is a tendency of diminishing labor productivity growth over time. The main reason for this observation is that the services sectors become more important over time at the expense of industry. Furthermore, productivity growth diverges between industry (and here manufacturing in particular) and services. This brings about important challenges for wage negotiations. High productivity growth would enable high wage increases in industry. For the services sectors this implies that they might be forced to offer wage growth in access of the sector's productivity growth so as to remain attractive for qualified workers. This means that business services will have to innovate further, e. g. by making use of digitization. But for those services that require physical labor, such as health care, this brings about challenges for financing wage costs. Therefore, the budgetary burden of public services is likely to increase further in the future.

4. Total factor productivity (TFP)

Finally, if we shift away from labor and broaden the view to all relevant factors of production, *total factor productivity* (TFP) becomes the major issue. TFP is not only an essential determinant of labor productivity, but also of economic growth. The Joint Economic Forecast Group (see Gemeinschaftsdiagnose (2017)) for Germany and Fortin *et al.* (2017) for Austria identify TFP as the most important driver of medium-term growth. Due to the decline of the population in working age, TFP will play an increasingly important role in maintaining economic growth and thus the creation of material well-being in the future. In this respect it is worrisome that in most EU countries as well as in the U.S. and in Japan, TFP growth has decreased over time.

Figures 12 and 13 show that since the 1960s, TFP growth has slowed down in all major economies. The figures depict the growth rates of trend TFP – the trend has been estimated by applying a Hodrick-Prescott filter to actual total factor productivity. In particular since the Great Financial Crisis of 2009, TFP more or less stagnated in many industrialized economies. Prior to the onset of the COVID-19 pandemic in 2020, trend TFP growth settled around 0.5 % per year in most (Western) European countries. Most Central European countries (not displayed here) are still in the catching-up process and thus experience higher TFP growth than the Western countries.

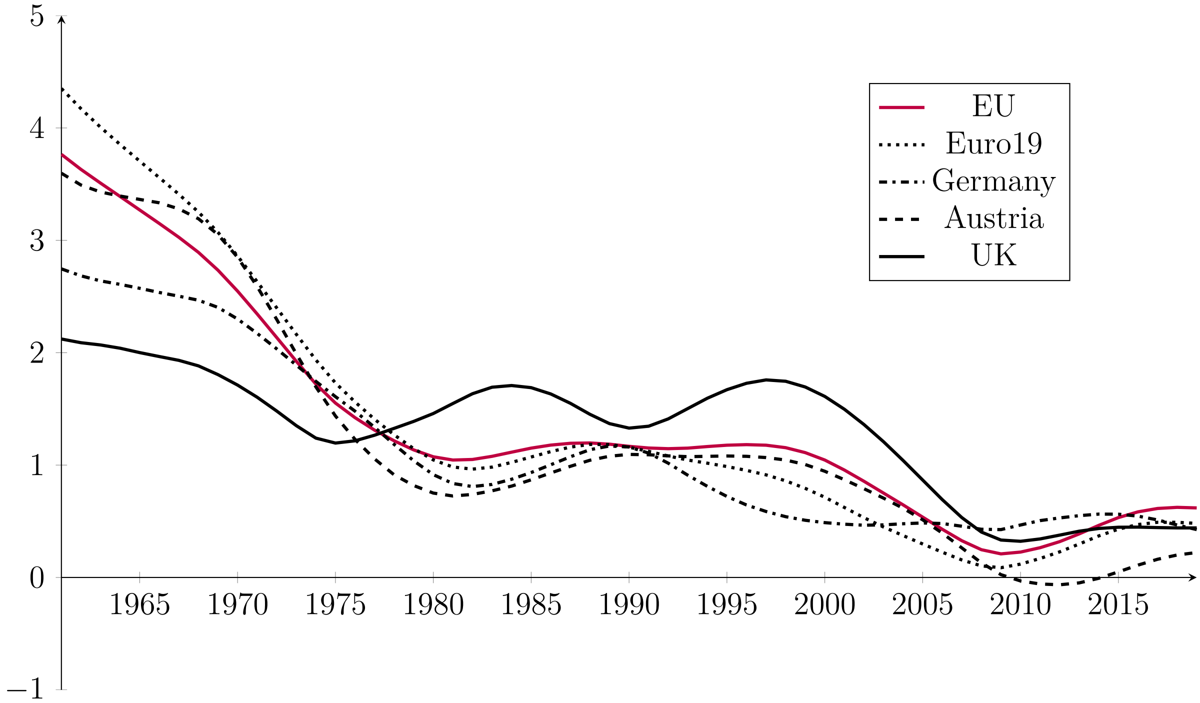
In an update of Weyerstraß (2018a,b), determinants of TFP were determined empirically. Data on the TFP were taken from the AMECO database of the European Union. Alternatively, the TFP could have been estimated econometrically or calculated as the so-called Solow residual. In any case, the starting point is a production of the following form:

$$Y = A \cdot K^{\alpha} \cdot L^{\beta}. \tag{2}$$

Economic output Y, e. g. in a macroeconomic context GDP, is produced with the input factors capital K and labor L. The parameters α and β are the production elasticities,

Figure 12

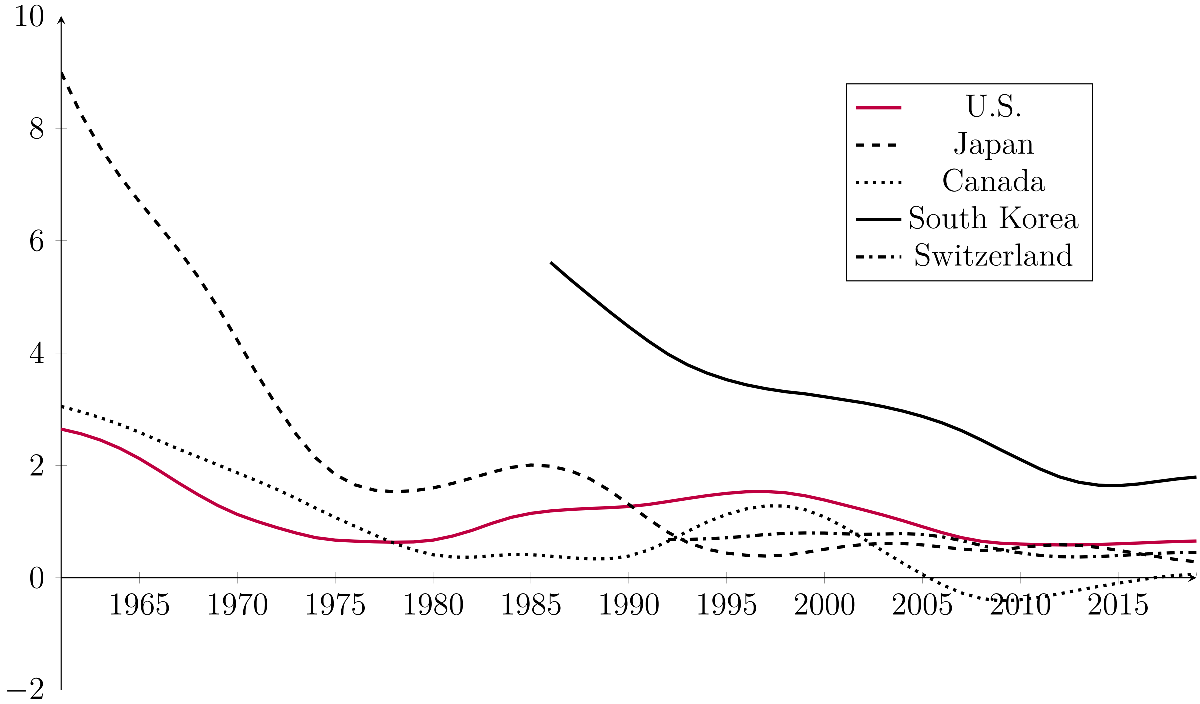
Development of TFP growth in selected EU countries



Sources: Eurostat, AMECO, OECD; own estimations and illustration.

Figure 13

Development of TFP growth in selected non-EU countries



Sources: Eurostat, AMECO, OECD; own estimations and illustration.

and A measures technical progress. Empirical estimations and also calculations of total factor productivity would be based on a logarithmic form of this general Cobb-Douglas production function:

$$ln(Y) = ln(A) + \alpha \cdot ln(K) + \beta \cdot ln(L). \quad (3)$$

The parameters α and β could either be freely estimated, or β could be restricted to be $1 - \alpha$, in accordance to constant returns to scale. In such an estimation, a time trend would be included to approximate $ln(A)$, and the estimated coefficient would be interpreted as TFP.

Alternatively, TFP can be calculated by re-arranging the above equation in the following way:

$$ln(A) = ln(y) - \alpha \cdot ln(K) - \beta \cdot ln(L). \quad (4)$$

In this case, parameters have to be specified for α and β. According to the empirical observation that the labor share in total income is about 2/3, the European Commission sets α to 0.65 and, assuming constant returns to scale, β to 0.35. The calculations of TFP in the AMECO database are based on these parameter settings. After calculating TFP in this way, it is transformed to an index. Hence, absolute values of TFP have no meaning, and only its development over time should be interpreted.

For a panel of 32 countries (EU plus Switzerland, USA, Canada, Japan and South Korea), Weyerstraß (2018a) identifies significantly positive influences of the number of patents (or, in alternative specifications, spending on R&D), the investment share in GDP, the industry share in GDP, openness, economic freedom, and a positive regulatory environment on TFP. Negative influences are found for the share of public consumption in GDP and for the share of services. Weyerstraß (2018b) finds that the capital intensity, a high share of information technology in the total capital stock, as well as the number of industrial robots per employee are conducive for TFP growth. Due to limited data availability, the influence of the robot density is less robust than the positive effect of the industry share in value added, R&D spending or the number of patents. On the contrary, a large government sector is found to influence TFP growth negatively.

The endogenous variable in this panel analysis is total factor productivity as published in the AMECO database. It is used in levels (as, e. g., in Dettori *et al.* (2012)); hence, the explanatory variables explain shifts in TFP but not in growth rates. The following explanatory variables were considered in different model variants: number of patents, spending on research and development (R&D) as share of GDP, share of services in value added, public consumption as share of GDP, investment as share of GDP, investment in information and communication equipment as share of GDP, openness of the economy, regulatory quality, and the Freedom of the World index published by the Fraser Institute. The index on regulatory quality is published by the World Bank and measures the quality of the regulatory framework, where a higher index indicates a higher quality of the legislation. The Freedom of the World index is published by the Fraser Institute; a higher index is associated with fewer government interventions. Table 1 shows details on the definitions and sources of the data.

Table 1
List of variables

Variable	Description	Sources
TFP	Index of total factor productivity	AMECO database
PATENTS	Number of triadic patent applications (patent applications in the U.S., the EU and Japan) per million inhabitants	Eurostat, OECD
R&D	Spending on research and development in percent of GDP	Eurostat, OECD
SERVICES	Share of services in value added	Eurostat, OECD
INVEST	Gross fixed capital formation as a percentage of GDP	Eurostat, OECD
G	Public consumption as a percentage of GDP	Eurostat, OECD
OPEN	Degree of openness, defined as the average of the share of exports and imports in GDP	Eurostat, OECD
REGULATION	Regulatory quality Index	World Bank
FREE	Freedom of the world index	Fraser Institute
ICT	Investment in information and communication equipment as percentage of GDP	Eurostat, OECD

The analysis was performed for a panel of the current 27 EU member states, as well as the United Kingdom, Switzerland, the U.S., Japan, and South Korea. However, data for some variables and some countries were unavailable. The estimations were performed for the maximum period 1975 to 2018, but for most variables and countries data were available only from 1995 onward. The panel Ordinary Least Squares (OLS) models include fixed effects for countries and time periods. Time dummies control for influences that are constant across entities but vary over time, while the country dummies control for country heterogeneity in the development of TFP. Table 2 shows the estimation results for three models with different sets of explanatory variables.

Table 2
Determinants of TFP: Estimation results

Dep. var.:	**Model 1**		**Model 2**		**Model 3**	
TFP	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Constant	94.969***	12.359	88.139***	19.664	57.257***	8.285
INVEST	34.095***	4.639	34.624***	5.159		
REGULATION	10.038**	7.680	10.861***	9.048		
PATENTS	0.019	1.376				
SERVICES	−37.312***	−3.812			−25.203**	−2.957
ICT					1.255**	1.959
FREE					6.564***	14.969
OPEN			11.436***	3.649	7.640***	3.015
R&D			2.758***	3.489		
G			−125.375***	−8.339		
Adjusted R^2	0.733		0.747		0.819	
No. of countries	32		32		29	
Estimation period	1996–2018		1996–2019		1975–2018	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Panel OLS with country and period fixed effects.
Sources: Eurostat, AMECO, OECD, World Bank, Fraser Institute; own estimations.

Spending on *R&D* was significant only in model 2. The number of patents (*PATENTS*) was at the edge of being significant in model 1. As a third proxy for spending on innovation activities, the investment in information and communication equipment (*ICT*) turned out to be significant in model 3. In addition to these innovation related variables, the openness of the economy, the freedom of the world index as well as good governance were identified to be conducive to TFP. Furthermore, general investment in equipment also influences TFP positively. This latter finding is in line with the argument that technical progress is often embodied in new capital goods. To the contrary, a large share of services in value added or a large share of government consumption in GDP spending put a brake on TFP growth. While a priori the sign of government consumption on TFP is not clear, it is more likely that the effect is negative than positive. The reason is not much related to the spending side, but to the financing side of the public budget. Government consumption has to be financed by taxes, and if a large part of them is distortionary (which is the case for most taxes), this might negatively influence TFP. If, on the other hand, tax revenues – even if they are distortionary – are used for productive expenditures such as investment in broad band internet connections, then the impact on TFP might be positive.

5. Conclusions

This module has shown key figures about productivity and has put them into a global context in order to approach the concept of competitiveness. The diagnosis for the EU gives some cause for concern: Unit labor costs have increased massively over the last 20 years. The Great Financial Crisis of 2009 came with considerable shifts inside the EU as the Southern countries were forced to become more competitive while Eastern countries are still in their catch-up process and immensely increase labor costs. Other countries in the core of the Euro area, in particular Germany, have maintained their competitive advantage, despite higher labor cost growth after the GFC.

On the other hand, the growth rate of labor productivity has declined in the EU, as in the U.S. and in Japan. While before the GFC, labor productivity growth in the EU was higher than in the U.S., the EU fell behind afterwards. Japan has continuously experienced low labor productivity growth over the past centuries, which might be related to its rapidly ageing population. A shift-share analysis showed that growth of productivity within sectors (i. e. the growth effect) contributed positively to labor productivity growth in the period 2000 to 2017 as well as before and after the GFC in the traditional EU countries ("EU14"), in the Central and Eastern European Countries, in the U.S., and in Japan. On the other hand, in particular after 2009, structural change contributed positively only in the CEECs to the labor productivity development, while it contributed negatively in the other regions. This is due to the ongoing shift of economic activities from industry towards services. Regarding the balance between wage growth in the services sectors and in industry, this poses a challenge. Since high productivity growth enables high wage growth in industry, while the lower productivity growth in services would require lower wage growth. If wages grow at the same pace in all sectors, this leads to an increase in unit labor costs in services relative to industry. With regard to public services, this puts a burden to the public wage bill and hence to public finances. In addition, the structural change towards services increases the necessity to increase productivity also in the services sectors via digitization. On the other hand, such labor-saving technical progress might result in higher structural unemployment, putting challenges on social security financing based solely on the wage bill.

As far as TFP growth is concerned, the literature has identified a wide range of variables that might be conducive: a large share of industry in value added, equipment investment, research and development, good governance or openness to foreign direct investment and international trade. The presented analyses in this module have corroborated these findings. In addition, investment in information and communication equipment, spending on R&D, as well as the number of a country's patent applications were found to be conducive to TFP. Based on the empirical results, policies that are beneficial for capital formation in general, investment in computer technology and in R&D as well as a business-friendly regulatory environment are beneficial for total factor productivity.

Part II.

Module B: Efficiency and its Determinants

1. Introduction

The search for the determinants of economic prosperity has a long tradition in the economic literature as politicians around the world are interested in knowing which levers to move in order to make their economies flourish. In this paper, we investigate the determinants that enable economies in the European Union (EU) to use their means of production efficiently. Achieving high scores in the identified determinants shall be rendered *competitiveness*.

Competitiveness seems an iridescent concept that has become a catch-all term for a wide range of economic concepts. The World Economic Forum (2017, p. 11) defines competitiveness as *"the set of institutions, policies, and factors that determine the level of productivity of an economy"*. This definition is appealing as it relates to productivity as a well-defined concept that measures output per unit of input. Hence – and contrary to the view by Krugman (1994) – competitiveness in this sense does not equal productivity but is assumed to work as a pre-condition for productivity.

The World Economic Forum provides comprehensive suggestions concerning *"the set of institutions, policies and factors"* in its annual Global Competitiveness Reports. The most recent report includes 141 economies and monitors no less than 103 individual indicators. Countries like Switzerland, Singapore or the United States are usually among the top performers while many African countries are to be found at the bottom of the table.

One can easily argue against such indicator systems as they are fuzzy, hardly complete and often lack a sound theoretical concept (see, e. g., Lall (2001) for a comprehensive critique of the Global Competitiveness Report); but even if the rankings and the weighting schemes might be somewhat ad hoc, such systems still are an inexhaustible source of indicators of which some might well be associated with an efficient functioning of an economy (even though others or even most of them might not). The fact that those indicator systems are potentially fuzzy is only natural because so is the concept of total factor productivity (TFP), the most important (see, e. g., Easterly and Levine (2001)) but largely mysterious driver of GDP variations.

In this paper, we argue that a set of indicators which jointly make up for an economy's competitiveness can be related to TFP growth. We proceed in three steps: First, we estimate TFP growth in the EU after the 2009 crisis using Stochastic Frontier Analysis (SFA). Second, we decompose TFP growth into four components, namely changes in technical progress (CTP), in technical efficiency (CTE), in scale efficiency (CSC) and in allocative efficiency (CAE). And finally, we aim to identify the determinants of TFP growth and its four components by analyzing the indicators provided by the Global Competitiveness Report using a non-parametric Bayesian approach from statistical learning.

The remainder of this article will be structured as follows: The literature review is divided into two parts. The first part (subsection 2.1) describes how our study fits into the literature on economic growth; the second part (subsection 2.2) discusses the channels through which the competitiveness indicators might influence the way economies can translate inputs into outputs. Section 3 gives details about the methodological approach and describes the data. The results are shown in Section 4 and summarized in Section 5.

2. Literature

2.1. General overview

The literature relevant for our study can be roughly divided into two strands: The first one tries to find the determinants of economic growth; the second one argues that such determinants will not affect growth rates directly but via total factor productivity (TFP).

The first strand of literature is dedicated to the search for relationships between economic outcomes – mostly GDP growth rates – and a wide range of potential determinants. In contrast to the research that rests upon widely agreed production functions as in the second strand (see further below), this research is mostly theory-free and purely data-driven. As the authors are aware of the fact that available models can not explicitly distinguish the importance of a wide range of variables, they have established Bayesian estimation techniques as the standard in the field. The advantage of Bayesian methods is that they do not require pre-built estimation set-ups claiming to be "true" models of the matter at hand. They can deal with model uncertainty and give insights about what variables should be included in explaining variations in economic outcomes. Among the most famous works of this kind is certainly the one by Sala-i-Martin *et al.* (2004): They use a Bayesian approach in order to explain long-run growth in 88 countries using 67 variables. They find that, i. a., primary schooling, the prices of investment goods and the initial income levels are strongly connected to growth rates; the authors interpret the high impact of the last-mentioned as evidence for economic convergence. Fernandez *et al.* (2001) use a Bayesian Model Averaging (BMA) approach for 41 variables and 140 countries; they also find initial GDP to have a strong impact on long-run growth. Crespo Cuaresma *et al.* (2016) revisit both of the works mentioned (and the data sets they have used) and combine a BMA model with Latent Class Analysis (LCA) in order to analyze joint inclusion patterns of variables. Further examples for Bayesian analyses are Brock and Durlauf (2001), Durlauf *et al.* (2008), Moral-Benito (2012), Ley and Steel (2009) or – for a regional application – Crespo Cuaresma *et al.* (2011).

This first strand of literature gives valuable insights into the determinants of economic growth but – as mentioned above – often rests upon methodological rather than economic reasoning. Hence, the second strand of literature takes neoclassical growth theory as a starting point. The aim is to isolate the contributions of direct production factors, such as capital and labor, and attribute the remaining variation in GDP growth to TFP. The results shed light on the proportions of economic growth that can be explained by measurable determinants and the ones that elude further explanation as they are driven by unobservable sources. Such exercises often reveal that TFP growth holds accountable for a considerable share of GDP growth in many countries (see, i. a., Easterly and Levine (2001), Baier *et al.* (2006), Islam *et al.* (2006) or Burda and Severgnini (2009)). Applying decomposition techniques – based on both parametric (Stochastic Frontier Analysis (SFA)) or non-parametric (Data Envelopment Analysis (DEA)) frontier analysis – allow to further disentangle TFP growth. Such analyses can be more detailed in terms of policy recommendations as they manage to explain whether economies increase their (residual) TFP growth due to, say, accelerated technical progress or technical efficiency. Such decomposition exercises have been applied to individual industries (see, e. g., Kim and Han (2001), See and Coelli (2013) or Laurenceson and O'Donnell (2014)) and also to national economies (see, e. g., Färe *et al.* (1994b) or Pires and Garcia (2012)).

In this article, we aim at picking the most interesting aspects of both strands of literature and thereby try to learn as much as possible about the composition of TFP growth and their respective drivers. The paper closest to ours is probably the one by Danquah *et al.* (2014) who also perform a TFP growth decomposition and apply a Bayesian approach in order to identify relevant indicators. They identify unobserved heterogeneity and the initial GDP level as the main drivers of TFP growth, while other indicators, like, e. g., trade openness or the consumption share, seem less important.

We contribute to this kind of research in three ways: First, we deploy an SFA based decomposition technique in order to disentangle TFP growth into as many components as possible. In contrast to many DEA based studies, we will be able to investigate not only changes in technical progress and technical efficiency but also in scale and allocative efficiency. The parametric nature of SFA will allow to interpret the results against the background of the growth accounting literature. Second, we introduce a new approach from statistical learning (Bayesian additive regression trees (BART), see Chipman *et al.* (2010)) to this kind of literature. In contrast to the widely deployed BMA exercises, BART – as a non-parametric technique – is very flexible in terms of the functional form of relationships and stable when it comes to multicollinearity. Finally, we use data for the EU that covers the post 2008/09 crisis period. We are therefore able to analyze the recovery process and its most important drivers. In order to form expectations about how the indicators in the Global Competitiveness Reports influence variables of economic performance – in particular TFP growth – we will review them in the following section.

2.2. Hypotheses and Descriptive Statistics

The Global Competitiveness Index (GCI) includes twelve major areas (referred to as "pillars"). The construction of the GCI changes over time so that comparisons between years are difficult. We use here the historical data set (*version 20180712*)[1] that includes consistent data between 2007 and 2017 and follows the GCI definition described by the World Economic Forum (2017).

The twelve pillars are divided into three subgroups, which represent different stages of development: Pillars 1 to 4 are labeled *factor-driven*. At this stage, an economy's competitiveness primarily rests on factors such as natural resources and cheap labor. The

[1] http://reports.weforum.org/global-competitiveness-index-2017-2018/downloads/

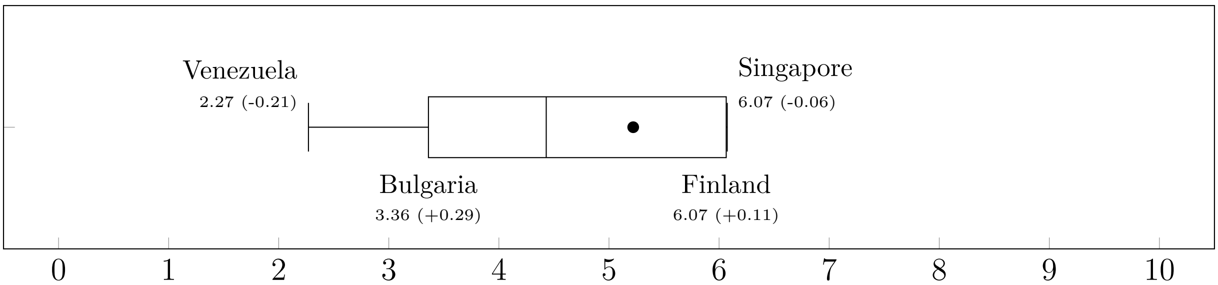
second, *efficiency-driven* stage incorporates pillars 5 to 10 and builds on an increasingly skilled labor force, a well-functioning, large market and technological readiness. The third stage is *innovation-driven* and requires highly sophisticated business practices (pillar 11) and the ability to innovate (pillar 12). In order to compute the individual country scores, the three subgroups are weighted depending on a country's respective development stage. The report combines data from international organizations, such as the World Bank and the International Monetary Fund (IMF) as well as the Executive Opinion Survey (EOS) conducted by the World Economic Forum (2017).

The GCI pillars are formulated in such a way, that higher scores are always "better"; hence, we would expect positive signs for each one of them when regressed on any measure of economic development. The methodological challenge will be to disentangle the effects from one another and to find the indicators that affect TFP growth the most. The following section will provide some economic reasoning for the channels through which each of the pillars might affect a country's economic performance.

2.2.1. 1^{st} Pillar: Institutions

The GCI pillar *institutions* is composed of 21 indicators, including the protection of property rights, the strength of investor protection, the efficiency of the legal framework in settling disputes and the occurrence of irregular payments and bribes. As the box plot in Figure 14 shows, the best performing EU country during our observation period between 2009 and 2017 is Finland with an average score of 6.1; Bulgaria is at the bottom of the EU table with an average of 3.4.

Figure 14
Institutions (1^{st} Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses). Austria is denoted by •.

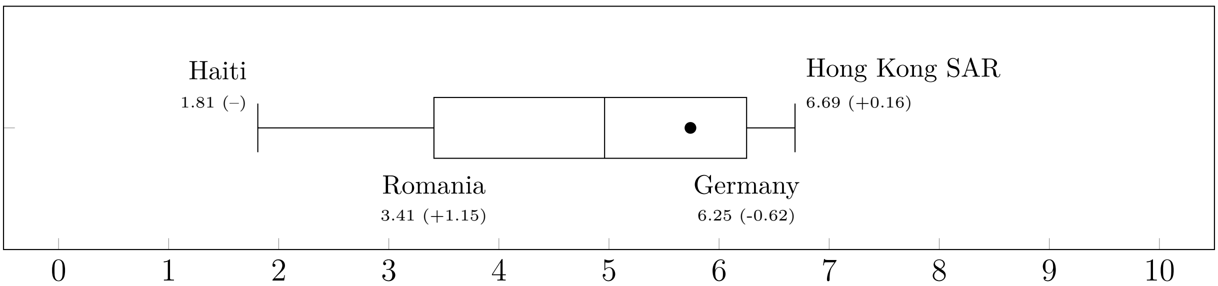
North (1987) states that complex economic structures and the trend towards specialization and division of labor lead to a growing importance of confidence in contract enforcement. Insecure property rights – according to Acemoglu *et al.* (2005) – reduce incentives to invest and innovate. The empirical results by several authors confirm this view. For instance, Knack and Keefer (1995) find that the security of property rights affects the extent of investment as well as the efficiency of allocation of inputs. Coe *et al.* (2009) report that a strong patent protection is a significant determinant of TFP, becoming presumably effective through the channel of incentives for R&D spending. Égert (2016) observes for OECD countries that a higher rule of law and better law enforcement increase the effect of R&D on TFP. And according to Mauro (1995), corruption leads to less investment and consequently lowers economic growth.

Since institutions in the EU are comparatively highly developed and as there is only little variation over time and any improvements would need a long time to become effective (see, e. g., Chong and Calderón (2000)), we do not expect this pillar to be a major predictor of TFP growth in the EU.

2.2.2. 2nd Pillar: Infrastructure

The GCI pillar *infrastructure* consists of nine indicators for transport, electricity and telephone infrastructure. The highest average score in the EU holds Germany with 6.2, the lowest score has Romania with 3.4 (see Figure 15).

Figure 15
Infrastructure (2nd Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses). Austria is denoted by •.

The main mechanisms through which infrastructure affects productivity are included in models of the New Economic Geography (see, e. g., Krugman (1991) or Fujita *et al.* (1999)): A reduction of time and transport costs results in a higher productivity of intermediates, increases trading activities and enables a better access to larger markets, which in turn helps to take advantage of scale economies, and causes greater competition.

Since the seminal work by Aschauer (1989), contradictory results have been found concerning the effects of infrastructure on economic growth and productivity. This is due to the fact that different types of infrastructure have been investigated and that various methods of measurement and models have been applied (see, e. g., Calderón *et al.* (2015), Esfahani and Ramírez (2003),Gramlich (1994), Canning and Pedroni (2008), Röller and Waverman (2001), Fernald (1999), and Melo *et al.* (2013)). Calderón and Servén (2004) take both quantity and quality of infrastructure into account and find that the quantity of infrastructure has a positive effect on long-run economic growth, while the relationship between quality and growth is empirically less robust. Since the the focus of this pillar is on quality, we do not expect it to be a major predictor of TFP growth in the EU.

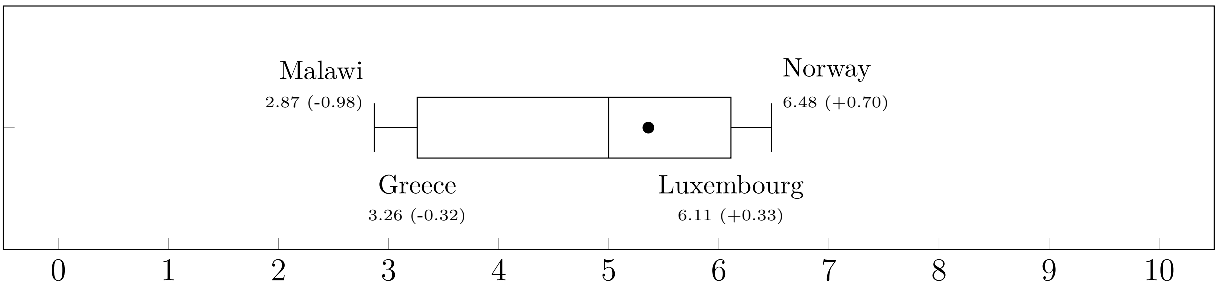
2.2.3. 3rd Pillar: Macroeconomic Environment

The macroeconomic environment represents the overall state of an economy and provides the framework within which all entities operate.

The GCI pillar *macroeconomic environment* captures budget balances, public debts and gross national savings. It also includes credit ratings and inflation rates. As shown in Figure 16, Luxembourg achieves the highest score in the EU (6.1) while Greece – shaken by the 2008/09 crisis – is only slightly above the global minimum.

Figure 16

Macroeconomic Environment (3rd Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses). Austria is denoted by •.

Government spending has an impact on how an economy develops and can be important in times of crisis, though it may increase public debt. Many studies raise concerns about excessive debts leading to distrust in the ability of governments to meet financial obligations and point towards negative effects of high public debt-to-GDP ratios on growth (see, e. g., Baum *et al.* (2013), Reinhart and Rogoff (2010), Diamond (1965), Saint-Paul (1992) or Bohn (2011)).

A high government debt ratio combined with a general doubt about a country's solvency may also cause a downgrade in sovereign credit ratings. Such downgrades could result in a bond and stock market downturn as well as a loss in value of a country's currency (see, e. g., Afonso *et al.* (2014) or Brooks *et al.* (2004)).

Another crucial component of the macroeconomic framework is inflation.

According to the World Economic Forum (2019), inflation by itself is not the main concern, but price volatility and uncertainty, as those have a considerable effect on investment decisions. In accordance with previous research, for instance by Mundell (1965) or Fischer (1993), several more recent studies agree on negative ramifications of inflation rates above a certain threshold (see, e. g., Omay and Kan (2010) or Drukker *et al.* (2005)).

2.2.4. 4th Pillar: Health and Primary Education

The GCI places *health* and *primary education* in one pillar as both of them are among the most basic preconditions for an economy.

The GCI pillar *health* is composed of eight indicators. Most of them measure the prevalence and business impact of diseases like tuberculosis and malaria. Although these indicators have a strong bearing on the competitiveness of poorer countries they are rather uncommon in most parts of Europe. In terms of *primary education*, the GCI focuses on the quality of primary education (based on the EOS) and primary education enrollment.

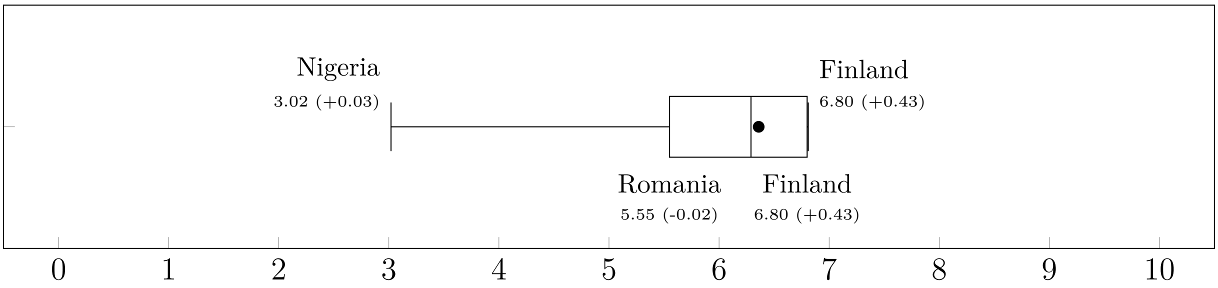
Figure 17 shows the average scores between 2009 and 2017. Finland heads the global ranking with an average score of 6.8; Romania achieved 5.6. The plot demonstrates a comparatively high standard of public health and primary education in the entire EU.

A classic approach to the economic impact of education has been offered by human capital theory, which was pioneered by the works of Mincer (1958), Schultz (1961) and Becker (1962). Human capital theory postulates that investing in human capital leads to a more productive workforce with a better set of skills, abilities etc. and subsequently, a higher individual income.

More recent studies on the topic tend to focus on more specific aspects, such as the importance of qualitative schooling, which is usually measured by comparing test scores.

Figure 17

Health and Primary Education (4^{th} Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses). Austria is denoted by •.

Quality of education, some stress, contributes more to economic growth than the sheer years of schooling (see, e. g. Hanushek and Kimko (2000), Hanushek and Wößmann (2007) or Barro (2013)).

Due to the strong focus of this pillar on diseases that are comparably uncommon in the EU, along with the rather high public health and primary education standards, we do not expect this pillar to be a major predictor for TFP growth in EU countries.

2.2.5. 5^{th} Pillar: Higher Education and Training

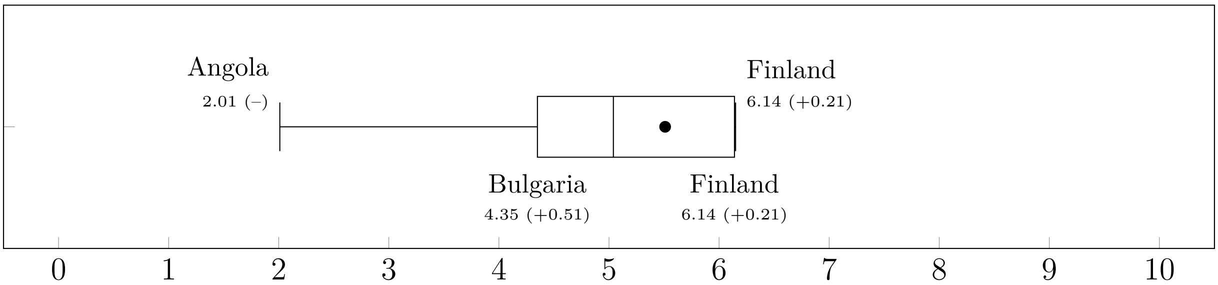
While basic education primarily enters the production process, higher education makes a substantial contribution to innovation and technology, as Papageorgiou (2003) notes.

The respective GCI pillar consists of eight indicators including secondary and tertiary education enrollment rates, the overall quality of the education system with a special focus on math and science as well as management schools and internet access in schools. Vocational training enters the pillar with another two indicators: the availability of specialized training services and the extent of staff training.

Figure 18 shows the data. Finland reaches the top score worldwide (6.1), while Bulgaria marks the lowest value in the EU (4.4). As for primary education and health (see subsection 2.2.4), the EU maintains high scores compared to the rest of the world.

Researchers usually explain the effect of higher education based on human capital accumulation (see, e. g., Temple (1999), Barro (2001), Papageorgiou (2003) or Abu-Qarn and Abu-Bader (2007)). The endogenous growth model as proposed by Romer (1990) provides insight into the relationship between human capital and economic growth. Within this model, human capital – measured by the years of schooling and vocational training

Figure 18
Higher Education and Training (5^{th} Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses). Austria is denoted by •.

– defines the speed of technological progress, as a large and well-educated work force is presumed to be more capable to perform thorough research, create innovative production techniques as well as new products and product variations. Technological progress, in turn, is seen as a key facilitator of growth. Several authors in the field have built upon Romer (1990) and stressed the crucial role of human capital (see, e. g., Lucas (1988), Benhabib and Spiegel (1994) or Barro (2013)). Some have also emphasized its importance for the diffusion of new technologies as a highly educated workforce is more likely to be able to absorb the latest advancements from technologically advanced countries (see, e. g., Barro (2013) or Papageorgiou (2003)).

As higher education is a major precondition for R&D and/or the adoption of new technologies, we expect this pillar to be a relevant predictor for TFP growth in the advanced, *innovation-driven* EU economies.

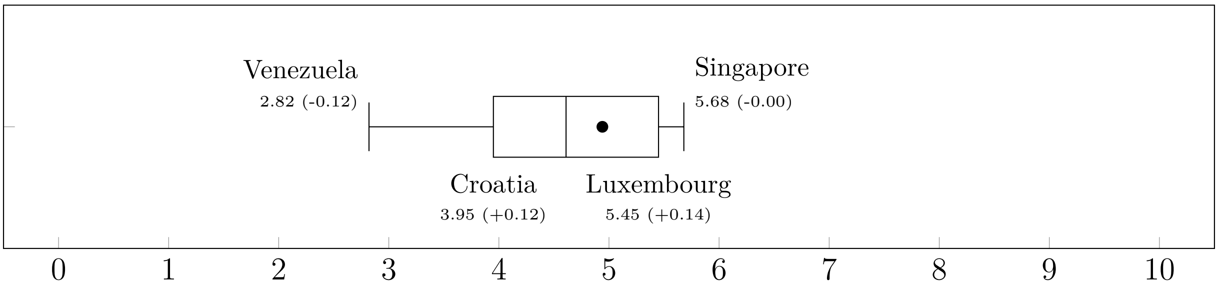
2.2.6. 6^{th} Pillar: Goods Market Efficiency

The GCI pillar *goods market efficiency* is composed of 16 indicators. It includes, i. a., barriers to market entry and indicators for the measurement of domestic and foreign competition. Figure 19 shows that the EU country with the highest average score is Luxembourg (5.4), while Croatia comes off worst (3.9).

Product market regulations affect the costs to enter a market and the degree of competition (see, e. g., Blanchard and Giavazzi (2003)). Nicoletti and Scarpetta (2003) find in their analysis of OECD countries a positive relationship between market entry liberalization and TFP growth in all observed countries. With every successful market entry, rivalry between suppliers increases. Vickers (1995) mentions three mechanisms to explain

Figure 19

Goods Market Efficiency (6^{th} Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses). Austria is denoted by •.

how stronger competition can lead to higher productivity: It forces companies to produce more efficiently, it allocates production to the most efficient companies, and provides innovation incentives. At some point, however, competition might lead to a decrease in productivity growth as it diminishes post-entry rents and thereby discourages innovations (see, e. g., Aghion *et al.* (2005)).The empirical literature finds mostly positive effects of competition on productivity (e.g.Buccirossi *et al.* (2013), Égert (2016), Nickell (1996) and Fernandes *et al.* (2018), for a review see Holmes and Schmitz (2010)).

As this pillar involves aspects that influence productivity in various ways, it is hard to derive a hypothesis about TFP growth. A positive effect seems reasonable, though.

2.2.7. 7^{th} Pillar: Labor Market Efficiency

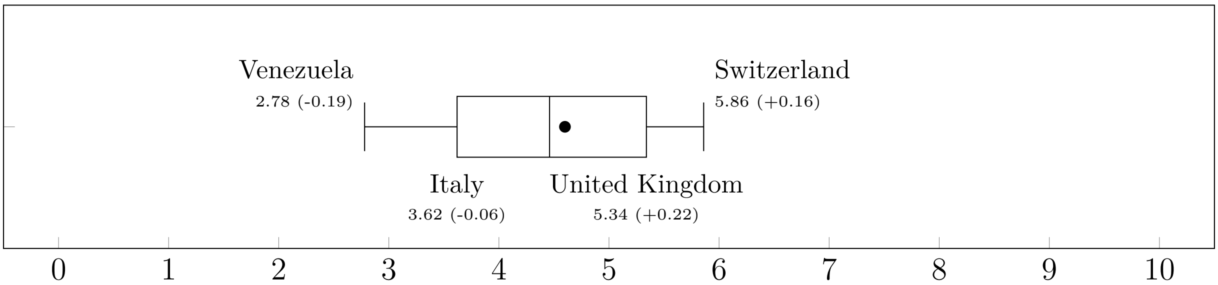
Efficient labor markets allow the optimal allocation of labor. A highly flexible labor market would be able to respond to changing requirements with minimum cost and effort and provide the required resilience to external shocks (see, e. g., Chen *et al.* (2003)).

Accordingly, the GCI pillar *labor market efficiency* is measured by taking a look at the allocation of workers. Indicators include, i. a., cooperation in labor-employer relations, flexibility of wage determination, hiring and firing practices, redundancy costs, effects of taxation on incentives to work, pay and productivity, and female labor force participation. Furthermore, it rates a country's capacity to attract and retain talented workers.

The most efficient labor market in the EU is that of the UK with a score of 5.3 (see Figure 20). With a score of 3.6, Italy is located at the bottom of the EU table.

Many authors have emphasized the need for flexible labor markets, which are often considered a necessary requirement for competitiveness (see, e. g., Bentolila and Bertola

Figure 20
Labor Market Efficiency (7^{th} Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses). Austria is denoted by •.

(1990), Hopenhayn and Rogerson (1993), Nickell (1997), Fitoussi *et al.* (2000) or, more recently, Cunat and Melitz (2012)). Bentolila and Bertola (1990) particularly stress the importance of hiring and firing practices. High firing costs, they conclude, constrain a firm's flexibility to adapt to changes. They might also be detrimental to innovation, Saint-Paul (1997) argues, as countries with high firing costs tend to focus on mature rather than new products in order to increase job security. A flexible labor market goes hand in hand with the flexibility of wage determination. Pissarides (1998) argues for unemployment benefits to be indexed to wages, as it helps to ensure wage flexibility and the absorption of the effects of tax changes.

The focus on a deregulated labor market, however, is not undisputed. Labor market regulations do play a crucial role, as they moderate certain forms of rigidities, such as power inequalities and information asymmetries (see, e. g., Gruber (2004)). Effective labor market policies and some cooperation in labor-employer relations could help to balance those inequalities. Active labor market policies, Boeri and Burda (1996) find, also enhance the job matching process.

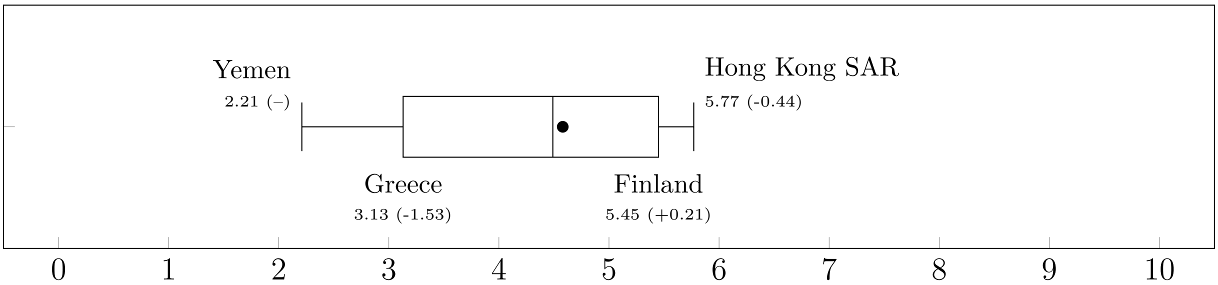
As some of the indicators in this pillar directly relate to labor productivity, we expect it to be a considerable predictor for TFP growth in the EU.

2.2.8. 8^{th} Pillar: Financial Market Development

The GCI pillar *financial market development* includes eight indicators and contains, i. a., the availability and affordability of financial services for businesses and indicators for the stability of the financial sector. In the EU, the average score for this pillar varies between 3.1 for Greece and 5.5 for Finland as depicted in Figure 21.

Figure 21

Financial Market Development (8^{th} Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses). Austria is denoted by •.

King and Levine (1993b) stress four types of mechanisms through which financial markets affect productivity: They make capital available to entrepreneurs in order to convert their inventions into innovation, help to diversify risks, evaluate entrepreneurs and provide resources to the most productive ones, and have the ability to estimate the expected profits from innovations.

Many authors (see, e. g., King and Levine (1993a,b), Levine and Zervos (1998), Beck *et al.* (2000), Benhabib and Spiegel (2000), Calderón and Liu (2003), Levine (2004), and Madsen and Ang (2016)) conclude that financial market development boosts economic growth.

Other authors find that the relationship between financial and economic development may vary across countries, stages of development and over time (see, e. g., Calderón and Liu (2003), Arestis and Demetriades (1997), Demetriades and Hussein (1996), Arestis *et al.* (2001), Rioja and Valev (2004), De Gregorio and Guidotti (1995), and Shan *et al.* (2001)).

During the financial crisis, credit misallocation, the prevalence of "zombie" firms and "zombie" lending, and worsening credit conditions for firms that consequenlty reduced their innovation activities caused TFP loss, especially in Southern Europe, as shown by Gopinath *et al.* (2017), Acharya *et al.* (2019), Schivardi *et al.* (2017), and Duval *et al.* (2020). Therefore, we expect a negative relationship for those countries but assume a positive association for those countries with more developed financial markets.

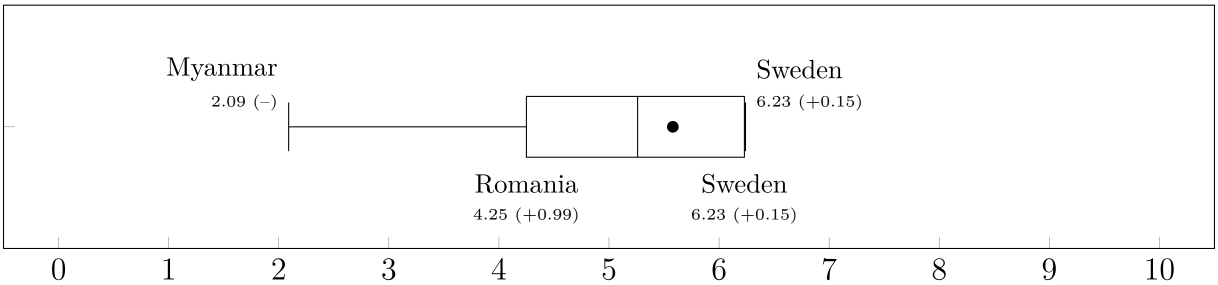
2.2.9. 9^{th} Pillar: Technological Readiness

Technological readiness is considered a key factor for growth as economies are constantly required to adapt in order to stay or become competitive in global markets (see, e. g., Romer (1990)).

The GCI pillar particularly focuses on the absorption of information and communication technologies (ICTs). The emphasis on ICTs is reflected by four indicators: the percentage of internet users, fixed-broadband internet subscriptions, internet bandwidth and mobile-broadband subscriptions. Other indicators measure the availability of the latest technologies and the capacity of companies to absorb them. The pillar also includes foreign direct investment (FDI) and the technology transfer expected to come with it.

As depicted in Figure 22, Sweden was the best performing country in the EU with an average score of 6.2, while Romania only reached a score of 4.3. According to the data, Central and Northern European countries have all performed comparably well in this area.

Figure 22
Technological Readiness (9^{th} Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses). Austria is denoted by •.

Technological progress is generally expected to foster productivity. ICTs, in particular, are often presented as prerequisites of an efficient production process, facilitators of innovation and, in turn, contributors to TFP (see, e. g., Pilat (2005)). Although initial effects tend to be rather small, several researchers find positive impacts of investing in technological innovations on firm-level performance and overall productivity (see, e. g., Lichtenberg (1995), Gretton *et al.* (2004) or Crafts (2010)).

Sustained efforts and considerable investments are required to allow for a sufficient diffusion and adoption of the latest technologies. Qosasi *et al.* (2019), who study the capability of small businesses to use ICTs strategically, found that, above all, businesses required a certain organizational flexibility and an entrepreneurial orientation to be able to gain a competitive advantage. Moreover, Cohen and Levinthal (1989, 1990) stress that the capacity to effectively absorb technologies depends, i. a., on a company's R&D activities as they not only promote innovation, but also help firms to properly understand and utilize external technologies.

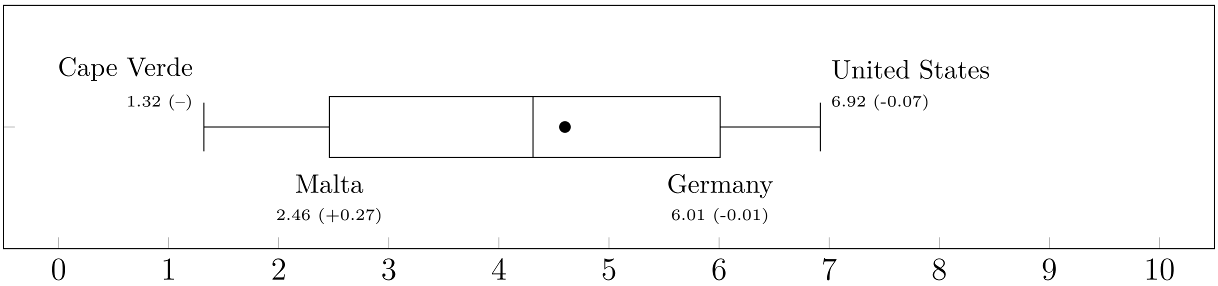
Foreign direct investments (FDI) and the resulting technology transfers can also contribute to technological readiness. Host countries anticipate long-term benefits from multinational enterprises (MNEs) through knowledge and, in particular, technology spillovers (see, e. g., Fu *et al.* (2011)). Spillovers often occur when multinationals share technologies with their foreign subsidiaries (see, e. g., Markusen (2002)) and interact with local firms and customers (see, e. g., Javorcik (2004)). FDI are expected to lead to increased productivity and income growth (see, e. g., Goldstein (2004), Javorcik *et al.* (2015) or Peluffo (2015)).

This pillar is related to *innovation* (see subsection 2.2.12 below). While *innovation* might be important for economies near the technology frontier, backward countries might benefit from increasing their absorption capacities first. Therefore, we expect *technological readiness* to be a good predictor for TFP growth.

2.2.10. 10^{th} Pillar: Market Size

The GCI pillar *market size* contains only few indicators: a domestic and a foreign market size index, GDP in purchasing power parity and exports as a percentage of GDP. Germany ranks first among the EU countries with an average score of 6.0 (see Figure 23); Malta's average of 2.5 is the lowest.

Figure 23
Market Size (10^{th} Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses). Austria is denoted by •.

According to Alesina *et al.* (2005), larger countries have the advantage of lower per capita costs for public goods and services. Such economies of scale are also assumed for the private sector, especially for manufacturing (see, e. g., Krugman (1991) or MacDonald (1994)). Armstrong and Read (2003) argue that – due to their disadvantages in scale economies – small countries can not compete with larger countries in low skilled, labor-intensive export sectors; this is why they have to specialize in higher value-added activities with intensive use of human capital. But according to Romer (1990), the restricted availability of working force can be a critical factor for small countries. Furthermore, such specialization might increase the exposure to trade shocks, as shown by Easterly and Kraay (2000). Market size and trade often go hand in hand, but the findings and explanations concerning this relationship are mixed (i. a. Ramondo *et al.* (2016), Rose (2006), Alcalá and Ciccone (2004), Badinger (2007) or Easterly and Kraay (2000)). For instance, Acemoglu and Linn (2004), MacDonald (1994), and Guadalupe *et al.* (2012)) state that larger markets encourage greater investment in innovation and thus productivity growth. Grossman and Helpman (1991) argue that an integration into global markets increases the exchange of information and makes spillover effects possible. And according to Melitz and Ottaviano (2008), larger markets trigger tougher competition with selection effects.

Since no clear relationship between market size and productivity was found, we do not expect this pillar to predict major differences in TFP growth in the EU.

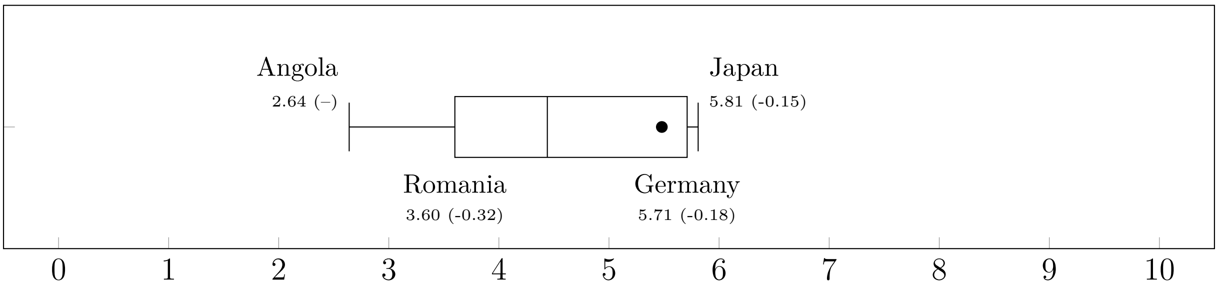
2.2.11. 11^{th} Pillar: Business Sophistication

According to the Global Competitiveness Report, *business sophistication* is of particular importance for *"countries at an advanced stage of development, when, to a large extent, the more basic sources of productivity improvements have been exhausted"* (World Economic Forum, 2017, p. 319).

The GCI approaches *business sophistication* by taking a look at existing business networks at the country-level as well as strategies and operations at the firm level. A set of nine indicators, including the quantity and quality of local suppliers, evaluates how well companies and industries are able to create clusters. This pillar also incorporates the nature of competitive advantages, the length of value chains, the control of international distribution and the sophistication of the overall production process. Further indicators are added to capture the extent of marketing and the readiness to delegate authority.

Figure 24 depicts the average scores between 2009 and 2017. In the EU, the average score varies between 5.7 for Germany and 3.6 for Romania.

Figure 24
Business Sophistication (11^{th} Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses). Austria is denoted by •.

According to, e. g., Porter (1990) or Kaplinsky (2000), companies would be well-advised to focus on increasing the efficiency of both production and internal processes, improving their products or shifting attention to other aspects, such as design. In order to achieve these goals, some researchers highlight the importance of strengthening local economic development, for instance by supporting the development of clusters. Both local clusters as well as international linkages can be a source of competitiveness. Humphrey and Schmitz (2002), for instance, analyze how clusters can be integrated into global value chains. By becoming part of a global value chain, local firms hope for opportunities to *upgrade* by acquiring new skills, competences and knowledge that enable them to move to higher value-added tasks within the chain (see, e. g., Henderson *et al.* (2002)).

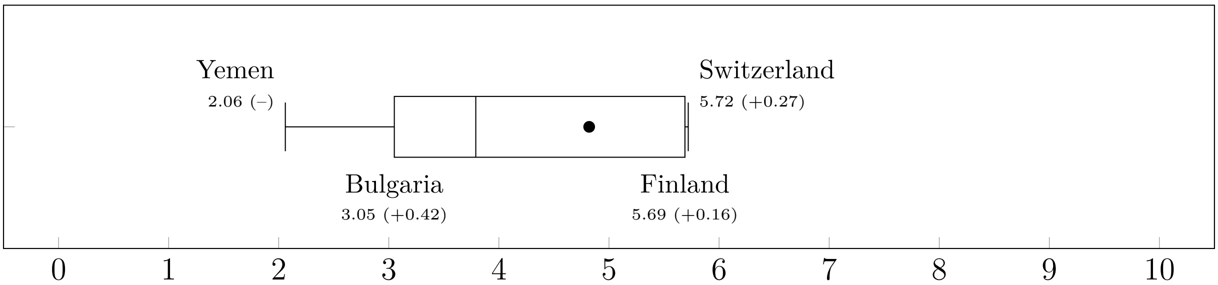
Other aspects of business sophistication are more concerned with professional management at the firm level. Those include the high relevance of innovative marketing practices (see, e. g., Gupta *et al.* (2016)). In a quantitative study on U.S. and European firms, Bloom and Van Reenen (2007) assess the impact of management practices on productivity. The findings suggest that high-quality management practices are strongly correlated with a better overall performance, leading to, i. a., higher productivity and profitability.

This pillar measures capabilities that are important for more developed economies. Due to its "soft" nature, however, it is hard to formulate a clear hypothesis. If at all, it might be able to predict TFP in more developed EU countries.

2.2.12. 12th Pillar: Innovation

The last pillar of the GCI is dedicated *innovation* and is composed of seven indicators (i. a. company spending on R&D). As depicted in Figure 25, Finland achieves the highest average score (5.7) within the EU; Bulgaria the lowest (3.0).

Figure 25
Innovation (12th Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses). Austria is denoted by •.

Since the empirical studies by Griliches (1958) and Mansfield (1965), and the creation of models of endogenous technological change (see, i. a., Romer (1986, 1990), Lucas (1988), Grossman and Helpman (1991) or Aghion and Howitt (1992)), several studies have examined the link between innovation and productivity. In these models – and according to Schumpeter (1961) – the incentive to innovate comes from the expectation of monopoly rents/profits.

Griffith *et al.* (2004) find that R&D expenditures foster productivity growth directly through innovation and indirectly through technology transfer. More recently, Égert (2016) identifies a strong positive link between to R&D funded by industry and TFP. Similary, Pegkas *et al.* (2019) find that business R&D expenditure has the highest positive effect on innovation in EU countries.

Innovation and its expected impact on productivity are embedded in public policy and depend on macroeconomic and sector-specific conditions (see, e. g., Furman *et al.* (2002), Scarpetta and Tressel (2002), Coe *et al.* (2009), Ortega-Argilés *et al.* (2011) or Aghion *et al.* (2015)), and the type of innovation (see, e. g., Griffith *et al.* (2006) and Lee and Kang (2007)).

In particular, the stage of development plays a crucial role for the effect of innovation on productivity. According to Acemoglu *et al.* (2006), the closer a country gets to the world technology frontier, the higher is the relative importance of *innovation* relative to *imitation*. Therefore, we expect the pillar *innovation* to be a good predictor of TFP growth only in the higher-income economies in the EU.

3. Methodology

Our main aim is to identify the extent to which the twelve GCI pillars described in the last section relate to TFP growth and its components. Hence, we want to distinguish not only the speed at which TFP in a respective country has been growing in the aftermath of the 2008/09 crisis but also *why* it has done so. Was a particular country successful due to increased technical progress, has it learned to use its production factors more efficiently or has it just moved towards the right mix of production factors or the optimal level of output? And – in turn – *why* was it able to do so, i. e. what are the determinants of technical progress, technical efficiency, scale efficiency and allocative efficiency?

In order to find answers to those questions, we will proceed in three steps: First, we will estimate an aggregate production function using Stochastic Frontier Analysis (SFA). Second, we will use the SFA results to construct measures of TFP growth and its four components (technical progress, technical efficiency, scale efficiency and allocative efficiency). And finally, we will make use of a non-parametric modeling approach (BART = Bayesian Additive Regression Trees) in order to identify the most relevant determinants of TFP growth.

3.1. Stochastic Frontier Analysis (SFA)

Our TFP decomposition will be based on Stochastic Frontier Analysis (SFA). SFA traces back to the works by Aigner *et al.* (1977) and Meeusen and van Den Broeck (1977). It has originally been developed for operations research purposes and has been used extensively for the analysis of efficiency in agricultural production (see, e. g., Latruffe (2010) for a survey). However, as firm-level production functions are reflected in macroeconomic growth models, it seems straightforward to use SFA to analyze the economic performance of regions (see, e. g., Chandra (2003, 2005) or Kluge (2018)) and even national economies (see, e. g., Kumbhakar and Wang (2005) or Pires and Garcia (2012)).

We deploy Stochastic Frontier Analysis to a standard neoclassical production function:

$$Y_{i,t} = f(K_{i,t}, L_{i,t}, \boldsymbol{\beta}) \tag{1}$$

where $Y_{i,t}$ captures GDP in country i at time t, $K_{i,t}$ is the net capital stock, $L_{i,t}$ measures annual hours worked and $\boldsymbol{\beta}$ is a vector of elasticities. Table 3 shows descriptive statistics.

Table 3
Descriptive statistics

Variable	Mean	s.d.	Min.	Max.
GDP (in billions of €)	517.86	794.92	7.06	3,174.00
Annual hours worked (millions)	13,411.14	16,577.73	345.03	61,564.00
Net Capital Stock (in billions of €)	1,493.47	2,302.19	15.16	8,894.53
Adjusted wage share (as % of GDP)	52.66	5.15	35.20	63.78

Source: AMECO (as of 2nd July, 2020). $n = 252$, $t = 9$, $Countries = 28$

SFA assumes that the observational units produce less than they could due to random output variations but also due to systematic deficiencies. The standard way to model that (see, e. g., Kumbhakar and Lovell (2003)) is simply:

$$Y_{i,t} = f(K_{i,t}, L_{i,t}, \boldsymbol{\beta}) \cdot \xi_{i,t} \cdot exp(\upsilon_{i,t}) \tag{2}$$

where $\xi_{i,t} \in (0, 1]$ and $\upsilon_{i,t}$ is the remaining idiosyncratic error term. Assuming a translog production function and setting $u_{i,t} = -ln(\xi_{i,t})$ allows taking natural logs in order to reach our final estimation equation:

$$\begin{aligned} ln(Y_{i,t}) = \beta_{0,i} &+ \beta_n \cdot t + \beta_k \cdot ln(K_{i,t}) + \beta_l \cdot ln(L_{i,t}) \\ &+ \frac{1}{2} \cdot \beta_n \cdot t^2 + \frac{1}{2} \cdot \beta_{kk} \cdot ln(K_{i,t})^2 + \frac{1}{2} \cdot \beta_{ll} \cdot ln(L_{i,t})^2 \\ &+ \beta_{kl} \cdot ln(K_{i,t}) \cdot ln(L_{i,t}) + \beta_{kn} \cdot ln(K_{i,t}) \cdot t + \beta_{ln} \cdot ln(L_{i,t}) \cdot t + \upsilon_{i,t} - u_{i,t} \end{aligned} \tag{3}$$

The model is estimated via maximum likelihood. Distributional assumptions are required in order to identify $u_{i,t}$ and to distinguish it from $\upsilon_{i,t}$. The idiosyncratic error term $\upsilon_{i,t}$ is supposed to be normally distributed ($N(0, \sigma_v)$) while we assume the inefficiency term to follow a truncated normal distribution ($N^+(\mu, \sigma_u^2)$) (with truncation point at 0).

It is possible to explicitly model the mean of the inefficiency term in order to estimate how the supposed determinants of competitiveness correlate with higher or lower (in-)efficiency scores. We include the twelve pillars from Section 2.2:

$$u_{i,t} = \delta_0 + \sum_{p=1}^{12} \delta_p \cdot ln(Pillar_{p,i,t}) + \omega_{i,t} \tag{4}$$

Equations 3 and 4 should not be estimated sequentially in a two-stage approach as econometric issues well-known in the SFA literature will arise (see, e. g., the comprehensive explanation in Schmidt (2011)).[2] We will avoid running into such problems by estimating the entire model – i. e. the frontier part (see Equation 3) and the inefficiency part (see Equation 4) – simultaneously as it is standard in the SFA literature. Hence, we make sure that the model is estimated properly and that the derived TFP decomposition (see next subsection) will be valid.

In the formulation above, the inefficiency term is treated as time-variant. In order to estimate Equation (3), we will deploy the so-called "true" fixed-effects estimator as proposed by Greene (2005). This method solves an issue that is inherent to time-invariant panel SFA models; namely that any time-invariant (unobserved) heterogeneity will inevitably be absorbed by the inefficiency term. Hence, countries with large within-group variation might be considered less efficient than they actually are. The "true" fixed-effects estimator allows to identify the inefficiency term more precisely by making $\beta_{0,i}$ country-specific.

3.2. TFP decomposition

The results of our SFA exercise can now be used for a TFP decomposition. TFP growth thus stems from four sources: changes in technical progress (CTP), technical efficiency (CTE), scale efficiency (CSC) and allocative efficiency (CAE). Decomposition exercises have become standard in the literature (see, e. g., Pires and Garcia (2012), Kim and Han (2001) or Coelli *et al.* (2003)). There are slightly different approaches; we will stick to the

[2] The first issue is that the frontier is not estimated properly when variables that have an influence on $u_{i,t}$ enter the analysis only at the second stage. Hence, if such variables show significant effects on the inefficiency term, they should have been included in the first stage. The otherwise resulting omitted variable bias occurs regardless of how the frontier is modeled. Also, the effect of covariates on $u_{i,t}$ will be underestimated and tests for $\delta_p = 0$ are generally invalid in two-stage approaches of this kind.

one in Coelli *et al.* (2003).[3] TFP growth between periods 0 and 1 can be expressed as:

$$\underbrace{ln\left(\frac{TFP_{i,1}}{TFP_{i,0}}\right)}_{\text{TFP growth}} = \underbrace{\frac{1}{2}\cdot\left(\sum_{t=0}^{1}\frac{\partial ln(Y_{i,t})}{\partial t}\right)}_{\text{CTP}}$$

$$+\underbrace{ln\left(\frac{e^{-u_{i,1}}}{e^{-u_{i,0}}}\right)}_{\text{CTE}}$$

$$+\underbrace{\frac{1}{2}\cdot\left(\left(\sum_{t=0}^{1}S_t\cdot\varepsilon_{k,t}\right)\cdot(K_{i,1}-K_{i,0})+\left(\sum_{t=0}^{1}S_t\cdot\varepsilon_{l,t}\right)\cdot(L_{i,1}-L_{i,0})\right)}_{\text{CSC}}$$

$$+\underbrace{\frac{1}{2}\cdot\left(\left(\sum_{t=0}^{1}\lambda_{k,t}-(1-c_{l,t})\right)\cdot(K_{i,1}-K_{i,0})+\left(\sum_{t=0}^{1}\lambda_{l,t}-c_{l,t}\right)\cdot(L_{i,1}-L_{i,0})\right)}_{\text{CAE}} \tag{5}$$

where $\varepsilon_{k,t}$ and $\varepsilon_{l,t}$ are the derivatives of Equation 3 with respect to capital and labor, $S_t = (RS_t - 1)/RS_t$ with $RS_t = (\varepsilon_{k,t} + \varepsilon_{l,t})$ and $\lambda_{k_t} = \varepsilon_{k_t}/RS_t$ resp. $\lambda_{l_t} = \varepsilon_{l_t}/RS_t$. The parameter $c_{l,t}$ captures the respective wage share.

Most analyses using TFP decomposition stop here as the reader will have learned something about the speed and the sources of TFP growth in the sample of companies, industries or countries under observation. This mere technical decomposition sheds light into the fuzzy, "residual-like" concept of TFP. However, it still does not give answers about what actually drives TFP growth and what policies would make economies flourish. Going one step further and investigating the determinants of TFP growth (and its four ingredients) would be of great use for decision-makers.

As shown in the last subsection, we have already included the twelve pillars from the Global Competitiveness Index in our SFA model. So in theory, we should be able to identify the policy fields that correlate with technical (in-)efficiency. This exercise, however, will not provide us with the answers we want to give: First, it will only tell us

[3] There are mainly two approaches: The one by Bauer (1990) and Kumbhakar *et al.* (2000) that is based on total differentials and the one by Caves *et al.* (1982a,b) and Orea (2002) based on index numbers. Coelli *et al.* (2003) argue that both tend to yield very similar results but the latter is better suited for the matter at hand as time is measured on a discrete rather than on a continuous scale.

something about technical efficiency scores but not about TFP growth and its components. Second, the twelve variables have been tailored in such a way that they necessarily impose a considerable multicollinearity problem so that the individual coefficients can hardly be interpreted in a meaningful manner. And finally, including these twelve variables is somewhat arbitrary as – in the absence of a theoretical model – any number of possible determinants could be included (e. g. instead of the twelve pillars, their >100 subindices). This is what Brock and Durlauf (2001) call "open-endedness" of economic theory.

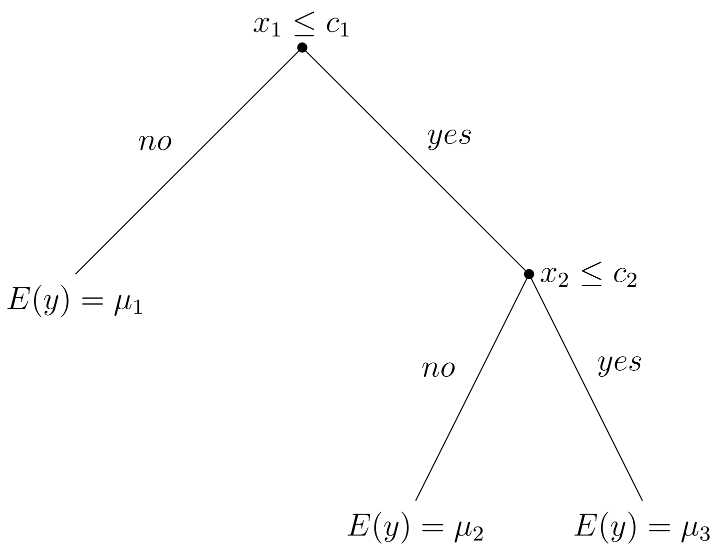
Hence, the inclusion of the twelve pillars in the SFA model lets us get rid of the methodological problems outlined in the last subsection, but it will not help us in truly identifying what – apart from capital and labor – drives economic growth. This issue is much more of a model selection problem which we will tackle in the next section.

3.3. Bayesian Additive Regression Trees (BART)

Economic variables – especially those for which we lack sound theoretical models – tend to be regressed on a potentially endless number of covariates. Only the capacities of statistical offices set a limit to what we could throw into our estimation equations. Unfortunately though, as already apprehended in the last subsection, such approaches come with enormous econometric problems as multicollinearity and nonlinearities will become unmanageable as the number of variables increases. For instance, we would have wished to include squared terms in Equation 4 in order to capture (inverse) u-shaped relationships that have been described in the literature (see Section 2.2); however, the resulting maximum likelihood functions quickly get out of control. Hence, we need an approach that is capable of dealing with potentially complex and highly nonlinear relationships. The complexity drives us into the realm of machine learning; the sketchiness of functional relationships leads us to Bayesian statistics. Both combined give us BART.

BART is a Bayesian nonparametric estimation technique. It was first introduced by Chipman *et al.* (2010) and is based on the idea of regression trees. Regression trees are tools to estimate y as a function of p predictors. The estimation procedure is based on the recursive partitioning of the p dimensional predictor space in such a way that observations assigned to the same partition are as similar as possible but preferably much different from those in other partitions. At each stage of the regression tree, the procedure will set a splitting rule $x \leq c$ (where x is a variable from the set of predictors and c is a threshold) according to some formal criteria (e. g. what split will decrease the sum of squared errors the most) and thereby divide the predictor space into two partitions that can again be split into two partitions and so on. Splitting will continue until further splitting would not increase the quality of the prediction. The final result can be displayed in the shape of a decision tree as shown in Figure 26. The terminal nodes (i. e. the "leaves") contain the predictions of y in their respective partitions.

Figure 26
Example of a regression tree



In order to further increase the quality of the prediction, it has become standard not to rely on one particular tree but to grow a number of trees and to combine the knowledge they have generated. Such ensemble-of-trees approaches can rely simply on averaging over a set of trees using *bagging* algorithms (see, e. g., Breiman (1996)). The main challenge is hereby to eliminate the influence of particular trees on the overall result and to prevent overfitting. This can be achieved by more complex aggregation mechanisms (like *gradient boosting*; see e. g. Friedman (2001)). BART solves the problem by using regularization priors to keep the influence of individual trees low. Formally, BART can be described as follows:[4]

$$Y = f(X) + \varepsilon = \sum_{j=1}^{m} g(X, T_j, M_j) \tag{6}$$

The functional relationship between X and Y is approximated via a sum over m trees. Each of the trees is characterized by a tree structure T_j including the depth of the tree, the

[4] See also the tutorial paper by Tan and Roy (2019) from whom we adopt the notation.

number of nodes, the splitting rules etc. and the vector of terminal node parameters $M_j = \{\mu_{1,j}, ..., \mu_{b,j}\}$ which contains the predictions for Y. Equation 6 by itself is not BART-specific as it depicts the logic behind many ensemble-of-trees methods. The interesting detail is how BART generates the m trees: First, it sequentially grows m shallow trees by randomly picking the variables and thresholds for the respective splitting rules within a special MCMC sampling algorithm. Priors control that the trees do not grow too deep as individual trees must not be allowed to influence the overall result too strongly. When this is done, BART iteratively generates alternative proposals to the tree structure in multiple rounds. Besides gradually improving the fit of the model to the data, this also allows statistical inference.

What is appealing about BART is the underlying prior structure that ensures very stable and robust tree ensembles. What is most interesting for our purpose, however, is the straightforward way to identify relevant predictors: Those variables that have frequently been chosen for splitting during the MCMC iterations and have therefore proven to increase the prediction quality, are obviously the most relevant predictors. The decision to consider a variable x_i relevant, therefore, depends on its respective inclusion proportion, i. e. the share of the overall number of conducted splits that x_i was involved in. Bleich *et al.* (2014) have proposed thresholds which variables' inclusion proportions have to exceed in order to be identified as relevant predictors. Those thresholds are based on BART being applied to the original set of predictors and a permuted response vector to destroy the actual relationship with the predictors. These permutations then yield null distributions. A variable must exceed the $1 - \alpha$ quantile of its own null distribution in order to be considered relevant; this is what Bleich *et al.* (2014) call *local* procedure. The much stricter *global max* procedure requires variables to beat the respective quantile of the distribution of maxima across all permutations. The *global SE* procedure is a compromise between both variants using means and standard deviations of the null distributions.

We will use all three procedures and analyze only those indicators from the Global Competitiveness Report in depth that will have proven to be relevant for TFP growth.

4. Results

We will present our results according to the structure of the last section. Hence, we will first show the SFA estimation results (described in subsection 3.1) that the TFP decomposition is derived from (described in subsection 3.2). Finally, we will display the BART results (described in subsection 3.3) in order to find what indicators from the Global Competitiveness Report are related to TFP growth and how their contributions look like. As the literature review in Section 2 has revealed that there may be considerable differences between developed and emerging economies, we will run the SFA on the complete data set as well as on two subsets excluding the top/bottom quartile according to GDP per hour worked, respectively.

4.1. SFA estimation results

The SFA results estimated in Equations 3 and 4 are presented in Table 4.[5] The upper part contains the stochastic frontier model for $ln(Y_{i,t})$; the lower part presents the inefficiency model for $u_{i,t}$. SFA diagnostics are shown at the bottom of Table 4. Before we turn to the inefficiency results, we will first establish the shape of the frontier and conduct the TFP decomposition.

All the variables from the translog production function are statistically significant and show plausible signs. Capital and labor yield positive coefficients. The squared term for labor (β_{ll}) indicates an inverse u-shaped relationship; we observe the same for capital (β_{kk}) only in the set of higher-income economies. As all variables are expressed as deviations from their sample means (as in Coelli *et al.* (2003)), β_k and β_l can be directly interpreted as the marginal effects of capital and labor; the scores of 0.30 for capital and 0.88 for labor seem well inside the agreeable range. The positive interaction term between capital and labor (β_{kl}) renders both factors complements. The coefficients for the interaction between capital and time, β_{kn}, are negative. Recalling that these parameters go into *technical progress* (CTP in Equation 5) indicates that technical progress is capital saving.

[5] We use the Stata package *sfpanel* by Belotti *et al.* (2013).

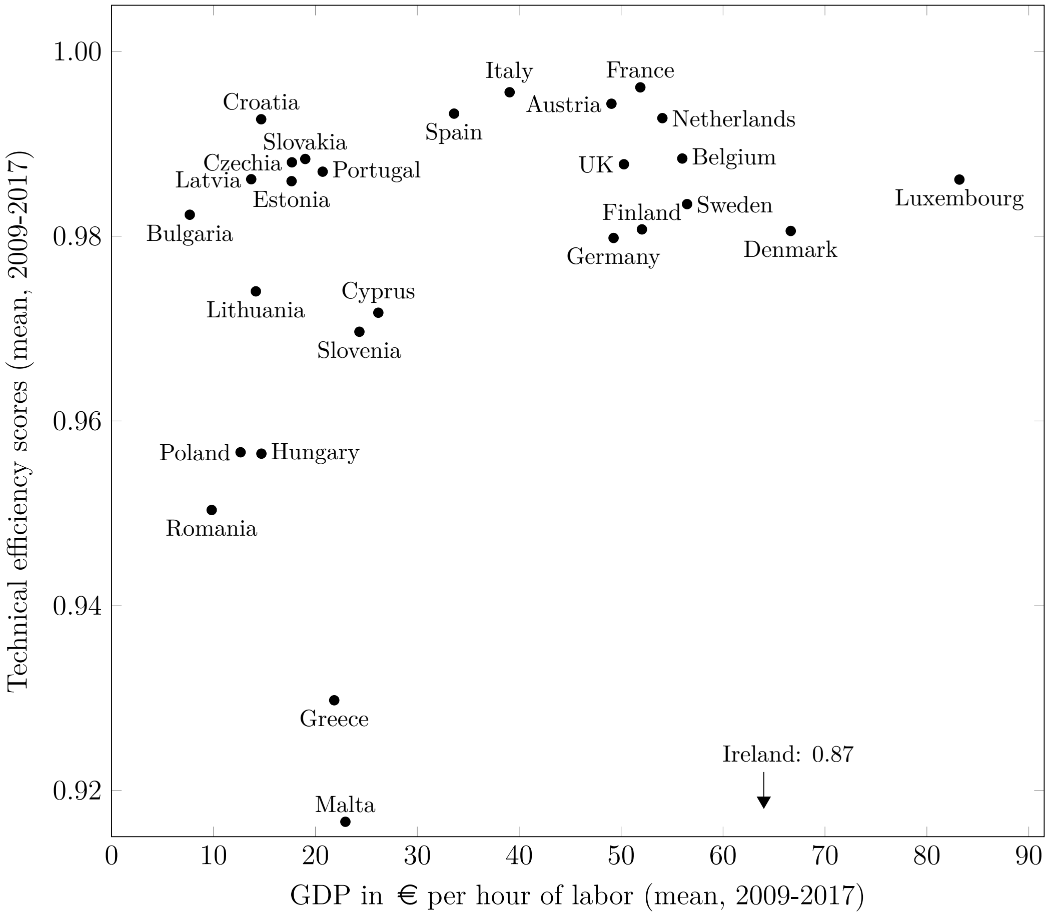
Table 4
Results from Stochastic Frontier Analysis (SFA) with "true" fixed-effects

Set of EU member states: $\longrightarrow$	**all countries**	**high-income**	**low-income**
Frontier part - Dep. var.: $ln(Y_{i,t})$			
Time (β_n)	0.010***	0.006***	0.011***
Capital (β_k)	0.304***	0.377***	0.379***
Labor (β_l)	0.881***	0.960***	0.839***
Time^2 (β_{nn})	0.001***	0.002***	0.001***
Capital^2 (β_{kk})	0.059***	−0.125***	0.150***
Labor^2 (β_{ll})	−0.165***	−0.527***	−0.128***
Capital × Labor (β_{kl})	0.123***	0.397***	0.045***
Capital × Time (β_{kn})	−0.008***	−0.006***	−0.009***
Labor × Time (β_{ln})	0.006***	0.004***	0.009***
Inefficiency part - Dep. var.: $ln(u_{i,t})$			
Pillar 1 (δ_1) - Institutions	2.206**	2.021***	0.657*
Pillar 2 (δ_2) - Infrastructure	−1.516**	−1.658***	−0.408
Pillar 3 (δ_3) - Macroeconomic Environment	−0.979**	−0.596***	−0.405**
Pillar 4 (δ_4) - Health & Primary Education	−2.722*	−1.625**	−2.187**
Pillar 5 (δ_5) - Higher Education	1.105	0.491	1.243
Pillar 6 (δ_6) - Goods Market Efficiency	2.926*	−1.078*	2.159*
Pillar 7 (δ_7) - Labor Market Efficiency	−1.568**	−0.361	−1.676**
Pillar 8 (δ_8) - Financial Development	−0.533*	−0.613***	0.121
Pillar 9 (δ_9) - Technological Readiness	0.678	0.835**	0.243
Pillar 10 (δ_{10}) - Market Size	−0.133	−0.242*	−0.112
Pillar 11 (δ_{11}) - Business Sophistication	−0.898	1.422***	−0.954
Pillar 12 (δ_{12}) - Innovation	−1.095	−0.982**	−0.552
Constant	−0.513**	−0.255***	−0.234*
σ_u (constant)	−4.605***	−5.604***	−5.299***
σ_v (constant)	−43.919	−43.893	−43.469
σ_u	0.100***	0.061***	0.071***
σ_v	2.90e-10	2.94e-10	3.64e-10
λ	3.44e+08***	2.06e+08***	1.94e+08***
Countries (Observations):	28 (252)	21 (189)	21 (189)

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

The resulting technical efficiency scores are depicted in Figure 27. The plot shows average efficiency scores (between 0 and 1) over the average GDP per hour of labor (in €). The results seem to be in line with common expectations: There is a compact cluster of old EU members with efficiency scores above 0.98 in the upper right. Most of the new member states (as well as Portugal and Greece) are located further to the left and are much more diverse in terms of technical efficiency. While, e. g., the Baltic states have achieved decent scores in the range of the old member states, countries like Greece or Romania are much further below. Ireland scores the lowest average efficiency score.[6]

Figure 27
Results from Stochastic Frontier Analysis (SFA) with "true" fixed-effects



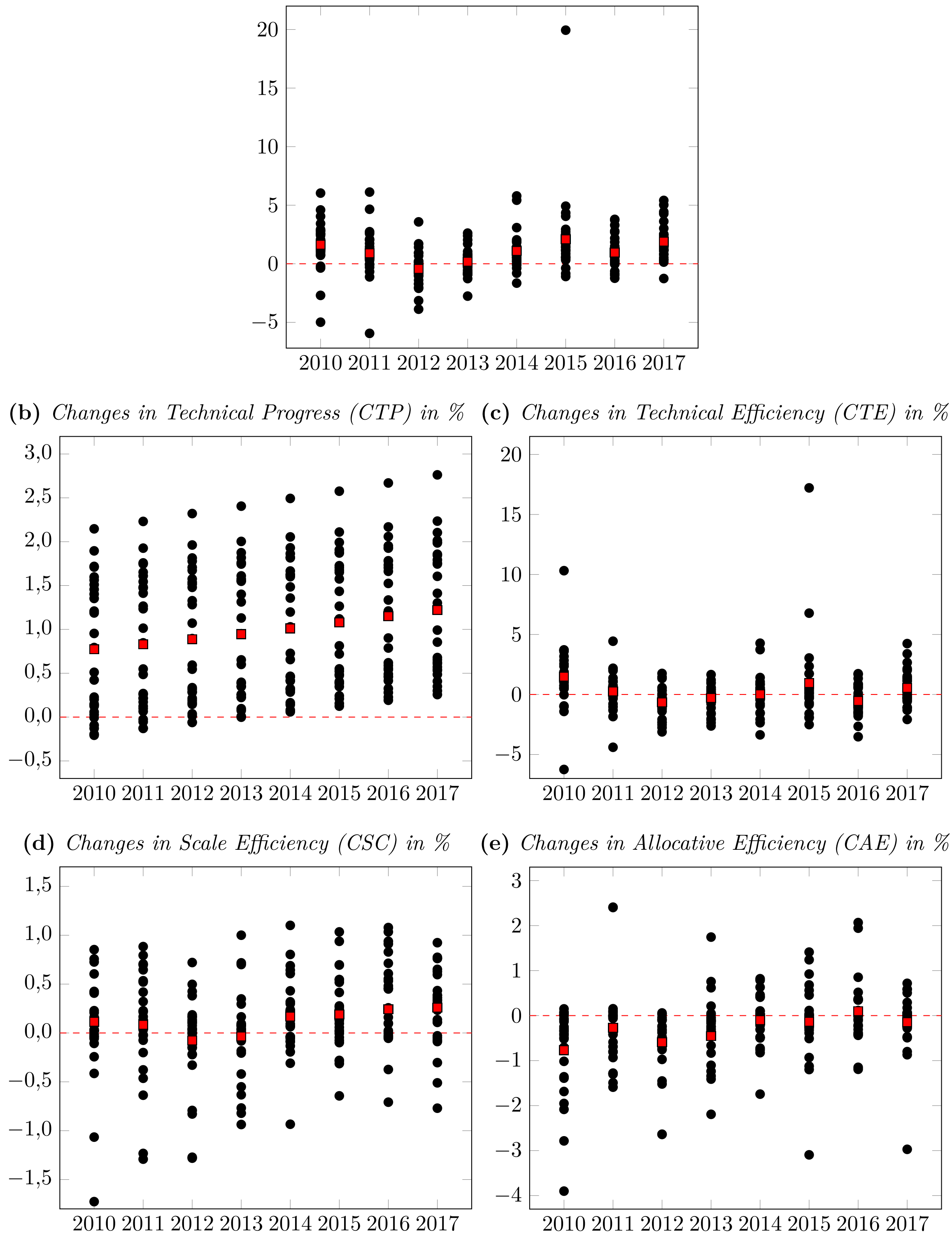
4.2. TFP decomposition results

The SFA results will now be used to construct a measure for TFP growth and to decompose it into changes in technical progress (CTP), technical efficiency (CTE), scale efficiency (CSC) and allocative efficiency (CAE) as shown in Equation 5.

Figure 28 displays how TFP growth and its four components have developed over time (the squares represent annual means). We see that the main components of TFP growth

[6] The country was hit severely by the economic crisis in 2008/09 but has managed massive GDP growth rates since 2014. The key to success was to attract international enterprises with very low corporate tax rates. As their contribution to GDP is accounted for in Ireland but the actual production activities remain elsewhere, the country was (technically) among the most efficient in 2017.

Figure 28
Results from TFP decomposition



(a) *Changes in TFP (gTFP) in %*

(b) *Changes in Technical Progress (CTP) in %*

(c) *Changes in Technical Efficiency (CTE) in %*

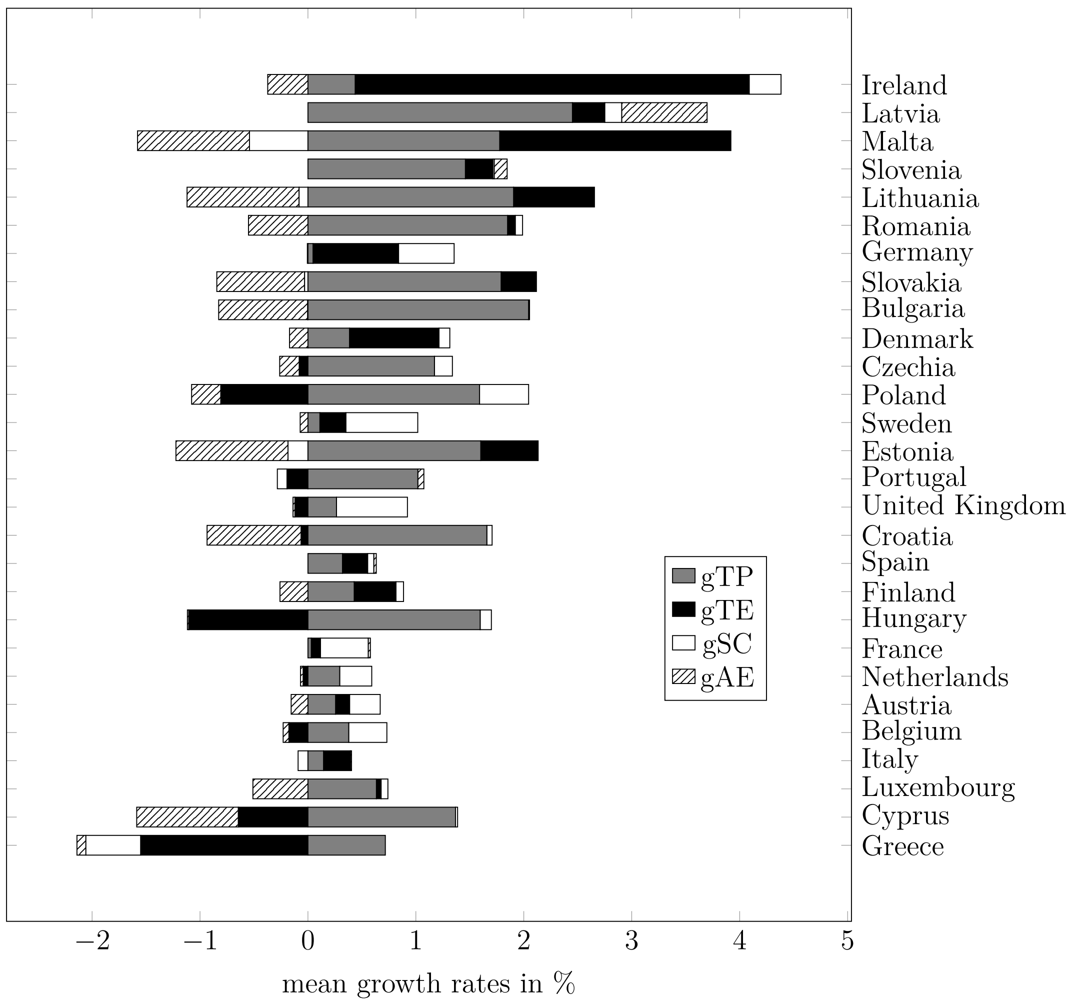
(d) *Changes in Scale Efficiency (CSC) in %*

(e) *Changes in Allocative Efficiency (CAE) in %*

are changes in technical progress (see panel (b)) and changes in technical efficiency (see panel (c)); the high mean of the former delivers large and stable average contributions to overall TFP growth, the high variation of the latter crucially determines its development over time (see panel (a)). Mean technical efficiency growth was in decline and even took negative values in many countries in the years after the 2008/09 crisis before it eventually recovered. The development of TFP growth closely follows that path. Changes in technical progress have been positive in most countries and accelerated smoothly over time (due to the neutral part of CTP that depends only on t). Changes in scale efficiency (panel (d)) and allocative efficiency (panel (e)) have been small and make up only for a minor share in overall TFP growth.

A further graphical impression of the decomposition exercise is given in Figure 29.

Figure 29
TFP decomposition by country



Note: The bars depict mean growth rates (g) over the observation period (2009–2017) for technical progress (TP), technical efficiency (TE), scale efficiency (SC) and allocative efficiency (AE).

It confirms that TFP growth in most countries is mainly driven by changes in technical progress and changes in technical efficiency; hence, they are the ones whose determinants will be most interesting. We also find stark differences between old and new EU member states: Eastern European countries have made much more technical progress; hence, their catch-up process was driven to a considerable extent by CTP rather than by advancements in terms of efficiency.

4.3. BART results

4.3.1. General findings

Finally, we get to analyze the results from our BART exercise in order to find the indicators from the Global Competitiveness Report that can be related to TFP growth.[7]

First of all, we go through the variable selection process. Figure 30 shows the three procedures proposed by Bleich *et al.* (2014). The columns on the left depict the thresholds for the *local* procedure; the columns on the right depict the ones for the *global SE* procedure. The dashed lines show the respective *global max* thresholds. Filled/empty dots indicate that a variable has/has not exceeded the respective threshold.

The yield is rather disappointing. We find that only four indicators prove to be relevant predictors for the response variables at hand. None of the 12 pillars are able to predict neither overall TFP growth nor changes in technical efficiency. The variables do not even manage to survive the local procedure.

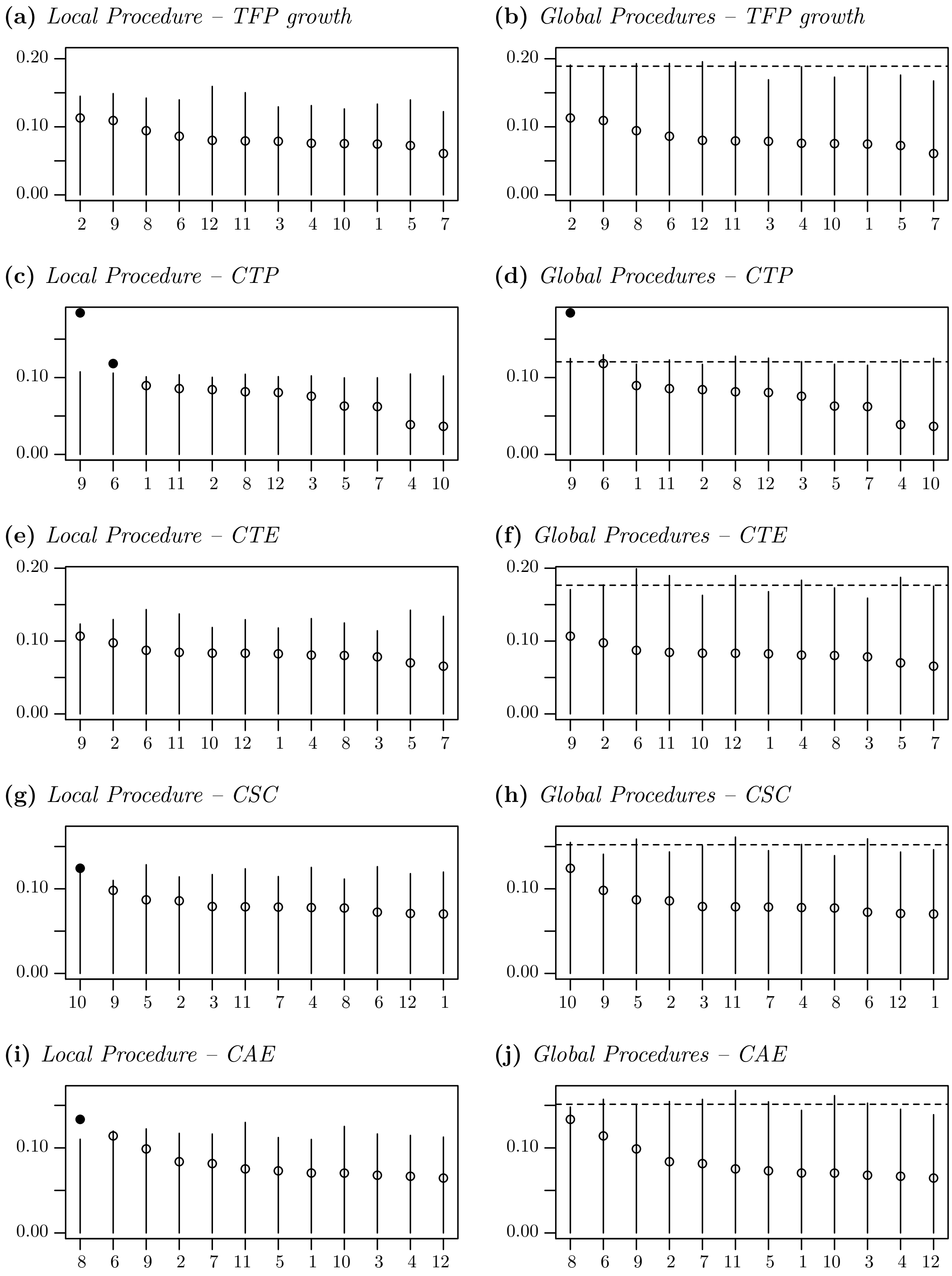
We can, however, identify relevant predictors for technical progress: Pillar 9 ("Technological readiness") easily exceeds all three thresholds; pillar 6 ("Goods market efficiency") survives at least the local procedure. Hence, the two variables help producing good predictions for CTP. The respective partial dependence plots are shown in Table 5.

The plots indicate that increasing scores in pillars 6 and 9 indeed predict faster technical progress. Both results seem highly plausible as pillar 9 captures technology availability and absorption whereas pillar 6 measures how well the goods market is regulated and is attractive for FDI and competition.

However, two puzzling findings catch the eye: Pillar 10 ("Market size") is chosen as a relevant predictor for CSC. While this in itself seems very plausible, the partial dependence plot reveals a negative effect. Hence, countries with declining access to large markets make

[7] We deploy the R package *bartmachine* by Kapelner and Bleich (2016). All variables have been centered.

Figure 30
Variable selection

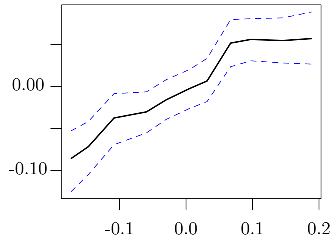


faster progress in terms of scale efficiency. Also, high scores of pillar 8 ("Financial market development") predict slower growth in allocative efficiency (CAE). As already discussed in the literature section (see Section 2.2), it might be that "zombie" companies that have easy access to loans and other kinds of financial assistance are able to stick to suboptimal

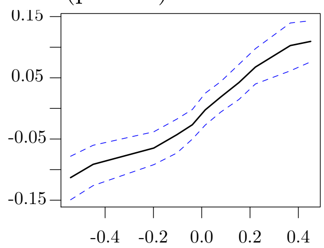
Table 5
Partial dependence plots

<table>
<tr><td>TFP growth</td><td>No relevant variables identified (see Figure 30).</td></tr>
<tr><td>CTP</td><td>

“Goods market efficiency” (pillar 6)

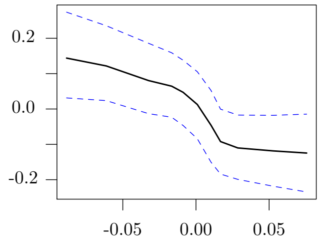


“Technological readiness” (pillar 9)



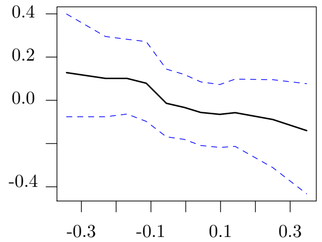
</td></tr>
<tr><td>CTE</td><td>No relevant variables identified (see Figure 30).</td></tr>
<tr><td>CSC</td><td>

“Market size” (pillar 10)



</td></tr>
<tr><td>CAE</td><td>

“Financial market efficiency” (pillar 8)



</td></tr>
</table>

Note: The vertical axis depicts the partial effects. Blue lines represent 95 % credible intervals.

production set-ups (in the sense of wrong factor combinations) over considerable periods of time, whereas those that do not get any quick infusion are forced to make tough (but efficient) production decisions. This explanation would require the assumption that efficient financial markets – at least in the sense that the GCI measures this kind of efficiency – would help hiding and keeping up with bad production decisions.

4.3.2. Robustness check A: Higher- and lower-income economies

Interesting differences arise when we split our data set into "richer" and "poorer" economies as described before. Figure 31 in the Appendix shows the variable selection process for the set of higher-income economies. Pillar 12 (*innovation*) has now been chosen as an additional predictor for CTP; the corresponding partial dependence plots in Table 6 (see Appendix) show the expected positive relationship. This clearly reflects the thoughts in the literature review in Section 2.2: While the strategy for lower-income economies is to collect the capability to *imitate* and to learn how to master existing technologies, developed countries closer to the world technology frontier must truly *innovate*. This is why pillar 12 is a relevant predictor for higher-income economies but not for "poorer" ones (see Figure 32 in the Appendix).

The analysis for the set of lower-income economies shows that pillars 6 ("Goods market efficiency") and 9 ("Technological readiness") are picked again for the prediction of CTP (see Figure 32 in the Appendix); this is the most stable result in our paper. We also find pillar 9 to be a halfway relevant predictor for changes in scale efficiency (according to the local procedure). The partial dependence plot in Table 7 reveals the expected positive relationship. The negative relationships between CSC and "Market size" (pillar 10) and between CAE and "Financial market efficiency" (pillar 8) have already been observed in the overall data set.

4.3.3. Robustness check B: 88 indicators instead of 12 pillars

The twelve pillars of the Global Competitiveness Index have been computed from more than one hundred individual indicators. We will now check if we can sharpen our policy implications when we use those indicators instead of the aggregated pillars. This exercise will show what exactly needs to be improved in order to capitalize on, e. g. the observed effect of "Technological readiness" on CTP.[8]

The variable selection process is shown in Figure 33 in the Appendix;[9] Table 8 presents the partial dependence plots. Concerning the positive relationships of pillar 9 and CTP, we now learn that it is mostly the indicators 9.04 ("Individuals using internet, in %")

[8] As data availability is lower at this level, we drop indicators with missings between 2009 and 2017. We also drop indicators that do not make sense when only EU countries are compared (as they, e. g., have identical trade tariffs (indicator 6.10)).

[9] Due to space constraints, we only show the 20 indicators with the highest inclusion proportions.

and 9.05 (“Fixed broadband internet subscriptions”) that have driven the results for this pillar in the sections above. It seems straightforward that enhanced internet access and usage are related to the technological readiness of an economy's labor force which, in turn, might speed up the rate of technical progress. What is also favorable for CTP is, i. a., a high performing airline industry (indicator 2.06) and a growing life expectancy (indicator 4.08).

Most of the remaining results have meaningful interpretations as well: “Inflation” (indicator 3.03) is a relevant and negative predictor for CTE (that is strong enough to even influence overall TFP growth). Another interesting result is that “Government debt” (indicator 3.04) works as a positive predictor for allocative efficiency growth (CAE) (that is even more noticeable in overall TFP growth). The pattern is two-staged: Those countries that were free to increase their debt ratios at will in the aftermath of the 2008/09 crisis,[10] managed to achieve more favorable combinations of capital and labor and, thereby, experienced TFP growth. Those that maintained or even reduced their 2009 debt ratio suffered negative effects.

5. Conclusion

The identification of indicators that determine economic development has a long tradition in the economic literature. Comprehensive knowledge about what drives growth and productivity could be translated into helpful policy recommendations. Unfortunately though, economic theory is somewhat “open-ended” when it comes to the choice of relevant indicators which makes it hard to find robust results and to give clear-cut policy advice.

This paper aims at identifying relevant predictors of TFP growth in EU countries during the recovery phase after the 2008/09 economic crisis. We proceed in three steps: First, we estimate TFP growth by means of Stochastic Frontier Analysis (SFA). Second, we perform a TFP growth decomposition in order to get measures for changes in technical progress (CTP), technical efficiency (CTE), scale efficiency (CSC) and allocative efficiency (CAE). And third, we use BART – a non-parametric Bayesian statistical learning technique – in order to identify relevant predictors from the Global Competitiveness Reports.

[10] Those were mainly countries with initially rather low debt levels. Some of them (e. g. Slovenia, Lithuania or Croatia) more than doubled their debt ratios between 2009 and 2017.

We find that only a handful of indicators are good predictors of how EU countries have performed after the 2008/09 crisis. Improvements in "Technological readiness" (mainly broadband internet access and usage) as well as "Goods market efficiency" are positively linked to changes in technical progress (CTP). "Innovation" joins the list of relevant predictors of CTP when only the most developed EU countries are considered. The remaining TFP components show less clear patterns: "Market size" is a negative predictor for changes in scale efficiency. "Financial market efficiency" yields negative effects on changes in allocative efficiency (CAE). The latter might be attributed to "zombie" companies keeping up with inefficient production set-ups when they have easy access to loans.

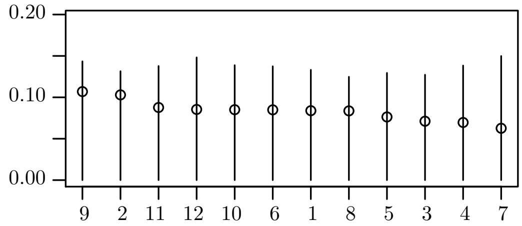
The results presented in this paper can be guidelines to policymakers as they identify areas in which further action could be taken in order to increase economic growth. Even though it seems straightforward that broadband internet access is crucial for the technological readiness of an economy's labor force, a lot of catching-up is necessary even in higher-income EU economies. It is remarkable how this result stands out from the vast number of possible indicators included in this study.

Concerning the bigger picture, it becomes obvious that advanced machine learning techniques can not replace sound economic theory but they help separating the wheat from the chaff when it comes to selecting the most important factors. They might be key for the further exploration of the widely capricious phenomenon TFP.

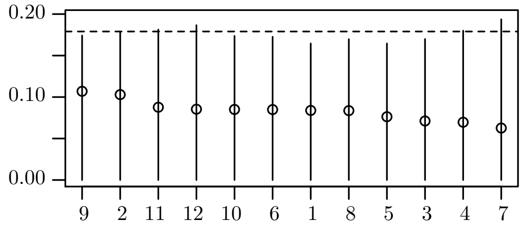
6. Appendix

Figure 31
Variable selection – set of higher-income economies

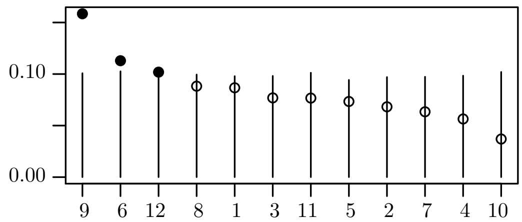
(a) *Local Procedure – TFP growth*



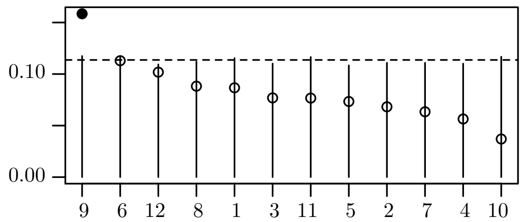
(b) *Global Procedures – TFP growth*



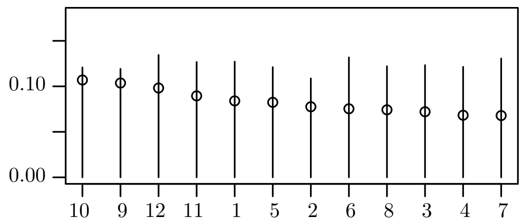
(c) *Local Procedure – CTP*



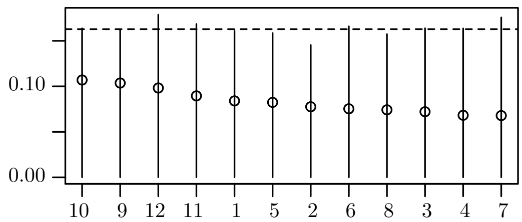
(d) *Global Procedures – CTP*



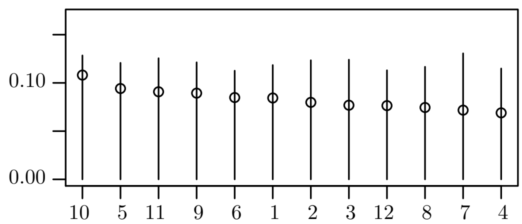
(e) *Local Procedure – CTE*



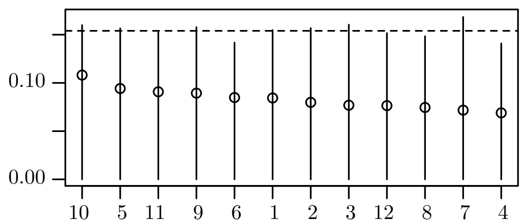
(f) *Global Procedures – CTE*



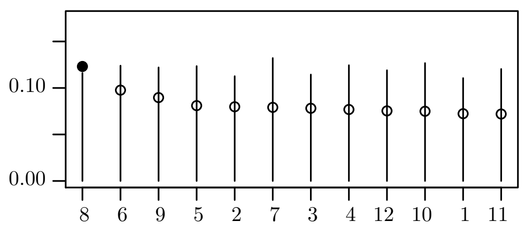
(g) *Local Procedure – CSC*



(h) *Global Procedures – CSC*



(i) *Local Procedure – CAE*



(j) *Global Procedures – CAE*

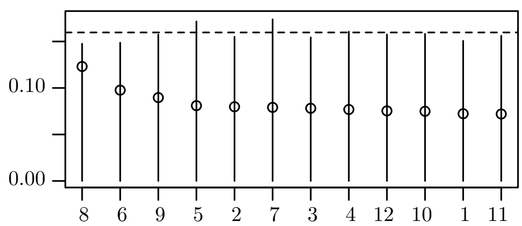


Figure 32

Variable selection – set of lower-income economies

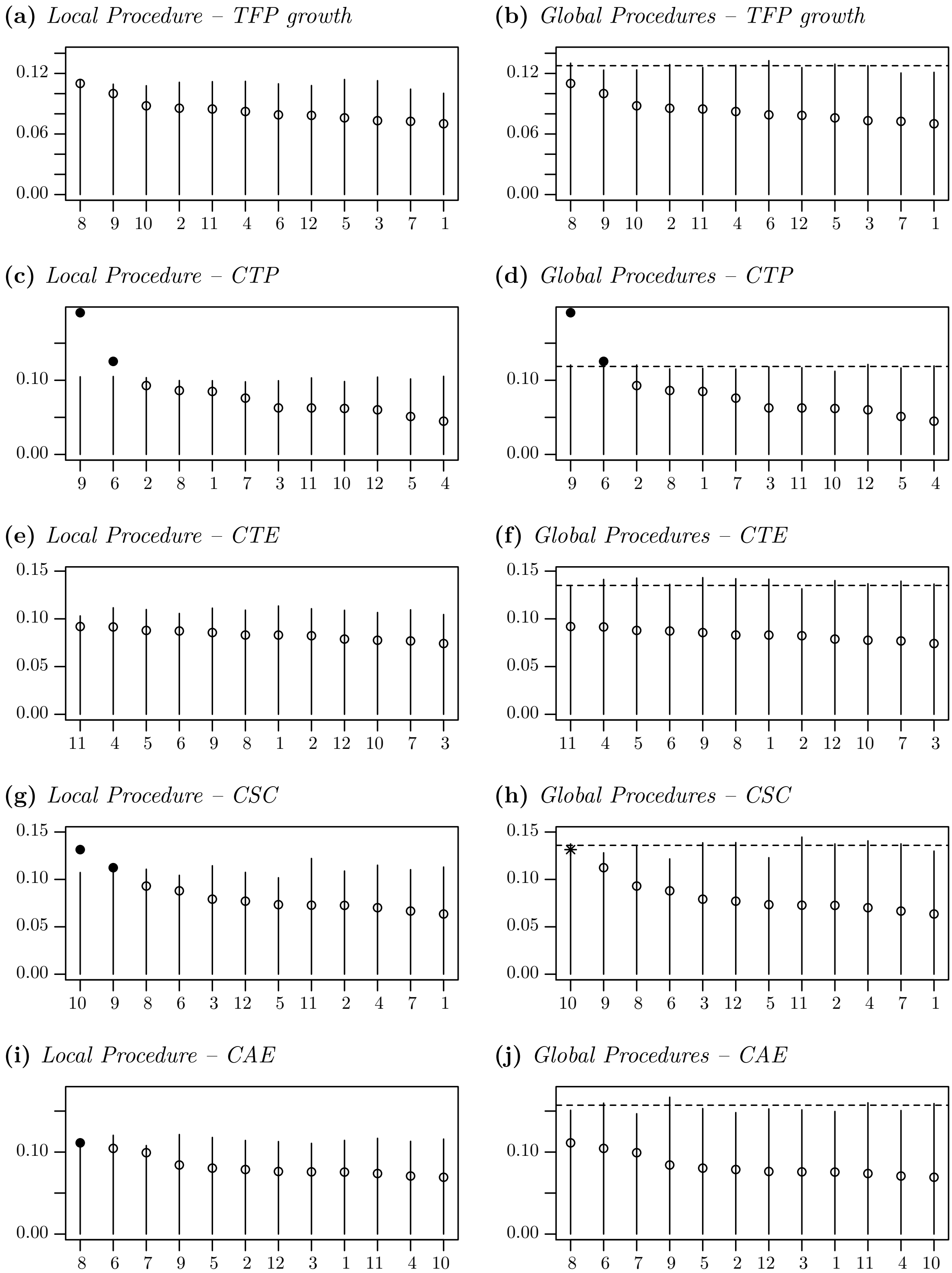
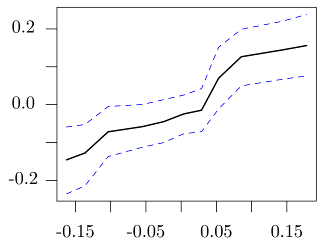
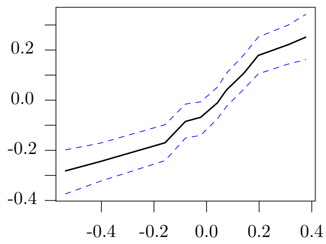
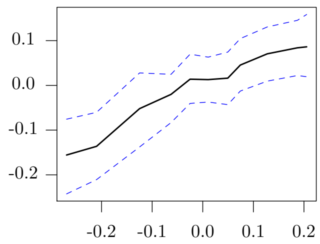
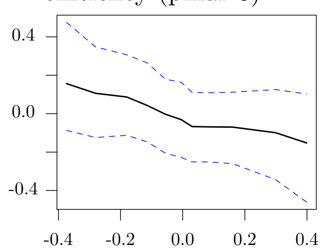
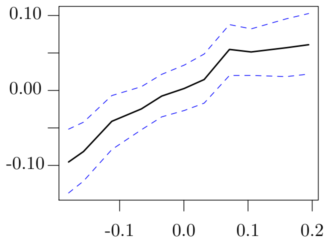
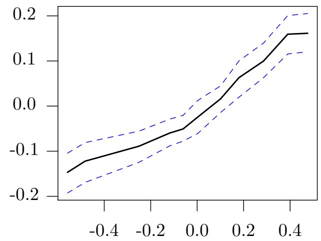
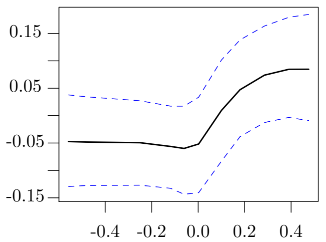
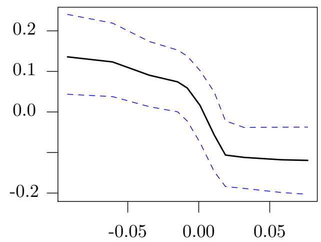
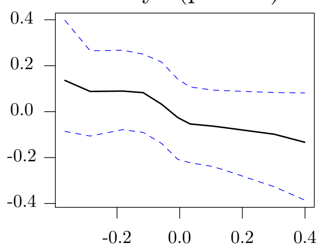


Table 6
Partial dependence plots – set of higher-income economies

<table>
<tr><td>TFP growth</td><td colspan="3">No relevant variables identified (see Figure 31).</td></tr>
<tr><td>CTP</td><td>“Goods market efficiency”
(pillar 6)
</td><td>“Technological readiness”
(pillar 9)
</td><td>“Innovation”
(pillar 12)
</td></tr>
<tr><td>CTE</td><td colspan="3">No relevant variables identified (see Figure 31).</td></tr>
<tr><td>CSC</td><td colspan="3">No relevant variables identified (see Figure 31).</td></tr>
<tr><td>CAE</td><td>“Financial market”
efficiency (pillar 8)
</td><td></td><td></td></tr>
</table>

Note: The vertical axis depicts the partial effects. Blue lines represent 95 % credible intervals.

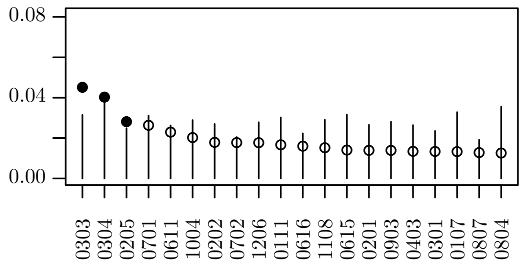
Table 7
Partial dependence plots – set of lower-income economies

TFP growth	No relevant variables identified (see Figure 32).
CTP	"Goods market efficiency" (pillar 6)  "Technological readiness" (pillar 9) 
CTE	No relevant variables identified (see Figure 32).
CSC	"Technological readiness" (pillar 9)  "Market size" (pillar 10) 
CAE	"Financial market efficiency" (pillar 8) 

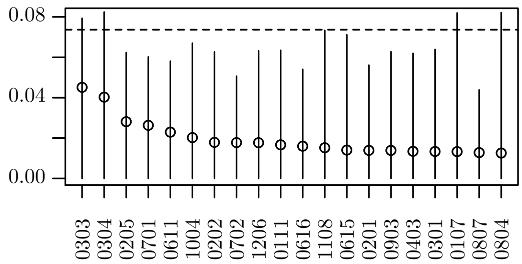
Note: The vertical axis depicts the partial effects. Blue lines represent 95 % credible intervals.

Figure 33
Variable selection – indicators

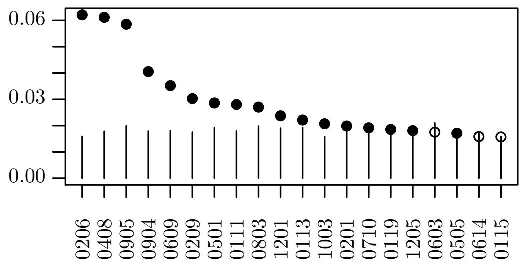
(a) *Local Procedure – TFP growth*



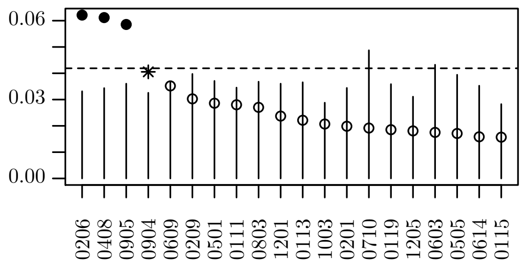
(b) *Global Procedures – TFP growth*



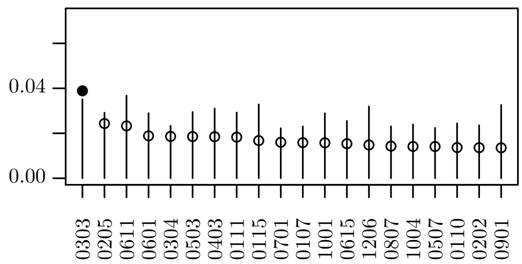
(c) *Local Procedure – CTP*



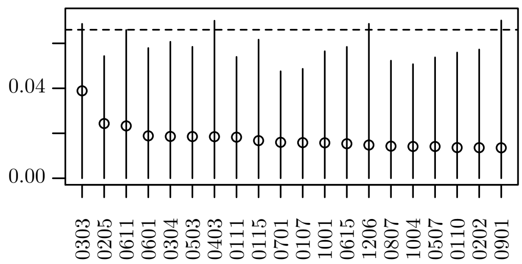
(d) *Global Procedures – CTP*



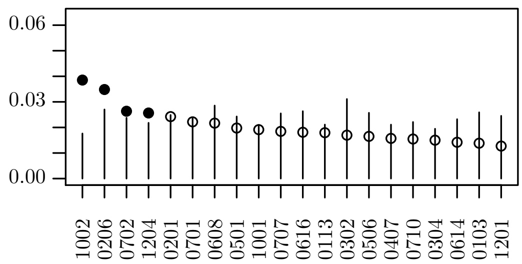
(e) *Local Procedure – CTE*



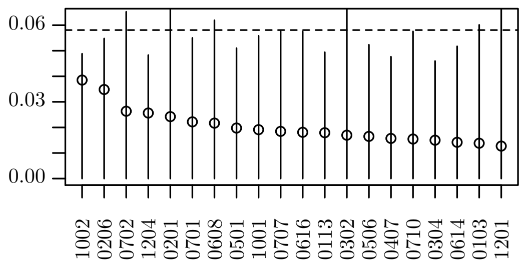
(f) *Global Procedures – CTE*



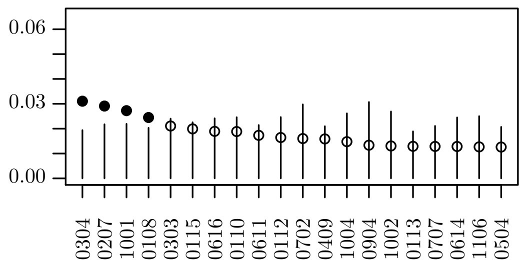
(g) *Local Procedure – CSC*



(h) *Global Procedures – CSC*



(i) *Local Procedure – CAE*



(j) *Global Procedures – CAE*

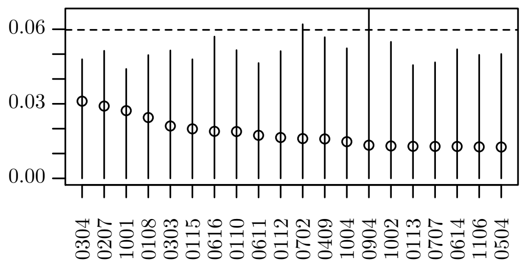
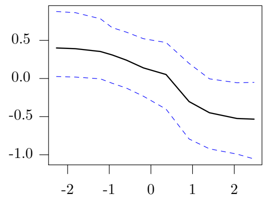


Table 8

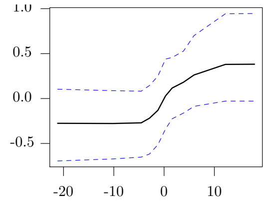
Partial dependence plots – indicators

TFP growth

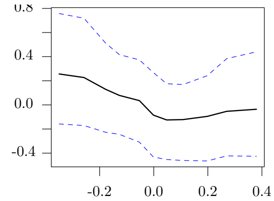
3.03: Inflation, in %



3.04: General government debt (in % of GDP)

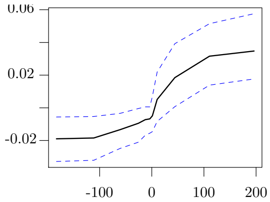


2.05: Quality of air transport infrastructure, 1-7

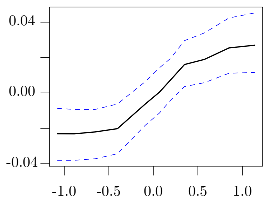


CTP

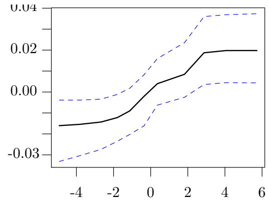
2.06: Available airline seat km/week



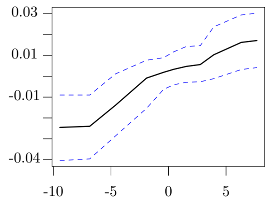
4.08: Life expectancy (in years)



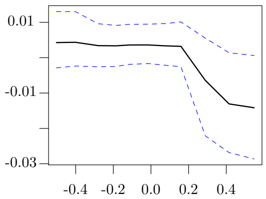
9.05: Fixed broadb. internet subscript. / 100 pop.



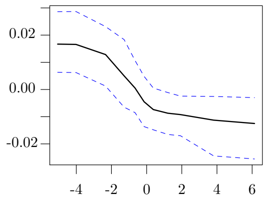
9.04: Individuals using internet, in %



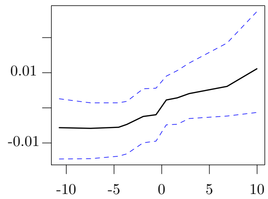
6.09: Prevalence of trade barriers, 1-7



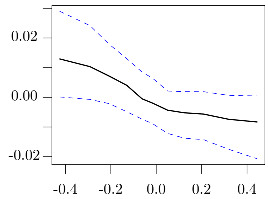
2.09: Fixed telephone lines / 100 pop.



5.01: Secondary education enrollment, in %

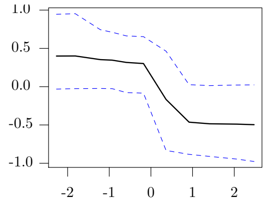


1.11: Eff. of legal framew. in challeng. regs., 1-7



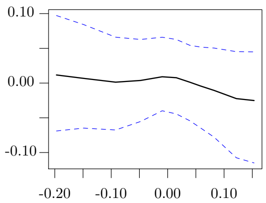
CTE

3.03: Inflation, in %

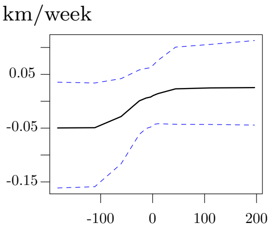


CSC

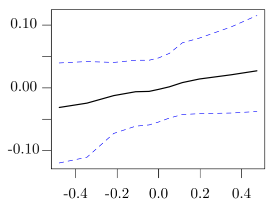
10.02: Foreign market size index, 1-7



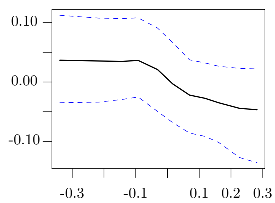
2.06: Available airline seat km/week



7.02: Flexibility of wage determination, 1-7

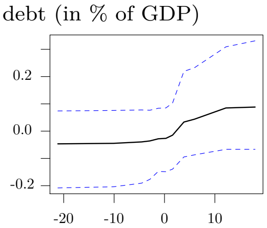


12.04: University-industry collaboration in R&D, 1-7

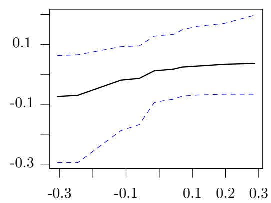


CAE

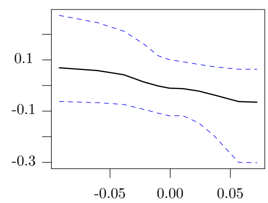
3.04: General government debt (in % of GDP)



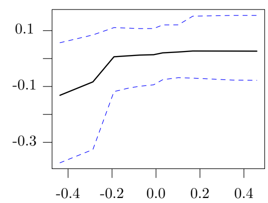
2.07: Quality of electricity supply, 1-7



10.01: Domestic market size index, 1-7



1.08: Wastefulness of government spending, 1-7



Note: The vertical axis depicts the partial effects. Blue lines represent 95 % credible intervals.

Part III.

Module C: The Potential

1. Introduction

The aim of this paper is to investigate the economic potentials of the 27 EU member states (and the United Kingdom) and their deviations from these potentials. Generations of economists have aimed at tackling the question of how to maximize the productivity and efficiency within an individual firm, an industry and, perhaps most importantly, a national economy. The literature offers two major approaches to the calculation or estimation of efficiency and productivity levels, those being neoclassical growth accounting and frontier analysis. In the context of this study, potentials are theoretical economic performance capabilities, which are calculated with the aid of virtual decision-making units (DMUs) through different data envelopment analysis (DEA) models.

This module contains three different parts. The first part is an economic analysis, the second and third part focus on environmental and social analysis, respectively, whereas both build up on the economic analysis.

In the economic analysis, the potential and the inefficiency of the individual countries are measured on an annual basis in a static framework. In this phase we can identify the individual potentials in each single year from 2000 to 2014 (with few exceptions due to data issues) and the corresponding distances of each country. We find that roughly half of the countries remain at a fairly low inefficiency level. Furthermore, an intertemporal analysis is conducted: A crucial element for the efficiency measurement of countries is to know whether there has been productivity growth and/or technical progress from 2000 to 2014. We measure the development via using DEA to create a Malmquist productivity index and a Luenberger productivity indicator, which allows the distinction between a "catch-up" process and a "frontier shift". As a consequence, we can identify the causes for productivity changes for each country individually. The development in Austria is compared to developments in the other countries. Additionally, we get the attribution of these effects to individual input and/or output factors, when utilizing the Luenberger indicator. We find that technical change ("frontier shift") is the main driver of productivity. Changes in efficiency ("catch-up" processes) contribute to productivity to a lesser extent, especially in countries that have already been close to their respective efficiency frontiers. The majority of analyzed countries experienced an overall positive development of productivity throughout the period in question.

The second part of this module then focuses on environmental analysis: Again, a static analysis is carried out, but this time including data on greenhouse gas (GHG) emissions by adding additional restrictions to the model. This analysis is of particular interest for the proposed climate targets by the EU Commission. To the best of our knowledge, a DEA-based potential analysis considering GHG emissions with a focus on such a wide set of countries has never been conducted before. Due to data availability reasons, an intertemporal analysis is not feasible in the environmental analysis for the chosen time period.[1] Nevertheless, the static analysis alone delivers novel insights. For a subset of countries we find that all of them could achieve their climate goals if they used their unused production potential for abatement activities.

Even though the analysis proposed above has been conducted for Austria for the years 1995 to 2007 by Mahlberg and Luptáčik (2014),[2] it seems valuable to repeat this procedure for the years 2000 to 2014 for countries where data is available. The analysis is carried out for the 56 industries defined in the World Input-Output Database (WIOD). Especially in the environmental analysis, higher aggregation levels with respect to industries are necessary due to data issues. We use a classical radial DEA, directional distance function (DDF) DEA as well as a slacks-based measure (SBM) DEA model. As input factors we use intermediate (domestic) consumption, capital stock as well as labor. Our outputs are the deliveries to final demand.

The third part focuses on a social analysis, which to our knowledge has not been conducted in this context before. Essentially, the same data set as in the economic analysis is used, but now we allow workers to change their educational level. Again a static and an intertemporal analysis is carried out. Here, we find that allowing for changes in qualification increases the production potential of an economy.

[1] In order to demonstrate that an intertemporal analysis is possible in principal, it is calculated for two of the 28 countries under certain assumptions.

[2] Supported by the Anniversary Fund of the Oesterreichische Nationalbank (OeNB), project number 13802.

The remainder of this paper is structured as follows: Section 2 gives a literature overview. Section 3 describes the methods used for conducting the empirical analysis. Section 4 deals with the data used in the empirical analysis. Section 5 shows the results and section 6 concludes.

2. Literature

The neoclassical strand of research focuses on certain factors, or inputs, that influence productivity growth. A well-known early example is a paper by Debreu (1951), which presents an efficiency analysis using a coefficient of resource utilization. A few years later, Solow (1956) and Swan (1956) independently developed a neoclassic growth model that has gone on to become the standard approach to growth accounting. In its essence, the model relies on three main factors to account for changes in economic growth: capital, labor and, added by Solow (1957), technology. The so-called Solow residual is used as a measure of productivity growth and is most commonly referred to as the growth of multifactor or total factor productivity (TFP).

The second approach uses data envelopment analysis (DEA), as first proposed by Charnes *et al.* (1978), to estimate efficiency frontiers of comparable decision making units (DMUs) and their deviation from these frontiers. Both neoclassical and frontier approaches perceive productivity as an output-input-ratio and seek to examine its changes. However, as Ten Raa and Mohnen (2002) point out, only frontier analysis differentiates between an advance towards the efficiency frontier (efficiency change) and a position change of the frontier itself (technical change). While neoclassical models ascribe productivity growth to individual inputs, frontier analysis aims at identifying how well an economy *could* perform within given limits. Moreover, the Luenberger indicator makes it possible to further decompose frontier shifts so that contributions of different input and output components can be calculated (for example with DEA methods). Stiglitz (2002) poignantly summed up the basic reasoning in a 2002 newspaper article by stating that *"recessions are easily recognizable from a decrease in GDP. What really should interest us, however, is the difference between the potential of an economy and its actual performance (...)."*

Based on Stiglitz' statement, Luptáčik and Böhm (2010) perform an efficiency analysis by zooming in on the gap between the potential economic capacity of an economy and its current performance. Building on Ten Raa and Mohnen (2002), who first merged both approaches, they quantify this gap by applying DEA to a single economy represented by the input-output-model of Leontief (1936) and extended by the constraints for primary inputs. Virtual efficient DMUs are created by utilizing a multi-objective optimization model. The results show that the solution of this DEA model and the models by Ten Raa (2006), who formulated the input-output-model as a linear programming model, share the same efficiency scores and as well as the same shadow prices. Contrary to the base model, this extension incorporates information about ecological consequences, such as the pollution structure of production in each sector (in the case of this study greenhouse gas emissions), in order to analyze the eco-efficiency of the economy in question. Another deviation is that within this model the final demand is endogenous.

Both Mahlberg and Luptáčik (2014) and Luptáčik and Mahlberg (2016) build on the described approach. Mahlberg and Luptáčik (2014) expanded on it by performing an intertemporal analysis on eco-efficiency and eco-productivity for Austria between 1995 and 2007. They further develop this model to allow for both a distinction between eco-efficiency and eco-technical change as well as an estimation of how individual production factors (primary inputs), commodities (desirable outputs) and pollutants (undesirable outputs) contribute to productivity changes over time, thus combining benefits of the neoclassical and the frontier approach. Similarly, Luptáčik and Mahlberg (2016) also quantify productivity changes in the U.S. over time by making use of the neoclassical and the frontier approach. Both papers use the Luenberger productivity indicator to distinguish between efficiency and technical changes (see, e. g. Chambers *et al.* (1996a) and Briec and Kerstens (2004)). A further application building on the work of Luptáčik and Mahlberg (2016) analyzing the economy of Columbia has been presented by Gilles and Javier (2017) at the 25^th IIOA Conference in Atlantic City (unpublished).

Another application, building on Mahlberg and Luptáčik (2014) and Leontief (1970), was recently conducted by Wang *et al.* (2020). In their study, the authors utilize a frontier-analysis-based approach in order to run a cost-benefit analysis of environmental policy taxation in China. More specifically, they focus on SO_X, NO_2 and soot and dust as pollutants and connect the reduction of the respective pollutant with welfare benefits in the form of avoided health costs.

3. Methodology

The aim of this project is to compute the theoretical economic performance capabilities („potentials“) for the 27 EU member states (and the United Kingdom) and their deviations from these potentials. The analysis is carried out for each of the 28 countries and for each year from 2000 to 2014, where data is available. The procedure is enriched by considering environmental and social indicators as well. The analysis is based on data envelopment analysis (DEA) described in section 3.1 and input-output-analysis (IOA) described in section 3.2. Next, these methods are described including the algorithm for potential measurement developed by Luptáčik and Böhm (2010) in section 3.3, a possibility for intertemporal comparisons (section 3.5) and our adaptation by flexibilization of labor qualification structures as an example for an important social component (section 3.6).

3.1. Data Envelopment Analysis

The idea of potential measurement shows analogies to efficiency measurement via the methodology of DEA, as Luptáčik and Böhm (2010) have demonstrated. DEA is an optimization based non-parametric technique proposed by Charnes *et al.* (1978) (revised 1979), to evaluate the relative performance of decision making units (DMUs), which are characterized by a multiple outputs and/or multiple inputs structure. Operational DMUs of this kind often include non-profit and governmental units such as schools, hospitals and universities, which produce outputs or use inputs for which prices are usually unknown.

Next, the first model presented by Charnes *et al.* (1978) is described. In section 3.1.2 one of the possible further developments for considering ecological elements is shown.

3.1.1. Base Models

In the DMUs mentioned above, the presence of a multiple output/multiple input situation makes it difficult to identify an evident efficiency indicator such as profit and complicates the search for satisfactory efficiency measures. DEA combines the multi-dimensional data to one single index via benchmarking without the necessity of the a priori knowledge of the production structure. Efficiency in this form is a multi-criteria based metric.

In DEA the efficiency measurement of a given DMU is working via comparison with other DMUs. Let's assume that l different DMUs are given ($k = 1, \ldots, l$) and k_0 identifies the DMU under evaluation, which is compared to the other DMUs (and itself). The DEA efficiency measure is defined originally as a ratio of a weighted sum of an DMU's n different output components (y_{ik_0}, $i = 1, \ldots, n$) to the weighted sum of m different input components (x_{jk_0}, $j = 1, \ldots, m$; $k = 1, \ldots, l$). This fractional problem can be converted into an equivalent linear programming problem which can be solved easily (Charnes and Cooper, 1962, 1963, 1973). The maximization problem is:

$$max \sum_{r=1}^{t} u_i y_{ik_0} \tag{1}$$

subject to

$$\begin{aligned}
\sum_{j=1}^{m} v_j x_{jk_0} &= 1 \\
\sum_{i=1}^{n} u_i y_{ik} - \sum_{j=1}^{m} v_j x_{jk} &\leq 0, \quad \forall k = 1, \ldots, l \\
-u_i &\leq -\varepsilon \\
-v_j &\leq -\varepsilon
\end{aligned}$$

where v_j and u_i are input and output weights to be defined in an objective manner (and ε is non-Archimedean).

DEA evades ad-hoc judgements, as for each DMU the most favorable weights are chosen. With such a choice, the weights will generally differ for the various DMUs. However, a DMU that proves to be inefficient with respect to other ones even with the most favorable weights cannot call upon the fact that this depends on the choice of weights.

The higher the efficiency ratio, the more efficient the DMU, whereas most favorable weights are chosen as the ones which maximize the efficiency ratio of the DMU considered, subject to the constraint that the efficiency ratios of all DMUs, computed with the same particular weights, have an upper bound of one. Therefore, an efficiency measure equal to one characterizes the efficient DMUs: at least with the most favorable weights, the other ones in the set cannot dominate these DMUs.

The result is a piecewise linear production surface (the so-called efficiency frontier), which is a production frontier from an economic point of view: it represents the maximum output empirically obtainable from a DMU given its level of inputs. At the same time, it represents the minimum amount of input required to achieve the given output levels. DEA-models measure the relative distance between the DMUs and this efficiency frontier. The evaluated distance describes the (in)efficiency of the given DMUs. An important feature of DEA is its ability to both verify if a DMU is efficient relative to the other DMUs, and also suggest for the inefficient ones a virtual DMU that they could imitate in order to improve their efficiency. Additionally, for each inefficient DMU a set of peer units is detected, which are efficient with the inefficient DMU's weights. As a consequence, DEA enables an analysis of the weaknesses and strengths of each specific DMU and enables policy makers to identify policies for improvements.

Though created to evaluate the efficiency of non-profit organizations, soon afterwards DEA was applied to measure the efficiency of any organizational unit. It has, for example, been largely used to compare the performance of different bank branches, airlines or hospitals (e. g. Hofmarcher *et al.* (2005)) or national employment service bureaus (e. g. Koettl *et al.* (2016)). Emrouznejad and Yang (2018) record 10,300 DEA-related journal articles and 2,200 articles in working papers, book chapters and conference proceedings till 2016.

A variety of models have now been developed for implementing the concepts of DEA, that are particularly important for this project. Ecological models considering pollution as special (negative) output components have become very popular in the last decade. Several new models have been published – „Eco-efficiency“, which combines technical and ecological efficiency, became an important keyword. Lábaj *et al.* (2014) went further and developed a measure for economical, ecological and social efficiency based on DEA.

3.1.2. Ecological Models

DEA models do not require any price information but work with quantities. This is particularly advantageous when considering pollutants, as there are generally no valid or stable prices for these. Soon after the development of the basic DEA models, the first static environmental DEA models were developed (e. g. Färe *et al.* (1989)). The fundamental problem with environmental factors is that harmful environmental factors are atypical output factors in that (1) they are generated as co-products together with the desired output factors in non-negative quantities, and (2) the amounts of pollutants have to be minimized. They are therefore not input factors either, since they are not required as resources (in the technical or physical sense) for production. In any case, it is generally assumed that a reduction of pollutants costs something - be it that the quantity of goods has to be reduced, i.e. the production volume is reduced (short-term measure) and thus the income (and expenses) decrease, or that the input factors have to be increased, e.g. in order to implement end of pipe environmental protection measures (medium-term measure), or that further capital investments are necessary to enable the use of more environmentally friendly technology (long-term measure) (Dakpo *et al.*, 2016, 350). Another option is that any technical inefficiencies are reduced. These would not be associated with any additional costs.

Eco-efficiency now means that production can no longer be increased without increasing the use of resources and/or increasing environmental pollution. In the report at hand the pollutants are treated like inputs as in Mahlberg and Luptáčik (2014, 888). They argue that both inputs and pollutants incur costs for economies, since the use of productive inputs from the production of desirable outputs is required for abatement activities. Other possibilities to regard the special properties of pollutants are summarized in Dakpo *et al.* (2016).

The central element of the model of Luptáčik and Böhm (2010) for the potential measurement of economies is the structure of the investigated economies which are described by the input-output tables constructed for input-output analysis (IOA). These are portrayed in the next section. Afterwards the idea of Luptáčik and Böhm (2010) of relating the concepts of DEA and IOA is presented in section 3.3.

3.2. Input Output Analysis

3.2.1. Base model

The concept of input-output analysis was developed by Leontief (1936). With the input-output analysis, which is based on the very detailed input-output tables of the national accounts, the mutually linked supply and purchase structures of the individual sectors of an economy are recorded.

In an input-output analysis the economy is structured in different industrial or goods sectors. Each sector needs primary inputs (capital, labor) and intermediary goods (delivered by the different sectors) for production to fulfill the final demand (household consumption, exports, etc.). Input-output tables are usually structured as (goods $\times$ goods) matrices. This means that the goods classes are specified in both rows and columns. Input-output tables can be divided into four sub-areas, which are usually referred to as quadrants:

The first quadrant represents the actual core of the input-output table and deals with the supplies and purchases of the individual goods sectors (intermediate consumption). The second quadrant contains the individual components of the final demand. The third quadrant shows the primary inputs used in the production of the individual production sectors according to its components employee compensation, depreciation, operating surpluses and, if applicable, imports. The goods for intermediate consumption can be produced domestically or imported. As a consequence imported goods can be separated in the input-output-table (so called *version B* tables contrary to *version A* tables without separation).

Table 1 shows the structure of an version A table:

Table 1

Structure of an input-output-table, version A

	good 1	$\cdots$	good n	final demand	total use
good 1	x_{11}	$\cdots$	x_{1n}	y_1	$x_{1.}$
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$
good n	x_{n1}	$\cdots$	x_{nn}	y_2	$x_{n.}$
primary inputs	w_{11}	$\cdots$	w_{n1}		
	$\vdots$	$\ddots$	$\vdots$		
	wm1	$\cdots$	w_{mn}		
production	$x_{.1}$	$\cdots$	$x_{.n}$		

For each good sector j, $j = 1, \ldots, n$, the equality between production $x_{.j}$ and total use $x_{j.}$ applies:

$$\sum_{i=1}^{n} x_{ij} + \sum_{i=1}^{m} w_{ij} = x_{.j} = x_{j.} = \sum_{k=1}^{n} x_{jk} + y_j, \quad \forall j = 1, \ldots, n \tag{2}$$

The x_{ij} are the required intermediary good volumes from sector i for sector j; y_j the final demand volumes for good j; w_{ij} the required primary input volumes i for sector j; $x_{.j}$ the production volume of good j and $x_{j.}$ the total used volume of good j (usually the volumes are measured in monetary units).

By normalization of the intermediary and primary inputs by production volumes, the required volumes of each input for the production of one unit of output result the input coefficients:

$$\frac{x_{ij}}{x_{.j}} =: a_{ij} \quad \forall i, j = 1, \ldots, n;$$
$$\frac{w_{ij}}{x_{.j}} =: b_{ij} \quad \forall j = 1, \ldots, n; i = 1, \ldots, m$$

The following relations hold:

$$x_{.j} = \sum_{i=1}^{n} a_{ji} x_{j.} + y_j \quad \forall j = 1, \ldots, n$$
$$z_j = \sum_{i=1}^{m} b_{ji} x_{j.} + y_j \quad \forall j = 1, \ldots, n$$

Defining the matrices $A_{11} = (a_{ij})$ and $B_1 = (b_{ij})$ and the vectors $x_1 = (x_{.j})$, $y_1 = (y_j)$ and $z = (z_j)$, we get (I is the identity matrix):

$$x_1 = A_{11} \cdot x_1 + y_1 \Rightarrow y_1 = (I - A_{11}) x_1$$
$$z = B_1 \cdot x_1$$

The input-coefficient matrix A_{11} with dimension $(n \times n)$ describes the required intermediary input shares for the production of each individual good, matrix B_1 describes the necessary amounts of primary inputs for the production of one unit of good i and is $(m \times n)$-dimensional. x_1 is the n-dimensional gross output vector and y_1 the n-dimensional final demand vector. z represents the individual sum of each primary input component and is m-dimensional.

In principle, overproduction is possible and the resources of primary inputs can be higher then needed (e. g. existing unemployment). For these reasons Raa (2005, 108ff) abolished the equality conditions in 3 and permits inefficiencies in production so that the following conditions must be met, where it is implicitly assumed that the individual factors can be used in every sector:

- It is produced at least as much so that the final demand can be met:

$$y_1 \leq (I - A_{11})x_1$$

- A (separate) capacity limit is assumed for each primary factor:

$$z \geq B_1 x_1 \cdot x$$

This input output model can be enriched by environmental elements which is shown in the next section.

3.2.2. Environmental augmented model

The input-output model can be augmented by environmental elements (Leontief, 1970). o is the number of different pollutants; the $(o \times n)$-dimensional A_{21} shows the pollution production (e. g. GHG emissions) per unit of produced good i; the $(n \times o)$-dimensional A_{12} the input of good i to eliminate one unit of pollutant k; the $(o \times o)$-dimensional A_{22} the pollutant production to eliminate one unit of pollutant k, where the latter can just contain a zero. x_2 is a o-dimensional vector which describes the effect of abatement activities on pollution, for example the reduction of GHG emissions expressed in tons. y_2 contains the maximum tolerated level of generated pollution after abatement, which can be certain goals defined by policy makers. B_2 describes the required level of primary inputs required for abatement, for example the amount of capital and labour required to reduce pollution by one unit. This results in the following model (Mahlberg and Luptáčik, 2014):

$$\begin{bmatrix} (I - A_{11}) & -A_{12} \\ -A_{21} & (I - A_{22}) \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \geq \begin{bmatrix} y_1 \\ -y_2 \end{bmatrix} \tag{3}$$

$$\begin{bmatrix} B_1 & B_2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \leq \begin{bmatrix} z \end{bmatrix}$$

whereas B_1 and x_1 are described in section 3.2.1.

3.3. Measuring Potentials

As mentioned in section 2, Luptáčik, Böhm and Mahlberg have developed a method to measure the potential economic capacity of an economy and the gap between this potential and its current performance. Luptáčik and Böhm (2010) developed two different algorithms to determine the potential and the aforementioned gap. One algorithm is using DEA and the other one Leontief's input-output analysis. Their algorithms enable the consideration of linkages between different economic sectors of an economy in efficiency analyses. As (Mahlberg and Luptáčik, 2014, 886) mention, the algorithms evaluate the economy's potential and the gap to it based on its own economic structure, but without comparison to other economies which possibly have different structures and could be more efficient. In the remainder of this subsection, these algorithms are presented briefly using its formulation, including environmental terms following Mahlberg and Luptáčik (2014). First, the algorithm based on the environmentally augmented Leontief (1970) input-output model is depicted as presented in Mahlberg and Luptáčik (2014).

We are now looking for the (empirical) production possibility set of the economy. There are two extreme possibilities to measure the efficiency of the observed economic activities: Either the output production is maximized by given inputs or the input usage is minimized by given output levels. Certain arbitrary combinations of these extreme variants are possible. The first option is to maximize the net production y_1 with given restrictions of primary input factors z^0 (Mahlberg and Luptáčik, 2014, 887). This results in the following multi-objective linear programming model:

$$\underset{x_1,x_2,y_1,y_2}{\text{Max}}\, y_1 \tag{4}$$

subject to

$$\begin{aligned}
-(I-A_{11})x_1 + A_{12}x_2 + y_1 &\leq 0 \\
A_{21}x_1 - (I-A_{22})x_2 - y_2 &\leq 0 \\
B_1x_1 + B_2x_2 &\leq z^0 \\
x_1, x_2, y_1, y_2 &\geq 0
\end{aligned}$$

For the generation of units which restrict the production possibility set for each good j, the final demand is maximized individually with the restrictions of (4):

$$\max_{x_1,x_2,y_1,y_2} y_1^j \tag{5}$$

(5) has to be solved for each individual good resulting in n different solutions delivering n optimal gross production vectors x^{*j} and n optimal net production vectors y_1^{*j}.

Alternatively to the maximization of the final demand the usage of primary factors can be minimized for given final demand y_1^0 and tolerated pollution levels y_2^0 (Mahlberg and Luptáčik, 2014, 887):

$$\operatorname*{Min}_{x_1,x_2,z} z \tag{6}$$

subject to

$$\begin{aligned}
(I - A_{11})x_1 - A_{12}x_2 &\geq y_1^0 \\
-A_{21}x_1 + (I - A_{22})x_2 &\geq -y_2^0 \\
-B_1x_1 - B_2x_2 + z &\geq 0 \\
x_1, x_2, z &\geq 0
\end{aligned}$$

Analogous to (4) and (5), a single objective problem can be formulated with the restrictions of (6) and the i-th primary input component:

$$\min_{x_1,x_2,z} z^i \tag{7}$$

(7) has to be solved for each individual primary input component resulting in m different linear programs delivering m optimal gross production vectors x^{*i} and m optimal primary input vectors z^{*i}, defining $(n+m)$ **virtual** DMUs (Mahlberg and Luptáčik, 2014, 887).

Collecting the $(n+m)$ results from (5) and (7) gives the following $(n+o+m)\times(n+m)$-dimensional pay-off matrix, where s are the optimal slacks of the different optimization problems (Mahlberg and Luptáčik, 2014, 887):

$$Q = \left[\begin{array}{ccc|ccc} y_1^{*1} & \cdots & y_1^{*n} & y_1^0 + s_{y_1}^1 & \cdots & y_1^0 + s_{y_1}^m \\ y_2^1 & \cdots & y_2^n & y_2^0 - s_{y_2}^1 & \cdots & y_2^0 - s_{y_2}^m \\ z^0 - s_z^1 & \cdots & z^0 - s_z^n & z^{*1} & \cdots & z^{*m} \end{array}\right] \equiv \begin{bmatrix} Q_1 \\ Q_2 \\ Z \end{bmatrix} \tag{8}$$

Each column of the pay-off matrix in (8) represents an optimal result of either the n problems in (5) or the m problems in (7), delivering the eco-efficient frontier of the economic system describing the multiple-input multiple-output macroeconomic production function (Mahlberg and Luptáčik, 2014, 887). Based on matrix Q in (8), a (environmental) DEA-model can be constructed (Luptáčik and Böhm, 2010), with Q covering the $(n+m)$ DMUs in the columns, Q_1 containing the input vectors, Z the output vectors and Q_2 the pollution factors. An input-oriented formulation following DEA model is resulting in (Mahlberg and Luptáčik, 2014, 887):

$$\min_{\theta,\mu} \theta \tag{9}$$

subject to

$$\begin{aligned} Q_1\mu &\geq y_1^0 \\ -Q_2\mu &\geq -y_2^0 \\ \theta z - Z\mu &\geq 0 \\ \mu &\geq 0 \end{aligned}$$

θ measures the eco-efficiency and μ is the intensity vector. Its dual program is given by

$$\max_{u_1,u_2,v} u_1' y_1^0 - u_2' y_2^0 \tag{10}$$

subject to

$$\begin{aligned} u_1' Q_1 - u_2' Q_2 - v' Z &\leq 0 \\ v' z^0 &= 1 \\ u_1, u_2, v &\geq 0 \end{aligned}$$

Mahlberg and Luptáčik (2014, 888f) showed based on Luptáčik and Böhm (2010, 613ff) that the input-oriented DEA-model in (9) and (10) have equal efficiency scores and shadow prices as following linear program (11) and (12), which is based on the augmented Leontief input-output analysis:

$$\min_{\gamma,x_1,x_2} \gamma \tag{11}$$

subject to

$$
\begin{aligned}
(I - A_{11})x_1 - A_{12}x_2 &\geq y_1^0 \\
-A_{21}x_1 + (I - A_{22})x_2 &\geq -y_2^0 \\
-B_1x_1 - B_2x_2 + \gamma z^0 &\geq 0 \\
x_1, x_2, \gamma &\geq 0
\end{aligned}
$$

and its dual:

$$
\max_{p_1, p_2, r} p_1' y_1^0 - p_2' y_2^0 \tag{12}
$$

subject to

$$
\begin{aligned}
p_1'(I - A_{11}) - p_2' A_{21} - r' B_1 &\leq 0 \\
-p_1' A_{12} + p_2'(I - A_{22}) - r' B_2 &\leq 0 \\
r' z^0 &\leq 1 \\
u_1, u_2, v &\geq 0
\end{aligned}
$$

p_1 is the vector of the shadow prices of the n goods, p_2 the vector of the shadow prices for abating pollutants and r the vector of the m primary inputs.

As the linear program (11) and (12) deliver equal efficiency scores and shadow prices as the DEA model in (9) and (10), in principle it is sufficient to calculate only one of these models (but calculating both can help to find errors), i. e., the following report can concentrate on one type of model, in this study it will be the Leontief based model.

In the following the models considering environmental indicators are called **environmental** models, the models without environmental components are called **economic** models.

As the environmental models introduce restrictions which are not part of the economic models (as can be seen in 11) the distance of an economy to its own economic-environmental potential frontier is smaller or equal to its economic potential frontier. This circumstance can be explained easily: In the environmental model the tolerated pollution level is restricted, in the economic model it is not. There exist production possibilities in the economic model which are not feasible in the environmental model because of disregarding any pollution restrictions in the economic model. Thus, the theoretic potential is higher in the economic than in the environmental model.

In the report at hand several different DEA-look alike models are used for the analysis of economic and economic-environmental potentials of countries, these are described in the next section.

3.4. Applied DEA Models

In the above section the Leontief based model is constructed in analogy to the radial input-oriented DEA-model (see section 3.1). In principle, other DEA models can be used as well.

For this study, several different static DEA models are applied - the input-oriented radial model as in (9) and (10), the non-oriented proportional directional distance function model (Chung *et al.*, 1997) - non-oriented proportional DDF as in Mahlberg and Luptáčik (2014) and the input-oriented slacks-based measure (SBM) model (Cooper *et al.*, 2007b, 99ff). In the following, the Leontief based analogous formulations of the non-oriented proportional DDF and the input-oriented SBM are presented.

The non-oriented proportional DDF of the augmented Leontief input-output based model is given by (see, e. g. Chung *et al.* (1997)):

$$\max_{\beta, x_1, x_2} \beta \tag{13}$$

subject to

$$\begin{aligned} -(I - A_{11})x_1 + A_{12}x_2 + \beta y_1^0 &\leq -y_1^0 \\ A_{21}x_1 - (I - A_{22})x_2 &\leq y_2^0 \\ B_1x_1 + B_2x_2 + \beta z^0 &\leq z^0 \\ x_1, x_2 &\geq 0 \end{aligned}$$

and its dual:

$$\min_{p_1, p_2, r} -p_1'y_1^0 + p_2'y_2^0 + r'z^0 \tag{14}$$

subject to

$$-p_1'(I - A_{11}) + p_2'A_{21} + r'B_1 \geq 0$$
$$p_1'A_{12} - p_2'(I - A_{22}) + r'B_2 \geq 0$$
$$p_1'y_1^0 + r'z^0 = 1$$
$$p_1, p_2, r \geq 0$$

The input-oriented slacks-based measure model of the augmented Leontief input-output based model is given by (see, e. g. Cooper *et al.* (2007a)):

$$\min_{s^-, x_1, x_2} 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{z_i^0} \tag{15}$$

subject to

$$(I - A_{11})x_1 - A_{12}x_2 \geq y_1^0$$
$$-A_{21}x_1 + (I - A_{22})x_2 \geq -y_2^0$$
$$-B_1x_1 - B_2x_2 - s^- = -z^0$$
$$x_1, x_2, s^- \geq 0$$

and its dual:

$$\max_{p_1, p_2, r} p_1'y_1^0 - p_2'y_2^0 - r'z^0 - 1 \tag{16}$$

subject to

$$p_1'(I - A_{11}) - p_2'A_{21} - r'B_1 \leq 0$$
$$-p_1'A_{12} + p_2'(I - A_{22}) - r'B_2 \leq 0$$
$$-r' \leq -\frac{1}{m}\frac{1}{z_i^0}$$
$$p_1, p_2 \geq 0$$

If data of an economy is given for several periods in time, then not only static potential analyses for several periods which are independent of each other are possible, but also analyses of the development between two periods are feasible. This so called intertemporal analysis based on above described models is presented in the following section.

3.5. Intertemporal Analysis

For the project at hand several different static DEA models, as described in section 3.4, are used. The originally static DEA models have been further developed for the simultaneous analysis of several periods by evaluating productivity changes between two points in time (intertemporal analysis). This is done by calculating the cross-period distances to the efficiency frontier of one period with the input-output data of the other period. This concept, originally from Caves *et al.* (1982a) was introduced into the DEA model family by Färe *et al.* (1994a) and is presented in the following.

3.5.1. Malmquist Productivity Index

Such a cross-period distance can be evaluated in principle with each of the above mentioned models, e. g. based on the input-oriented radial Leontief based model (11) and the time periods s and t we get following intertemporal distance measure:

$$D_s^t = \min_{\gamma, x_1, x_2} \gamma_s^t \tag{17}$$

subject to

$$\begin{aligned} (I - A_{11}^t)x_1 - A_{12}^t x_2 &\geq y_{1s}^0 \\ -A_{21}^t x_1 + (I - A_{22}^t)x_2 &\geq -y_{2s}^0 \\ -B_1^t x_1 - B_2^t x_2 + \gamma_s^t z_s^0 &\geq 0 \\ x_1, x_2, \gamma &\geq 0 \end{aligned}$$

The superscript (^{t}) indicates the period of which the economic system is used to create the production possibility set, the subscript ($_s$) the period of which the limitations are taken. D_s^t is the corresponding distance measure, it shows the distance (measured by model 17) to the potential frontier.

In the static ($t = s$) input-oriented radial model - **economic** version - the efficiency value γ_t^t lies between 0 and 1 (1 is indicating efficiency, i. e. full used potential), as the limitations y_{1t}^0 and z_t^0 are realizations of the same period. In the **environmental** version the tolerated pollution level y_{2t}^0 theoretically can be chosen too strict, i. e. with the given production possibilities, boundaries on the primal inputs and the required final demand, the tolerated pollution level y_{2t}^0 is not reachable with the given economic system represented by different matrices A and B. This case would be indicated by a $\gamma_t^t > 1$. In DEA-terminology this situation is called **superefficiency** (the idea of superefficiency was first presented by Andersen and Petersen (1993)).

The same situation can also happen in the economic version if the production capabilities change over time (e. g. because of increasing productivity) or the limitations change (e. g. stricter tolerated pollution levels, aging population) so that limitations of one period are not satisfiable with the compared economic system of the other period, i. e., the economic potential is too low or the economic structure differs a lot between the periods.

Several different productivity indices and indicators allow to measure the productivity changes between periods. The most well known in the DEA community is the Malmquist-based productivity index ($\forall t \geq s$) presented by Färe *et al.* (1994a):

$$M = \left(\frac{D_s^t}{D_s^s} \cdot \frac{D_t^t}{D_s^t} \right)^{\frac{1}{2}}, \tag{18}$$

where D_s^t describes the distance of the given DMU (in the given case - the observed economy) of period s to the efficiency frontier (in the given case - potential frontier) in period t. The Malmquist productivity index can be decomposed into a so called „Catchup"-process (CP) and a „Frontier Shift" (FS). The easiest decomposition was given by Färe *et al.* (1994a, 257):

$$M = CP_M \cdot FS_M, \tag{19}$$

where

$$CP_M = \frac{D_t^t}{D_s^s} \tag{20}$$

and

$$FS_M = \left(\frac{D_s^t}{D_t^t} \cdot \frac{D_s^s}{D_s^t} \right)^{1/2} \tag{21}$$

The Frontier Shift in (21) is interpreted as the influence of technical change on the possible input-output-combinations set; i. e., technical progress[3] enables the production more output using fewer resources (improvement of productivity). Thus, the efficiency frontier is shifted above and to the left. The catch-up-process in (20) describes if an economy

[3] The term technical progress summarizes not only progress in a technical sense but also changes in processes or in the political environment.

loses (falls behind) or gains (comes nearer) compared to the frontier shift development (Färe *et al.*, 1994a).

3.5.2. Luenberger Productivity Indicator

Another popular productivity indicator is the Luenberger productivity indicator (Chambers *et al.*, 1996b). It applies calculated cross-period distances, based on the DDF DEA model but instead of comparing them via ratios as in the Malmquist productivity index, now the comparison goes via differences:

$$L = \frac{1}{2}\left[\left(D_t^s - D_s^s\right) + \left(D_t^t - D_s^t\right)\right], \tag{22}$$

The decomposition into efficiency change and frontier shift goes analogous by Mahlberg and Sahoo (2011):

$$L = CP_L + FS_L, \tag{23}$$

where

$$CP_L = D_t^t - D_s^s \tag{24}$$

and

$$FS_L = \frac{1}{2}\left[\left(D_t^t - D_t^s\right) + \left(D_s^t - D_s^s\right)\right], \tag{25}$$

One advantage of the Luenberger productivity indicator compared to the Malmquist productivity index is that the efficiency change can be decomposed further, so that the contribution of each individual input and output component and each pollutant to efficiency change, technical change and productivity change can be calculated (Mahlberg and Luptáčik, 2014, 890):

$$\begin{aligned}
CP_L^i &= r_{is}^s z_{is}^0 - r_{it}^s z_{it}^0 \\
CP_L^j &= p_{1js}^s y_{1is}^0 - p_{1it}^s y_{1it}^0 \\
CP_L^k &= p_{2ks}^s y_{2ks}^0 - p_{2kt}^s y_{2kt}^0
\end{aligned}$$

$$\begin{aligned}
FS_L^i &= \frac{1}{2}\left[\left(r_{it}^t z_{it}^0 - r_{it}^s z_{it}^0\right) + \left(r_{is}^t z_{is}^0 - r_{is}^s z_{is}^0\right)\right] \\
FS_L^j &= \frac{1}{2}\left[\left(p_{1jt}^t y_{1jt}^0 - p_{1jt}^s y_{1jt}^0\right) + \left(p_{1is}^t y_{1is}^0 - p_{1is}^s y_{1is}^0\right)\right]
\end{aligned}$$

$$FS_L^k = \frac{1}{2}\left[\left(p_{2kt}^t y_{2kt}^0 - p_{2kt}^s y_{2kt}^0\right) + \left(p_{2ks}^t y_{2ks}^0 - p_{2ks}^s y_{2ks}^0\right)\right]$$

$$\begin{aligned}
L^i &= \frac{1}{2}\left[\left(r_{is}^t z_{is}^0 - r_{it}^t z_{it}^0\right) + \left(r_{is}^s z_{is}^0 - r_{it}^s z_{it}^0\right)\right] \\
L^j &= \frac{1}{2}\left[\left(p_{1js}^t y_{1js}^0 - p_{1jt}^t y_{1jt}^0\right) + \left(p_{1js}^s y_{1js}^0 - p_{1jt}^s y_{1jt}^0\right)\right] \\
L^k &= \frac{1}{2}\left[\left(p_{2ks}^t y_{2ks}^0 - p_{2kt}^t y_{2kt}^0\right) + \left(p_{2ks}^s y_{2ks}^0 - p_{2kt}^s y_{2kt}^0\right)\right]
\end{aligned}$$

Following relations hold (Mahlberg and Luptáčik, 2014, 890):

- The contributions of each primary input, each good and each pollutant summed up is equal to the overall productivity change:

$$\begin{aligned}
L &= \sum_{i=1}^{m} L^i + \sum_{j=1}^{m} L^j + \sum_{k=1}^{o} L^k \\
CP_L &= \sum_{i=1}^{m} CP_L^i + \sum_{j=1}^{m} CP_L^j + \sum_{k=1}^{o} CP_L^k \\
FS_L &= \sum_{i=1}^{m} FS_L^i + \sum_{j=1}^{m} FS_L^j + \sum_{k=1}^{o} FS_L^k
\end{aligned}$$

- The sum of the contribution of i'th primal input (j'th good, i. e. k'th pollutant) to the catch up and of its contribution to the frontier shift is its contribution to productivity change:

$$\begin{aligned}
L^i &= CP_L^i + FS_L^i \\
L^j &= CP_L^j + FS_L^j \\
L^k &= CP_L^k + FS_L^k
\end{aligned}$$

The input-oriented radial model and the DDF model can be used directly for the intertemporal analysis analogous to model in (17). This constitutes a difference to the input-oriented SBM models in (15) and (16). SBM models measure inefficiency as the sum of weighted slacks s_i^-. These slacks have to be non-negative (if not the boundary z^0 would not be a boundary). In situations of "superefficiency" (where the limitations are not satisfiable at the same time), at least some slacks should be negative to be able measure the distance to the frontier in order to make the linear program solvable. To solve this problem the SuperSBM model is applied (Cooper *et al.*, 2007a, 334), where the signs in front of the slacks are changed from a minus to a plus:

$$\min_{s^-, x_1, x_2} \ 1 + \frac{1}{m} \sum_{i=1}^{m} \frac{s_i^-}{z_i^0} \tag{26}$$

subject to

$$\begin{aligned}
(I - A_{11})x_1 - A_{12}x_2 &\geq y_1^0 \\
-A_{21}x_1 + (I - A_{22})x_2 &\geq -y_2^0 \\
B_1x_1 + B_2x_2 - s^- &= z^0 \\
x_1, x_2, s^- &\geq 0
\end{aligned}$$

and its dual:

$$\max_{p_1, p_2, r} p_1'y_1^0 - p_2'y_2^0 + r'z^0 - 1 \tag{27}$$

subject to

$$\begin{aligned}
p_1'(I - A_{11}) - p_2'A_{21} + r'B_1 &\leq 0 \\
-p_1'A_{12} + p_2'(I - A_{22}) + r'B_2 &\leq 0 \\
-r' &\leq \frac{1}{m}\frac{1}{z_i^0} \\
p_1, p_2 &\geq 0
\end{aligned}$$

Using this methodological tool-kit, the economic potential of the countries in our data set can be computed.

Next we adapt the conditions for the labor qualification structures as an example for an important social component.

3.6. Social Aspects

For reasons of simplicity the following formulations are based on the economic model defined above, in which environmental aspects are not addressed. In principle, the approach described below can be adapted to the environmental model as well.

In the models above the limitations of the primary inputs and of the labor force z^0 were strictly given beforehand. The results from these models deliver the potentials of an economy, i. e. the distance of this economy to its potential. As a next step it is analyzed how much this potential is increasing, if some flexibility were allowed. More specifically, we want to investigate what happens to the potential, if individuals, companies and/or governments invest in human capital to increase the individuals' qualification levels.[4]

This can be done via different components of the primary input limitation vector z^0 and the primary input coefficients matrix B_1. If we assume three different levels of qualification (high, medium and low), we have the limitations z_1^0, z_2^0 and z_3^0 (i. e. the labor endowment by skill level) and the rows b_{11}, b_{12} and b_{13} of the matrix B_1, describing the requirements of personnel per qualification level for the production. z_4^0 and b_{14} are the corresponding data for the capital stock.

This flexibility is introduced via the "upgrade" variables z_{21} and z_{32}. z_{21} describes the number of people of qualification level "medium", who upgrade their qualification to "high", and z_{32} the corresponding number, who upgrade from low to medium. As in reality only a limited number of people have the willingness and abilities to upgrade their qualifications, the share of possible upgrades are constrained to ζz_2^0 and ζz_3^0. We call ζ the "qualification eligibility". If only moving up one level per period is possible, the corresponding model is given by:

$$\max_{\beta, x_1, z_{21}, z_{32}} \beta \tag{28}$$

subject to

$$\begin{aligned}
-(I - A_{11})x_1 + \beta y_1^0 &\leq -y_1^0 \\
\sum_{k=1}^{n} b_{11} x_{1k} + \beta z_1^0 - z_{21} &\leq z_1^0 \\
\sum_{k=1}^{n} b_{12} x_{1k} + \beta z_2^0 + z_{21} - z_{32} &\leq z_2^0 \\
\sum_{k=1}^{n} b_{13} x_{1k} + \beta z_3^0 + z_{32} &\leq z_3^0 \\
\sum_{k=1}^{n} b_{14} x_{1k} + \beta z_4^0 &\leq z_4^0 \\
z_{21} &\leq \zeta z_2^0
\end{aligned}$$

[4] As described in section 5, in most analyzed economies and years the available number of high qualified workers limits the potential.

$$z_{32} \leq \zeta z_3^0$$

$$x_1, z_{21}, z_{32} \geq 0$$

and its dual:

$$\min_{p_1, r, \alpha_{21}, \alpha_{32}} -p_1' y_1^0 + r' z^0 + \alpha_{21} \zeta z_2^0 + \alpha_{32} \zeta z_3^0 \tag{29}$$

subject to

$$-p_1'(I - A_{11}) + r' B_1 \geq 0$$

$$p_1' y_1^0 + r' z^0 = 1$$

$$-r_1 + r_2 + \alpha_{21} \geq 0$$

$$-r_2 + r_3 + \alpha_{32} \geq 0$$

$$p_1, r, \alpha_{21}, \alpha_{32} \geq 0$$

Due to the linear structure of Leontief's production function, the number of people who upgrade their qualifications is limited to the unemployed population. That does not mean that only unemployed people can upgrade their qualification. But if an employed person achieves a higher skill level, it is assumed that her or his (former) position has to be filled by a previously unemployed person of the required lower skill level. The corresponding constraints in (28) then change to:

$$z_{21} \leq \zeta z_{2a}^0 \tag{30}$$

$$z_{32} \leq \zeta z_{3a}^0 \tag{31}$$

where z_{2a}^0 and z_{3a}^0 are the numbers of unemployed persons with medium and low qualification, respectively.

The objective function of (29) changes to

$$\min_{p_1, r, \alpha_{21}, \alpha_{32}} -p_1' y_1^0 + r' z^0 + \alpha_{21} \zeta z_{2a}^0 + \alpha_{32} \zeta z_{3a}^0 \tag{32}$$

The social model is formulated on the Leontief based algorithm for potential measurement described in section 3.3. Contrary to the economic and the environmental models, the social model does not have a DEA-model as a counterpart because of its terms, which make the labor limitations flexible in the second to fourth constraints in (28) with constraints (30). Furthermore, the efficiency value β is slightly biased, because the efficiency value is applied on the labor endowment before qualification measures z^0 (e.g. z_1^0 instead of the optimized endowment $(z_1^0 + z_{21})$). A DDF DEA model for example would be formulated with the following adapted second, third and fourth constraints of (28) with constraints (30):

$$\sum_{k=1}^{n} b_{11}x_{1k} + \beta(z_1^0 + z_{21}) \leq z_1^0 + z_{21}$$
$$\sum_{k=1}^{n} b_{12}x_{1k} + \beta(z_2^0 - z_{21} + z_{32}) \leq z_2^0 - z_{21} + z_{32}$$
$$\sum_{k=1}^{n} b_{13}x_{1k} + \beta(z_3^0 - z_{32}) \leq z_3^0 - z_{32}$$

And after reformulation:

$$\sum_{k=1}^{n} b_{11}x_{1k} + \beta(z_1^0 + z_{21}) - z_{21} \leq z_1^0$$
$$\sum_{k=1}^{n} b_{12}x_{1k} + \beta(z_2^0 - z_{21} + z_{32}) + z_{21} - z_{32} \leq z_2^0$$
$$\sum_{k=1}^{n} b_{13}x_{1k} + \beta(z_3^0 - z_{32}) + z_{32} \leq z_3^0$$

Now, this problem is a non-linear program. However, as the number of people who participate in qualification measures (e. g. z_{21}) is expected to be rather small in our model, especially relative to the respective endowment (e.g. z_1^0),[5], the bias of the efficiency value will be negligible.

The model given by (28) to (32) is applied to calculate the gains in the economy's potential by possible qualification upgrades for the 28 countries and the years 2000 to 2014 in section 5.3.

[5]Since $z_{32} \leq \zeta z_{3a}^0$.

4. Data

The subsections of this chapter describe the data sources for the economic and environmental analysis of this paper. Note that in the application of the environmental and social analyses, data utilized in the economic analysis is included too. For several data processing steps, the free software environment R (R Core Team, 2017) and the packages `readr` (Wickham and Hester, 2020), `stringr` (Wickham, 2019), `dplyr` (Wickham *et al.*, 2020) and `tidyr` (Wickham and Henry, 2020) were used.

4.1. Economic Analysis

4.1.1. Input-Output Relations: WIOD

Data used for the economic analysis mainly comes from the World Input-Output Database (2020) (in the following: WIOD) release 2016. The WIOD provides data for 43 countries which are consolidated in a multiregional input-output-table (Timmer *et al.*, 2015).[6] The main advantage of the WIOD compared to other multiregional IOT projects (e. g. the European FIGARO project)[7] is that consistent data is available for the entire period from 2000 to 2014, which is necessary for intertemporal analyses. Furthermore, the Socio Economic Accounts (*WIOD SEA*) provide complementary data on employment, capital and prices, which is also consistent with the main input output tables. A minor drawback is that the WIOD is expressed in USD, whereas complementary data used is frequently in national currencies or Euros, which makes currency conversions necessary. This conversion, however, can easily be conducted as the WIOD specifies several economic key variables in both USD and the respective national currency. As the WIOD is denoted at current prices, we further need to deflate the data before we can utilize it for intertemporal comparisons. This is done using a (slightly adjusted) public script by Perrier *et al.* (2019), which is available at GitHub (GICN, 2019). This, in turn, builds heavily on Los *et al.* (2014) as well as the GRAS algorithm for matrix balancing described by Junius and Oosterhaven (2003) and its implementation by Temurshoev *et al.* (2013). As a result,

[6] In the following, *WIOD* (=World Input-Output Database) refers to the entire dataset including the socio-economic accounts, whereas *WIOT* (=World Input-Output Tables) refers to the input-output tables contained in the WIOD.

[7] https://ec.europa.eu/eurostat/web/experimental-statistics/figaro

multiregional input-output-tables in constant 2010 USD are created for further use in this study.

4.1.2. Output: Final demand

Final demand and total output are also taken from the WIOD and adjusted accordingly for price levels.

Table 2 summarizes the total final demand for 2000 and 2014 for all EU countries.[8] Between 2000 and 2014, Slovakia and Romania saw the strongest relative increase in final demand, amounting to almost 300 %, while final demand in the Greece, Italy and the UK only increased by around 30 %. Both in 2000 and 2014, Germany had the highest overall final demand, followed by the United Kingdom and France.

In line with Luptáčik and Mahlberg (2016), we use input-output-tables with domestic intermediate inputs only for our calculations (so-called "version B"). The inclusion of imports is possible by aggregating the respective inter-regional flows from the WIOD.

[8] Note that for a better overview, only summarized data for the years 2000 and 2014 is presented and described in this subsection.

Table 2
Descriptive statistics on final demand, 2000 and 2014

Country	Abbreviation	2000 *(Mil. Euros)*	2014 *(Mil. Euros)*	Growth rate *(Percent)*
Austria	AT	240,353	400,736	66,73
Belgium	BE	343,319	572,094	66,64
Bulgaria	BG	16,776	56,926	239,32
Cyprus	CY	12,788	20,648	61,46
Czech Republic	CZ	84,395	228,275	170,48
Germany	DE	2,293,027	3,347,463	45,98
Denmark	DK	200,877	316,691	57,65
Estonia	EE	7,728	27,528	256,20
Greece	EL	151,644	192,834	27,16
Estonia	ES	741,075	1,168,900	57,73
Finland	FI	151,533	238,654	57,49
France	FR	1,603,323	2,369,599	47,79
Croatia	HR	26,304	49,096	86,65
Hungary	HU	70,249	156,340	122,55
Ireland	IE	153,056	302,015	97,32
Italy	IT	1,351,058	1,763,735	30,54
Lithuania	LT	13,751	47,878	248,17
Luxembourg	LU	40,745	112,845	176,96
Latvia	LV	9,928	28,607	188,16
Malta	MT	7,387	15,846	114,50
Netherlands	NL	540,305	857,307	58,67
Poland	PL	214,899	498,977	132,19
Portugal	PT	146,719	200,649	36,76
Romania	RO	47,701	179,813	276,96
Sweden	SE	323,534	494,407	52,81
Slovenia	SI	25,818	46,925	81,75
Slovakia	SK	28,800	113,523	294,17
United Kingdom	UK	1,819,141	2,445,664	34,44

Note: The values are sums over all sectors in the model. All EUR values expressed in current prices. Sources: World Input-Output Database (2020), Timmer *et al.* (2015), own calculations.

4.1.3. Primary Input: Labor

Analogous to Luptáčik and Mahlberg (2016), our model uses four primary inputs: Labor – broken down by skill level in high qualified, medium qualified and low qualified – and capital. The qualification data is thereby based on the LFS (see below), which denotes the educational attainment of an individual, i. e., the highest level of education successfully completed. According to the ISCED 2011 classification[9] it is classified by ISCED levels from 0 (no formal education or less than primary education) to 8 (doctoral or equivalent). However, in publicly available statistics education levels are usually aggregated as follows and will be used likewise in our model:

1. Low: ISCED levels 0-2; no formal education or less than primary education to lower secondary education.
2. Medium: ISCED levels 3-4; upper secondary education to post-secondary, non-tertiary education.
3. High: ISCED levels 5-8; tertiary education.

In 2014, the ISCED classification used in the EU Labor Force Survey changed from ISCED 97 to ISCED 2011.[10] While those are comparable in principle, for some countries – among others Austria – this seems to result in a considerable break in the time series between 2013 and 2014, especially regarding the distribution between the medium and high-skilled level. This has to be kept in mind when interpreting the intertemporal results of 2014.

Industry-level data on total sectoral labor input comes from the WIOD Socio Economic Accounts and is measured as the number of persons engaged by sector (Variable *EMP = Number of persons engaged (expressed in thousands)*). Earlier releases of the WIOD also provided shares for labor compensation by qualification (high, medium, low). This, however, was discontinued in the 2016 release, assumingly due to data availability issues. Therefore, alternative data sources have to be utilized: A special data extract from the Labour Force Survey (EU LFS) database by Eurostat (2020h), which Eurostat has kindly made available to us, provides us with data concerning persons engaged by skill level

[9] See ISCED (2011).

[10] For details see the relevant sections of the methodological description of the EU labor force survey, available on https://ec.europa.eu/eurostat/statistics-explained/index.php/EU_labour_force_survey_-_methodology.

and NACE sector for all EU Member States as well as all required years (2000-2014). Before the data can be used, it has to be further processed, as for statistical reasons it contains gaps, especially regarding smaller countries and NACE sectors. Those values are estimated based on data available from the Eurostat Database on a more aggregated level.

The estimation procedure is done using a R script as follows:

1. In a first step, the total number of persons engaged in each sector is extracted from Eurostat (2020d, tables *lfsa_egana2d* and *lfsa_egan22d*). Since these tables also contain some gaps, those are estimated by using data from broader sectors (*lfsa_egana* and *lfsa_egan2*) and other sources by (1) using difference values (preferred), (2) by interpolating values from previous or subsequent years or, if (1) or (2) are impossible, by using sectoral employment shares from EU aggregates in order to estimate the missing values. Subsequently, these are (3) adapted by using an adjustment procedure (RAS algorithm), so that totals are consistent.[11]

2. In a second step, the gaps in the sectoral data by skill level provided in the Eurostat data extract are filled using a similar procedure: First, by calculating missing values as the difference of known values. Secondly, if that is not possible, by interpolating data from previous and subsequent years or by using EU averages and subsequently applying the RAS algorithm to match the estimates with the known totals.

3. Thirdly, the employment data for 2000-2008, which is still in the older NACE rev. 1.1 classification, has to be transformed to NACE rev. 2, so that consistent intertemporal comparisons from 2000 to 2014 are possible. This is done based on the count-seed RAS procedure suggested by Cai and Rueda-Cantuche (2019). In doing so, employment data for 2008 in NACE rev. 1.1 classification are estimated using the sectoral totals from table *lfsa_egana2d* and applying the sectoral qualification shares from 2007. Again, using the RAS algorithm and the number of correspondences from the NACE rev. 2 / NACE rev. 1.1 correspondence tables available from RAMON[12] as starting point, bridging matrices for every single country are created, fitted for every year 2000 to 2007 to total employment by qualification (Eurostat,

[11] In some cases additional steps and assumptions were necessary (e. g. for Poland LFS data on NACE 2-digit level are not available before 2004, the years 2000-2003 therefore had to be estimated based on 1-digit-data and 2004 2-digit shares.

[12] This is Eurostat's metadata server, see also https://ec.europa.eu/eurostat/ramon/.

2020d, table *lfsa_egaed*) and applied to the 2000-2007 employment data. Of course, this procedure merely produces estimates, but as we are mainly interested in the qualification shares, the bias should be negligible.

4. Finally, we apply the qualification shares from the LFS data to the number of persons engaged per sector as taken from the WIOD SEA to split it according to qualification levels.[13]

The resulting numbers of persons engaged by sector and qualification level constitute our first three primary inputs.[14] Alternatively, data on working hours could be used, which are available as well.

Data on labor endowment (available labour input) by skill category are calculated by aggregating employment by skill level as estimated in the previous step and the number of unemployed persons by skill level as taken from Eurostat (2020d, table *une_educ_a*). We therefore, in contrast to Luptáčik and Mahlberg (2016) or Mahlberg and Luptáčik (2014), interpret the labor endowment on the economy only as the active population, not the entire population of a certain age.[15]

Table 3 shows descriptive statistics on total labor input for the 28 countries in the years 2000 and 2014. For both 2000 and 2014, Germany shows the highest amount of labor input expressed in number of persons, followed by the United Kingdom, France and Italy. As an overall pattern, the values are located between 40 to 60 % of the population size of the country in the respective year, whereas exceptions from this rule exist in some cases.

[13] For some countries and sectors, the sectoral employment data differs substantially between EU LFS, which is based on survey data, and WIOT SEA, which estimates employment via employment-to-value-added ratios (although also based in part on the EU LFS).

[14] While this bridging procedure between NACE Rev. 1.1 and NACE Rev. 2 seems to work fairly well in general, there still seem to be certain instances where it leads to breaks in the time series of the qualification structure between 2007 and 2008, especially when the sectoral structure was sharply changed (e. g. the NACE Rev. 1.1 sector IA64 (post and telecommunications) was split into the NACE Rev. 2 sectors H53 (postal and courier activities) and J61 (telecommunications), which seems to cause issues regarding the qualification shares of these two sectors). While the effects on the overall results are expected to be minimal, it can have an influence on the analysis on a sectoral level until 2007. We are still looking for a better solution in that respect, for now it has to be kept in mind when interpreting the results.

[15] Alternative approaches would be an estimation based on the total population by skill level as done by Luptáčik and Mahlberg (2016) (using the Eurostat tables *lfsa_pganws* and *edat_lfse*) or using LFS data on the active population (Eurostat table *lfsa_agaed*). However, given the discrepancies between WIOD SEA and LFS employment numbers, relying on fully consistant WIOD numbers as far as possible seems preferable.

4.1.4. Primary Input: Capital

Besides labor in various skill levels, capital is the fourth primary input in the model. Data is taken from the World Input-Output Database (2020) SEA (variable *K - Nominal capital stock (in millions of national currency)*). However, this measure cannot be taken into the model directly, but must be converted to USD in constant prices beforehand. This is done by using the WIOD-implicit currency conversion factors and capital stock price indices calculated from the EU KLEMS (2019) capital accounts on the most disaggregated industry level available.[16] In accordance with Luptáčik and Mahlberg (2016), we interpret the capital stock stated in the WIOD SEA as the available capital stock and estimate the capital stock actually used by multiplying it by the average utilization rate of the industry as available from Eurostat (2020c). While we originally aimed at using sector specific utilization data, this information is only available for most sectors from 2011 onwards. For those years more sophisticated calculations based on detailed sector-specific utilization rates as provided by Eurostat (2020b) would be feasible. However, as our aim is to cover the entire 2000 to 2014 period, we chose to rely on the overall utilization rates (for a summary of the 2000 and 2014 utilization rates, see table 33 in the Appendix).

Table 3 shows descriptive statistics on total capital for the 28 countries in the years 2000 and 2014. For both years, Germany shows the highest values for capital, followed by France, the United Kingdom and Italy, whereas the latter overtook the UK in the considered time span.

[16] However, a detailed sectoral capital stock price index is not available for every country, in which case we usually rely on aggregates. For Estonia, Hungary, Lithuania, Latvia and Slovenia e. g. only data on NACE sections (1-digit) are available, for Greece, Ireland and Portugal only aggregate data for the entire economy. No data on capital stocks is contained in EU KLEMS database for Bulgaria, Cyprus, Malta and Poland, for these countries the price indices for gross fixed capital formation are used. In the case of Croatia we have to rely on the price data for Slovenia.

Table 3
Descriptive statistics on primary input requirements, 2000 and 2014

Country	Labor in 2000 *(Thousand persons)*	Labor in 2014 *(Thousand persons)*	Capital in 2000 *(Mil. EUR)*	Capital in 2014 *(Mil. EUR)*
AT	3,756	4,268	772,798	1,326,350
BE	4,109	4,550	728,579	1,190,645
BG	3,319	3,600	49,650	149,172
CY	316	358	32,115	55,229
CZ	4,859	5,109	329,009	650,140
DE	39,917	42,706	6,782,866	9,518,660
DK	2,736	2,765	557,086	839,569
EE	589	619	16,082	59,997
EL	4,308	3,963	457,098	474,356
ES	16,691	17,965	1,719,177	3,233,835
FI	2,298	2,499	401,773	663,950
FR	25,672	27,295	4,030,817	7,169,740
HR	1,598	1,570	72,682	119,662
HU	4,237	4,234	240,269	410,451
IE	1,712	1,914	227,900	479,362
IT	23,021	24,368	3,490,133	5,770,276
LT	1,399	1,317	44,785	102,820
LU	263	405	48,073	107,828
LV	924	898	24,402	70,205
MT	151	194	11,453	22,830
NL	8,207	8,727	1,293,645	2,012,041
PL	14,777	15,572	332,736	614,550
PT	5,042	4,545	294,486	591,801
RO	10,707	8,804	138,896	463,935
SE	4,301	4,750	716,805	1,347,510
SI	906	940	75,874	129,508
SK	2,013	2,223	135,130	343,278
UK	27,482	30,726	3,615,836	5,223,499

Note: The values are sums over all sectors in the model. All EUR values expressed in current prices. Labor shows the total of all three skill levels. Values for capital include non-utilized assets. For utilization rates see Table 33 in the Appendix. Sources: World Input-Output Database (2020), Timmer *et al.* (2015), Eurostat (2020d), own calculations.

4.2. Environmental Analysis

As described in sections 1 and 3, we extend the economic analysis by utilizing data on GHG emissions for our environmental analysis. In doing so, we stick closely to the methodology and data used in the empirical analysis conducted by Mahlberg and Luptáčik (2014). In their paper, besides relying on other non-publicly available data, they use freely available data on Austrian industries from the *National Accounting Matrix including Environmental Accounts* (NAMEA), which is provided by Statistics Austria (2020) on a yearly basis. Besides other key environmental variables, the NAMEA includes data on pollution, employment and abatement expenditure in the most important Austrian industries.

As we are using the same approach as Mahlberg and Luptáčik (2014), we also aim at using similar or the same data sources as in their analysis. To our knowledge, no other statistical office of any EU-27 member state or the UK provides data in a similar way as in the NAMEA. This is the reason for us almost exclusively relying on environmental variables published by Eurostat. Moreover, time series data on several crucial variables only starts in 2014, which is also why we have to restrict our environmental analysis to mainly this year. Nevertheless, we also conduct the intertemporal analysis for two selected countries, for which the largest part of the required data is available, whereby we have to make additional assumptions for certain variables. Similar to Mahlberg and Luptáčik (2014), we use data on pollution, abatement activities, labor and capital. The remainder of this section describes these environmental variables in detail.

Due to data availability reasons mentioned before, the environmental analysis can only be conducted for 16 of the 28 countries, for which calculations are made in the economic analysis. Note that if one of the variables is not available (see Table 4 for missing values), it is generally not possible to compute the whole model as assuming that one vector and/or matrix is empty can potentially distort results or make computation non-feasible. Moreover, data availability is restricted with respect to sectors. In general, data on abatement activities is only available for sectors B-E, where some of these sectors will have to be aggregated. The number of sectors per country can be taken from Table 15 in chapter 5.2.

Data on pollution for constructing the A_{12} and A_{21} matrices come from the Eurostat *Air Emissions Accounts* (AEA) (Eurostat, 2020a). More specifically, we use the data set on air emissions accounts by NACE Rev. 2 activity (table *env_ac_ainah_r2*) and extract the greenhouse gas emissions (GHG) expressed in tonnes of CO_2-equivalent for the industries of the individual countries and years for constructing A_{21}. Unlike Mahlberg and Luptáčik (2014), we restrict the analysis to types of pollution which can be expressed in CO_2-equivalents, as it is not clear how to weight further types of air pollutants when added up to GHG. This implies that in our analysis A_{12} and A_{21} are a column and a row vector, respectively.

Moreover, our analysis makes it necessary to define a tolerated level of pollution, represented in the y_2-vectors, in order to calculate the anti-pollution activity level, represented in the x_2-vectors. For calculating the tolerated pollution, we first extend the pollution time series data mentioned above to the year 1990 by utilizing index data on air emissions for the single countries, which can be also found in the AEA (Eurostat, 2020a, table *sdg_13_10*). In a next step we define a reduction goal in accordance with the newly proposed goal of the *2030 Climate Target Plan* of the European Commission (2020a). As part of this package, by mid 2021 the EU Commission will come forward with a detail legislative proposal on how to cut GHG emissions by 55 % from 1990-levels by 2030. Assuming that all countries anticipate that these goals will soon be legally binding and want to reach them, a tolerated pollution level is calculated for every country and industry, which simply amounts to 45 % of the respective 1990 values. For a sensitivity analysis we define an alternative reduction goal of 100 %, which is in line with the long term goal of the EU to be climate-neutral by 2050 (European Commission, 2020b).

Table 4 shows descriptive statistics on the environmental variables of the remaining countries in the data set for the year 2014. Germany is the biggest polluter in terms of GHG emissions of the countries in the data set. Overall, pollution levels seem to be strongly correlated with size and GDP of the respective country. While some countries, such as Spain and Cyprus, are relatively far away from reaching the agreed tolerated pollution levels in relative terms, Lithuania and Latvia actually already overachieve the agreed goals. This also means that for these two countries it is not possible to calculate the 55 % reduction scenario as non-positive values for the difference between gross and tolerated pollution are not meaningful.

Data on abatement activities for A_{12} comes from Eurostat's *Environmental Protection Expenditure Accounts* (EPEA) (Eurostat, 2020g). Mahlberg and Luptáčik (2014) utilize data on pollution abatement expenditure for climate protection and pollution control from the NAMEA for the different years and industries. According to information from Statistics Austria, these expenditures are the sum of yearly investment in so-called end-of-pipe and integrated equipment (table *sbs_env_dom_r2*) and yearly current expenditures on production of environmental protection services related to ancillary output (table *env_ac_pepsnsp*). We use the same approach in summing up those three posts, where we only take expenditure on protection of ambient air and climate (variable *CEPA1*) into account. This gives us the abatement expenditure for the single countries and industries in 2014. Overall, abatement activities seem only to be loosely connected to size, GDP and pollution level of the respective country (see Table 4). This might indicate that (private) abatement activities in a certain year largely depend on national policy measures and monetary incentives at that point in time.

To our knowledge, data on environmental capital stock for computing matrix B_2 is not available for the single industries of the 28 countries. This problem is also mentioned by Mahlberg and Luptáčik (2014) for the case of Austria. For this reason, data has to be estimated. The best public data source available is time series data on the investments in end-of-pipe and integrated equipment mentioned above. We compute the capital stock on environmental capital for the protection of ambient air and climate from the sum of the two posts. As we have no further information on the exact nature and quality of the investment made in the single countries and industries, we assume a depreciation period of seven years, which is at the lower end of the *Abschreibungstabelle für allgemein verwendbare Anlagegüter* of the German Federal Ministry of Finance (2020), in order to achieve a rather conservative estimate of the capital stock. In a final step we multiply the capital stock by the utilization rate, as described in section 4.1. Again, Table 4 shows data on the environmental capital stock of the countries in the data set. Overall, ranking the countries by environmental capital stock loosely corresponds to ranking the counties by GDP or pollution, though exceptions from this rule exist. The Polish environmental capital stock, for instance, exceeds the capital stock of all other 21 countries for which data is available, while only having a fraction of the GDP of Germany in 2014. A closer inspection of the data reveals that the biggest part of the investments is located in the energy sector, as Poland has by far the highest share of electricity produced from fossil fuels compared to the other countries (Eurostat, 2020f), which in turn could make relatively high investments in environmental capital necessary.

Furthermore, computing B_2 requires data on environmental workers. We utilize data from Eurostat (2020e, table *env_ac_egss1*) on employment in the environmental goods and services sector. In a first step we extract total employment for the single countries and industries for the year 2014 (variable *CEPA1*), expressed in full time equivalents (FTE). Next, we calculate the sum for the entire economy of every country and distribute the sum of FTEs to the three skill levels. This is done by utilizing the respective skill ratios in the single industries, described in section 4.1. Finally, we convert FTEs to number of persons using the average numbers of actual weekly hours of work in the main job for persons employed full-time or in total from Eurostat (2020d, table *lfsa_ewhan2*). Similar to abatement activities, the number of environmental workers seems to be only loosely connected to country size, GDP and pollution, as shown in Table 4.

Even though the data issues mentioned above make an intertemporal analysis difficult, the environmental analysis is conducted for two countries under certain assumptions in order to demonstrate that intertemporal comparisons are possible in principle. Assuming that the French and the Austrian environmental capital stocks did not change between 2008 and 2014, it is possible to carry out the analysis for these two years. Table 5 shows descriptive statistics on the environmental variables for the two countries in 2008. For both countries, pollution was higher in 2008, while abatement activities and labor endowment show slightly different levels compared to 2014.

Table 4
Descriptive statistics on environmental variables, 2014

Country	Pollution *(Mil. t CO_2-e)*	Tol. Pol. (45 %) *(Mil. t CO_2-e)*	Pol./ Tol. Pol.	Abatement *(Mil. EUR)*	Capital *(Mil. EUR)*	Labor *(FTEs)*
AT	58.08	26.48	2.19	359.30	463.10	8,920.00
BE	88.94	50.15	1.77	394.90	481.50	1,140.00
BG	48.63	37.93	1.28	145.50	236.40	25.00
CY	6.57	2.09	3.15	9.20	3.40	-
CZ	104.97	73.35	1.43	360.10	704.20	9,152.00
DE	780.86	478.08	1.63	3,298.00	2,665.70	29,250.00
DK	76.36	46.19	1.65	27.60	-	3,266.00
EE	20.59	17.65	1.17	(X)12.40	62.90	1,729.00
EL	84.51	39.41	2.14	4.70	43.40	-
ES	276.42	107.42	2.57	563.00	1,270.90	7,538.00
FI	55.24	29.59	1.87	224.90	454.80	1,381.00
FR	345.15	184.02	1.88	1,189.60	1,837.40	7,012.00
HR	18.48	11.19	1.65	14.50	49.20	3,691.00
HU	47.19	34.64	1.36	86.70	172.00	-
IE	52.51	22.44	2.34	-	-	160.00
IT	326.42	175.49	1.86	339.30	1,475.00	10,163.00
LT	21.97	23.54	0.93	104.50	267.70	236.00
LU	7.66	3.78	2.03	-	-	6.00
LV	10.56	10.87	0.96	1.30	1.60	467.00
MT	3.74	1.42	2.62	-	-	5.00
NL	174.56	89.57	1.95	-	-	3,371.00
PL	347.03	190.44	1.82	1,455.30	2,725.30	21,027.00
PT	54.95	22.31	2.46	55.40	221.60	526.00
RO	103.30	98.90	1.04	279.50	776.90	5,282.00
SE	51.68	30.05	1.72	378.80	1,007.30	1,379.00
SI	13.82	6.97	1.98	131.40	522.50	2,064.00
SK	35.16	28.46	1.24	45.00	153.70	-
UK	448.55	292.53	1.53	149.20	-	13,384.00

Note: The values are sums over all sectors in the model. Labor shows the total of all three skill levels. Values for capital include non-utilized assets. For utilization rates see Table 33 in the Appendix. (X) indicates that data is not reliable and therefore not used in calculations. Sources: Eurostat (2020a), Eurostat (2020g), Eurostat (2020e), own calculations.

Table 5
Descriptive statistics on environmental variables, 2008

Country	Pollution *(Mil. t CO_2-e)*	Tol. Pol. (45 %) *(Mil. t CO_2-e)*	Pol./ Tol. Pol.	Abatement *(Mil. EUR)*	Capital *(Mil. EUR)*	Labor *(FTEs)*
AT	68.19	26.48	2,58	420.10	463.10	8,078.00
FR	399.24	184.02	2,17	1,194.90	1,837.40	8,107.00

Note: The values are sums over all sectors in the model. Labor shows the total of all three skill levels. Values for capital include non-utilized assets. For utilization rates see table 33 in the Appendix. Sources: Eurostat (2020a), Eurostat (2020g), Eurostat (2020e), own calculations.

4.2.1. Estimating Data

As theoretical considerations and empirical results (see section 5.2) indicate that the environmental analysis analogous to Mahlberg and Luptáčik (2014) does not yield meaningful results in the context of this study, data on x_2 for calculating A_{12} is estimated. This means that we estimate the amount of GHG emmissions reduction that is induced by a one unit increase in abatement activities. Sophisticated literature on carbon abatement cost and influencing factors of GHG emissions exists (see for example Du *et al.* (2015) or Wen and Shao (2019)), but the corresponding empirical models are not applicable in the context of this study due to restricted data availability. This is why we utilize a simple first difference ordinary least squares (OLS) estimator (see for example Baltagi (2008) or Wooldridge (2010)) in order to estimate the emissions reduction per unit of abatement activity for our set of countries. Suppose GHG emissions (y) in a specific point in time (t) can be expressed by the following function:

$$y_t = f(x_t; Z_t) \tag{33}$$

where x are abatement activities, Z are covariates and $f(\cdot)$ is the function relating to these. Our regression model then is:

$$y_t = \alpha\iota + \delta t + \beta x_t + \gamma Z + \epsilon_t \tag{34}$$

where y is an $N \times 1$ vector of the observations of the dependent variable (GHG emissions, as described in secion 4.2) for every unit i ($i = 1, \ldots, N$) in the data set.[17] ι is an $N \times 1$ vector consisting of ones associate with the intercept parameter α, where α is a scalar. x is an $N \times 1$ vector constituted by the observations on the independent variable (abatement activities, as described in secion 4.2) and β is a parameter scalar associated with x. δ is a trend term scalar and t is an $N \times 1$ vector that indicates the period (the year 2015). Z is an $N \times K$ vector of dummy variables for the industries and countries, γ is the associated $K \times 1$ parameter vector. Note that characteristics captured by Z do not change over time. ϵ is the error term. It is an $N \times 1$ vector consisting of N independently and identically distributed random variables centered around zero with a variance of σ^2.

[17] Note: The units in the data set for the regression model are aggregated industries A, B, C, D, E36 and an "other"-sector as definded by Eurostat (2020g) for every country of the 28 countries where data is available, summing up to 73 data points in total.

Now obviously:

$$y_{t-1} = \alpha\iota + \delta(t-1) + \beta x_{t-1} + \gamma Z + \epsilon_{t-1} \tag{35}$$

Note that t indicates the year 2015 and $t-1$ the year 2014. The difference of equation 34 and 35 gives:

$$y_t - y_{t-1} = \alpha\iota + \delta t + \beta x_t + \gamma Z + \epsilon_t - [\alpha\iota + \delta(t-1) + \beta x_{t-1} + \gamma Z + \epsilon_{t-1}] \tag{36}$$

Which further simplifies to:

$$\Delta y_t = \delta + \beta \Delta x_t + \Delta \epsilon_t \tag{37}$$

where Δ is the difference operator. Note that the time invariant intercept parameter α disappears and only the time trend δ remains. Assuming that the error term consists of a time invariant and a time variant component, only the latter, captured by $\Delta\epsilon_t$, remains. Furthermore, time invariant dummy variables in Z cancel out as well. Assuming that our explanatory variables and the error term are uncorrelated, OLS is unbiased.

Using this model allows us to estimate how much one unit change in abatement activities changes the emission of GHG, while controlling for industry, country and other unobserved characteristics, as well as the time trend. Table 6 shows empirical results of the described estimation procedure, where column (1) shows results for the model without and model (2) for the model with intercept parameter. Model (2), from which results are further used in this study, shows that increasing abatement activities by one million euros decreases emissions by 12,684.36 tons. Coefficient estimates for abatement activities are highly significant in both model specifications.

The estimation procedure above is carried out in order to demonstrate the capabilities of the environmental model. We want to stress again that our estimation very likely suffers from several shortcomings. Most importantly, the true functional form of equation 33 is not known to us. It is very likely that the relationship between emissions is nonlinear, with decreasing marginal effects and probably several threshold effects when certain abatement levels are reached. Moreover, due to restricted data availability, only one single parameter is estimated for our whole data set, while relying on industry and country dummies to control for specific characteristics. If a larger data set was available, it would be more adequate to estimate several coefficients for single countries or single industries.

Table 6
First difference OLS estimation results

	Dependent variable:	
	Emissions (tons)	
	(1)	(2)
Abatement (Mill. EUR)	−11,549.300***	−12,684.360***
	(3,796.978)	(3,898.818)
Constant (Time trend)		256,177.800
		(211,364.200)
Observations	73	73
R^2	0.114	0.130
Adjusted R^2	0.102	0.117
Residual Std. Error	1,758,726.000 (df = 72)	1,753,025.000 (df = 71)
F Statistic	9.252*** (df = 1; 72)	10.585*** (df = 1; 71)
Note:		*p<0.1; **p<0.05; ***p<0.01

5. Results

5.1. Economic Analysis

This chapter shows the results regarding the economic potentials of the countries in our data set and their deviations from it. First, the findings for Austria are presented and thoroughly discussed. Secondly, a depiction of the results for the other 26 EU members and the UK is provided. While all three described models, namely the SBM, DDF and radial model (see chapter 3 for their definitions), have been calculated, we often use the DDF model as a primary source for the presented results. A detailed comparison between the results for all three models will only be made in selected cases.

5.1.1. Economic Analysis for Austria

This section shows the results of the economic analysis for Austria for the years 2000 to 2014. Table 7 offers a direct comparison between the static results of the three models.

Static (in)efficiency scores indicate how far the production of an economy deviates from its current potential. In case of the SBM and radial model, the results can be interpreted as follows: The closer a value is to one, the closer the country was to realizing its full economic potential (both are input-oriented models, i. e., they aim at producing given outputs using minimal inputs) in the respective year. The values of the SBM model are always lower than those of the radial model due to the inherent properties of the models. The reason is that the radial model only considers the scarcest and most utilized primary input (in most cases high-skilled labor) when calculating efficiency, while the SBM model integrates slacks of all inputs, leading to overall lower levels of efficiency. This difference is also apparent from Figure 1. The DDF model, in contrast, provides inefficiency scores, which means that the higher a particular value (deviations from zero), the more the economy deviates from its full potential. Furthermore, it is an unoriented model, aiming at increasing outputs and reducing inputs at the same time.

The results in Table 7 and their graphical depiction in Figure 1 show a fairly similar pattern across models, which indicates an overall robustness of the models in question. Particularly the DDF and the radial model share similar paths. Both start at a highly efficient level (0.75 % DDF; 98.5 % radial) and keep up their performance over the time period considered. After rising inefficiency levels between 2003 and 2004, efficiency improved again the following years, only to drop considerably as a result of the financial crisis. In 2009, the DDF model shows an inefficiency score of 1.3 % and the radial model an efficiency score of 97.4 %. Although the results somewhat improved in 2012 (1.2 % DDF; 97.7 % radial), inefficiency rose sharply in the two years that followed. For 2013, this can be explained by a clear increase of the unemployment rate, especially among high qualified (from 2.4 % to 3.5 % of the active high qualified population). The unfavorable scores of 2014 must be attributed to data peculiarities.[18] All in all, the SBM model depicts sharper rises and declines of efficiency. With an efficiency score of less than 90 % in 2009, no other model shows the effect of the financial crisis more clearly. This is not a surprise, as it is the only of the three models to account for unutilized inputs beyond the scarcest one (see below).

[18] A data break caused by the switch from ISCED 97 to ISCED 2011 leads to a considerable increase of high qualified labor in the statistics, which is why the comparability of the results for 2014 to earlier years is very limited.

Table 7
(In)efficiency scores for Austria, 2000-2014

Years	DDF	radial	SBM
2000	0.0075	0.9850	0.9438
2001	0.0073	0.9854	0.9396
2002	0.0079	0.9843	0.9319
2003	0.0097	0.9809	0.9305
2004	0.0165	0.9675	0.9223
2005	0.0151	0.9702	0.9200
2006	0.0145	0.9715	0.9269
2007	0.0135	0.9733	0.9320
2008	0.0093	0.9816	0.9331
2009	0.0131	0.9740	0.8996
2010	0.0125	0.9753	0.9157
2011	0.0127	0.9748	0.9257
2012	0.0115	0.9772	0.9215
2013	0.0172	0.9662	0.9144
2014	0.0196	0.9615	0.9118

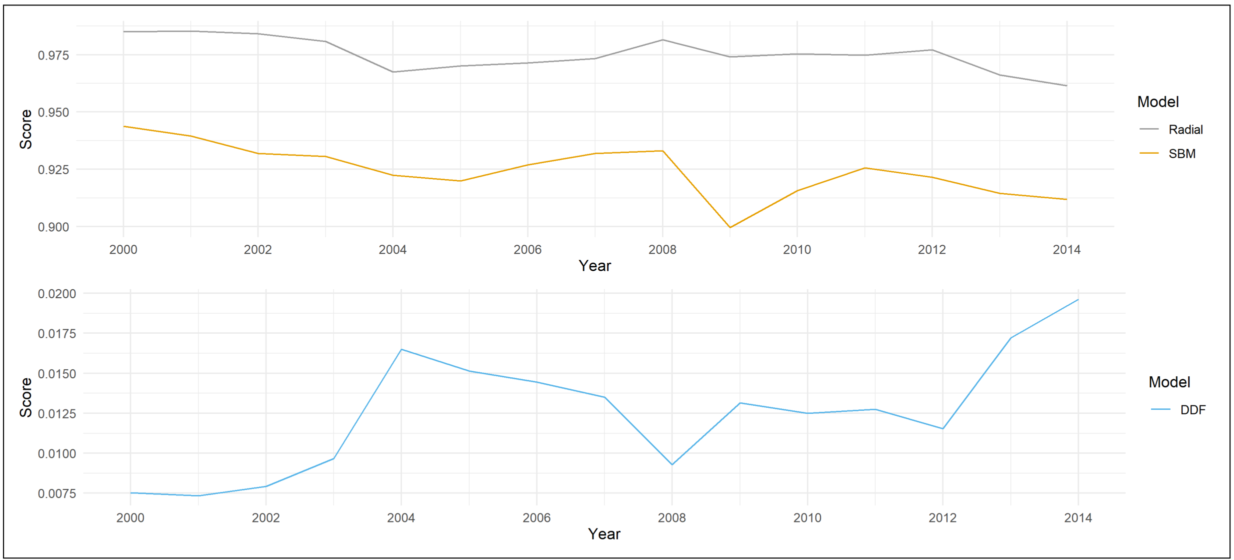
So far we have had a look on the static (in)efficiency scores for Austria obtained from the different models. They, however, reveal little about the sources of the existing inefficiencies. Further insight in that respect can be obtained from the shadow prices for the different primary inputs and commodities, which can be obtained from the dual formulation of the respective models.

We start with the DDF model, the properties of which have already been discussed by Luptáčik and Mahlberg (2016). For primary inputs, the shadow prices in their model formulation are non-negative. They express the effect of a change in the respective input ceteris paribus on inefficiency. On the one hand, a positive shadow price indicates that an increase in the endowment of the respective input raises inefficiency (or decreases efficiency), because now a larger portion of that input is not utilized. On the other hand, a shadow price of zero implies that additional input endowment does not influence the inefficiency scores. Shadow prices regarding final demand are non-positive. Negative values signal that an increase in final demand of the respective commodity reduces inefficiency (or increases efficiency) of the economy.

The shadow prices obtained for Austria are displayed in Table 34 in the appendix. In the DDF model, only the scarcest primary input is assigned a positive shadow price, as inefficiency only depends on that scarcest input. For Austria this is high qualified labor (ISCED levels 5-8) over the entire analyzed period. It can also be seen that the shadow

Figure 1

(In)Efficiency scores for Austria, DDF, radial and SBM model, 2000-2014



price has decreased steadily, from 0.00084 in 2000 to 0.00056 in 2013, indicating that high qualified labor became less scarce over time. This is in line with unemployment data, according to which unemployment among highly qualified has increased from 1.6% of the active population in 2000 to 3.5% in 2013. On the other hand, the decrease of shadow prices was offset by an increased number of high qualified persons engaged in the economy, with the effect that the virtual costs of high qualified labor (shadow price multiplied by quantity) remained more or less unchanged.[19] Taking a look at the output side (i. e. final demand) we see that an increase in the final demand for any commodity would decrease inefficiency in any year and therefore push the economy closer towards its potential. However, the effects vary substantially between sectors and over time. The highest shadow prices and therefore the biggest steps towards Austria's potential are present in sectors P85 (education), M72 (scientific research and development) and M74_M75 (other professional, scientific and technical activities; veterinary activities), indicating that an increased demand in those sectors would reduce inefficiency the most. This is not surprising, given that those sectors are especially high-skilled labor intensive. Although the top sectors were relatively stable over time, a few sectors also experienced considerable changes of the shadow prices during the analyzed period. An example is the clearly negative trend of C19 (manufacture of coke and refined petroleum products), especially after 2009, which seems to indicate less demand for high-skilled labor in this

[19] For the relevant labor market data see Eurostat (2020d)

sector. Conversely, the shadow prices of several industrial and transport sectors (e. g. C18, C23, C25) have increased over time. Furthermore, it can be observed that the shadow prices for commodities in general became more equal over time, an observation also made by Luptáčik and Mahlberg (2016) for the United States. The shadow prices from the input-oriented radial model developed by Luptáčik and Böhm (2010) essentially yield similar results, while those from the SBM model are less informative.[20]

Up until now, only static results for individual years have been discussed. These (in)efficiency scores simply indicate, how far the actual production of an economy deviates from its current potential. They do however not reveal whether productivity at large has increased or decreased over time and which factors have contributed to that development.

These questions are addressed by the intertemporal analysis models introduced in section 3.5. Both intertemporal productivity measures presented there - the Malmquist-based productivity index as well as the Luenberger productivity indicator - are based on intertemporal or mixed period (in)efficiency scores, which relate the outputs (final demand for various commodities) and inputs (primary inputs capital and labor) of a certain year to the production possibilities (technology) of another year. Table 8 displays these intertemporal inefficiency scores for Austria in the DDF model. The main diagonal contains the single period scores already shown in Table 7. Interestingly enough, the values on both sides of the main diagonal quickly become negative as the year of the technology used diverges from the year of inputs and outputs analyzed. If we take the years 2000 and 2013 as an example, the value of -0.156 (inputs and outputs of 2013 evaluated using the technology of 2000) indicates super-efficiency, i. e., the final demand of 2013 cannot be met using the endowment of primary inputs of 2013 and the technology of 2000. On the other hand, the final demand of 2000 cannot be produced using 2000's available inputs and the technology of 2013 either, which is why the respective value (-0.075) is negative as well. This is a first sign that technological changes have taken place. If we take a closer look at required inputs and their respective endowments, it becomes clear that production became considerably more skill-intensive over time. While in 2000 only 15.8 % of persons engaged in production had an education level of ISCED 5-8, the share had increased to 20.9 % in 2013. At the same time the share of low qualified labor (ISCED

[20] Due to the model formulation, the shadow prices of the SBM model mainly reflect labor endowment, not scarcity.

0-2) declined steadily. Therefore, in mixed period analyses using newer technology, high qualified labor is often lacking. An evaluation of more recent years combined with the use of older technology shows that there are frequently not enough low qualified workers available to meet the demand. Basically, the same observations can be drawn from the mixed period efficiency scores of the input-oriented radial and the SBM model presented in Tables 23 and 24 in the appendix. Note that super-efficiency is represented by numbers greater than one in these models.

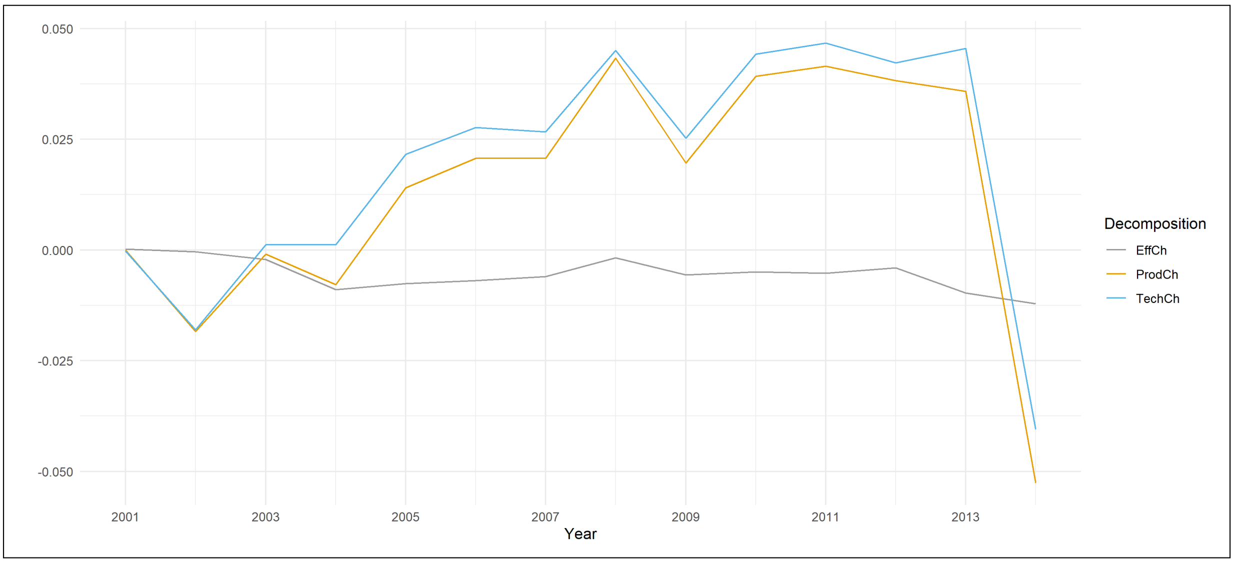
Table 8

Intertemporal inefficiency scores for Austria, DDF model, 2000-2014

-	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
2000	0.008	0.005	-0.047	-0.025	-0.068	-0.032	-0.015	-0.011	-0.011	-0.050	-0.041	-0.042	-0.064	-0.075	-0.276
2001	0.005	0.007	-0.045	-0.023	-0.065	-0.029	-0.012	-0.008	-0.007	-0.047	-0.038	-0.038	-0.060	-0.072	-0.274
2002	-0.011	-0.004	0.008	0.011	-0.012	0.024	0.041	0.046	0.040	0.006	0.015	0.015	-0.007	-0.019	-0.223
2003	-0.026	0.000	-0.013	0.010	-0.033	0.004	0.021	0.025	0.025	-0.015	-0.006	-0.006	-0.028	-0.039	-0.243
2004	-0.061	-0.036	-0.017	0.005	0.017	0.024	0.039	0.041	0.038	0.022	0.027	0.035	0.021	0.010	-0.196
2005	-0.068	-0.042	-0.024	-0.001	-0.020	0.015	0.032	0.035	0.037	-0.004	0.007	0.007	-0.015	-0.027	-0.231
2006	-0.064	-0.038	-0.020	-0.010	-0.039	-0.003	0.014	0.019	0.019	-0.022	-0.012	-0.011	-0.034	-0.045	-0.249
2007	-0.058	-0.040	-0.026	-0.026	-0.044	-0.009	0.007	0.014	0.007	-0.030	-0.019	-0.019	-0.040	-0.052	-0.257
2008	-0.099	-0.073	-0.055	-0.032	-0.046	-0.012	0.006	0.004	0.009	-0.032	-0.022	-0.021	-0.043	-0.054	-0.258
2009	-0.095	-0.070	-0.052	-0.029	-0.004	0.023	0.014	0.005	0.038	0.013	0.022	0.022	0.000	-0.011	-0.214
2010	-0.125	-0.100	-0.082	-0.059	-0.016	-0.005	-0.015	-0.024	0.013	0.002	0.012	0.012	-0.010	-0.020	-0.223
2011	-0.130	-0.105	-0.087	-0.065	-0.022	-0.010	-0.020	-0.029	0.008	0.001	0.011	0.013	-0.010	-0.020	-0.224
2012	-0.144	-0.120	-0.102	-0.080	-0.036	-0.025	-0.035	-0.044	-0.008	0.003	0.015	0.024	0.012	0.001	-0.204
2013	-0.156	-0.132	-0.115	-0.092	-0.049	-0.038	-0.048	-0.057	-0.021	-0.010	0.011	0.017	0.021	0.017	-0.188
2014	-0.183	-0.159	-0.142	-0.119	-0.077	-0.071	-0.075	-0.084	-0.054	-0.069	-0.063	-0.054	-0.056	-0.054	0.020

Figure 2

Decomposition of efficiency change, technical change and productivity change, DDF model, Austria, 2000-2014



In the next step, we calculate the Luenberger productivity indicator for the DDF model as applied by Luptáčik and Mahlberg (2016). The corresponding method can be found in section 3.5. The non-oriented proportional Luenberger indicator describes the productivity change (ProdCh) between two years and expresses it as the sum of efficiency change (EffCh or “catch-up”) and technical change (TechCh or “frontier shift”). The results for the DDF model are summarized in Figure 2. The lines represent the changes of productivity, technology and efficiency relative to the year 2000. Furthermore, the Luenberger indicator and both components can be decomposed in a way that displays the respective contributions of the individual commodities and primary inputs (see Luptáčik and Mahlberg (2016)). The Luenberger indicator, relative to the year 2000, and the contributions of inputs and sectors are displayed as an example in Table 26 in the appendix, technical change and efficiency change are covered in Tables 27 and 28. Similar tables have been calculated for every possible combination of years between 2000 and 2014, but are not included in the report, as their depiction would be too lengthy.

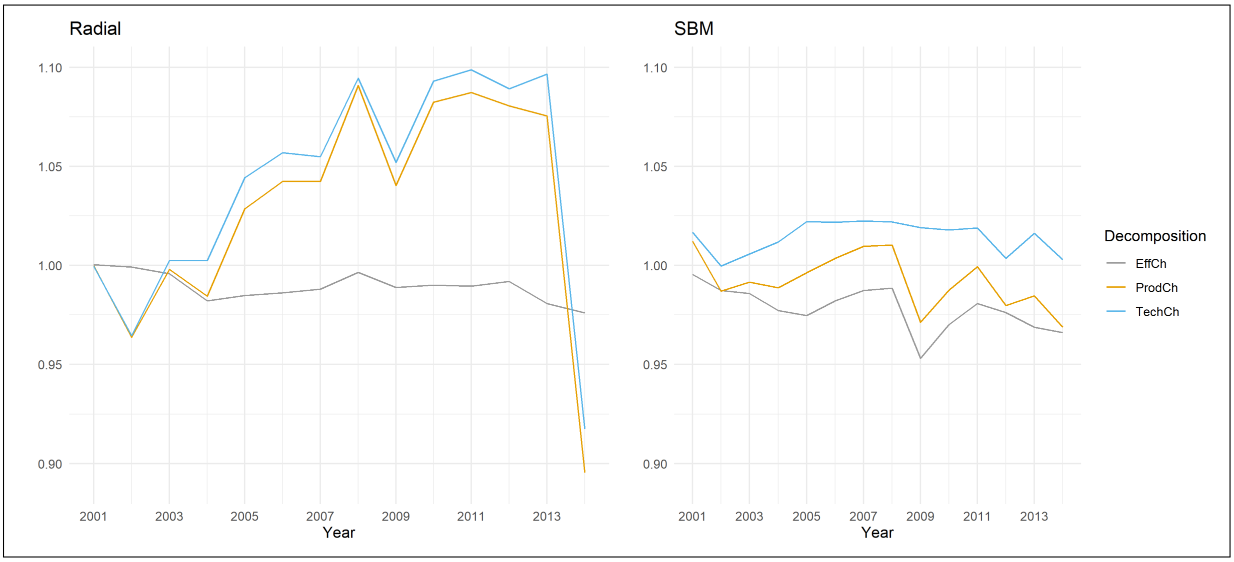
Starting with productivity change, the productivity in the Austrian economy merely stagnated between 2000 and 2001, but decreased by around 2.1 % in 2002 and, after recovering in 2003, again in 2004 (-2.2%). From 2004 until 2008 a steady productivity growth of 4.6 % in total (2008 relative to 2004) can be observed, mainly driven by technical change. During the financial crisis, the Austrian economy experienced a considerable productivity drop in 2009 (-3.7 %). Surprisingly, productivity almost fully recovered in 2010 and afterwards merely stagnated until 2013. Finally, the results for 2014 display another severe productivity drop, which, however, is mainly due to data peculiarities and is therefore not further analyzed.

To shed further light on the reasons for this development, we take a look at both components of the Luenberger indicator as well as their decomposition. First, it can be noted that productivity development was almost exclusively driven by technical change, while efficiency changes - although still relevant - only contributed to a very limited extent, as the Austrian economy was relatively near its potential through the entire observation period. Still, as already covered in this chapter, inefficiency fluctuated slightly and was approximately 1.0 percentage points higher in 2013 than in 2000. On the input side this can primarily be attributed to high qualified labor, the utilization of which decreased over time, especially between 2003 and 2004 and again between 2012 and 2013. Given the increase of the unemployment rates of highly qualified persons in the respective years, this result is plausible. Regarding outputs, most sectors only had marginal effects on efficiency development between 2000 and 2013. Most noteworthy are a positive contribution to efficiency development from the human health and social work activities-sector (Q) and a negative from education (P85).

Technical development (TechCh) on the other hand had a much stronger impact on productivity and therefore displays a similar development as productivity change (ProdCh). After remaining nearly unchanged in 2001, it decreased by around 2.0% in 2002. This decline can be mainly attributed to medium-skilled labor and the sectors P85 and Q, while at the same time it was offset to some degree by the positive impacts of high qualified labor and - to a smaller degree - several commodity sectors (first of all G47, F, I and G46). Between 2002 and 2008 technical change led to a considerable expansion of the production potential by 4.7 % in total (compared to 2002). Both inputs and outputs contributed thereto. On the primary input side medium qualified labor had a large positive effect - in some years also high qualified labor -, which was thwarted by a less pronounced negative effect of low qualified labor. During the financial crisis, in which the Austrian economy suffered from a considerable productivity drop in 2009 (-3.7 %), technical regress (-3.3 %) was the main factor as well, but also efficiency decreased to some extent (-0.4 %), as we have already seen from the inefficiency scores. This technical regress of 2009 can be further traced back to a (relative) decrease in the supply of medium-skilled labor, which reduced the production potential, while an the increase in the number of highly qualified persons in the workforce mitigated the effect. On the output side, the model attributes most of the negative technical change to the education sector (P85), whereas retail (G47) and accommodation and food service activities (I) had a positive effect on Austria's potential. Afterwards, technology (and productivity) quickly recovered in 2010 and more or less stagnated until 2013.

To check these results, we can have a look at the Malmquist productivity indices calculated for the radial and the SBM model, which are depicted in Figure 3. As can be seen, the trends of the Malmquist productivity index of the radial model as well as both components (TechCh and EffCh) are indeed very similar to the DDF model, which is no surprise, given the models share a similar structure. The SBM model, in contrast, displays a less pronounced technical development, but stronger efficiency changes. This seems plausible, given that efficiency is defined more broadly and includes also non-scarce primary inputs, and also technology is less dependent on scarce inputs than the other models. For that reason, the severe decline in technology seen in the radial and DDF models in 2014, which is merely a consequence of a sudden hike in the share of high qualified labor due to the ISCED-reclassification, is not that pronounced in the SBM model.

Figure 3
Decomposition of efficiency change, technical change and productivity change, io radial and SBM models, Austria, 2000-2014, base year 2000



Similar calculations as for Austria were conducted for the other 26 Member States and the UK. The results are summarized in the following section.

5.1.2. Economic Analysis for the EU 27 and the UK

This subsection covers the results of the economic analysis at the EU level (27 EU members and the UK). Tables 9 to 14 show efficiency scores for the years 2000 to 2014 for all three models, those being the non-oriented proportional directional distance function model (DDF), the input-oriented radial model as well as the input-oriented slacks-based measure model (SBM).

Tables 9 and 10 describe the deviations from the individual annual economic potential with given inputs in a static manner within the DDF model. Table 9 provides an overview of the inefficiency scores between the years 2000 and 2007, while Table 10 shows the results for 2008 to 2014. Just like in Table 7, the scores of the DDF model describe inefficiencies rather than efficiency levels (radial and SBM model). Here, inefficiency levels decrease the closer a value is to 0. Unlike the DDF model, the radial and the SBM model (Tables 11 to 14) operate with efficiency levels. The closer a value is to 1, the closer the respective country is to tapping its full economic potential, which means the maximum production output feasible for the given level of inputs.

Roughly half of the countries start at a fairly low inefficiency level at below 2 %, as can be seen in Table 9. These countries are Austria, Germany, Belgium, the Netherlands, Denmark, Sweden, Luxembourg, Slovenia, the United Kingdom, the Czech Republic, Hungary, Ireland and Portugal. It should be noted that each country's score has been calculated based on their very own potential. A few countries, those being Austria, the Netherlands, Luxembourg and the Czech Republic, remain under 2 % throughout the period considered. Another group, including France, Italy and Finland, share similar scores mainly between 2 % and 3 %. A third group of countries show comparably high inefficiency scores during the whole period ranging from around 3 % to over 10 %. Among these rather poorly performing countries are Spain, Greece, Estonia, Latvia and Lithuania. The only country within this data set to fully maximize their output and therefore reaching its full potential with given inputs is Malta in 2008. The reason for that is an only minuscule number of unemployed people categorized as highly skilled in this particular year, which was rounded down to zero. In other words, every measurable increase of output would have required an expansion of capacity.

The financial crisis of 2007-2008 has shaken national economies worldwide. Its consequences can also be detected in the results of this study as an increase of inefficiency in

2009 compared to the previous year. The extent of the decline between 2008 and 2009 varies between -0.04 % (Germany) and -2.03 % (Latvia). Among the countries with a particular steep decline are Spain and the Baltic Member States (Estonia, Latvia and Lithuania), which can be traced back, in part, to a more severe increase in unemployment than in most other European countries (see Eurostat (2020d)). As a result, available inputs, such as labor, could not be utilized as efficiently as in previous years. The exceptions are Slovenia and Portugal, both with a slight increase between 2008 and 2009, but, slightly delayed, with a significant drop in the years that followed. Another noteworthy example is Ireland, which performed rather well until 2008 with inefficiency scores of less than 2 %, only to experience a sharp rise from 2009 to 2012 with a maximum inefficiency of 4.12 %. In some cases, notably Greece and Cyprus, efficiency levels continued to decrease sharply in the subsequent years. Missing data for the years 2000 to 2007, however, does not permit a thorough analysis of the effect of the financial crisis for Cyprus and Hungary. To sum up, the effect of the crisis is clearly visible for the vast majority of countries in all three models (see also Tables 11, 12, 13 and 14).

Figure 4

Inefficiency scores for selected countries, DDF model, 2000-2014

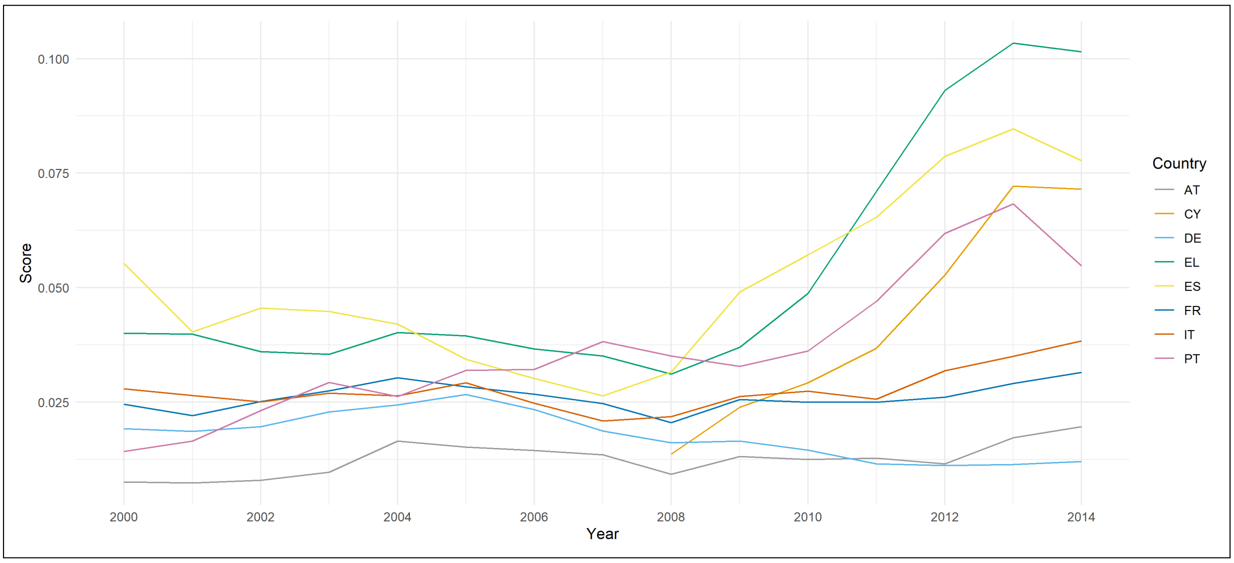


Table 9
Inefficiency scores for the EU 27 and the UK, 2000-2007, DDF model

Country	2000	2001	2002	2003	2004	2005	2006	2007
AT	0.0075	0.0073	0.0079	0.0097	0.0165	0.0151	0.0145	0.0135
BE	0.0164	0.0173	0.0202	0.0225	0.0236	0.0223	0.0226	0.0189
BG	0.0346	0.0446	0.0417	0.0330	0.0272	0.0197	0.0184	0.0115
CY	NA	NA	NA	NA	NA	NA	NA	NA
CZ	0.0140	0.0123	0.0106	0.0104	0.0105	0.0113	0.0115	0.0075
DE	0.0192	0.0186	0.0197	0.0228	0.0244	0.0267	0.0234	0.0187
DK	0.0162	0.0195	0.0204	0.0242	0.0241	0.0193	0.0159	0.0142
EE	0.0358	0.0370	0.0334	0.0350	0.0282	0.0217	0.0170	0.0109
EL	0.0401	0.0398	0.0360	0.0354	0.0402	0.0395	0.0366	0.0351
ES	0.0553	0.0403	0.0455	0.0448	0.0420	0.0343	0.0302	0.0264
FI	0.0263	0.0243	0.0215	0.0219	0.0242	0.0231	0.0191	0.0189
FR	0.0245	0.0220	0.0251	0.0274	0.0303	0.0284	0.0268	0.0247
HR	NA	NA	NA	NA	NA	NA	NA	NA
HU	0.0081	0.0073	0.0092	0.0085	0.0114	0.0134	0.0131	0.0135
IE	0.0082	0.0107	0.0139	0.0152	0.0133	0.0132	0.0141	0.0141
IT	0.0279	0.0264	0.0251	0.0269	0.0264	0.0292	0.0247	0.0209
LT	0.0495	0.0383	0.0352	0.0350	0.0335	0.0197	0.0133	0.0102
LU	0.0069	0.0050	0.0052	0.0114	0.0157	0.0121	0.0148	0.0111
LV	0.0348	0.0324	0.0258	0.0242	0.0241	0.0222	0.0196	0.0180
MT	NA	NA	NA	0.0149	0.0200	0.0191	0.0183	0.0169
NL	0.0094	0.0074	0.0106	0.0134	0.0153	0.0176	0.0138	0.0115
PL	0.0249	0.0282	0.0357	0.0391	0.0383	0.0368	0.0303	0.0236
PT	0.0142	0.0165	0.0231	0.0293	0.0262	0.0319	0.0321	0.0382
RO	NA	0.0197	0.0226	0.0178	0.0183	0.0191	0.0187	0.0144
SE	0.0138	0.0115	0.0136	0.0174	0.0196	0.0213	0.0217	0.0177
SI	0.0099	0.0105	0.0127	0.0163	0.0157	0.0173	0.0158	0.0169
SK	0.0277	0.0252	0.0224	0.0236	0.0278	0.0245	0.0161	0.0197
UK	0.0141	0.0124	0.0142	0.0137	0.0134	0.0131	0.0141	0.0130

Table 10
Inefficiency scores for the EU 27 and the UK, 2008-2014, DDF model

Country	2008	2009	2010	2011	2012	2013	2014
AT	0.0093	0.0131	0.0125	0.0127	0.0115	0.0172	0.0196
BE	0.0180	0.0223	0.0226	0.0189	0.0199	0.0246	0.0234
BG	0.0107	0.0136	0.0211	0.0238	0.0275	0.0307	0.0234
CY	0.0136	0.0239	0.0293	0.0368	0.0528	0.0722	0.0715
CZ	0.0075	0.0116	0.0137	0.0138	0.0140	0.0136	0.0140
DE	0.0161	0.0165	0.0145	0.0115	0.0111	0.0113	0.0120
DK	0.0111	0.0182	0.0233	0.0259	0.0246	0.0234	0.0244
EE	0.0149	0.0312	0.0498	0.0413	0.0325	0.0300	0.0233
EL	0.0311	0.0370	0.0487	0.0710	0.0931	0.1034	0.1015
ES	0.0316	0.0490	0.0572	0.0654	0.0786	0.0847	0.0777
FI	0.0164	0.0202	0.0224	0.0200	0.0198	0.0222	0.0260
FR	0.0205	0.0254	0.0250	0.0250	0.0260	0.0291	0.0315
HR	0.0265	0.0318	0.0428	0.0476	0.0564	0.0590	0.0513
HU	0.0134	0.0191	0.0230	0.0210	0.0223	0.0194	0.0154
IE	0.0197	0.0379	0.0417	0.0424	0.0412	0.0387	0.0362
IT	0.0218	0.0262	0.0274	0.0257	0.0319	0.0350	0.0384
LT	0.0150	0.0311	0.0397	0.0316	0.0284	0.0257	0.0211
LU	0.0107	0.0128	0.0125	0.0119	0.0148	0.0140	0.0154
LV	0.0202	0.0405	0.0559	0.0380	0.0340	0.0312	0.0283
MT	0.0000	0.0152	0.0139	0.0129	0.0124	0.0109	0.0101
NL	0.0104	0.0136	0.0154	0.0155	0.0167	0.0205	0.0199
PL	0.0195	0.0225	0.0257	0.0268	0.0288	0.0293	0.0242
PT	0.0351	0.0328	0.0362	0.0470	0.0618	0.0683	0.0547
RO	0.0136	0.0222	0.0246	0.0237	0.0262	0.0279	0.0295
SE	0.0180	0.0235	0.0248	0.0223	0.0231	0.0232	0.0231
SI	0.0162	0.0157	0.0207	0.0249	0.0308	0.0306	0.0302
SK	0.0177	0.0212	0.0300	0.0300	0.0348	0.0367	0.0326
UK	0.0143	0.0206	0.0209	0.0223	0.0221	0.0202	0.0163

Table 11
Efficiency scores for the EU 27 and the UK, 2000-2007, radial model

Country	2000	2001	2002	2003	2004	2005	2006	2007
AT	0.9850	0.9854	0.9843	0.9809	0.9675	0.9702	0.9715	0.9733
BE	0.9677	0.9659	0.9603	0.9559	0.9538	0.9564	0.9557	0.9628
BG	0.9331	0.9146	0.9199	0.9361	0.9471	0.9614	0.9639	0.9773
CY	NA	NA	NA	NA	NA	NA	NA	NA
CZ	0.9724	0.9756	0.9790	0.9795	0.9791	0.9776	0.9773	0.9851
DE	0.9623	0.9635	0.9614	0.9553	0.9523	0.9481	0.9543	0.9633
DK	0.9681	0.9618	0.9601	0.9527	0.9529	0.9621	0.9687	0.9719
EE	0.9308	0.9286	0.9354	0.9323	0.9451	0.9576	0.9665	0.9785
EL	0.9230	0.9234	0.9304	0.9316	0.9227	0.9240	0.9293	0.9322
ES	0.8952	0.9224	0.9129	0.9143	0.9194	0.9336	0.9414	0.9486
FI	0.9487	0.9525	0.9579	0.9571	0.9528	0.9548	0.9625	0.9629
FR	0.9521	0.9569	0.9510	0.9466	0.9411	0.9448	0.9479	0.9518
HR	NA	NA	NA	NA	NA	NA	NA	NA
HU	0.9839	0.9855	0.9817	0.9832	0.9775	0.9736	0.9741	0.9735
IE	0.9838	0.9789	0.9726	0.9701	0.9737	0.9739	0.9722	0.9722
IT	0.9457	0.9485	0.9511	0.9476	0.9486	0.9432	0.9517	0.9591
LT	0.9057	0.9263	0.9320	0.9323	0.9352	0.9613	0.9737	0.9798
LU	0.9863	0.9900	0.9896	0.9775	0.9690	0.9761	0.9709	0.9780
LV	0.9328	0.9373	0.9497	0.9527	0.9528	0.9566	0.9616	0.9646
MT	NA	NA	NA	0.9706	0.9607	0.9624	0.9640	0.9669
NL	0.9815	0.9852	0.9791	0.9736	0.9698	0.9653	0.9727	0.9773
PL	0.9514	0.9452	0.9311	0.9248	0.9262	0.9290	0.9411	0.9538
PT	0.9720	0.9676	0.9548	0.9431	0.9489	0.9381	0.9378	0.9264
RO	NA	0.9614	0.9558	0.9650	0.9640	0.9625	0.9633	0.9716
SE	0.9728	0.9773	0.9731	0.9657	0.9616	0.9582	0.9574	0.9652
SI	0.9805	0.9793	0.9749	0.9679	0.9690	0.9660	0.9689	0.9668
SK	0.9461	0.9508	0.9561	0.9540	0.9460	0.9521	0.9684	0.9613
UK	0.9722	0.9754	0.9720	0.9730	0.9736	0.9741	0.9722	0.9744

Table 12
Efficiency scores for the EU 27 and the UK, 2007-2014, radial model

Country	2008	2009	2010	2011	2012	2013	2014
AT	0.9816	0.9740	0.9753	0.9748	0.9772	0.9662	0.9615
BE	0.9646	0.9563	0.9559	0.9629	0.9610	0.9521	0.9542
BG	0.9789	0.9731	0.9586	0.9534	0.9465	0.9405	0.9543
CY	0.9731	0.9534	0.9431	0.9291	0.8997	0.8654	0.8665
CZ	0.9851	0.9770	0.9730	0.9727	0.9723	0.9731	0.9723
DE	0.9683	0.9675	0.9714	0.9773	0.9780	0.9776	0.9763
DK	0.9780	0.9642	0.9544	0.9495	0.9521	0.9542	0.9524
EE	0.9707	0.9395	0.9051	0.9206	0.9370	0.9418	0.9544
EL	0.9397	0.9286	0.9070	0.8674	0.8297	0.8126	0.8157
ES	0.9388	0.9065	0.8918	0.8773	0.8542	0.8439	0.8557
FI	0.9678	0.9604	0.9562	0.9609	0.9612	0.9565	0.9494
FR	0.9598	0.9502	0.9512	0.9512	0.9492	0.9435	0.9389
HR	0.9484	0.9384	0.9180	0.9091	0.8932	0.8885	0.9025
HU	0.9736	0.9626	0.9550	0.9588	0.9564	0.9619	0.9697
IE	0.9615	0.9269	0.9200	0.9186	0.9209	0.9256	0.9301
IT	0.9573	0.9489	0.9467	0.9500	0.9382	0.9324	0.9261
LT	0.9705	0.9397	0.9236	0.9387	0.9447	0.9498	0.9587
LU	0.9789	0.9748	0.9754	0.9765	0.9707	0.9723	0.9696
LV	0.9604	0.9222	0.8941	0.9269	0.9342	0.9396	0.9450
MT	1.0000	0.9700	0.9725	0.9746	0.9755	0.9784	0.9800
NL	0.9795	0.9731	0.9698	0.9695	0.9671	0.9599	0.9609
PL	0.9617	0.9559	0.9498	0.9478	0.9440	0.9431	0.9527
PT	0.9322	0.9365	0.9301	0.9102	0.8835	0.8722	0.8962
RO	0.9731	0.9565	0.9519	0.9537	0.9489	0.9458	0.9428
SE	0.9646	0.9538	0.9515	0.9564	0.9549	0.9547	0.9549
SI	0.9681	0.9691	0.9594	0.9514	0.9402	0.9407	0.9414
SK	0.9652	0.9586	0.9417	0.9417	0.9327	0.9292	0.9369
UK	0.9717	0.9596	0.9590	0.9565	0.9568	0.9604	0.9680

Table 13
Efficiency scores for the EU 27 and the UK, 2000-2007, SBM model

Country	2000	2001	2002	2003	2004	2005	2006	2007
AT	0.9438	0.9396	0.9319	0.9305	0.9223	0.9200	0.9269	0.9320
BE	0.9079	0.9068	0.8936	0.8859	0.8865	0.8823	0.8914	0.8978
BG	0.7855	0.7678	0.7787	0.8109	0.8274	0.8439	0.8577	0.8846
CY	NA	NA	NA	NA	NA	NA	NA	NA
CZ	0.8729	0.8859	0.8918	0.8818	0.8762	0.8788	0.8865	0.9082
DE	0.9129	0.9102	0.8973	0.8890	0.8857	0.8772	0.8884	0.9030
DK	0.9207	0.9201	0.9167	0.9086	0.9115	0.9201	0.9315	0.9423
EE	0.7916	0.8249	0.8361	0.8444	0.8474	0.8720	0.8916	0.8966
EL	0.8684	0.8692	0.8713	0.8735	0.8662	0.8613	0.8761	0.8835
ES	0.8571	0.8761	0.8669	0.8674	0.8729	0.8863	0.8926	0.8961
FI	0.8885	0.8895	0.8843	0.8818	0.8876	0.8944	0.9011	0.9099
FR	0.8971	0.9063	0.9023	0.9025	0.8952	0.8970	0.9017	0.9108
HR	NA	NA	NA	NA	NA	NA	NA	NA
HU	0.9149	0.9163	0.9090	0.9068	0.9061	0.9012	0.9018	0.9010
IE	0.9200	0.9197	0.9079	0.9039	0.9056	0.9032	0.9062	0.9058
IT	0.8803	0.8831	0.8831	0.8844	0.8888	0.8878	0.8980	0.9052
LT	0.7503	0.7744	0.8026	0.8208	0.8344	0.8559	0.8830	0.8977
LU	0.9539	0.9567	0.9457	0.9401	0.9355	0.9253	0.9340	0.9471
LV	0.7859	0.8001	0.8288	0.8324	0.8396	0.8508	0.8690	0.8781
MT	NA	NA	NA	0.8414	0.8816	0.8916	0.9142	0.9162
NL	0.9407	0.9458	0.9378	0.9274	0.9234	0.9134	0.9205	0.9294
PL	0.8195	0.7968	0.7855	0.7920	0.8002	0.8039	0.8336	0.8676
PT	0.9333	0.9341	0.9208	0.9079	0.9110	0.9024	0.8973	0.9027
RO	NA	0.9010	0.8915	0.9136	0.8996	0.9039	0.9092	0.9183
SE	0.9261	0.9235	0.9193	0.9149	0.9132	0.9046	0.9091	0.9174
SI	0.9033	0.9109	0.9093	0.9059	0.9072	0.9066	0.9164	0.9265
SK	0.7959	0.7887	0.7671	0.7725	0.7647	0.7649	0.7932	0.8112
UK	0.9146	0.9140	0.9108	0.9091	0.9147	0.9132	0.9080	0.9145

Table 14
Efficiency scores for the EU 27 and the UK, 2008-2014, SBM model

Country	2008	2009	2010	2011	2012	2013	2014
AT	0.9331	0.8996	0.9157	0.9257	0.9215	0.9144	0.9118
BE	0.9005	0.8648	0.8747	0.8899	0.8805	0.8687	0.8740
BG	0.8877	0.8632	0.8411	0.8412	0.8299	0.8238	0.8435
CY	0.8990	0.8733	0.8603	0.8458	0.8025	0.7501	0.7590
CZ	0.9137	0.8619	0.8645	0.8787	0.8646	0.8677	0.8812
DE	0.9068	0.8676	0.8921	0.9171	0.9149	0.9120	0.9175
DK	0.9337	0.8899	0.8829	0.8889	0.8898	0.8899	0.8966
EE	0.8740	0.7668	0.7653	0.8135	0.8211	0.8500	0.8655
EL	0.8869	0.8600	0.8327	0.7966	0.7460	0.7261	0.7389
ES	0.8715	0.8024	0.7903	0.7818	0.7544	0.7460	0.7629
FI	0.9074	0.8488	0.8663	0.8823	0.8788	0.8726	0.8705
FR	0.9114	0.8700	0.8778	0.8911	0.8838	0.8749	0.8725
HR	0.8791	0.8499	0.8335	0.8201	0.8044	0.7915	0.7903
HU	0.8952	0.8458	0.8494	0.8538	0.8469	0.8525	0.8803
IE	0.8833	0.8265	0.8298	0.8176	0.8113	0.8288	0.8435
IT	0.8965	0.8644	0.8695	0.8821	0.8602	0.8496	0.8504
LT	0.8722	0.7733	0.7388	0.7690	0.7881	0.8032	0.8192
LU	0.9394	0.8876	0.9254	0.9354	0.9156	0.8822	0.8876
LV	0.8480	0.7362	0.7404	0.7790	0.8004	0.8204	0.8278
MT	0.9206	0.8819	0.9006	0.9055	0.9014	0.9061	0.9103
NL	0.9319	0.9081	0.9107	0.9150	0.9036	0.8892	0.8952
PL	0.8915	0.8577	0.8510	0.8494	0.8465	0.8405	0.8567
PT	0.9009	0.8735	0.8701	0.8540	0.8294	0.8236	0.8456
RO	0.9161	0.8827	0.8913	0.9041	0.8998	0.8947	0.9002
SE	0.9119	0.8627	0.8755	0.8955	0.8838	0.8740	0.8771
SI	0.9262	0.8815	0.8814	0.8840	0.8753	0.8616	0.8743
SK	0.8216	0.7648	0.7696	0.7865	0.7748	0.7773	0.7945
UK	0.9080	0.8706	0.8790	0.8872	0.8874	0.8869	0.9038

For closer inspection, Figure 4 depicts the DDF inefficiency scores for a selection of countries between 2000 and 2014. Two groups of countries can be distinguished. The first group, consisting of Austria, Germany, France and Italy, demonstrate a comparably efficient use of inputs. Austria and Germany's inefficiency scores range from 0.83 % (AT, 2001) to 2.67 % (DE, 2005), while France and Italy, the latter one being more crisis-ridden, reach higher scores up to 3.84 % (IT, 2014), translating to a greater deviation from their respective potentials. Their patterns are similar: all of them show an increase in inefficiency at three to four years in a row sometime between 2002 and 2005, followed by a decrease and, again, by a noticeable increase in inefficiency due to the financial crisis. After a slight recovery, another drop in efficiency can be detected since 2012 (France and Italy) and 2013 (Austria and Germany).

The comparative group, consisting of Spain, Greece, Portugal and Cyprus, exhibit diverging paths with considerably higher inefficiency scores. These countries count among those that were hit particularly hard by the financial crisis, as depicted in the substantial inefficiency increases in Figure 4. Portugal starts with a rather efficient economy (deviation from full potential of less than 2 %), but experienced a rise in inefficiency of up to almost 7 %. In the case of Cyprus, missing data only allows for an illustration of the development 2008 to 2014 with a steep decline in efficiency until 2013. Spain (5.53 %) and Greece (4.01 %) already show high levels of inefficiency in 2000. While both manage to improve their efficiency in some of the following years, their inefficiency levels skyrocketed as a result of the financial crisis with inefficiency scores of up to 8.47 % (Spain) and 10.34 % (Greece). In most cases, the scarcest input factor is high-skilled labor. Cyprus is an exception in this group with medium qualified labor being the scarcest factor.

Just like in chapter 5.1.1, we now move on to the intertemporal analysis. The question which factors contributed most to the development of productivity in certain economies will be addressed.

The Luenberger productivity indicator for the DDF model for all 28 countries can be found in the appendix in Tables 29 and 30, contrasted with the results of the Malmquist productivity index for the radial model in Tables 31 and 32. The results are shown relative to the year 2000 with the exception of four countries, those being Cyprus, Croatia, Malta and Romania, due to data availability issues. Every other combination between 2000 and 2014 has been calculated as well but will not be included, as their depiction would go beyond the scope of this report. For this reason we also focus on a selection of countries for a more detailed investigation (see Figure 5).

Figure 5
Luenberger productivity indicator for selected countries, DDF model, base year 2000

The Luenberger productivity indicator enables a distinction between efficiency change ("catch-up") and technical change ("frontier shift"), both of which make up productivity change. Figure 5 shows the Luenberger productivity indicator for Austria (AT), Germany (DE), France (FR), Spain (ES), Italy (IT), Greece (EL), Bulgaria (BG) and Slovenia (SI) between 2001 and 2014 in relation to the base year 2000. When interpreting the figure, it should be noted that the range of the different scores varies.

Austria's development has already been thoroughly discussed in chapter 5.1.1. Germany displays a more positive performance than Austria with a rise in productivity of 10.5 % in total between 2000 and 2014. After a drop in 2003 and 2004, productivity rose to 5.5 % in 2008 (relative to 2000). The financial crisis led to a drop of 2.8 percentage points (pp) in 2009 (again, both years relative to 2000), but Germany managed to recover quickly. Productivity slightly dropped once again in 2012 and 2013 and picked up speed by 2014. As in most cases, productivity change is mainly driven by technical change. Efficiency changes only account for minimal shifts of the production change line, as Germany was already near its potential during the period in question. Of the 10.5 % overall productivity growth until 2014, 9.7 % can be attributed to technical changes and only 0.7 % to efficiency changes.

In France, productivity decreased between 2000 and 2002, but took off in the years that followed. France only experienced a productivity decrease of 1.7pp in 2009 (2009 compared to 2008), 1.2pp of which stemmed from technical change. After a quick recovery in 2010, productivity continued to rise in the years that followed, despite a negative development of efficiency 2012 and onwards (-0.7pp EffCh 2014 relative to 2010).

Slovenia's productivity decreased by 2.1 % between 2001 and 2003 as a result of both a decline in efficiency and a negative technical development. Afterwards, productivity quickly caught up due to generally improving technical conditions. Productivity dropped visibly between 2009 and 2010 (-4.2pp in 2010 compared to 2008). After a brief recovery in 2011, productivity declined once again in 2012 and 2013 and marginally improved by 2014. This is a pattern we have already seen with Austria. Interestingly enough, Slovenia's efficiency decreased during the majority of observed years (-1.8 % in 2014 relative to 2000). This can readily be explained by the steady increase of the unemployment rate for high-skilled labor, which is the scarcest input factor in the entire observation period. Compared to 2008, efficiency declined by 1.5pp in 2012 (both years relative to 2000).

Bulgaria experienced a significant productivity growth over the greater part of the relevant period, resulting in an increase of 22.6 % in 2008 (relative to 2000), 20.3% of which can be attributed to a "frontier shift" (TechCh). While the financial crisis constituted a setback, Bulgaria recovered comparably quickly. By 2011, productivity was 1.5pp above the 2008 level. On average, efficiency changes contributed around 1pp to Bulgaria's development.

Compared to countries like Austria, Germany and France, Spain did not experience a particularly sharp increase in productivity between 2000 and 2008 (0.2 % in total). The effects of the financial crisis are all the more visible and last longer than in many European counterparts: in comparison to 2008, there is a 2.8pp drop in productivity in 2009 (-1pp TechCh and -1.8pp EffCh) and a 5pp drop in 2013. The 5pp drop in 2013 (relative to 2008) has almost exclusively been driven by a changed efficiency. In contrast to the countries already discussed, Spain exhibits a peculiar pattern, as changes in efficiency have affected productivity to a far greater extent than in most other countries. On the input side, the main reason for efficiency changes lies in the development of high qualified labor. In almost all cases, high skilled labor is the scarcest primary input factor considered within this model. Exceptions from this rule are, for instance, Denmark and Luxembourg, where medium qualified labor turned out to be even scarcer. Following this, Spain's exceptionally high unemployment rate following the financial crisis led to a large portion of high qualified labor not being utilized. Among highly-qualified persons unemployment rose from 6.3 % to 9.7 % between 2008 and 2009 and continued to rise to 11.2 % in 2010. Despite Spain's noticeable increase in efficiency between 2003 and 2008 (a "catch-up" process), efficiency continued to drop until 2013. At the same time, labor potential decreased slightly in 2009, while final demand dropped considerably (domestic demand -5.3 % and exports -14.3 %), resulting in a negative "frontier shift". On the output side, the construction sector and some business-oriented services had the biggest impact on the decline in final demand. The development of most crisis-ridden countries within this study follow a similar logic.

In Greece, productivity increased by 6.7 % until 2004. After a brief setback, productivity climbed up to 7 % (2008 relative to 2000), before the financial crisis hit as well. Just like in Spain, productivity reached its lowest level in 2013 with a total decrease of 16.9pp (2013 relative to 2008). Both components (TechCH and EffCh) contributed to the major reduction in productivity. Until 2008/2009, technical change can be considered the major driving factor of the positive development of productivity change and led to a strong increase of potential. As a result of the crisis, technical change decreased by 9.7pp in 2013 (compared to 2008). While efficiency mostly stagnated in the first half of the time period considered, it decreased significantly until 2013 (-7.2pp compared to 2008), signalling a strong impact on productivity during the second half. On the input side, the main reason for this development can, again, be traced back to the stark increase in unemployment. Furthermore, labor potential roughly decreased by half a million (2012 compared to 2008) for low qualified labor. When looking at the decrease in final demand, several sectors particularly contributed to the negative development. Similarly to Austria, those include education, human health and social work activities.

Italy's development is clearly distinguishable from that of most other countries. In comparison to the starting point in 2000, productivity decreased drastically over the analysed period (-10.4 % in 2014). Productivity increased by 1.1pp between 2003 and 2004 and remained mostly stagnant until 2008. After an initial drop of 1.9pp between 2008 and 2009, productivity continuously decreased until 2014 (-5.7pp relative to 2008). Again, technical development accounted for the bulk of changes in productivity. The reason for the negative impact of technical change lies mainly in the strong decrease of the total output and thus the final demand. In 2014, more than 60 % of all economic sectors recorded a lower final demand than in 2000 (in constant prices). At the same time, a greater amount of inputs is used to meet the final demand. This applies above all to the scarcest input, which is high qualified labor. As a result, Italy's economic potential decreased. Together with other countries that were particularly strongly affected by the financial crisis, Italy experienced a slow and rocky recovery.

5.2. Environmental Analysis

5.2.1. Original Model

In a next step we apply the extended model developed by Mahlberg and Luptáčik (2014), which - in addition to the inputs of capital and labor - also accounts for GHG emissions and respective abatement activities to a sample of 16 EU Member States, for which the necessary data is available. As data on environmental capital stock is only available for 2014 (see section 4.2), we focus on this year. Table 15 summarizes the eco-efficiency (Rad (io) and SBM (io)) and eco-inefficiency (DDF (uo))[21] scores for 16 EU Member States in 2014. Furthermore, the table includes results for France and Austria for 2008 carried out under certain assumptions (also see section 4.2).

As can be taken from Table 15, virtually all static results in all three models for all countries only differ marginally from the results of the economic models, which are shown in the same table. This holds for both 2014 and 2008. At a first glance, this is surprising. A closer inspection of the model of Mahlberg and Luptáčik (2014), also described in section 3.2.2, hints at a possible explanation for this empirical observation: The x_2-vector is defined as the difference of the gross pollution of the respective year minus the tolerated level of net pollution. It is therefore implicitly assumed that in the status quo of the considered year and in the potential estimated by the model) the pollution target can always be achieved given the abatement expenditure of the respective year. This is a strong assumption, which might deliver interesting insights in other applications, but not in the case of this study. As a consequence, the results of the ecological analysis only differ slightly from the results of the economic models.

Table 16 shows the results for the intertemporal environmental analysis for France and Austria. The DDF model and the radial model again display similar results, while the SBM results diverge in some cases due to the different model formulation. As can be seen, technical change and - as a consequence - productivity change are different from the economic model.

The following subsection shows the results of an alternative approach, utilizing estimated data on x_2 for calculating A_{12} in the static analysis.

[21] Note: io . . . input-oriented; uo . . . unoriented

Table 15

Eco(in)efficiency scores for Austria and 15 further EU Member States, original model, 2008 and 2014

Country	No. of	Economic model			Eco(in)efficiency score (-55 %)			Eco(in)efficiency score (-100 %)		
	sectors	DDF (uo)	Rad (io)	SBM (io)	DDF (uo)	Rad (io)	SBM (io)	DDF (uo)	Rad (io)	SBM (io)
AT	23	0.0196	0.9615	0.9118	0.0196	0.9616	0.9120	0.0196	0.9616	0.9120
BE	23	0.0234	0.9542	0.8740	0.0234	0.9542	0.8740	0.0234	0.9542	0.8740
BG	5	0.0234	0.9543	0.8435	0.0233	0.9543	0.8436	0.0234	0.9543	0.8436
CZ	23	0.0140	0.9723	0.8812	0.0140	0.9724	0.8813	0.0140	0.9724	0.8813
DE	23	0.0120	0.9763	0.9175	0.0120	0.9763	0.9176	0.0120	0.9763	0.9176
ES	23	0.0777	0.8557	0.7629	0.0777	0.8558	0.7630	0.0777	0.8558	0.7630
FI	23	0.0260	0.9494	0.8705	0.0259	0.9494	0.8706	0.0260	0.9494	0.8706
FR	22	0.0315	0.9389	0.8725	0.0315	0.9390	0.8725	0.0315	0.9390	0.8725
HR	5	0.0513	0.9025	0.7903	0.0510	0.9027	0.7906	0.0511	0.9027	0.7906
IT	23	0.0384	0.9261	0.8504	0.0384	0.9261	0.8504	0.0384	0.9261	0.8504
LT	22	0.0211	0.9587	0.8192	-	-	-	0.0211	0.9587	0.8195
LV	23	0.0283	0.9450	0.8278	-	-	-	0.0282	0.9451	0.8278
PL	5	0.0242	0.9527	0.8567	0.0242	0.9527	0.8569	0.0242	0.9527	0.8569
RO	23	0.0295	0.9428	0.9002	0.0288	0.9428	0.9003	0.0294	0.9428	0.9003
SE	5	0.0231	0.9549	0.8771	0.0231	0.9549	0.8772	0.0231	0.9549	0.8772
SI	23	0.0302	0.9414	0.8743	0.0301	0.9415	0.8747	0.0301	0.9415	0.8747
AT (2008)	5	0.0093	0.9816	0.9331	0.0093	0.9816	0.9332	0.0093	0.9816	0.9332
FR (2008)	5	0.0205	0.9598	0.9114	0.0205	0.9598	0.9115	0.0205	0.9598	0.9115

Table 16

Intertemporal results of the (original) environmental model, -55 % target (both years), Austria and France, 2008 vs. 2014

Country	Economic Model			Environment Model (original)		
	DDF (uo) (Luenberger)	radial (io) (Malmquist)	SBM (io) (Malmquist)	DDF (uo) (Luenberger)	radial (io) (Malmquist)	SBM (io) (Malmquist)
			Austria			
ProdCh	-0.1074	0.8020	0.9484	-0.1082	0.8003	1.0980
TechCh	-0.0970	0.8188	0.9705	-0.0979	0.8170	1.1126
EffCh	-0.0104	0.9795	0.9773	-0.0103	0.9795	0.9773
			France			
ProdCh	0.0181	1.0371	0.9393	0.0081	1.0164	0.9214
TechCh	0.0291	1.0601	0.9813	0.0191	1.0390	0.9626
EffCh	-0.0110	0.9783	0.9573	-0.0110	0.9783	0.9573

5.2.2. Utilizing estimated abatement data

As mentioned above, results from models with A_{12} defined after Mahlberg and Luptáčik (2014) deliver limited additional information in the context of our study. This is why we construct A_{12} utilizing estimated data on x_2. The estimation procedure, described in 4.2.1, produces a single estimate for our whole set of countries: Increasing abatement activities by one million euros in any industry in any country in our data set on average decreases emissions by 12,684.36 tons. Note that this estimate comes from a simple estimation procedure, which was merely conducted to demonstrate the capabilities of the environmental analysis. Moreover, this estimate only allows us to run a static analysis, while we cannot use it for the intertemporal analysis.

Table 17

Results of the amended environmental models, -55 % target, 2014

Country	No. of sectors	Eco(in)efficiency score (-55 %)			Share of unused potential required for abatement		
		DDF (uo)	Rad (io)	SBM (io)	DDF (uo)	Rad (io)	SBM (io)
AT	23	0.0116	0.9770	0.9266	41.1 %	40.2 %	16.8 %
BE	23	0.0205	0.9598	0.8800	12.7 %	12.1 %	4.8 %
BG	5	0.0181	0.9638	0.8550	22.8 %	20.8 %	7.3 %
CZ	23	0.0081	0.9837	0.8963	42.3 %	41.0 %	12.7 %
DE	23	0.0072	0.9856	0.9257	40.2 %	39.4 %	9.9 %
ES	23	0.0692	0.8700	0.7770	11.0 %	9.9 %	6.0 %
FI	23	0.0200	0.9605	0.8799	22.9 %	21.9 %	7.2 %
FR	22	0.0286	0.9441	0.8780	9.0 %	8.5 %	4.3 %
HR	5	0.0031	0.9933	0.8536	93.9 %	93.2 %	30.2 %
IT	23	0.0297	0.9417	0.8679	22.6 %	21.2 %	11.7 %
LT	22	0.0156	0.9690	0.8345	26.0 %	24.9 %	8.4 %
LV	23	0.0098	0.9801	0.8464	65.4 %	63.9 %	10.8 %
PL	5	0.0068	0.9861	0.8954	71.8 %	70.6 %	27.0 %
RO	23	0.0284	0.9433	0.9007	3.7 %	0.9 %	0.4 %
SE	5	0.0220	0.9569	0.8797	4.9 %	4.6 %	2.1 %
SI	23	0.0238	0.9531	0.8916	21.1 %	20.0 %	13.8 %

Tables 17 and 18 show the results of the amended environmental models. The so-called (in)efficiency scores now allow a somewhat different conclusion and indicate, which part of the economic potential of the respective country would still be unused, if abatement activities were boosted to a level that actually satisfies the emission target. This target is assumed to be at 45 % and 0 % (i. e., 55 and 100 % reduction) of the pollution values of 1990 (see 4.2). Taking Austria and the 55 % reduction goal in Table 17 as an example, the eco-inefficiency score in the economic model (DDF variant) amounted to 1.96 %. In other words, without taking pollution into account, deliveries to final demand could be increased by 1.96 % while simultaneously using 1.96 % less inputs (as the model is unoriented). If

Table 18
Results of the amended environmental models, -100% target, 2014

Country	No. of sectors	Eco(in)efficiency score (-100%) DDF (uo)	Rad (io)	SBM (io)	Share of unused potential required for abatement DDF (uo)	Rad (io)	SBM (io)
AT	23	0.0040	0.9920	0.9410	79.6 %	79.3 %	33.0 %
BE	23	0.0163	0.9680	0.8890	30.5 %	30.0 %	11.9 %
BG	5	-0.0023	1.0045	1.0842	109.6 %	109.9 %	153.8 %
CZ	23	-0.0093	1.0188	1.0754	166.4 %	168.0 %	163.5 %
DE	23	-0.0014	1.0027	1.0566	111.2 %	111.4 %	168.6 %
ES	23	0.0642	0.8794	0.7863	17.4 %	16.4 %	9.9 %
FI	23	0.0127	0.9748	0.8919	50.9 %	50.3 %	16.5 %
FR	22	0.0253	0.9506	0.8849	19.6 %	19.2 %	9.8 %
HR	5	-0.0637	1.1361	1.1592	224.4 %	239.6 %	175.9 %
IT	23	0.0202	0.9605	0.8888	47.5 %	46.5 %	25.7 %
LT	22	0.0066	0.9868	0.8604	68.5 %	68.0 %	22.8 %
LV	23	-0.0147	1.0298	1.0710	151.9 %	154.1 %	141.3 %
PL	5	-0.0158	1.0321	1.0832	165.3 %	167.9 %	158.1 %
RO	23	0.0004	0.9993	0.9471	98.8 %	98.7 %	46.9 %
SE	5	0.0201	0.9607	0.8841	13.1 %	12.9 %	5.7 %
SI	23	0.0159	0.9688	0.9144	47.4 %	46.7 %	31.9 %

the environmental standards are to be fulfilled, the 2014 level of pollution (58.1 mil. t) must be reduced to 26.5 mil. tons. After increasing abatement activities to the required level, the DDF eco-inefficiency score for Austria is lower, but still amounts to 1.16 %. In addition to reducing emissions to the tolerated level, final demand for commodities could be increased by 1.16 %, using 1.16 % less inputs. In other words, the emission target for Austria could easily be achieved using only the currently unused domestic potential.

This is also true for all other 15 countries, although the share from the currently unused potential required for abatement considerably differs between 3.7 % (Romania, which was already pretty close to its pollution target in 2014) and 93.9 % (Croatia, where high-skilled labor is close to full employment due to the required abatement activities). The input-oriented radial model and the input-oriented SBM model confirm this observation. Here, too, the unused potential suffices to achieve the emission target. However, if we set stricter pollution limits as for the results in Table 18, this is frequently not the case anymore.

We want to mention here that, besides the issues induced by the estimation procedure already discussed in section 4.2.1, the environmental model in this formulation suffers from several additional shortcomings, which in most cases currently cannot be addressed due to data issues: (1) The model implicitly assumes that abatement activities come from domestic production, which is probably not the case; (2) substitution effects set off by higher abatement activities are not taken into account; (3) Ideally, the abatement sector should represent the commodities needed for abatement, not the sectoral expenses, and the intermediate inputs of the respective producing sectors should be corrected accordingly, but currently this information is not available.[22]

5.3. Social Analysis

All models presented above take the structure of the available inputs of a year as given. The potential as measured by the models only relies on the current qualification levels of the workforce. In case of the DDF model and the input-oriented radial model only the scarcest input is reflected in the potentials.[23] As chapter 5.1 reveals, in most countries high skilled labor is the bottleneck throughout the analysis period. In practice, however, the qualification of the workforce can be actively changed, e. g. in the longer term by increasing access to quality education or by encouraging continuous education, but also in a shorter term, e. g. by active labor market policies aiming at a better match of the skills of unemployed with the labor demand.

In the following, we deal with this last aspect: What are the effects on the potentials of the economies, if unemployed persons can receive qualification measures to better match demand? Therefore, we use the slightly extended DDF model presented in section 3.6 to allow for a transition of a certain share of the unemployed persons to a higher skill level. It can be assumed that this enacts a positive influence on the production potential of an economy, which, in turn, leads to lower static efficiency scores.

We first take a look at Austria. Table 19 displays the inefficiency scores of the social model for Austria for different limits regarding the share of the unemployed persons who can attend qualification measures and move to the next skill level (in steps of 10 %; see parameter ζ in section 3.6), as well as the differences with respect to the economic model (with predetermined skill levels). Figure 6 depicts the development of the respective efficiency scores over time.

Even when only 10 % of low and medium-skilled unemployed persons are given the opportunity to attend qualification measures and reach the next skill level,[24] the econ-

[22] Therefore, since currently the abatement sectors in our model are still rather small, we simple increased total production by abatement for now without reducing the producing sectors. This should be addressed in a future model update.

[23] This is not the case in the SBM model.

[24] In the following, we refer to that rate as the "qualification eligibility".

omy's potential increases substantially, causing the inefficiency scores to rise by 0.6 to 0.8 percentage points. We now take the year 2000 as an example. In the original economic (DDF) model outputs could be increased by 0.75 % while reducing inputs by 0.75 % simultaneously, in the social model with 10 %-"qualification eligibility" (i. e. at most 10 % of the unemployed of each skill level can reach the next skill level) this value is increased to 1.39 %.

Allowing more people to improve their qualification further increases the economic potential of the economy. Nevertheless, it can be noticed that the largest effect is for the first 10 % (i. e. a 10 % qualification eligibility compared to 0 % in the economic model), but declines as the limit is further increased in 10 %-steps. The maximum potential is achieved, when 50 % (in some years 60 %) of the unemployed are trained (indicated in Table 19 in blue letters). Increasing the "qualification eligibility" after this threshold does not further increase the potential anymore. As can be seen from the shadow prices (see Table 34 in the Appendix), all labor inputs are then equally scarce.[25] Where exactly this point is depends - among other factors - on the relative initial scarcity of the different skill levels in the respective year. The biggest gaps between the potential indicated by the economic model and that of the social models occur in the years 2005, 2009 and 2012. This is plausible given that the unemployment rate of low and medium qualified was relatively high in these years compared to that of high qualified (see Eurostat (2020d)).

Another observation from the shadow prices is that they are identical to those of the economic model, unless the qualification measures suffice to balance the scarcity of the inputs to such an extent that another input becomes equally scarce. For Austria this is the case for a 10 % qualification eligibility in the years 2004 to 2007, 2011 and 2013 to 2014. Those years can also be identified as the years in which the limit of 10 % qualification eligibility is not entirely used up, neither for the qualification on low to medium-skilled nor (as in the case of Austria) the qualification of medium to high-skilled.

Before we take a look at other countries, Table 20 summarizes the effects a 10 % "qualification eligibility" for Austria (compared to the economic model without qualification measures in 5.1.1). As can be seen, the maximum of a 10 % qualification limit is used in every single year for low qualified unemployed, but its shadow price still remains at zero, which indicates that even after fully utilizing the limit low-skilled labor is still not

[25] As our model does not allow to lose skill levels, it is possible that lower skill levels remain scarcer, which, however, is not the case for Austria.

Table 19

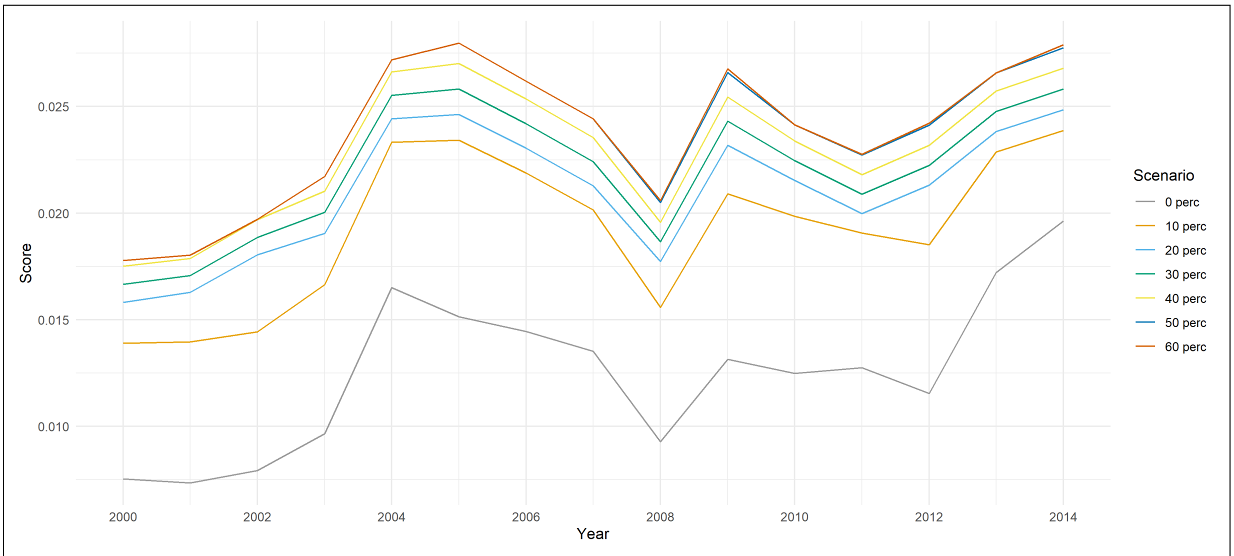
Inefficiency scores of the social model for different qualification eligibility limits, Austria, 2000-2014, DDF model

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
0 % (Econ. Mod.)		0.0075	0.0073	0.0079	0.0097	0.0165	0.0151	0.0145	0.0135	0.0093	0.0131	0.0125	0.0127	0.0115	0.0172	0.0196
10 %	score	0.0139	0.0140	0.0144	0.0166	0.0233	0.0234	0.0219	0.0202	0.0156	0.0209	0.0199	0.0191	0.0185	0.0229	0.0239
	diff.	*0.0064*	*0.0066*	*0.0065*	*0.0070*	*0.0068*	*0.0083*	*0.0074*	*0.0066*	*0.0063*	*0.0078*	*0.0074*	*0.0063*	*0.0070*	*0.0057*	*0.0042*
20 %	score	0.0158	0.0163	0.0180	0.0191	0.0244	0.0246	0.0230	0.0213	0.0177	0.0232	0.0215	0.0200	0.0213	0.0238	0.0248
	diff.	*0.0083*	*0.0089*	*0.0101*	*0.0094*	*0.0079*	*0.0095*	*0.0086*	*0.0078*	*0.0085*	*0.0100*	*0.0091*	*0.0072*	*0.0098*	*0.0066*	*0.0052*
30 %	score	0.0167	0.0171	0.0189	0.0200	0.0255	0.0258	0.0242	0.0224	0.0187	0.0243	0.0225	0.0209	0.0222	0.0248	0.0258
	diff.	*0.0091*	*0.0097*	*0.0109*	*0.0104*	*0.0090*	*0.0107*	*0.0097*	*0.0089*	*0.0094*	*0.0112*	*0.0100*	*0.0081*	*0.0107*	*0.0076*	*0.0062*
40 %	score	0.0175	0.0179	0.0197	0.0210	0.0266	0.0270	0.0254	0.0236	0.0196	0.0255	0.0234	0.0218	0.0232	0.0257	0.0268
	diff.	*0.0100*	*0.0105*	*0.0118*	*0.0114*	*0.0101*	*0.0119*	*0.0109*	*0.0100*	*0.0103*	*0.0123*	*0.0109*	*0.0091*	*0.0116*	*0.0085*	*0.0072*
50 %	score	0.0178	0.0180	0.0197	0.0217	0.0272	0.0280	0.0262	0.0244	0.0205	0.0266	0.0241	0.0227	0.0241	0.0266	0.0278
	diff.	*0.0102*	*0.0107*	*0.0118*	*0.0121*	*0.0107*	*0.0128*	*0.0117*	*0.0109*	*0.0112*	*0.0134*	*0.0117*	*0.0100*	*0.0126*	*0.0094*	*0.0081*
60 %	score	0.0178	0.0180	0.0197	0.0217	0.0272	0.0280	0.0262	0.0244	0.0206	.0268	0.0241	0.0228	0.0242	0.0266	0.0279
	diff.	*0.0102*	*0.0107*	*0.0118*	*0.0121*	*0.0107*	*0.0128*	*0.0117*	*0.0109*	*0.0113*	*0.0136*	*0.0117*	*0.0100*	*0.0127*	*0.0094*	*0.0083*
70 %	score	0.0178	0.0180	0.0197	0.0217	0.0272	0.0280	0.0262	0.0244	0.0206	0.0268	0.0241	0.0228	0.0242	0.0266	0.0279
	diff.	*0.0102*	*0.0107*	*0.0118*	*0.0121*	*0.0107*	*0.0128*	*0.0117*	*0.0109*	*0.0113*	*0.0136*	*0.0117*	*0.0100*	*0.0127*	*0.0094*	*0.0083*
80 %	score	0.0178	0.0180	0.0197	0.0217	0.0272	0.0280	0.0262	0.0244	0.0206	0.0268	0.0241	0.0228	0.0242	0.0266	0.0279
	diff.	*0.0102*	*0.0107*	*0.0118*	*0.0121*	*0.0107*	*0.0128*	*0.0117*	*0.0109*	*0.0113*	*0.0136*	*0.0117*	*0.0100*	*0.0127*	*0.0094*	*0.0083*
90 %	score	0.0178	0.0180	0.0197	0.0217	0.0272	0.0280	0.0262	0.0244	0.0206	0.0268	0.0241	0.0228	0.0242	0.0266	0.0279
	diff.	*0.0102*	*0.0107*	*0.0118*	*0.0121*	*0.0107*	*0.0128*	*0.0117*	*0.0109*	*0.0113*	*0.0136*	*0.0117*	*0.0100*	*0.0127*	*0.0094*	*0.0083*
100 %	score	0.0178	0.0180	0.0197	0.0217	0.0272	0.0280	0.0262	0.0244	0.0206	0.0268	0.0241	0.0228	0.0242	0.0266	0.0279
	diff.	*0.0102*	*0.0107*	*0.0118*	*0.0121*	*0.0107*	*0.0128*	*0.0117*	*0.0109*	*0.0113*	*0.0136*	*0.0117*	*0.0100*	*0.0127*	*0.0094*	*0.0083*

Remark: *score* refers to the inefficiency score calculated by the social model, *diff* indicates the difference to the (base) economic model, which is equal to a 0 % qualification eligibility (see row 1)

Figure 6

Inefficiency scores of the social model (different scenarios), Austria, DDF model, 2000-2014



scarce. In contrast, the limit is not exhausted for medium-skilled unemployed in 7 out of the 15 years. In those years, enough medium-skilled unemployed can be qualified to become high-skilled, so that both skill levels become equally scarce, as indicated by identical shadow prices. If we compare these results to the unemployment rates from Eurostat, we see that this happens in those years, where the relative difference in unemployment between medium and high skilled is the smallest.

Table 20

Properties of the social model, Austria, 2000-2014, DDF model

Inefficiency scores	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Economic model	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075	0.0075
Social model (10 %)	0.0139	0.0140	0.0144	0.0166	0.0233	0.0234	0.0219	0.0202	0.0156	0.0209	0.0199	0.0191	0.0185	0.0229	0.0239
difference	0.0064	0.0064	0.0069	0.0091	0.0158	0.0159	0.0143	0.0126	0.0080	0.0134	0.0123	0.0115	0.0110	0.0153	0.0163

Qualification measures	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
low –>medium (z_{32}) (in tsd. persons)	5.1	4.9	5.1	6.2	7.1	7.8	7.6	7.5	6.3	7.9	6.5	6.5	6.8	7	7.3
in % of unemployed	*10.0 %*	*10.0 %*	*10.0 %*	*10.0 %*	*10.0 %*	*10.0 %*	*10.0 %*	*10.0 %*	*10.0 %*	*10.0 %*	*10.0 %*	*10.0 %*	*10.0 %*	*10.0 %*	*10.0 %*
medium –>high (z_{21}) (in tsd. persons)	7.6	8.1	9.0	9.4	10.3	12.0	10.8	9.8	9.5	12.4	11.8	10.4	12.1	10.2	11.7
in % of unemployed	*10.0 %*	*10.0 %*	*10.0 %*	*10.0 %*	*8.8 %*	*9.8 %*	*9.4 %*	*9.3 %*	*10.0 %*	*10.0 %*	*10.0 %*	*9.6 %*	*10.0 %*	*7.8 %*	*9.9 %*

Shadow prices	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Labor lq	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Labor mq	0.00000	0.00000	0.00000	0.00000	0.00016	0.00015	0.00015	0.00015	0.00000	0.00000	0.00000	0.00014	0.00000	0.00014	0.00013
Labor hq	0.00084	0.00082	0.00072	0.00074	0.00016	0.00015	0.00015	0.00015	0.00066	0.00063	0.00062	0.00014	0.00058	0.00014	0.00013
Capital	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
qualification low –>medium (z_{32})	0.00000	0.00000	0.00000	0.00000	0.00016	0.00015	0.00015	0.00015	0.00000	0.00000	0.00000	0.00014	0.00000	0.00014	0.00013
qualification medium –>high (z_{21})	0.00084	0.00082	0.00072	0.00074	0.00000	0.00000	0.00000	0.00000	0.00066	0.00063	0.00062	0.00000	0.00058	0.00000	0.00000

Unemployment rates by skill level (Eurostat)	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
low qualified	6.3 %	6.3 %	6.9 %	8.2 %	10.3 %	11.1 %	10.1 %	9.3 %	8.4 %	10.7 %	9.2 %	9.1 %	9.8 %	10.4 %	11.4 %
medium qualified	3.1 %	3.3 %	3.6 %	3.7 %	4.8 %	4.9 %	4.5 %	4.1 %	3.6 %	4.6 %	4.4 %	4.0 %	4.4 %	4.7 %	5.0 %
high qualified	1.6 %	1.5 %	1.7 %	2.1 %	3.4 %	3.0 %	2.9 %	2.7 %	1.9 %	2.6 %	2.5 %	2.6 %	2.4 %	3.5 %	4.0 %

Analogous to the economic model, we also calculate the intertemporal model for this variant of the social model. From now on, we assume that at most 10 % of the currently unemployed by skill level can move up to the next skill level. This seems plausible, since qualification measures take time, not everyone might be prepared to attend them and ideally they should expand on the education the person already possesses. Table 21 displays the mixed-period inefficiency scores. Compared to the economic model (Table 8), inefficiency now increases as technology progresses, because a shortage of high-skilled workers could now be alleviated by improving the qualification of lower-skilled workers, which increases the economy's potential. Values below the main diagonal, which denote given technology associated with more recent primary input endowment, however, do not change in most cases. This corresponds to expectations, because in these intertemporal comparisons usually low-skilled labor is scarce (as the skill level of the active population increases over time) and the model does not allow unemployed to lose knowledge and reach lower skill levels.

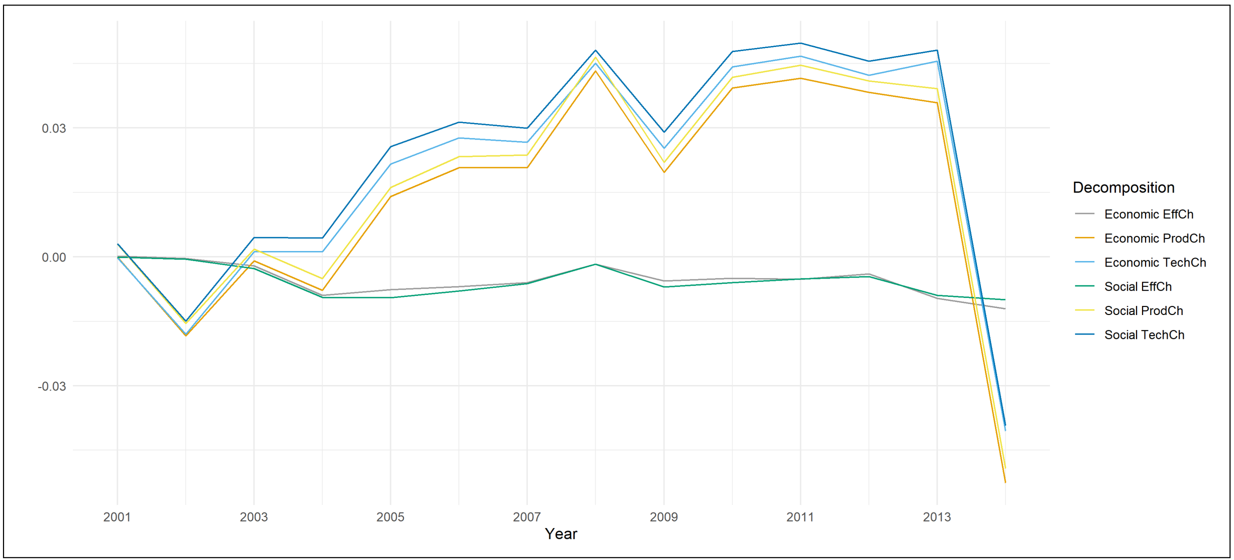
Table 21
Intertemporal (mixed period) inefficiency scores for Austria, social DDF model, 2000-2014

		technology														
	-	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
inputs & outputs	2000	0.014	0.011	-0.041	-0.019	-0.062	-0.026	-0.009	-0.005	-0.004	-0.044	-0.035	-0.035	-0.058	-0.069	-0.271
	2001	0.005	0.014	-0.038	-0.016	-0.059	-0.023	-0.005	-0.001	-0.001	-0.041	-0.032	-0.032	-0.054	-0.066	-0.269
	2002	-0.011	-0.003	0.014	0.012	-0.005	0.027	0.042	0.053	0.041	0.012	0.022	0.022	-0.001	-0.012	-0.218
	2003	-0.026	0.000	-0.006	0.017	-0.026	0.010	0.028	0.032	0.032	-0.008	0.001	0.001	-0.021	-0.033	-0.238
	2004	-0.061	-0.036	-0.017	0.005	0.023	0.026	0.040	0.041	0.039	0.023	0.029	0.037	0.029	0.017	-0.190
	2005	-0.068	-0.042	-0.024	-0.001	-0.012	0.023	0.039	0.035	0.039	0.005	0.015	0.015	-0.007	-0.018	-0.225
	2006	-0.064	-0.038	-0.019	-0.008	-0.031	0.005	0.022	0.027	0.022	-0.015	-0.004	-0.004	-0.026	-0.037	-0.244
	2007	-0.058	-0.039	-0.019	-0.025	-0.038	-0.008	0.008	0.020	0.008	-0.023	-0.012	-0.012	-0.034	-0.045	-0.251
	2008	-0.099	-0.073	-0.055	-0.032	-0.040	-0.005	0.012	0.004	0.016	-0.026	-0.016	-0.015	-0.037	-0.048	-0.254
	2009	-0.095	-0.070	-0.052	-0.029	0.004	0.023	0.014	0.005	0.039	0.021	0.028	0.030	0.008	-0.003	-0.208
	2010	-0.125	-0.100	-0.082	-0.059	-0.016	-0.005	-0.015	-0.024	0.013	0.009	0.020	0.020	-0.003	-0.013	-0.218
	2011	-0.130	-0.105	-0.087	-0.065	-0.022	-0.010	-0.020	-0.029	0.008	0.005	0.012	0.019	-0.003	-0.013	-0.219
	2012	-0.144	-0.120	-0.102	-0.080	-0.036	-0.025	-0.035	-0.044	-0.008	0.003	0.016	0.025	0.019	0.008	-0.199
	2013	-0.156	-0.132	-0.115	-0.092	-0.049	-0.038	-0.048	-0.057	-0.021	-0.010	0.011	0.017	0.022	0.023	-0.183
	2014	-0.183	-0.159	-0.142	-0.119	-0.077	-0.069	-0.075	-0.084	-0.053	-0.068	-0.062	-0.053	-0.055	-0.052	0.024

If we now take a look at the Luenberger productivity indicator and its decomposition (see Figure 7), we see that the efficiency change (EffCh) is only marginally different from the economic model, as the gap between the inefficiency scores remains mostly the same. Technical change and, as a consequence, productivity change are now slightly higher. This may be due to the increasing number of unemployed medium-skilled persons over time (76,000 in 2000 vs. 130,000 in 2013), which in turn means that more people can reach the highest skill level through qualification measures.

Figure 7

Luenberger productivity indicator and its decomposition for Austria, social model compared to economic model, DDF model, base year 2000



Finally, we calculate this social model for the other EU Member States and the United Kingdom, whereby we again assume that a maximum of 10 % of the currently unemployed by skill level can move up to the next skill level.

Table 22 displays the DDF inefficiency scores of the social model and the respective differences to the basic economic model from chapter 5.1.2, a selection of countries is depicted in Figure 8. As expected, economic potentials and the resulting inefficiency scores are higher for all countries, if transitioning between skill levels is possible. While the broad trends are similar to those observed in the economic model, additional conclusions can be drawn.

In most western and northern European countries (e. g. Austria, Belgium, France, Sweden, Finland, United Kingdom) the gap between the efficiency scores (and thus the potentials) identified by the economic and the social model remains more or less constant throughout the period of analysis. For Germany we see not only a steady movement of the economy towards its potential since 2005, but also a reduction of the gap between the social and economic model, thus indicating a more preferable distribution between skill levels. This is plausible considering the falling unemployment rate especially regarding the low qualified population. Another exception is Ireland, where after 2009 both the distance to the economy's potential and the gap between the economic and the social model strongly increased, indicating that less qualified were affected more severely by the crisis (again, this is in line with the development of the respective unemployment rates by skill level).

The same holds for most Southern European countries (Spain, Greece, Cyprus, Portugal), where the gap also clearly increases after 2008. In Italy the gap between the models first decreased until 2005, when, according to the social model, the maximization of the economic potential should only lead to around 6 % of the medium qualified persons attending qualification measures to become high qualified, rather than the 10 % allowed. From 2010 onwards, the 10 % limit is used up for both low and medium qualified, causing the gap to widen again.

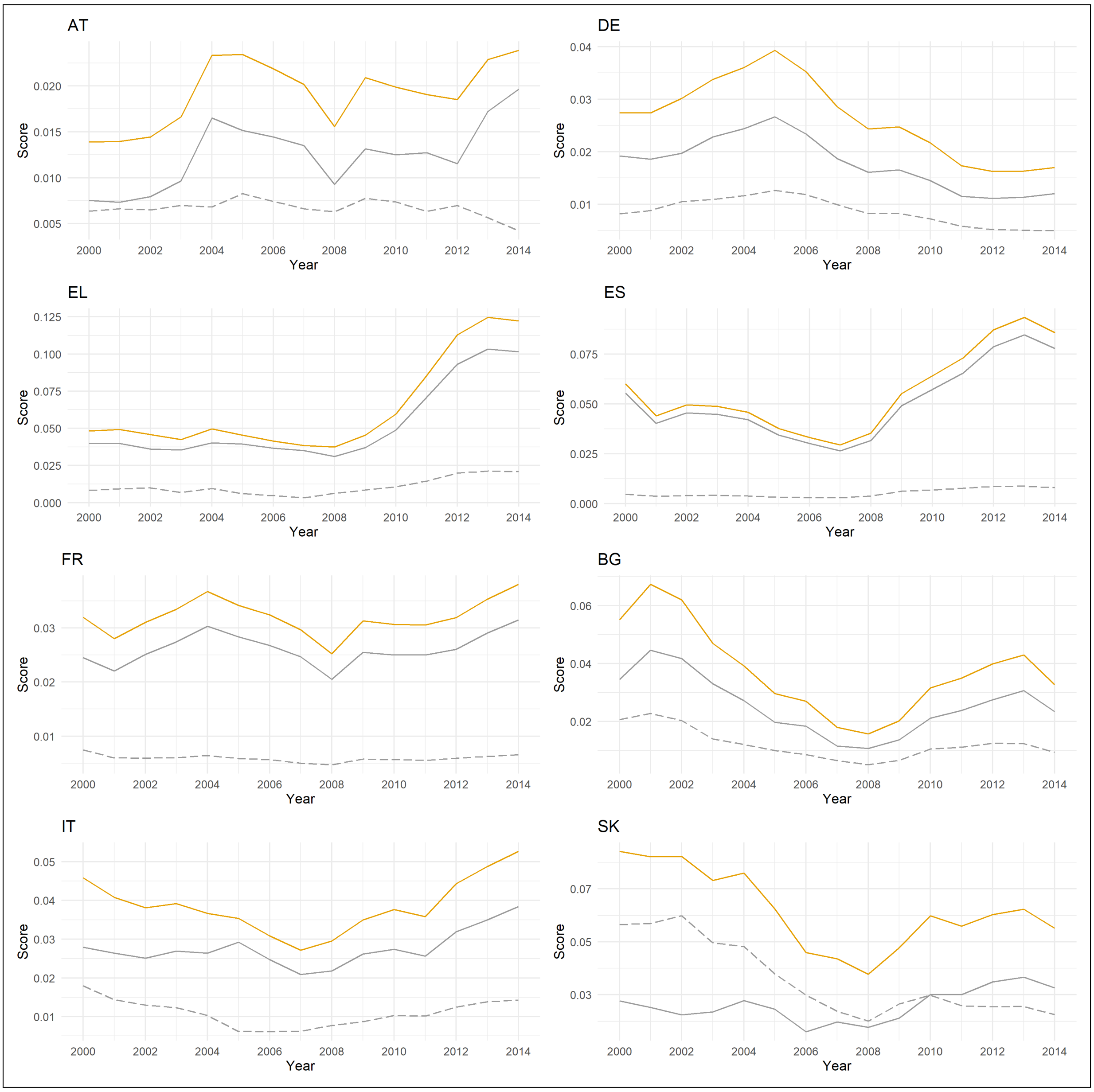
The developments of Eastern European countries on the other hand is somewhat inhomogeneous. Some, like the Baltic countries, show a clear movement towards their potentials in both models until 2008 and the gap decreased. In 2009 they were hit by the crisis, which again seems to have a stronger impact on low and medium qualified (as the gap between the models increases). In 2010 recovery began. Similar trends can be found e. g. in Bulgaria and the Czech Republic. In Poland on the other hand the distance to their potential did not increase so much due to the crisis and the effect of qualification measures on the potential remained relatively constant since then. Slovakia, according to the social model, has improved considerably between 2000 and 2008. This was not visible so much from the economic model. It seems to reflect that - although unemployment is still exceptionally high in 2014, especially among low qualified - the gap between the different skill levels has been somewhat reduced.

Finally, we also take a look at the intertemporal results of the social model for the other European countries. Figure 9 as an example displays the development of the Luenberger productivity indicator and its components for Germany and Spain, Tables 35 and 36 in the appendix provide them for all countries for the base year 2000.[26] A notable factor is that the development of the economic potential over time (TechCh) in the social model is very similar to the economic model, which seems plausible given that both model use the same underlying technology. Therefore, most deviations of productivity change (ProdCh) between the models originate from different developments of efficiency. The possibility

[26] The Luenberger index was also calculated based on every single year 2001 to 2013, but these numbers are not presented in the report. The same holds for the contributions of the individual industries and primary inputs.

Figure 8

Inefficiency scores of the social model (orange) and economic model (grey) and their difference (dashed), DDF model, 2000-2014



for unemployed to rise in skill level appears to not affect their changes much over time, despite having a considerable impact on the current potentials.

Figure 9

Luenberger productivity indicator and its decomposition for Germany and Spain, social model compared to economic model, DDF model, base year 2000

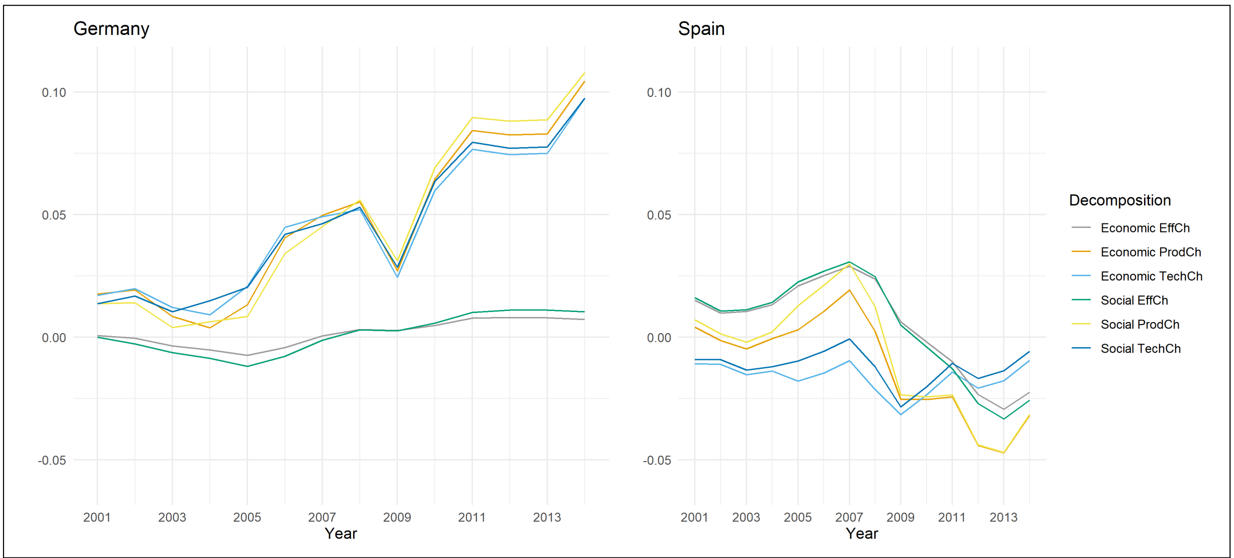


Table 22

Inefficiency scores of the social model (10 % qualification eligibility), EU, 2000-2014, DDF model

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
AT	score	0.0139	0.0140	0.0144	0.0166	0.0233	0.0234	0.0219	0.0202	0.0156	0.0209	0.0199	0.0191	0.0185	0.0229	0.0239
	diff	*0.0064*	*0.0066*	*0.0065*	*0.0070*	*0.0068*	*0.0083*	*0.0074*	*0.0066*	*0.0063*	*0.0078*	*0.0074*	*0.0063*	*0.0070*	*0.0057*	*0.0042*
BE	score	0.0164	0.0173	0.0202	0.0225	0.0236	0.0223	0.0226	0.0189	0.0180	0.0223	0.0226	0.0189	0.0199	0.0246	0.0234
	diff	*0.0039*	*0.0037*	*0.0040*	*0.0047*	*0.0047*	*0.0047*	*0.0043*	*0.0041*	*0.0039*	*0.0043*	*0.0041*	*0.0034*	*0.0038*	*0.0041*	*0.0041*
BG	score	0.0346	0.0446	0.0417	0.0330	0.0272	0.0197	0.0184	0.0115	0.0107	0.0136	0.0211	0.0238	0.0275	0.0307	0.0234
	diff	*0.0206*	*0.0227*	*0.0204*	*0.0139*	*0.0120*	*0.0099*	*0.0085*	*0.0065*	*0.0051*	*0.0066*	*0.0105*	*0.0111*	*0.0124*	*0.0123*	*0.0093*
CY	score	NA	NA	NA	NA	NA	NA	NA	NA	0.0136	0.0239	0.0293	0.0368	0.0528	0.0722	0.0715
	diff	-	-	-	-	-	-	-	-	*0.0020*	*0.0031*	*0.0020*	*0.0005*	*0.0065*	*0.0090*	*0.0089*
CZ	score	0.0140	0.0123	0.0106	0.0104	0.0105	0.0113	0.0115	0.0075	0.0075	0.0116	0.0137	0.0138	0.0140	0.0136	0.0140
	diff	*0.0236*	*0.0220*	*0.0203*	*0.0215*	*0.0215*	*0.0196*	*0.0167*	*0.0119*	*0.0086*	*0.0137*	*0.0146*	*0.0124*	*0.0118*	*0.0117*	*0.0099*
DE	score	0.0192	0.0186	0.0197	0.0228	0.0244	0.0267	0.0234	0.0187	0.0161	0.0165	0.0145	0.0115	0.0111	0.0113	0.0120
	diff	*0.0082*	*0.0088*	*0.0105*	*0.0109*	*0.0116*	*0.0127*	*0.0118*	*0.0099*	*0.0082*	*0.0082*	*0.0072*	*0.0058*	*0.0052*	*0.0050*	*0.0050*
DK	score	0.0162	0.0195	0.0204	0.0242	0.0241	0.0193	0.0159	0.0142	0.0111	0.0182	0.0233	0.0259	0.0246	0.0234	0.0244
	diff	*0.0044*	*0.0022*	*0.0012*	*0.0013*	*0.0025*	*0.0030*	*0.0013*	*0.0014*	*0.0021*	*0.0041*	*0.0049*	*0.0047*	*0.0046*	*0.0042*	*0.0040*
EE	score	0.0358	0.0370	0.0334	0.0350	0.0282	0.0217	0.0170	0.0109	0.0149	0.0312	0.0498	0.0413	0.0325	0.0300	0.0233
	diff	*0.0151*	*0.0138*	*0.0116*	*0.0105*	*0.0096*	*0.0074*	*0.0051*	*0.0039*	*0.0047*	*0.0121*	*0.0154*	*0.0097*	*0.0077*	*0.0070*	*0.0054*
EL	score	0.0401	0.0398	0.0360	0.0354	0.0402	0.0395	0.0366	0.0351	0.0311	0.0370	0.0487	0.0710	0.0931	0.1034	0.1015
	diff	*0.0082*	*0.0093*	*0.0099*	*0.0070*	*0.0094*	*0.0060*	*0.0048*	*0.0034*	*0.0063*	*0.0084*	*0.0108*	*0.0145*	*0.0199*	*0.0213*	*0.0208*
ES	score	0.0553	0.0403	0.0455	0.0448	0.0420	0.0343	0.0302	0.0264	0.0316	0.0490	0.0572	0.0654	0.0786	0.0847	0.0777
	diff	*0.0048*	*0.0036*	*0.0039*	*0.0040*	*0.0038*	*0.0032*	*0.0030*	*0.0030*	*0.0038*	*0.0062*	*0.0068*	*0.0076*	*0.0085*	*0.0087*	*0.0080*
FI	score	0.0263	0.0243	0.0215	0.0219	0.0242	0.0231	0.0191	0.0189	0.0164	0.0202	0.0224	0.0200	0.0198	0.0222	0.0260
	diff	*0.0076*	*0.0072*	*0.0073*	*0.0073*	*0.0067*	*0.0063*	*0.0058*	*0.0049*	*0.0043*	*0.0060*	*0.0057*	*0.0051*	*0.0051*	*0.0053*	*0.0055*
FR	score	0.0245	0.0220	0.0251	0.0274	0.0303	0.0284	0.0268	0.0247	0.0205	0.0255	0.0250	0.0250	0.0260	0.0291	0.0315
	diff	*0.0075*	*0.0060*	*0.0059*	*0.0060*	*0.0064*	*0.0058*	*0.0057*	*0.0050*	*0.0047*	*0.0058*	*0.0057*	*0.0056*	*0.0059*	*0.0062*	*0.0066*
HR	score	NA	NA	NA	NA	NA	NA	NA	NA	0.0265	0.0318	0.0428	0.0476	0.0564	0.0590	0.0513
	diff	-	-	-	-	-	-	-	-	*0.0168*	*0.0161*	*0.0182*	*0.0228*	*0.0278*	*0.0275*	*0.0262*
HU	score	0.0081	0.0073	0.0092	0.0085	0.0114	0.0134	0.0131	0.0135	0.0134	0.0191	0.0230	0.0210	0.0223	0.0194	0.0154
	diff	*0.0123*	*0.0104*	*0.0101*	*0.0098*	*0.0093*	*0.0109*	*0.0109*	*0.0103*	*0.0102*	*0.0132*	*0.0148*	*0.0138*	*0.0137*	*0.0126*	*0.0089*
IE	score	0.0082	0.0107	0.0139	0.0152	0.0133	0.0132	0.0141	0.0141	0.0197	0.0379	0.0417	0.0424	0.0412	0.0387	0.0362
	diff	*0.0020*	*0.0025*	*0.0031*	*0.0029*	*0.0027*	*0.0027*	*0.0027*	*0.0028*	*0.0039*	*0.0077*	*0.0086*	*0.0091*	*0.0090*	*0.0079*	*0.0067*
IT	score	0.0279	0.0264	0.0251	0.0269	0.0264	0.0292	0.0247	0.0209	0.0218	0.0262	0.0274	0.0257	0.0319	0.0350	0.0384
	diff	*0.0179*	*0.0143*	*0.0130*	*0.0123*	*0.0103*	*0.0062*	*0.0061*	*0.0063*	*0.0077*	*0.0087*	*0.0103*	*0.0101*	*0.0125*	*0.0138*	*0.0143*
LT	score	0.0495	0.0383	0.0352	0.0350	0.0335	0.0197	0.0133	0.0102	0.0150	0.0311	0.0397	0.0316	0.0284	0.0257	0.0211
	diff	*0.0114*	*0.0257*	*0.0206*	*0.0179*	*0.0137*	*0.0100*	*0.0068*	*0.0046*	*0.0060*	*0.0150*	*0.0187*	*0.0156*	*0.0133*	*0.0109*	*0.0096*
LU	score	0.0069	0.0050	0.0052	0.0114	0.0157	0.0121	0.0148	0.0111	0.0107	0.0128	0.0125	0.0119	0.0148	0.0140	0.0154
	diff	*0.0008*	*0.0006*	*0.0012*	*0.0010*	*0.0014*	*0.0016*	*0.0013*	*0.0015*	*0.0027*	*0.0013*	*0.0008*	*0.0013*	*0.0013*	*0.0021*	*0.0019*
LV	score	0.0348	0.0324	0.0258	0.0242	0.0241	0.0222	0.0196	0.0180	0.0202	0.0405	0.0559	0.0380	0.0340	0.0312	0.0283
	diff	*0.0246*	*0.0206*	*0.0191*	*0.0185*	*0.0175*	*0.0145*	*0.0084*	*0.0072*	*0.0091*	*0.0224*	*0.0245*	*0.0192*	*0.0172*	*0.0118*	*0.0107*
MT	score	NA	NA	NA	0.0149	0.0200	0.0191	0.0183	0.0169	0.0000	0.0152	0.0139	0.0129	0.0124	0.0109	0.0101
	diff	-	-	-	*0.0105*	*0.0040*	*0.0038*	*0.0037*	*0.0034*	*0.0032*	*0.0046*	*0.0042*	*0.0039*	*0.0025*	*0.0022*	*0.0020*
NL	score	0.0094	0.0074	0.0106	0.0134	0.0153	0.0176	0.0138	0.0115	0.0104	0.0136	0.0154	0.0155	0.0167	0.0205	0.0199
	diff	*0.0022*	*0.0017*	*0.0009*	*0.0020*	*0.0031*	*0.0041*	*0.0034*	*0.0028*	*0.0023*	*0.0027*	*0.0030*	*0.0030*	*0.0035*	*0.0046*	*0.0046*
PL	score	0.0249	0.0282	0.0357	0.0391	0.0383	0.0368	0.0303	0.0236	0.0195	0.0225	0.0257	0.0268	0.0288	0.0293	0.0242
	diff	*0.0482*	*0.0520*	*0.0536*	*0.0490*	*0.0434*	*0.0362*	*0.0257*	*0.0167*	*0.0116*	*0.0122*	*0.0138*	*0.0131*	*0.0129*	*0.0126*	*0.0105*
PT	score	0.0142	0.0165	0.0231	0.0293	0.0262	0.0319	0.0321	0.0382	0.0351	0.0328	0.0362	0.0470	0.0618	0.0683	0.0547
	diff	*0.0028*	*0.0027*	*0.0025*	*0.0030*	*0.0036*	*0.0045*	*0.0048*	*0.0036*	*0.0041*	*0.0053*	*0.0065*	*0.0077*	*0.0103*	*0.0106*	*0.0090*
RO	score	NA	0.0197	0.0226	0.0178	0.0183	0.0191	0.0187	0.0144	0.0136	0.0222	0.0246	0.0237	0.0262	0.0279	0.0295
	diff	*NA*	*0.0022*	*0.0150*	*0.0101*	*0.0224*	*0.0145*	*0.0187*	*0.0157*	*0.0126*	*0.0134*	*0.0035*	*0.0106*	*0.0079*	*0.0063*	*0.0045*
SE	score	0.0138	0.0115	0.0136	0.0174	0.0196	0.0213	0.0217	0.0177	0.0180	0.0237	0.0248	0.0223	0.0231	0.0232	0.0231
	diff	*0.0044*	*0.0048*	*0.0049*	*0.0055*	*0.0063*	*0.0063*	*0.0054*	*0.0044*	*0.0046*	*0.0067*	*0.0065*	*0.0056*	*0.0054*	*0.0052*	*0.0048*
SI	score	0.0099	0.0105	0.0127	0.0163	0.0157	0.0173	0.0158	0.0169	0.0162	0.0157	0.0207	0.0249	0.0308	0.0306	0.0302
	diff	*0.0138*	*0.0133*	*0.0127*	*0.0114*	*0.0110*	*0.0106*	*0.0092*	*0.0065*	*0.0049*	*0.0078*	*0.0088*	*0.0094*	*0.0092*	*0.0101*	*0.0095*
SK	score	0.0277	0.0252	0.0224	0.0236	0.0278	0.0245	0.0161	0.0197	0.0177	0.0212	0.0300	0.0300	0.0348	0.0367	0.0326
	diff	*0.0565*	*0.0569*	*0.0598*	*0.0496*	*0.0482*	*0.0379*	*0.0299*	*0.0238*	*0.0201*	*0.0266*	*0.0298*	*0.0259*	*0.0255*	*0.0256*	*0.0225*
UK	score	0.0141	0.0124	0.0142	0.0137	0.0134	0.0131	0.0141	0.0130	0.0143	0.0206	0.0209	0.0223	0.0221	0.0202	0.0163
	diff	*0.0034*	*0.0030*	*0.0029*	*0.0033*	*0.0034*	*0.0034*	*0.0039*	*0.0036*	*0.0039*	*0.0053*	*0.0053*	*0.0052*	*0.0050*	*0.0045*	*0.0037*

score ... inefficiency score of the social model, diff ... difference to economic model from chapter 5.1.2

6. Conclusion

Economic Model

The economic models have shown that in a large majority of the EU Member States and the UK the production potentials as well actual productivity have considerably increased between 2000 and 2014, with few exceptions (e. g. Italy, Portugal, Greece). Productivity growth is almost exclusively driven by technical change, while fluctuations in efficiency contribute to a much lesser extent. Many countries operate relatively close to their production potential, however, in a majority of countries the gap to their production potential has increased.

The financial crisis is clearly visible in the results for all countries and in all models. In 2009, all countries in our data set experienced a decline in both their production potential and their actual productivity and only two were able to reduce the gap towards their potential slightly in that year (i. e. Portugal and Slovenia). Still, large differences can be observed regarding the recovery after the crisis: While some countries recovered quickly and already exceeded their performance from 2008 by 2010 or 2011 (e. g. the Netherlands, Ireland, Denmark), others like Greece, Cyprus or Spain were affected much longer. In 2014, the latter ones still suffered from both a lower production potential and lower efficiency than in 2008.

As the models also enable conclusions regarding individual inputs and outputs, a common observation is that for most countries high-qualified labor is the scarcest primary input, although with a decreasing trend. Furthermore, increases in the production potential are mostly associated to high-skilled labor.

Taking a look at the different models applied, all have shown to yield consistent results. Still, the properties of the SBM model are different from the radial and the DDF model. The latter estimate an efficiency frontier, which could realistically be achieved in the short run, because the required production factors are already available. However, on the input side they only account for unused inputs if they are scarce. Therefore, the efficiency scores do not explicitly indicate structural problems of the economy, such as an unfavorable distribution of available primary inputs like a qualification structure of the active population, which does not match the demand on the labor market. These are neither represented by the efficiency scores of the static analysis nor the potentials estimated in the intertemporal analysis.

The SBM model, in contrast, offers a more complete picture regarding the overall unused primary inputs and, thus, the inefficiencies found in an economy. However, it uses an efficiency frontier, which might only be achievable in the long run and does not depict a realistic short-term potential. Both models provide valuable findings, but answer slightly different questions.

We primarily applied input-oriented models, as both radial and SBM model are used in their input-oriented versions. In order to give a comprehensive picture of an economy's potential, we originally intended to use an unoriented version of the SBM model as well, which also accounts for inefficiencies on the output side. This turned out to be impracticable, as such a model tends to assign the free primary inputs to often relatively small sectors with a high output-to-input-ratio. As a result, such sectors would grow to several multitudes of their original size, which (1) is not a realistic assumption, even in the long run, and (2) massively influences the efficiency scores to reach unrealistically small values.[27]

An observation specific to the DEA-type formulation of the models (see e. g. Luptáčik and Mahlberg (2016, 4-5)) is, that the payoff-matrix usually takes a specific form: While the first n columns corresponding to the maximization of the individual inputs tend to portray a diagonal matrix (except for the last m rows, which contain the necessary inputs), the last n columns, which are constructed by minimizing the individual inputs, are usually identical.

As is characteristic for DEA, the models are quite versatile regarding the selection of inputs and outputs. Depending on the specific research question, different variables can be included. While we adopted the approach of Luptáčik and Mahlberg (2016) in most respects, we chose differing approaches in some aspects. One of these is labor endowment. Luptáčik and Mahlberg (2016) used working hours, which were estimated by multiplying the working age population (all persons aged 15 years and older) with the average number of hours worked per year. This is a very broad definition of labor endowment (as it includes e. g. students, persons on parental leave or retirees). We deviate from this definition in

[27] This, in turn, is due to the construction of the objective function in the unoriented SBM model, which builds on the arithmetic mean of the relative slacks. If individual slacks are extremely large compared to their current output, the objective value is massively impacted.

two aspects: (1) We use the number of persons instead of the number of usually worked hours. (2) As such a broad definition of the labor endowment suits the US labor market well, but not so much the European, we defined labor endowment as the active population to account for persons of the working age population, who are currently not available to the labor market. This approach, similar to Mahlberg and Luptáčik (2014), seems to be better suited for the European countries analyzed in this study.

Concerning the data required for the calculation of the economic models, we learned that most of the data is readily available, albeit, with one main limitation: Intertemporal analyses are hampered by the lack of long, consistent time series. For the analysis at hand, at least two severe breaks in the time series due to classification changes might have impacted the intertemporal results to some degree. First, the change regarding industry classification from NACE Rev. 1.1 to NACE Rev. 2 in 2008, and second - although this seems to impact only certain countries - the change from ISCED 97 to ISCED 2011 regarding skill levels in 2014. Although we tried to compensate for them as far as possible, they still might lead to biases in certain cases, especially when it comes to sectoral results between the periods before 2007 and after 2008.

Environmental Model

Regarding the environmental model, our empirical results reveal that carrying out the analysis strictly after Mahlberg and Luptáčik (2014) delivers limited additional insights when compared to the economic analysis. In fact, for all our models the (in-)efficiency scores are almost identical to the scores in the economic analysis. Theoretical considerations reveal that the problem lies in the definition of the x_2-vectors describing the level of anti-pollution activity (gross pollution minus tolerated level of net pollution). This, in turn, means that it is implicitly assumed that the abatement activities in a specific year are just enough to reach the pollution target of the same year. While this assumption might be interesting for other applications, this is less the case for the analysis conducted in this study. We therefore define an alternative x_2-vector to calculate A_{12}. Utilizing a simple first difference regression we get an estimate for the average effectiveness of abatement activities for the countries in our data set.

The results from the environmental analysis using the alternative x_2 vector now differ from the economic analysis and deliver novel insights for our subset of countries. We find that if all available unused production potentials would be channeled towards greenhouse gas abatement activities, all countries would reach the collectively agreed climate goals.

The environmental analysis comes with several shortcomings, mostly due to restricted data availability. Data for several environmental variables is only available from 2014 onward, which is why we restrict our analysis to the year 2014 (under certain assumptions regarding the environmental capital stock the model is also calculated for two countries for the year 2008). Moreover, many sectors have to be aggregated because data is not available and/or confidential on a finer scale. For 12 of the 28 countries the analysis cannot be conducted because at least one environmental variable is not available at all. These data issues also translate to our estimation procedure described above, as the same data set is used. At this point we want to stress again that the estimation procedure was conducted to demonstrate that the environmental model can also deliver interesting insights in the context of this study. We are aware that the true functional form on the relationship between abatement activities and pollution is not known to us and is very likely highly non-linear.

Social Model

So far, all models assumed the structure of the primary inputs as given. However, in reality skill levels of the workforce are subject to change. The so called social model now allows for improving the skill level of the unemployed population through qualification measures. The model demonstrates that qualification measures can substantially increase the economic potential, as in most countries high-skilled labor is scarce. As a consequence the perceived deviation from this (improved) potential is considerably larger than in the economic model, resulting in lower efficiency scores. The size of this efficiency gap between the economic model (which does not account for qualification measures) and this social variant varies between countries and depends - among other factors - on the limit set for the number of persons who can reach the next skill level in a period. A sensitivity analysis for Austria reveals that the effect is largest for the first 10 % (i. e. 10 % of the unemployed can reach the next skill level compared to 0 %), but gets smaller with every further 10 % step and therefore shows diminishing returns. In the further course of this study we assumed it to be 10 % of the unemployed population for each skill level.

On an intertemporal scale, the extension with qualification measures mainly affects efficiency change, not so much technical change.

From a modelling point of view the extension used in the social model would fit better to the SBM formulation of the economic model. However, unfortunately this does not yield meaningful results.[28] Therefore we applied the extension to the DDF model. We are aware that this is not an optimal solution, since the efficiency scores are still calculated as a fraction of the original endowment by skill levels, when using the (new) optimal endowment (with more higher-skilled people) would be more meaningful in this respect.[29] Inefficiency scores therefore tend to be still a bit smaller than they should actually be. Still, this simplified version of the model shows that qualification measures (e. g. special programs implemented by policy makers) to better match demand on the labor market can substantially increase an economy's potential.

Future research and alternative approaches

While this study tries to provide a comprehensive view on the economic potentials of the EU Member States and the UK under different assumptions, there are several aspects that could not be further analyzed in the course of this project. Future research could focus on the following issues in the single models:

Economic Model:

- Currently, the model focuses on domestic production, as analogous to Luptáčik and Mahlberg (2016) the domestic input-output tables ("version B") are used. Especially in times of crises (like the COVID pandemic) the question comes up, how self-sufficient a country is. Therefore it might be interesting to compare our results to a model, which accounts for imports as well ("version A" input-output tables).

- On the other hand one could also ask to which extent an economy is able to supply its own population, i. e. satisfy the domestic final demand without taking exports into account.

- This study evaluates every country individually, i. e. every country uses its own technology. While this is true in the short run it might also be interesting to see how

[28] Unemployed persons are assigned to the reachable qualification level with the highest shadow price, which - in case of the SBM - corresponds to the lowest total endowment, not the scarcest factor.

[29] Such a problem however can not be solved using linear optimization anymore.

the potentials would change if every country could use the production technology which achieves the best results.

Environmental Model:

- The pollution targets currently set by policy makers are different for every country insofar as they depend on a specific relative reduction from historic pollution values. An alternative approach would be to specify identical per capita pollution targets for every country in the model.

- The time series data on our environmental variables reveals that data quality increased in every year after 2014, whereas future research could make use of these improvements and could focus on (1) a broader set of countries including the majority of EU member states; (2) a more fine grained sectoral division; (3) an intertemporal analysis that takes more than two different points in time into account; (4) a more sophisticated approach in estimating the effectiveness of abatement measures or (5) an extension of the model with more than one pollution factor, for example solid waste or land use.

7. Appendix

Table 23

Intertemporal (mixed period) efficiency scores for Austria, economic input-oriented radial model, 2000-2014

		technology														
	-	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
inputs & outputs	2000	0.985	0.990	1.100	1.052	1.146	1.067	1.031	1.022	1.022	1.105	1.086	1.087	1.136	1.162	1.762
	2001	0.990	0.985	1.094	1.047	1.139	1.060	1.024	1.015	1.015	1.099	1.079	1.079	1.129	1.155	1.753
	2002	1.022	1.007	0.984	0.979	1.024	0.953	0.921	0.912	0.923	0.988	0.970	0.970	1.014	1.038	1.574
	2003	1.053	1.000	1.026	0.981	1.067	0.993	0.960	0.951	0.951	1.030	1.011	1.012	1.058	1.082	1.641
	2004	1.131	1.074	1.035	0.990	0.968	0.953	0.925	0.921	0.927	0.957	0.947	0.932	0.959	0.981	1.487
	2005	1.146	1.088	1.049	1.002	1.041	0.970	0.937	0.932	0.929	1.008	0.987	0.986	1.031	1.055	1.602
	2006	1.136	1.078	1.041	1.020	1.080	1.006	0.972	0.962	0.963	1.046	1.024	1.023	1.069	1.094	1.665
	2007	1.124	1.084	1.053	1.054	1.093	1.019	0.987	0.973	0.986	1.061	1.039	1.038	1.084	1.109	1.690
	2008	1.220	1.159	1.117	1.066	1.097	1.023	0.989	0.992	0.982	1.066	1.044	1.044	1.091	1.115	1.697
	2009	1.209	1.151	1.109	1.059	1.008	0.955	0.972	0.990	0.927	0.974	0.956	0.957	1.000	1.022	1.546
	2010	1.285	1.223	1.179	1.126	1.032	1.009	1.031	1.050	0.973	0.996	0.975	0.975	1.020	1.041	1.575
	2011	1.298	1.235	1.192	1.138	1.044	1.020	1.041	1.060	0.985	0.998	0.978	0.975	1.019	1.040	1.578
	2012	1.337	1.273	1.228	1.173	1.076	1.051	1.073	1.093	1.016	0.994	0.970	0.953	0.977	0.997	1.513
	2013	1.371	1.305	1.259	1.203	1.104	1.078	1.100	1.121	1.042	1.019	0.977	0.967	0.959	0.966	1.464
	2014	1.448	1.379	1.330	1.271	1.166	1.152	1.162	1.185	1.114	1.149	1.134	1.115	1.119	1.114	0.961

Table 24

Intertemporal (mixed period) efficiency scores for Austria, economic input-oriented SBM model, 2000-2014

		technology														
	-	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
inputs & outputs	2000	0.944	0.929	1.035	1.025	1.054	1.034	1.030	1.028	1.046	1.083	1.088	1.083	1.133	1.124	1.288
	2001	0.956	0.940	1.032	1.022	1.050	1.030	1.025	1.023	1.033	1.070	1.073	1.069	1.114	1.108	1.263
	2002	1.022	1.009	0.932	0.919	1.019	0.886	0.875	0.872	0.860	0.867	0.861	0.860	1.084	1.078	1.227
	2003	1.023	0.945	1.012	0.931	1.027	0.897	0.887	0.884	0.871	1.044	1.047	1.043	1.083	1.079	1.233
	2004	1.054	1.038	1.015	0.933	0.922	0.897	0.888	0.885	0.871	0.878	0.870	0.870	0.871	0.867	1.171
	2005	1.053	1.036	1.022	1.005	1.018	0.920	0.909	0.907	0.893	1.026	0.892	0.891	1.057	1.057	1.200
	2006	1.056	1.040	1.028	1.008	1.026	1.008	0.927	0.924	0.910	1.048	1.048	1.044	1.080	1.079	1.227
	2007	1.061	1.045	1.037	1.019	1.037	1.019	0.936	0.932	0.919	1.061	1.062	1.058	1.095	1.093	1.245
	2008	1.080	1.063	1.055	1.034	1.029	1.012	0.951	0.947	0.933	1.040	1.039	1.035	1.067	1.069	1.217
	2009	1.072	1.055	1.034	1.022	1.008	0.923	0.913	0.910	0.895	0.900	0.892	0.891	1.033	1.035	1.178
	2010	1.093	1.076	1.051	1.041	1.023	1.008	1.017	1.025	0.921	0.926	0.916	0.915	1.027	1.032	1.185
	2011	1.103	1.085	1.057	1.050	1.023	1.011	1.017	1.025	0.932	0.938	0.927	0.926	1.029	1.034	1.181
	2012	1.114	1.095	1.067	1.060	1.022	1.019	1.026	1.035	1.012	0.934	0.923	0.922	0.921	0.916	1.167
	2013	1.125	1.106	1.078	1.071	1.031	1.028	1.034	1.043	1.019	1.015	0.923	0.921	0.920	0.914	1.154
	2014	1.252	1.222	1.190	1.190	1.132	1.126	1.132	1.142	1.120	1.118	1.104	1.092	1.084	1.078	0.912

Table 25

Luenberger productivity indicator and Malmquist productivity index for Austria, economic models, base years 2000 and 2008

	2000 –>	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
base year 2000	Luenberger productivity indicator (DDF model)														
	ProdCh	-0.0001	-0.0184	-0.0010	-0.0078	0.0140	0.0207	0.0207	0.0433	0.0197	0.0393	0.0415	0.0382	0.0358	-0.0526
	TechCh	-0.0003	-0.0180	0.0012	0.0012	0.0216	0.0277	0.0267	0.0450	0.0253	0.0442	0.0467	0.0423	0.0455	-0.0405
	EffCh	0.0002	-0.0004	-0.0021	-0.0090	-0.0076	-0.0069	-0.0060	-0.0017	-0.0056	-0.0050	-0.0052	-0.0040	-0.0097	-0.0121
	Malmquist index (io radial model)														
	Productivity Change	0.9999	0.9638	0.9981	0.9845	1.0285	1.0424	1.0424	1.0908	1.0403	1.0824	1.0873	1.0805	1.0755	0.8954
	Frontier Shift	0.9995	0.9646	1.0024	1.0023	1.0443	1.0570	1.0549	1.0946	1.0521	1.0931	1.0987	1.0892	1.0965	0.9173
	Catchup	1.0004	0.9992	0.9958	0.9822	0.9849	0.9863	0.9881	0.9965	0.9888	0.9901	0.9896	0.9920	0.9808	0.9761
	Malmquist index (io SBM model)														
	Productivity Change	1.0122	0.9870	0.9916	0.9887	0.9963	1.0036	1.0097	1.0104	0.9713	0.9875	0.9993	0.9798	0.9846	0.9689
	Frontier Shift	1.0168	0.9996	1.0057	1.0118	1.0221	1.0219	1.0225	1.0221	1.0191	1.0179	1.0189	1.0035	1.0163	1.0029
	Catchup	0.9955	0.9874	0.9859	0.9772	0.9747	0.9821	0.9874	0.9886	0.9531	0.9702	0.9808	0.9763	0.9689	0.9661
	2008 –>									2009	2010	2011	2012	2013	2014
base year 2008	Luenberger productivity indicator (DDF model)														
	ProdCh									-0.0369	-0.0192	-0.0162	-0.0189	-0.0207	-0.1074
	TechCh									-0.0331	-0.0160	-0.0127	-0.0166	-0.0127	-0.0970
	EffCh									-0.0039	-0.0032	-0.0035	-0.0023	-0.0079	-0.0104
	Malmquist index (io radial model)														
	Productivity Change									0.9287	0.9623	0.9681	0.9630	0.9594	0.8020
	Frontier Shift									0.9360	0.9685	0.9749	0.9673	0.9748	0.8188
	Catchup									0.9923	0.9936	0.9931	0.9955	0.9843	0.9795
	Malmquist index (io SBM model)														
	Productivity Change									0.9108	0.9324	9452	0.9679	0.9664	0.9484
	Frontier Shift									0.9447	0.9501	0.9527	0.9801	0.9861	0.9705
	Catchup									0.9641	0.9814	0.9921	0.9876	0.9800	0.9773

Table 26

Luenberger productivity indicator - decomposition of ProdChange, economic DDF model for Austria, base year 2000

2000 –>	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
ProdChange	-0.0001	-0.0184	-0.0010	-0.0078	0.0140	0.0207	0.0207	0.0433	0.0197	0.0393	0.0415	0.0382	0.0358	-0.0526
A01	0.0087	0.0084	0.0086	0.0096	0.0085	0.0080	0.0093	0.0094	0.0091	0.0095	0.0094	0.0088	0.0080	0.0079
A02	-0.0004	-0.0003	0.0002	0.0006	0.0008	0.0010	0.0013	0.0012	0.0011	0.0014	0.0012	0.0014	0.0014	0.0014
A03	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
B	0.0003	0.0001	0.0003	0.0003	0.0004	0.0006	0.0007	0.0008	0.0006	0.0005	0.0008	0.0006	0.0006	0.0005
C10-C12	0.0123	0.0128	0.0137	0.0146	0.0151	0.0154	0.0151	0.0159	0.0157	0.0172	0.0175	0.0184	0.0190	0.0186
C13-C15	0.0066	0.0062	0.0057	0.0054	0.0049	0.0046	0.0040	0.0040	0.0031	0.0035	0.0035	0.0031	0.0033	0.0028
C16	0.0031	0.0032	0.0033	0.0034	0.0036	0.0039	0.0041	0.0035	0.0026	0.0033	0.0034	0.0032	0.0031	0.0025
C17	0.0018	0.0018	0.0017	0.0016	0.0017	0.0017	0.0017	0.0017	0.0015	0.0021	0.0020	0.0022	0.0020	0.0017
C18	0.0004	0.0002	0.0001	0.0001	0.0000	0.0001	0.0001	0.0001	0.0001	0.0002	0.0002	0.0000	-0.0002	-0.0001
C19	-0.0001	-0.0002	0.0000	0.0001	0.0004	0.0003	0.0004	0.0005	0.0005	0.0004	0.0003	0.0004	0.0003	0.0003
C20	0.0005	0.0005	0.0009	0.0006	0.0012	0.0014	0.0017	0.0016	0.0023	0.0043	0.0043	0.0046	0.0044	0.0046
C21	-0.0010	-0.0010	-0.0009	-0.0012	-0.0008	-0.0009	-0.0006	-0.0008	-0.0003	-0.0002	-0.0002	-0.0001	0.0000	0.0000
C22	0.0011	0.0010	0.0008	0.0009	0.0012	0.0015	0.0016	0.0016	0.0011	0.0017	0.0018	0.0017	0.0017	0.0016
C23	0.0018	0.0017	0.0018	0.0016	0.0019	0.0020	0.0020	0.0016	0.0010	0.0014	0.0013	0.0011	0.0011	0.0010
C24	0.0000	-0.0004	-0.0004	-0.0002	0.0006	0.0009	0.0014	0.0016	-0.0001	0.0010	0.0016	0.0015	0.0009	0.0004
C25	0.0024	0.0022	0.0022	0.0022	0.0026	0.0033	0.0036	0.0037	0.0022	0.0026	0.0030	0.0031	0.0031	0.0027
C26	0.0002	-0.0004	-0.0008	-0.0007	-0.0004	-0.0003	-0.0018	-0.0018	-0.0024	-0.0022	-0.0019	-0.0017	-0.0017	-0.0021
C27	0.0004	0.0005	0.0006	0.0006	0.0007	0.0009	0.0022	0.0029	0.0020	0.0026	0.0029	0.0028	0.0022	0.0019
C28	0.0005	0.0003	0.0005	0.0005	0.0010	0.0016	0.0022	0.0033	0.0012	0.0020	0.0032	0.0038	0.0033	0.0025
C29	-0.0009	-0.0005	-0.0009	0.0007	0.0012	0.0014	0.0010	0.0000	-0.0025	-0.0012	-0.0004	-0.0004	-0.0002	-0.0007
C30	-0.0001	0.0004	0.0005	0.0005	0.0004	0.0005	0.0005	0.0010	0.0007	0.0004	0.0004	0.0003	0.0004	0.0003
C31_C32	0.0014	0.0011	0.0008	0.0008	0.0010	0.0012	0.0015	0.0021	0.0016	0.0016	0.0024	0.0006	0.0010	-0.0002
C33	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001	0.0003	0.0006	0.0006	0.0011	0.0010	0.0012	0.0013	0.0015
D35	-0.0003	-0.0003	-0.0002	-0.0001	-0.0002	-0.0002	-0.0004	-0.0003	-0.0002	0.0000	-0.0003	0.0000	0.0001	-0.0003
E36	-0.0001	-0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
E37-E39	0.0002	0.0002	0.0002	0.0003	0.0003	0.0002	0.0003	0.0002	0.0003	0.0003	0.0003	0.0003	0.0004	0.0004
F	0.0099	0.0086	0.0106	0.0096	0.0095	0.0087	0.0089	0.0104	0.0072	0.0050	0.0041	0.0042	0.0037	-0.0006
G45	-0.0003	-0.0008	-0.0007	-0.0008	-0.0010	-0.0014	-0.0015	-0.0015	-0.0016	-0.0012	-0.0008	-0.0011	-0.0009	-0.0018
G46	0.0009	0.0008	0.0009	0.0000	0.0007	0.0006	0.0005	-0.0002	0.0003	0.0002	0.0001	0.0002	-0.0001	-0.0022
G47	0.0082	0.0086	0.0084	0.0082	0.0086	0.0080	0.0078	0.0083	0.0100	0.0108	0.0101	0.0101	0.0100	0.0071
H49	0.0028	0.0030	0.0031	0.0034	0.0029	0.0030	0.0029	0.0033	0.0035	0.0036	0.0038	0.0035	0.0037	0.0030
H50	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
H51	0.0016	0.0019	0.0018	0.0020	0.0019	0.0019	0.0020	0.0020	0.0017	0.0017	0.0015	0.0014	0.0014	0.0010
H52	0.0001	0.0002	0.0003	0.0006	0.0012	0.0013	0.0012	0.0014	0.0019	0.0023	0.0023	0.0025	0.0024	0.0025
H53	0.0036	0.0042	0.0041	0.0038	0.0047	0.0056	0.0048	0.0044	0.0046	0.0044	0.0040	0.0041	0.0042	0.0041
I	0.0205	0.0203	0.0211	0.0205	0.0205	0.0199	0.0196	0.0210	0.0216	0.0219	0.0216	0.0222	0.0226	0.0207
J58	-0.0004	-0.0006	-0.0006	-0.0007	-0.0006	-0.0005	-0.0004	-0.0002	-0.0003	-0.0005	-0.0005	-0.0006	-0.0006	-0.0009
J59_J60	-0.0007	-0.0008	-0.0008	-0.0008	-0.0008	-0.0008	-0.0009	-0.0009	-0.0009	-0.0010	-0.0009	-0.0010	-0.0009	-0.0012
J61	-0.0007	-0.0009	-0.0006	-0.0008	-0.0002	0.0002	-0.0002	-0.0004	-0.0005	-0.0008	-0.0011	-0.0012	-0.0014	-0.0022
J62_J63	-0.0040	-0.0038	-0.0038	-0.0036	-0.0033	-0.0033	-0.0033	-0.0033	-0.0031	-0.0029	-0.0017	-0.0013	-0.0005	-0.0009
K64	-0.0029	-0.0033	-0.0034	-0.0033	-0.0028	-0.0029	-0.0026	-0.0021	-0.0024	-0.0034	-0.0033	-0.0040	-0.0041	-0.0056
K65	-0.0011	-0.0010	-0.0012	-0.0012	-0.0010	-0.0011	-0.0011	-0.0013	-0.0013	-0.0011	-0.0007	-0.0006	-0.0008	-0.0013
K66	-0.0002	-0.0002	-0.0002	-0.0001	0.0000	0.0001	0.0001	0.0001	0.0002	0.0003	0.0003	0.0002	0.0002	0.0002
L68	0.0022	0.0022	0.0025	0.0026	0.0027	0.0026	0.0023	0.0025	0.0026	0.0028	0.0028	0.0030	0.0032	0.0023
M69_M70	-0.0017	-0.0018	-0.0014	-0.0012	-0.0009	-0.0007	-0.0002	-0.0002	-0.0006	-0.0008	-0.0005	-0.0003	0.0001	-0.0002
M71	-0.0039	-0.0046	-0.0044	-0.0050	-0.0043	-0.0039	-0.0038	-0.0040	-0.0053	-0.0058	-0.0058	-0.0054	-0.0054	-0.0065
M72	-0.0009	-0.0008	-0.0007	-0.0007	-0.0005	-0.0005	-0.0003	0.0001	0.0012	0.0017	0.0019	0.0020	0.0022	0.0016
M73	-0.0002	-0.0003	-0.0003	-0.0002	-0.0001	-0.0001	0.0000	0.0000	-0.0001	0.0001	0.0002	0.0003	0.0004	0.0003
M74_M75	-0.0009	-0.0010	-0.0010	-0.0010	-0.0009	-0.0013	-0.0015	-0.0017	-0.0019	-0.0019	-0.0019	-0.0019	-0.0020	-0.0021
N	0.0032	0.0031	0.0036	0.0039	0.0043	0.0049	0.0049	0.0058	0.0059	0.0061	0.0062	0.0069	0.0071	0.0069
O_U	-0.0063	-0.0078	-0.0071	-0.0089	-0.0080	-0.0081	-0.0095	-0.0081	-0.0074	-0.0083	-0.0094	-0.0098	-0.0103	-0.0148
P85	-0.0501	-0.0521	-0.0511	-0.0533	-0.0526	-0.0521	-0.0523	-0.0514	-0.0513	-0.0510	-0.0521	-0.0529	-0.0532	-0.0592
Q	-0.0132	-0.0151	-0.0139	-0.0143	-0.0137	-0.0135	-0.0134	-0.0121	-0.0106	-0.0100	-0.0111	-0.0111	-0.0113	-0.0163
R_S_T	-0.0044	-0.0050	-0.0048	-0.0051	-0.0051	-0.0055	-0.0057	-0.0050	-0.0055	-0.0059	-0.0063	-0.0070	-0.0071	-0.0095
PI:Labor_lq	-0.2513	-0.2472	-0.2436	-0.2347	-0.2330	-0.2341	-0.2355	-0.2253	-0.2263	-0.2188	-0.2176	-0.2139	-0.2109	-0.2043
PI:Labor_mq	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PI:Labor_hq	0.2513	0.2380	0.2431	0.2308	0.2400	0.2445	0.2458	0.2469	0.2361	0.2385	0.2383	0.2331	0.2288	0.1780
PI:Capital stock	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 27

Luenberger productivity indicator - decomposition of TechChange, economic DDF model for Austria, base year 2000

2000 –>	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
TechChange	-0.0003	-0.0180	0.0012	0.0012	0.0216	0.0277	0.0267	0.0450	0.0253	0.0442	0.0467	0.0423	0.0455	-0.0405
A01	0.0099	0.0087	0.0090	0.0094	0.0087	0.0082	0.0095	0.0098	0.0097	0.0102	0.0106	0.0100	0.0096	0.0096
A02	-0.0002	-0.0002	0.0001	0.0004	0.0005	0.0007	0.0009	0.0009	0.0008	0.0010	0.0009	0.0010	0.0009	0.0007
A03	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
B	0.0002	0.0002	0.0003	0.0003	0.0003	0.0004	0.0003	0.0004	0.0002	0.0002	0.0003	0.0002	0.0002	0.0001
C10-C12	0.0138	0.0117	0.0133	0.0151	0.0156	0.0154	0.0159	0.0165	0.0177	0.0188	0.0188	0.0195	0.0202	0.0197
C13-C15	0.0065	0.0067	0.0064	0.0061	0.0056	0.0052	0.0046	0.0047	0.0041	0.0046	0.0048	0.0041	0.0046	0.0033
C16	0.0032	0.0034	0.0035	0.0025	0.0032	0.0035	0.0039	0.0037	0.0027	0.0031	0.0026	0.0031	0.0031	0.0016
C17	0.0017	0.0019	0.0018	0.0015	0.0017	0.0018	0.0014	0.0015	0.0017	0.0017	0.0018	0.0018	0.0016	0.0011
C18	0.0002	0.0002	0.0001	0.0001	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0001	-0.0004	-0.0002
C19	-0.0001	-0.0001	0.0001	0.0001	0.0002	0.0002	0.0001	0.0002	0.0003	0.0004	0.0007	0.0007	0.0006	0.0005
C20	0.0003	0.0003	0.0004	0.0004	0.0005	0.0006	0.0007	0.0009	0.0011	0.0028	0.0025	0.0022	0.0025	0.0028
C21	-0.0008	-0.0007	-0.0010	-0.0008	-0.0008	-0.0008	-0.0006	-0.0006	-0.0010	-0.0004	-0.0005	0.0001	0.0001	-0.0001
C22	0.0011	0.0011	0.0014	0.0010	0.0015	0.0014	0.0016	0.0019	0.0015	0.0022	0.0024	0.0021	0.0018	0.0017
C23	0.0017	0.0015	0.0016	0.0009	0.0008	0.0008	0.0010	0.0008	0.0004	0.0003	0.0007	0.0006	0.0005	0.0003
C24	0.0000	-0.0002	0.0000	0.0006	0.0003	0.0006	0.0000	0.0002	-0.0008	-0.0004	0.0002	0.0003	0.0007	-0.0003
C25	0.0022	0.0022	0.0022	0.0021	0.0022	0.0025	0.0024	0.0005	0.0005	0.0004	0.0006	0.0008	0.0004	-0.0006
C26	-0.0006	0.0001	-0.0005	-0.0006	-0.0001	0.0005	-0.0003	0.0002	-0.0003	0.0010	0.0011	0.0007	0.0009	-0.0001
C27	0.0004	0.0006	0.0004	0.0004	0.0002	0.0007	0.0011	0.0000	-0.0004	-0.0005	-0.0004	0.0003	0.0000	-0.0014
C28	-0.0001	0.0001	0.0000	-0.0001	0.0000	0.0002	0.0000	-0.0032	-0.0046	-0.0038	-0.0031	-0.0033	-0.0026	-0.0075
C29	-0.0023	-0.0007	0.0004	0.0011	0.0003	0.0002	0.0002	0.0004	-0.0008	0.0011	0.0019	0.0019	0.0020	0.0008
C30	-0.0002	-0.0001	-0.0001	-0.0003	-0.0002	-0.0001	0.0000	-0.0007	-0.0007	-0.0005	-0.0005	-0.0005	-0.0002	-0.0004
C31_C32	0.0008	0.0016	0.0012	-0.0005	0.0002	0.0001	0.0006	0.0014	0.0009	0.0019	0.0023	0.0012	0.0021	0.0010
C33	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	-0.0002	-0.0005	-0.0005	-0.0003	-0.0002	0.0000	-0.0012
D35	0.0000	-0.0004	-0.0001	-0.0010	-0.0001	-0.0001	-0.0007	-0.0005	-0.0013	-0.0017	-0.0018	-0.0013	-0.0013	-0.0015
E36	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
E37-E39	0.0003	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0003	0.0003	0.0003	0.0003	0.0001
F	0.0118	0.0122	0.0149	0.0043	0.0102	0.0082	0.0077	0.0085	0.0059	0.0068	0.0053	0.0056	0.0060	-0.0003
G45	-0.0002	0.0005	0.0011	-0.0001	-0.0001	-0.0003	-0.0012	-0.0012	0.0002	0.0007	0.0003	-0.0010	0.0005	-0.0004
G46	-0.0017	0.0020	0.0030	-0.0014	0.0024	0.0030	0.0017	0.0018	0.0011	0.0004	0.0012	0.0004	0.0002	-0.0053
G47	0.0106	0.0117	0.0129	0.0048	0.0063	0.0059	0.0073	0.0079	0.0105	0.0120	0.0120	0.0095	0.0087	0.0027
H49	0.0021	0.0031	0.0048	0.0032	0.0042	0.0037	0.0044	0.0049	0.0040	0.0043	0.0044	0.0041	0.0040	0.0025
H50	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0001
H51	0.0017	0.0020	0.0020	0.0021	0.0019	0.0020	0.0021	0.0016	0.0011	0.0013	0.0010	0.0008	0.0008	0.0001
H52	0.0004	0.0004	0.0004	0.0006	0.0004	0.0004	0.0005	0.0007	0.0007	0.0005	0.0006	0.0002	0.0006	0.0001
H53	0.0034	0.0040	0.0038	0.0033	0.0044	0.0054	0.0047	0.0048	0.0050	0.0049	0.0045	0.0046	0.0047	0.0044
I	0.0208	0.0196	0.0194	0.0183	0.0193	0.0200	0.0215	0.0217	0.0220	0.0217	0.0215	0.0222	0.0221	0.0161
J58	-0.0006	-0.0001	-0.0002	-0.0005	-0.0007	-0.0005	-0.0003	-0.0001	-0.0001	-0.0002	-0.0006	-0.0006	-0.0012	-0.0010
J59_J60	-0.0008	-0.0006	-0.0007	-0.0006	-0.0006	-0.0004	-0.0005	-0.0006	-0.0007	-0.0012	-0.0008	-0.0007	-0.0003	-0.0006
J61	-0.0012	0.0002	0.0003	-0.0001	0.0009	0.0020	0.0015	0.0056	0.0050	0.0053	0.0046	0.0048	0.0045	0.0037
J62_J63	-0.0043	-0.0031	-0.0029	-0.0041	-0.0032	-0.0028	-0.0019	-0.0017	-0.0029	-0.0021	-0.0019	-0.0019	-0.0030	-0.0044
K64	-0.0017	-0.0016	-0.0017	-0.0015	-0.0023	-0.0019	-0.0011	-0.0011	-0.0008	-0.0007	-0.0009	-0.0012	-0.0006	-0.0034
K65	-0.0020	-0.0012	-0.0002	-0.0013	-0.0005	-0.0013	-0.0016	-0.0021	-0.0017	-0.0010	-0.0008	-0.0005	-0.0007	-0.0016
K66	-0.0002	-0.0001	0.0004	0.0003	0.0003	0.0002	0.0004	0.0003	0.0002	0.0004	0.0004	0.0005	0.0005	0.0005
L68	0.0033	0.0032	0.0024	0.0019	0.0017	0.0016	0.0011	0.0017	0.0010	0.0014	0.0021	0.0008	0.0004	-0.0013
M69_M70	-0.0022	-0.0017	-0.0018	-0.0026	-0.0024	-0.0024	-0.0030	-0.0027	-0.0026	-0.0029	-0.0021	-0.0025	-0.0033	-0.0032
M71	-0.0048	-0.0036	-0.0039	-0.0049	-0.0041	-0.0032	-0.0041	-0.0038	-0.0045	-0.0040	-0.0044	-0.0033	-0.0044	-0.0062
M72	-0.0011	-0.0007	-0.0004	-0.0004	-0.0010	-0.0013	-0.0012	-0.0013	-0.0022	-0.0022	-0.0024	-0.0026	-0.0022	-0.0014
M73	-0.0004	-0.0002	-0.0002	-0.0004	-0.0003	-0.0003	-0.0003	-0.0003	-0.0002	-0.0005	-0.0007	-0.0007	-0.0006	-0.0005
M74_M75	-0.0008	-0.0009	-0.0009	-0.0008	-0.0007	-0.0004	-0.0006	-0.0008	-0.0009	-0.0008	-0.0008	-0.0009	-0.0012	-0.0009
N	0.0032	0.0034	0.0035	0.0033	0.0035	0.0040	0.0039	0.0043	0.0038	0.0045	0.0041	0.0039	0.0047	0.0032
O_U	-0.0054	-0.0044	-0.0034	-0.0055	-0.0027	-0.0019	-0.0058	-0.0023	-0.0015	-0.0038	-0.0036	-0.0023	-0.0044	-0.0115
P85	-0.0476	-0.0348	-0.0361	-0.0369	-0.0458	-0.0438	-0.0378	-0.0405	-0.0369	-0.0378	-0.0397	-0.0350	-0.0298	-0.0192
Q	-0.0166	-0.0540	-0.0530	-0.0138	-0.0154	-0.0198	-0.0213	-0.0179	-0.0171	-0.0191	-0.0194	-0.0196	-0.0225	-0.0149
R_S_T	-0.0040	-0.0025	-0.0037	-0.0054	-0.0060	-0.0044	-0.0056	-0.0039	-0.0070	-0.0082	-0.0063	-0.0090	-0.0085	-0.0072
PI:Labor_lq	-0.2513	-0.2472	-0.2436	-0.2347	-0.2330	-0.2341	-0.2355	-0.2253	-0.2263	-0.2188	-0.2176	-0.2139	-0.2109	-0.2043
PI:Labor_mq	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PI:Labor_hq	0.2512	0.2382	0.2442	0.2352	0.2438	0.2479	0.2488	0.2478	0.2389	0.2409	0.2409	0.2351	0.2337	0.1840
PI:Capital stock	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 28

Luenberger productivity indicator - decomposition of EffChange, economic DDF model for Austria, base year 2000

2000 –>	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
EffChange	0.0002	-0.0004	-0.0021	-0.0090	-0.0076	-0.0069	-0.0060	-0.0017	-0.0056	-0.0050	-0.0052	-0.0040	-0.0097	-0.0121
A01	-0.0013	-0.0003	-0.0004	0.0003	-0.0002	-0.0002	-0.0002	-0.0004	-0.0006	-0.0007	-0.0011	-0.0011	-0.0016	-0.0018
A02	-0.0002	-0.0001	0.0000	0.0002	0.0002	0.0003	0.0004	0.0003	0.0003	0.0004	0.0003	0.0004	0.0004	0.0007
A03	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
B	0.0000	-0.0001	0.0000	0.0000	0.0001	0.0002	0.0005	0.0005	0.0003	0.0002	0.0005	0.0003	0.0003	0.0004
C10-C12	-0.0015	0.0012	0.0003	-0.0005	-0.0005	0.0000	-0.0008	-0.0006	-0.0020	-0.0017	-0.0013	-0.0011	-0.0011	-0.0011
C13-C15	0.0002	-0.0005	-0.0006	-0.0007	-0.0007	-0.0006	-0.0005	-0.0007	-0.0010	-0.0011	-0.0013	-0.0011	-0.0013	-0.0005
C16	-0.0001	-0.0001	-0.0002	0.0009	0.0004	0.0004	0.0002	-0.0002	-0.0001	0.0002	0.0008	0.0001	-0.0001	0.0009
C17	0.0001	0.0000	-0.0001	0.0001	0.0000	-0.0001	0.0003	0.0002	-0.0002	0.0004	0.0002	0.0003	0.0004	0.0006
C18	0.0002	0.0000	0.0000	0.0001	0.0000	0.0000	0.0001	0.0000	0.0000	0.0002	0.0002	0.0001	0.0002	0.0002
C19	0.0000	-0.0001	-0.0001	0.0000	0.0002	0.0002	0.0003	0.0003	0.0002	0.0000	-0.0004	-0.0002	-0.0003	-0.0002
C20	0.0001	0.0002	0.0005	0.0002	0.0007	0.0008	0.0009	0.0006	0.0013	0.0015	0.0018	0.0024	0.0019	0.0019
C21	-0.0002	-0.0003	0.0001	-0.0003	0.0000	-0.0001	-0.0001	-0.0002	0.0007	0.0003	0.0004	-0.0002	-0.0001	0.0001
C22	0.0000	-0.0002	-0.0006	-0.0001	-0.0003	0.0001	-0.0001	-0.0002	-0.0004	-0.0005	-0.0005	-0.0004	-0.0001	-0.0001
C23	0.0001	0.0002	0.0001	0.0008	0.0010	0.0011	0.0010	0.0008	0.0006	0.0011	0.0007	0.0006	0.0006	0.0007
C24	0.0000	-0.0002	-0.0005	-0.0009	0.0003	0.0003	0.0014	0.0013	0.0007	0.0014	0.0013	0.0012	0.0002	0.0007
C25	0.0002	0.0000	0.0001	0.0001	0.0004	0.0008	0.0012	0.0032	0.0018	0.0022	0.0024	0.0023	0.0027	0.0033
C26	0.0008	-0.0004	-0.0004	-0.0001	-0.0003	-0.0008	-0.0015	-0.0020	-0.0021	-0.0032	-0.0030	-0.0025	-0.0026	-0.0020
C27	0.0000	-0.0001	0.0003	0.0002	0.0004	0.0002	0.0011	0.0029	0.0025	0.0032	0.0033	0.0025	0.0022	0.0033
C28	0.0006	0.0002	0.0004	0.0007	0.0010	0.0015	0.0023	0.0065	0.0058	0.0058	0.0064	0.0071	0.0059	0.0099
C29	0.0014	0.0002	-0.0013	-0.0004	0.0009	0.0012	0.0008	-0.0003	-0.0016	-0.0024	-0.0024	-0.0023	-0.0023	-0.0015
C30	0.0001	0.0005	0.0006	0.0008	0.0006	0.0006	0.0005	0.0017	0.0014	0.0008	0.0008	0.0009	0.0006	0.0007
C31_C32	0.0006	-0.0004	-0.0003	0.0013	0.0008	0.0011	0.0009	0.0007	0.0007	-0.0003	0.0000	-0.0006	-0.0012	-0.0012
C33	0.0000	0.0000	0.0001	0.0000	0.0001	0.0001	0.0003	0.0008	0.0011	0.0017	0.0013	0.0014	0.0013	0.0027
D35	-0.0004	0.0001	0.0000	0.0009	-0.0002	-0.0001	0.0003	0.0002	0.0012	0.0017	0.0015	0.0013	0.0014	0.0012
E36	-0.0001	-0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
E37-E39	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001	0.0003
F	-0.0019	-0.0036	-0.0043	0.0052	-0.0007	0.0005	0.0012	0.0019	0.0013	-0.0018	-0.0012	-0.0014	-0.0023	-0.0003
G45	-0.0001	-0.0012	-0.0018	-0.0007	-0.0009	-0.0011	-0.0003	-0.0003	-0.0017	-0.0019	-0.0011	-0.0001	-0.0013	-0.0014
G46	0.0026	-0.0013	-0.0021	0.0014	-0.0017	-0.0025	-0.0013	-0.0021	-0.0008	-0.0002	-0.0012	-0.0002	-0.0003	0.0031
G47	-0.0024	-0.0030	-0.0045	0.0034	0.0022	0.0021	0.0005	0.0004	-0.0005	-0.0012	-0.0018	0.0006	0.0014	0.0044
H49	0.0006	-0.0001	-0.0017	0.0002	-0.0013	-0.0007	-0.0015	-0.0016	-0.0005	-0.0008	-0.0006	-0.0006	-0.0003	0.0006
H50	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0000	0.0001	0.0000	0.0000	0.0001
H51	-0.0001	-0.0001	-0.0002	-0.0001	0.0000	-0.0001	-0.0001	0.0005	0.0006	0.0004	0.0004	0.0005	0.0006	0.0009
H52	-0.0003	-0.0002	-0.0002	0.0000	0.0007	0.0009	0.0007	0.0008	0.0011	0.0018	0.0018	0.0022	0.0019	0.0024
H53	0.0002	0.0001	0.0003	0.0005	0.0003	0.0001	0.0001	-0.0005	-0.0004	-0.0005	-0.0004	-0.0005	-0.0005	-0.0003
I	-0.0003	0.0007	0.0017	0.0022	0.0012	0.0000	-0.0019	-0.0007	-0.0004	0.0002	0.0001	0.0000	0.0005	0.0046
J58	0.0002	-0.0004	-0.0004	-0.0002	0.0001	0.0001	-0.0001	-0.0002	-0.0003	-0.0004	0.0001	0.0000	0.0005	0.0001
J59_J60	0.0001	-0.0002	-0.0001	-0.0002	-0.0002	-0.0004	-0.0004	-0.0003	-0.0003	0.0002	-0.0001	-0.0003	-0.0006	-0.0006
J61	0.0005	-0.0010	-0.0009	-0.0007	-0.0012	-0.0018	-0.0017	-0.0060	-0.0055	-0.0061	-0.0057	-0.0059	-0.0060	-0.0059
J62_J63	0.0004	-0.0007	-0.0008	0.0006	-0.0001	-0.0006	-0.0015	-0.0016	-0.0002	-0.0009	0.0002	0.0006	0.0025	0.0035
K64	-0.0012	-0.0017	-0.0017	-0.0017	-0.0005	-0.0010	-0.0015	-0.0010	-0.0016	-0.0027	-0.0025	-0.0028	-0.0035	-0.0022
K65	0.0008	0.0002	-0.0010	0.0001	-0.0005	0.0002	0.0005	0.0008	0.0004	-0.0001	0.0001	-0.0001	-0.0001	0.0003
K66	0.0000	-0.0001	-0.0005	-0.0003	-0.0003	-0.0001	-0.0003	-0.0002	0.0000	-0.0001	-0.0001	-0.0003	-0.0004	-0.0003
L68	-0.0011	-0.0009	0.0001	0.0007	0.0010	0.0010	0.0012	0.0008	0.0016	0.0015	0.0007	0.0021	0.0027	0.0035
M69_M70	0.0005	-0.0002	0.0004	0.0014	0.0016	0.0017	0.0029	0.0026	0.0020	0.0021	0.0016	0.0023	0.0034	0.0030
M71	0.0009	-0.0009	-0.0005	-0.0001	-0.0002	-0.0007	0.0003	-0.0001	-0.0008	-0.0018	-0.0014	-0.0021	-0.0010	-0.0002
M72	0.0002	-0.0002	-0.0003	-0.0003	0.0005	0.0008	0.0009	0.0014	0.0033	0.0039	0.0043	0.0046	0.0043	0.0030
M73	0.0001	-0.0001	0.0000	0.0001	0.0002	0.0001	0.0003	0.0002	0.0002	0.0005	0.0009	0.0010	0.0010	0.0008
M74_M75	-0.0001	0.0000	-0.0001	-0.0002	-0.0002	-0.0008	-0.0009	-0.0009	-0.0009	-0.0011	-0.0011	-0.0010	-0.0008	-0.0012
N	0.0000	-0.0004	0.0001	0.0005	0.0008	0.0010	0.0010	0.0015	0.0021	0.0016	0.0021	0.0030	0.0024	0.0038
O_U	-0.0008	-0.0034	-0.0037	-0.0035	-0.0053	-0.0061	-0.0037	-0.0058	-0.0059	-0.0045	-0.0058	-0.0074	-0.0058	-0.0033
P85	-0.0025	-0.0173	-0.0150	-0.0164	-0.0068	-0.0083	-0.0145	-0.0109	-0.0143	-0.0132	-0.0124	-0.0178	-0.0233	-0.0400
Q	0.0035	0.0389	0.0391	-0.0005	0.0018	0.0062	0.0078	0.0058	0.0065	0.0091	0.0083	0.0085	0.0112	-0.0014
R_S_T	-0.0004	-0.0025	-0.0011	0.0003	0.0008	-0.0010	-0.0001	-0.0011	0.0015	0.0023	0.0000	0.0020	0.0014	-0.0022
PI:Labor_lq	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PI:Labor_mq	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PI:Labor_hq	0.0001	-0.0002	-0.0011	-0.0045	-0.0038	-0.0035	-0.0030	-0.0009	-0.0028	-0.0025	-0.0026	-0.0020	-0.0048	-0.0060
PI:Capital stock	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 29

Luenberger productivity indicator for the EU 28 (part 1), economic DDF model, base year 2000 (unless otherwise specified)

2000 –>	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
AT														
ProdCh	-0.0001	-0.0184	-0.0010	-0.0078	0.0140	0.0207	0.0207	0.0433	0.0197	0.0393	0.0415	0.0382	0.0358	-0.0526
TechCh	-0.0003	-0.0180	0.0012	0.0012	0.0216	0.0277	0.0267	0.0450	0.0253	0.0442	0.0467	0.0423	0.0455	-0.0405
EffCh	0.0002	-0.0004	-0.0021	-0.0090	-0.0076	-0.0069	-0.0060	-0.0017	-0.0056	-0.0050	-0.0052	-0.0040	-0.0097	-0.0121
BE														
ProdCh	-0.0057	-0.0023	0.0029	0.0157	0.0266	0.0342	0.0537	0.0755	0.0538	0.0597	0.0801	0.0767	0.0819	0.0934
TechCh	-0.0048	0.0015	0.0090	0.0229	0.0325	0.0404	0.0563	0.0771	0.0598	0.0659	0.0827	0.0802	0.0900	0.1004
EffCh	-0.0009	-0.0038	-0.0061	-0.0072	-0.0059	-0.0062	-0.0025	-0.0016	-0.0059	-0.0062	-0.0025	-0.0035	-0.0081	-0.0070
BG														
ProdCh	-0.0188	0.0110	0.0535	0.0851	0.1130	0.1662	0.2052	0.2264	0.1860	0.2057	0.2412	0.2442	0.2465	0.2250
TechCh	-0.0087	0.0181	0.0519	0.0777	0.0981	0.1500	0.1820	0.2025	0.1650	0.1922	0.2304	0.2371	0.2425	0.2138
EffCh	-0.0100	-0.0071	0.0016	0.0074	0.0149	0.0162	0.0231	0.0239	0.0210	0.0135	0.0108	0.0071	0.0039	0.0112
CY (2008)														
ProdCh	-	-	-	-	-	-	-	-	-0.0448	-0.0331	-0.0455	-0.0531	-0.0725	-0.0832
TechCh	-	-	-	-	-	-	-	-	-0.0346	-0.0175	-0.0224	-0.0140	-0.0139	-0.0253
EffCh	-	-	-	-	-	-	-	-	-0.0102	-0.0156	-0.0231	-0.0392	-0.0585	-0.0579
CZ														
ProdCh	0.0166	0.0303	0.0543	0.0819	0.1131	0.1350	0.1666	0.1626	0.1324	0.1553	0.1672	0.1536	0.1506	0.1753
TechCh	0.0149	0.0269	0.0507	0.0784	0.1104	0.1324	0.1601	0.1561	0.1300	0.1550	0.1670	0.1536	0.1502	0.1753
EffCh	0.0017	0.0034	0.0037	0.0035	0.0027	0.0026	0.0065	0.0065	0.0024	0.0004	0.0002	0.0000	0.0004	0.0000
DE														
ProdCh	0.0176	0.0193	0.0085	0.0038	0.0132	0.0406	0.0497	0.0551	0.0271	0.0645	0.0843	0.0826	0.0829	0.1045
TechCh	0.0170	0.0198	0.0121	0.0091	0.0207	0.0448	0.0491	0.0521	0.0244	0.0598	0.0766	0.0745	0.0751	0.0974
EffCh	0.0006	-0.0005	-0.0036	-0.0052	-0.0075	-0.0042	0.0005	0.0031	0.0027	0.0047	0.0077	0.0081	0.0079	0.0072
DK														
ProdCh	0.0194	0.0180	-0.0215	-0.0098	0.0017	0.0245	0.0594	0.0614	0.0373	0.0434	0.0436	0.0389	0.0419	0.0410
TechCh	0.0227	0.0221	-0.0135	-0.0019	0.0048	0.0082	0.0574	0.0563	0.0394	0.0505	0.0533	0.0473	0.0491	0.0492
EffCh	-0.0033	-0.0042	-0.0080	-0.0079	-0.0031	0.0162	0.0020	0.0051	-0.0020	-0.0071	-0.0097	-0.0084	-0.0072	-0.0082
EE														
ProdCh	0.0442	0.1000	0.1103	0.1133	0.1415	0.1748	0.1945	0.1844	0.1241	0.1089	0.1322	0.1706	0.1746	0.1937
TechCh	0.0454	0.0976	0.1095	0.1057	0.1273	0.1560	0.1695	0.1634	0.1195	0.1229	0.1377	0.1673	0.1688	0.1811
EffCh	-0.0012	0.0025	0.0008	0.0076	0.0142	0.0188	0.0250	0.0210	0.0047	-0.0140	-0.0055	0.0033	0.0059	0.0125
EL														
ProdCh	0.0123	0.0269	0.0578	0.0670	0.0663	0.0600	0.0695	0.0602	0.0364	-0.0036	-0.0517	-0.0894	-0.1090	-0.0910
TechCh	0.0121	0.0229	0.0532	0.0672	0.0657	0.0566	0.0646	0.0513	0.0334	0.0051	-0.0207	-0.0364	-0.0456	-0.0296
EffCh	0.0002	0.0040	0.0046	-0.0001	0.0006	0.0034	0.0050	0.0090	0.0031	-0.0087	-0.0309	-0.0530	-0.0633	-0.0614
ES														
ProdCh	0.0041	-0.0014	-0.0048	-0.0006	0.0030	0.0104	0.0193	0.0024	-0.0253	-0.0254	-0.0243	-0.0441	-0.0472	-0.0319
TechCh	-0.0109	-0.0112	-0.0153	-0.0139	-0.0179	-0.0146	-0.0096	-0.0213	-0.0316	-0.0235	-0.0142	-0.0208	-0.0178	-0.0095
EffCh	0.0150	0.0098	0.0105	0.0133	0.0209	0.0251	0.0289	0.0237	0.0063	-0.0019	-0.0101	-0.0233	-0.0294	-0.0225
FI														
ProdCh	0.0159	0.0221	0.0243	0.0443	0.0621	0.0747	0.0973	0.1022	0.0761	0.0999	0.1119	0.1186	0.1228	0.1249
TechCh	0.0140	0.0173	0.0199	0.0422	0.0588	0.0674	0.0899	0.0922	0.0700	0.0960	0.1056	0.1121	0.1187	0.1245
EffCh	0.0020	0.0048	0.0044	0.0021	0.0032	0.0072	0.0074	0.0100	0.0061	0.0039	0.0064	0.0065	0.0041	0.0003
FR														
ProdCh	-0.0111	-0.0149	-0.0105	0.0007	0.0058	0.0099	0.0247	0.0355	0.0183	0.0360	0.0459	0.0429	0.0611	0.0722
TechCh	-0.0136	-0.0143	-0.0076	0.0065	0.0096	0.0121	0.0249	0.0315	0.0192	0.0364	0.0464	0.0445	0.0656	0.0792
EffCh	0.0025	-0.0006	-0.0029	-0.0058	-0.0038	-0.0022	-0.0002	0.0040	-0.0009	-0.0004	-0.0004	-0.0015	-0.0046	-0.0070
HR (2008)														
ProdCh	-	-	-	-	-	-	-	-	-0.0589	-0.0908	-0.0724	-0.0572	-0.0587	-0.0672
TechCh	-	-	-	-	-	-	-	-	-0.0535	-0.0745	-0.0513	-0.0273	-0.0261	-0.0424
EffCh	-	-	-	-	-	-	-	-	-0.0053	-0.0163	-0.0212	-0.0299	-0.0326	-0.0248
HU														
ProdCh	0.0229	0.0457	0.0576	0.0819	0.0830	0.1105	0.1160	0.1249	0.0913	0.0936	0.1009	0.0865	0.1101	0.1191
TechCh	0.0221	0.0468	0.0580	0.0852	0.0883	0.1155	0.1214	0.1302	0.1022	0.1085	0.1138	0.1007	0.1215	0.1264
EffCh	0.0008	-0.0011	-0.0004	-0.0033	-0.0053	-0.0050	-0.0054	-0.0053	-0.0110	-0.0149	-0.0129	-0.0142	-0.0113	-0.0073

Table 30

Luenberger productivity indicator for the EU 28 (part 2), economic DDF model, base year 2000 (unless otherwise specified)

2000 –>	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
IE														
ProdCh	-0.0112	-0.0209	-0.0443	-0.0490	-0.0453	-0.0360	-0.0274	-0.0143	-0.0205	-0.0093	0.0000	0.0093	0.0057	0.0658
TechCh	-0.0088	-0.0152	-0.0373	-0.0438	-0.0403	-0.0301	-0.0215	-0.0028	0.0092	0.0242	0.0342	0.0423	0.0362	0.0939
EffCh	-0.0025	-0.0057	-0.0070	-0.0051	-0.0050	-0.0059	-0.0059	-0.0115	-0.0298	-0.0335	-0.0342	-0.0330	-0.0305	-0.0281
IT														
ProdCh	-0.0041	-0.0164	-0.0354	-0.0248	-0.0309	-0.0281	-0.0263	-0.0467	-0.0659	-0.0587	-0.0588	-0.0932	-0.1013	-0.1038
TechCh	-0.0056	-0.0193	-0.0364	-0.0263	-0.0296	-0.0312	-0.0333	-0.0528	-0.0677	-0.0592	-0.0611	-0.0893	-0.0942	-0.0933
EffCh	0.0015	0.0029	0.0010	0.0015	-0.0013	0.0032	0.0070	0.0061	0.0017	0.0006	0.0023	-0.0039	-0.0071	-0.0105
LT														
ProdCh	0.1160	0.1546	0.1967	0.2266	0.2701	0.3179	0.3674	0.4089	0.3431	0.3896	0.4131	0.4274	0.4393	0.4298
TechCh	0.1047	0.1402	0.1822	0.2105	0.2403	0.2817	0.3281	0.3744	0.3247	0.3799	0.3952	0.4063	0.4156	0.4014
EffCh	0.0112	0.0143	0.0144	0.0160	0.0298	0.0362	0.0393	0.0345	0.0184	0.0098	0.0179	0.0211	0.0237	0.0284
LU														
ProdCh	-0.0206	-0.0020	0.0708	0.0206	0.0078	0.0482	0.0503	0.0270	-0.0056	0.0309	0.0128	0.0142	0.0363	0.0466
TechCh	-0.0225	-0.0037	0.0753	0.0294	0.0130	0.0561	0.0546	0.0307	0.0003	0.0365	0.0178	0.0222	0.0435	0.0552
EffCh	0.0019	0.0017	-0.0045	-0.0088	-0.0052	-0.0079	-0.0042	-0.0038	-0.0059	-0.0056	-0.0050	-0.0080	-0.0071	-0.0086
LV														
ProdCh	-0.0116	0.0424	0.0799	0.0826	0.1276	0.1616	0.1837	0.1676	0.1139	0.1467	0.1749	0.2116	0.2288	0.2517
TechCh	-0.0140	0.0334	0.0693	0.0720	0.1150	0.1464	0.1669	0.1530	0.1196	0.1678	0.1780	0.2108	0.2251	0.2452
EffCh	0.0024	0.0090	0.0106	0.0106	0.0126	0.0152	0.0168	0.0146	-0.0057	-0.0211	-0.0032	0.0008	0.0036	0.0065
MT (2003)														
ProdCh	-	-	-	-0.0309	-0.0501	-0.0194	-0.0095	0.0264	0.0031	0.0122	0.0239	0.0510	0.0686	0.0689
TechCh	-	-	-	-0.0258	-0.0459	-0.0160	-0.0076	0.0115	0.0035	0.0112	0.0218	0.0485	0.0647	0.0640
EffCh	-	-	-	-0.0051	-0.0042	-0.0034	-0.0019	0.0149	-0.0003	0.0010	0.0021	0.0025	0.0040	0.0048
NL														
ProdCh	0.0229	0.0002	-0.0113	-0.0091	-0.0015	0.0094	0.0167	0.0188	0.0106	0.0244	0.0298	0.0263	0.0311	0.0449
TechCh	0.0210	0.0014	-0.0072	-0.0031	0.0068	0.0139	0.0188	0.0198	0.0148	0.0304	0.0359	0.0336	0.0423	0.0555
EffCh	0.0019	-0.0012	-0.0040	-0.0060	-0.0083	-0.0045	-0.0021	-0.0010	-0.0043	-0.0060	-0.0061	-0.0074	-0.0111	-0.0106
PL														
ProdCh	-0.0185	-0.0218	-0.0010	0.0079	0.0135	0.0507	0.0878	0.1024	0.0872	0.0959	0.1098	0.1106	0.1213	0.1443
TechCh	-0.0152	-0.0110	0.0132	0.0213	0.0254	0.0561	0.0866	0.0970	0.0848	0.0967	0.1117	0.1145	0.1257	0.1436
EffCh	-0.0033	-0.0108	-0.0142	-0.0134	-0.0119	-0.0054	0.0013	0.0054	0.0024	-0.0008	-0.0019	-0.0039	-0.0044	0.0007
PT														
ProdCh	-0.0059	-0.0153	-0.0359	-0.0502	-0.0480	-0.0471	-0.0443	-0.0493	-0.0569	-0.0526	-0.0773	-0.1012	-0.0919	-0.0869
TechCh	-0.0036	-0.0063	-0.0208	-0.0382	-0.0303	-0.0291	-0.0203	-0.0284	-0.0383	-0.0306	-0.0445	-0.0536	-0.0378	-0.0464
EffCh	-0.0023	-0.0089	-0.0151	-0.0120	-0.0177	-0.0179	-0.0240	-0.0209	-0.0186	-0.0220	-0.0328	-0.0476	-0.0541	-0.0405
RO (2001)														
ProdCh	-	0.0486	0.0849	0.1350	0.1349	0.1582	0.1514	0.1931	0.1525	0.1607	0.1744	0.1569	0.1764	0.1646
TechCh	-	0.0515	0.0830	0.1336	0.1343	0.1572	0.1461	0.1871	0.1551	0.1656	0.1784	0.1634	0.1846	0.1744
EffCh	-	-0.0029	0.0019	0.0014	0.0006	0.0010	0.0053	0.0061	-0.0025	-0.0049	-0.0040	-0.0065	-0.0082	-0.0098
SE														
ProdCh	0.0055	0.0096	0.0157	0.0444	0.0584	0.0165	0.0499	0.0475	0.0123	0.0528	0.0610	0.0579	0.0605	0.0610
TechCh	0.0170	0.0096	0.0157	0.0444	0.0584	0.0165	0.0676	0.0655	0.0359	0.0776	0.0833	0.0810	0.0836	0.0841
EffCh	-0.0115	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0177	-0.0180	-0.0237	-0.0248	-0.0223	-0.0231	-0.0232	-0.0231
SI														
ProdCh	0.0327	0.0229	0.0113	0.0380	0.0447	0.0631	0.0787	0.0846	0.0416	0.0426	0.0644	0.0430	0.0265	0.0336
TechCh	0.0333	0.0258	0.0178	0.0439	0.0521	0.0690	0.0857	0.0909	0.0474	0.0535	0.0795	0.0640	0.0472	0.0539
EffCh	-0.0006	-0.0028	-0.0065	-0.0059	-0.0074	-0.0059	-0.0070	-0.0063	-0.0058	-0.0109	-0.0151	-0.0210	-0.0207	-0.0203
SK														
ProdCh	0.0180	0.0221	-0.0103	0.0028	0.0212	0.0708	0.1112	0.1231	0.1071	0.0955	0.0925	0.0824	0.0893	0.0952
TechCh	0.0155	0.0168	-0.0144	0.0028	0.0180	0.0592	0.1032	0.1131	0.1006	0.0979	0.0948	0.0895	0.0983	0.1001
EffCh	0.0025	0.0053	0.0041	-0.0001	0.0032	0.0116	0.0080	0.0100	0.0066	-0.0023	-0.0023	-0.0071	-0.0090	-0.0049
UK														
ProdCh	0.0082	0.0156	0.0261	0.0505	0.0694	0.0870	0.0990	0.0980	0.0825	0.1020	0.1044	0.1100	0.1091	0.1216
TechCh	0.0065	0.0158	0.0257	0.0498	0.0684	0.0870	0.0979	0.0982	0.0890	0.1088	0.1126	0.1180	0.1152	0.1238
EffCh	0.0017	-0.0001	0.0004	0.0007	0.0010	0.0000	0.0011	-0.0002	-0.0065	-0.0069	-0.0082	-0.0080	-0.0061	-0.0022

Table 31

Malmquist productivity index for the EU 28 (part 1), economic input-oriented radial model, base year 2000 (unless otherwise specified)

2000 –>	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
AT														
ProdCh	0.9999	0.9638	0.9981	0.9845	1.0285	1.0424	1.0424	1.0908	1.0403	1.0824	1.0873	1.0805	1.0755	0.8954
TechCh	0.9995	0.9646	1.0024	1.0023	1.0443	1.0570	1.0549	1.0946	1.0521	1.0931	1.0987	1.0892	1.0965	0.9173
EffCh	1.0004	0.9992	0.9958	0.9822	0.9849	0.9863	0.9881	0.9965	0.9888	0.9901	0.9896	0.9920	0.9808	0.9761
BE														
ProdCh	0.9887	0.9954	1.0058	1.0319	1.0548	1.0710	1.1142	1.1646	1.1150	1.1284	1.1769	1.1687	1.1818	1.2109
TechCh	0.9905	1.0031	1.0182	1.0469	1.0673	1.0845	1.1198	1.1684	1.1282	1.1424	1.1828	1.1768	1.2012	1.2280
EffCh	0.9981	0.9924	0.9878	0.9856	0.9883	0.9876	0.9950	0.9967	0.9882	0.9878	0.9950	0.9931	0.9838	0.9861
BG														
ProdCh	0.9631	1.0222	1.1130	1.1860	1.2548	1.3995	1.5176	1.5886	1.4606	1.5247	1.6489	1.6634	1.6768	1.6004
TechCh	0.9827	1.0369	1.1095	1.1684	1.2179	1.3549	1.4490	1.5143	1.4006	1.4842	1.6138	1.6398	1.6636	1.5650
EffCh	0.9801	0.9858	1.0031	1.0150	1.0303	1.0329	1.0474	1.0490	1.0429	1.0273	1.0218	1.0144	1.0079	1.0227
CY (2008)														
ProdCh	-	-	-	-	-	-	-	-	0.9142	0.9358	0.9129	0.8991	0.8649	0.8465
TechCh	-	-	-	-	-	-	-	-	0.9331	0.9656	0.9562	0.9725	0.9725	0.9506
EffCh	-	-	-	-	-	-	-	-	0.9797	0.9692	0.9547	0.9246	0.8893	0.8905
CZ														
ProdCh	1.0338	1.0625	1.1148	1.1787	1.2570	1.3157	1.4063	1.3971	1.3126	1.3842	1.4292	1.3911	1.3880	1.4763
TechCh	1.0303	1.0553	1.1067	1.1706	1.2502	1.3090	1.3881	1.3791	1.3063	1.3832	1.4287	1.3911	1.3869	1.4763
EffCh	1.0034	1.0069	1.0073	1.0070	1.0054	1.0051	1.0131	1.0131	1.0048	1.0007	1.0004	1.0000	1.0008	1.0000
DE														
ProdCh	1.0359	1.0394	1.0171	1.0077	1.0268	1.0847	1.1045	1.1167	1.0557	1.1380	1.1846	1.1806	1.1815	1.2341
TechCh	1.0346	1.0404	1.0245	1.0183	1.0423	1.0938	1.1034	1.1098	1.0501	1.1273	1.1664	1.1617	1.1631	1.2165
EffCh	1.0012	0.9990	0.9927	0.9896	0.9852	0.9916	1.0010	1.0062	1.0053	1.0095	1.0155	1.0163	1.0158	1.0145
DK														
ProdCh	1.0396	1.0366	0.9578	0.9805	1.0034	1.0338	1.1270	1.1321	1.0781	1.0914	1.0918	1.0817	1.0884	1.0864
TechCh	1.0464	1.0453	0.9733	0.9961	1.0097	1.0331	1.1226	1.1206	1.0825	1.1070	1.1133	1.0999	1.1042	1.1043
EffCh	0.9935	0.9917	0.9841	0.9843	0.9938	1.0007	1.0039	1.0103	0.9959	0.9859	0.9808	0.9834	0.9856	0.9838
EE														
ProdCh	1.0926	1.2225	1.2481	1.2554	1.3295	1.4238	1.4838	1.4528	1.2835	1.2462	1.3109	1.4204	1.4333	1.4961
TechCh	1.0952	1.2165	1.2460	1.2364	1.2923	1.3711	1.4114	1.3931	1.2716	1.2817	1.3254	1.4110	1.4166	1.4591
EffCh	0.9977	1.0050	1.0017	1.0154	1.0288	1.0384	1.0513	1.0428	1.0094	0.9723	0.9891	1.0067	1.0118	1.0254
EL														
ProdCh	1.0250	1.0554	1.1227	1.1439	1.1424	1.1279	1.1499	1.1288	1.0760	0.9929	0.9011	0.8347	0.8015	0.8310
TechCh	1.0245	1.0469	1.1123	1.1443	1.1411	1.1202	1.1385	1.1088	1.0694	1.0103	0.9588	0.9285	0.9104	0.9403
EffCh	1.0005	1.0081	1.0093	0.9997	1.0012	1.0069	1.0100	1.0181	1.0062	0.9828	0.9398	0.8990	0.8804	0.8838
ES														
ProdCh	1.0082	0.9973	0.9905	0.9988	1.0061	1.0211	1.0394	1.0048	0.9507	0.9504	0.9525	0.9154	0.9097	0.9379
TechCh	0.9784	0.9779	0.9698	0.9726	0.9647	0.9711	0.9809	0.9582	0.9388	0.9540	0.9719	0.9593	0.9650	0.9812
EffCh	1.0304	1.0198	1.0213	1.0270	1.0429	1.0515	1.0597	1.0487	1.0127	0.9962	0.9800	0.9542	0.9426	0.9559
FI														
ProdCh	1.0324	1.0451	1.0499	1.0928	1.1323	1.1614	1.2159	1.2282	1.1655	1.2240	1.2549	1.2730	1.2857	1.2931
TechCh	1.0283	1.0352	1.0407	1.0881	1.1251	1.1447	1.1980	1.2040	1.1514	1.2144	1.2391	1.2565	1.2752	1.2922
EffCh	1.0040	1.0096	1.0088	1.0043	1.0065	1.0145	1.0150	1.0201	1.0123	1.0079	1.0128	1.0131	1.0082	1.0007
FR														
ProdCh	0.9780	0.9707	0.9792	1.0013	1.0116	1.0200	1.0508	1.0739	1.0371	1.0750	1.0969	1.0906	1.1326	1.1599
TechCh	0.9731	0.9719	0.9850	1.0130	1.0194	1.0245	1.0511	1.0653	1.0392	1.0760	1.0979	1.0939	1.1430	1.1762
EffCh	1.0050	0.9988	0.9942	0.9885	0.9924	0.9956	0.9996	1.0081	0.9980	0.9990	0.9991	0.9970	0.9909	0.9862
HR (2008)														
ProdCh	-	-	-	-	-	-	-	-	0.8888	0.8336	0.8649	0.8917	0.8888	0.8733
TechCh	-	-	-	-	-	-	-	-	0.8983	0.8613	0.9024	0.9468	0.9488	0.9178
EffCh	-	-	-	-	-	-	-	-	0.9894	0.9679	0.9585	0.9418	0.9368	0.9515
HU														
ProdCh	1.0468	1.0957	1.1224	1.1799	1.1826	1.2517	1.2670	1.2920	1.2054	1.2118	1.2324	1.1965	1.2584	1.2831
TechCh	1.0451	1.0982	1.1232	1.1876	1.1951	1.2643	1.2806	1.3058	1.2321	1.2485	1.2646	1.2310	1.2872	1.3020
EffCh	1.0016	0.9977	0.9993	0.9935	0.9895	0.9900	0.9893	0.9895	0.9783	0.9706	0.9745	0.9720	0.9776	0.9855

Table 32

Malmquist productivity index for the EU 28 (part 2), economic input-oriented radial model, base year 2000 (unless otherwise specified)

2000 –>	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
IE														
ProdCh	0.9778	0.9590	0.9151	0.9064	0.9130	0.9299	0.9459	0.9714	0.9593	0.9824	1.0024	1.0232	1.0160	1.1698
TechCh	0.9826	0.9700	0.9280	0.9158	0.9222	0.9409	0.9572	0.9939	1.0181	1.0505	1.0735	1.0931	1.0799	1.2373
EffCh	0.9951	0.9887	0.9861	0.9898	0.9900	0.9883	0.9882	0.9773	0.9422	0.9351	0.9338	0.9361	0.9408	0.9454
IT														
ProdCh	0.9918	0.9677	0.9316	0.9516	0.9400	0.9453	0.9485	0.9103	0.8756	0.8883	0.8879	0.8277	0.8138	0.8093
TechCh	0.9889	0.9622	0.9298	0.9487	0.9424	0.9393	0.9352	0.8992	0.8725	0.8873	0.8838	0.8342	0.8254	0.8264
EffCh	1.0030	1.0057	1.0020	1.0031	0.9974	1.0064	1.0142	1.0123	1.0035	1.0011	1.0045	0.9921	0.9860	0.9793
LT														
ProdCh	1.2668	1.3753	1.5016	1.5945	1.7464	1.9390	2.1672	2.4118	2.0671	2.3082	2.4831	2.5903	2.6855	2.6133
TechCh	1.2387	1.3364	1.4588	1.5441	1.6453	1.8035	2.0032	2.2507	1.9924	2.2633	2.3957	2.4833	2.5607	2.4687
EffCh	1.0228	1.0291	1.0294	1.0326	1.0614	1.0751	1.0819	1.0716	1.0375	1.0198	1.0365	1.0431	1.0487	1.0586
LU														
ProdCh	0.9596	0.9961	1.1542	1.0421	1.0158	1.1013	1.1063	1.0560	0.9888	1.0675	1.0275	1.0313	1.0821	1.1101
TechCh	0.9560	0.9927	1.1646	1.0607	1.0265	1.1188	1.1157	1.0640	1.0004	1.0795	1.0379	1.0478	1.0977	1.1292
EffCh	1.0038	1.0034	0.9911	0.9825	0.9896	0.9844	0.9916	0.9925	0.9883	0.9889	0.9900	0.9842	0.9858	0.9830
LV														
ProdCh	0.9770	1.0887	1.1737	1.1800	1.2922	1.3849	1.4497	1.4034	1.2582	1.3494	1.4327	1.5576	1.6236	1.7125
TechCh	0.9723	1.0692	1.1492	1.1551	1.2600	1.3434	1.4019	1.3630	1.2726	1.4077	1.4418	1.5553	1.6119	1.6902
EffCh	1.0049	1.0182	1.0214	1.0215	1.0256	1.0309	1.0341	1.0296	0.9887	0.9586	0.9937	1.0015	1.0073	1.0131
MT (2003)														
ProdCh	-	-	-	0.9400	0.9040	0.9615	0.9809	1.0544	1.0064	1.0250	1.0499	1.1097	1.1518	1.1540
TechCh	-	-	-	0.9496	0.9116	0.9681	0.9847	1.0234	1.0071	1.0230	1.0456	1.1042	1.1427	1.1430
EffCh	-	-	-	0.9898	0.9916	0.9932	0.9961	1.0303	0.9993	1.0019	1.0041	1.0050	1.0080	1.0097
NL														
ProdCh	1.0469	1.0004	0.9777	0.9819	0.9971	1.0190	1.0341	1.0384	1.0215	1.0504	1.0620	1.0547	1.0653	1.0959
TechCh	1.0429	1.0028	0.9856	0.9937	1.0137	1.0282	1.0384	1.0405	1.0302	1.0631	1.0751	1.0703	1.0893	1.1194
EffCh	1.0038	0.9976	0.9920	0.9881	0.9836	0.9911	0.9958	0.9980	0.9915	0.9881	0.9878	0.9854	0.9780	0.9791
PL														
ProdCh	0.9636	0.9573	0.9980	1.0160	1.0279	1.1096	1.1997	1.2390	1.2026	1.2281	1.2691	1.2756	1.3138	1.3948
TechCh	0.9700	0.9782	1.0268	1.0436	1.0527	1.1218	1.1967	1.2258	1.1969	1.2301	1.2739	1.2857	1.3254	1.3930
EffCh	0.9934	0.9787	0.9720	0.9735	0.9765	0.9892	1.0025	1.0108	1.0047	0.9983	0.9962	0.9922	0.9912	1.0013
PT														
ProdCh	0.9883	0.9699	0.9307	0.9042	0.9083	0.9099	0.9150	0.9057	0.8917	0.8992	0.8546	0.8130	0.8283	0.8346
TechCh	0.9928	0.9874	0.9592	0.9262	0.9410	0.9431	0.9600	0.9443	0.9255	0.9397	0.9126	0.8944	0.9231	0.9052
EffCh	0.9954	0.9823	0.9703	0.9762	0.9652	0.9648	0.9531	0.9590	0.9635	0.9569	0.9365	0.9090	0.8973	0.9221
RO (2001)														
ProdCh	-	1.1022	1.1855	1.3139	1.3132	1.3805	1.3592	1.4867	1.3673	1.3910	1.4399	1.3877	1.4548	1.4141
TechCh	-	1.1086	1.1811	1.3103	1.3117	1.3778	1.3449	1.4687	1.3743	1.4048	1.4515	1.4060	1.4788	1.4420
EffCh	-	0.9942	1.0037	1.0027	1.0012	1.0020	1.0107	1.0123	0.9949	0.9902	0.9920	0.9870	0.9838	0.9807
SE														
ProdCh	1.0252	1.0196	1.0282	1.0868	1.1268	1.0899	1.1205	1.1150	1.0659	1.1270	1.1458	1.1387	1.1450	1.1466
TechCh	1.0205	1.0193	1.0357	1.0995	1.1440	1.1074	1.1294	1.1245	1.0872	1.1522	1.1655	1.1601	1.1667	1.1681
EffCh	1.0046	1.0003	0.9927	0.9884	0.9850	0.9842	0.9921	0.9916	0.9804	0.9781	0.9831	0.9816	0.9814	0.9815
SI														
ProdCh	1.0675	1.0469	1.0229	1.0795	1.0944	1.1374	1.1752	1.1901	1.0892	1.0926	1.1466	1.0969	1.0600	1.0759
TechCh	1.0689	1.0529	1.0362	1.0923	1.1108	1.1509	1.1918	1.2053	1.1019	1.1166	1.1817	1.1439	1.1048	1.1205
EffCh	0.9988	0.9943	0.9871	0.9883	0.9852	0.9882	0.9860	0.9874	0.9884	0.9785	0.9703	0.9589	0.9594	0.9602
SK														
ProdCh	1.0367	1.0452	0.9796	1.0056	1.0433	1.1530	1.2515	1.2824	1.2426	1.2147	1.2085	1.1843	1.2016	1.2165
TechCh	1.0315	1.0343	0.9716	1.0057	1.0366	1.1265	1.2317	1.2570	1.2265	1.2204	1.2142	1.2013	1.2234	1.2284
EffCh	1.0050	1.0106	1.0083	0.9999	1.0064	1.0235	1.0160	1.0202	1.0132	0.9953	0.9953	0.9858	0.9822	0.9903
UK														
ProdCh	1.0165	1.0318	1.0537	1.1066	1.1495	1.1915	1.2210	1.2190	1.1821	1.2325	1.2394	1.2566	1.2554	1.2905
TechCh	1.0131	1.0320	1.0528	1.1049	1.1473	1.1915	1.2183	1.2196	1.1976	1.2495	1.2598	1.2768	1.2709	1.2962
EffCh	1.0033	0.9997	1.0008	1.0015	1.0019	1.0000	1.0022	0.9995	0.9870	0.9864	0.9838	0.9841	0.9878	0.9957

Table 33

Utilization rates Eurostat (2020b)

Country	2000 *(Percent)*	2014 *(Percent)*
AT	88.200	84.275
BE	84.050	79.275
BG	55.300	70.800
CY	N/A	53.900
CZ	81.575	82.975
DE	86.650	84.300
DK	82.350	79.675
EE	66.700	73.025
EL	78.300	67.675
ES	80.650	75.825
FI	86.150	78.950
FR	86.225	81.875
HR	N/A	68.975
HU	82.825	80.325
IE	79.825	78.700
IT	78.175	73.650
LT	53.625	74.875
LU	86.775	66.200
LV	58.350	72.225
MT	N/A	78.075
NL	84.525	80.150
PL	69.975	77.150
PT	84.725	78.425
RO	N/A	79.375
SE	86.650	80.925
SI	79.725	80.300
SK	84.475	80.650
UK	80.675	82.025

Table 34

Shadow prices in the social model for Austria, social DDF model, 2000-2014

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
0 % (Econ. Mod.)	LQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	MQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	HQ labor	0.000837	0.000816	0.000721	0.000743	0.000660	0.000688	0.000688	0.000676	0.000663	0.000626	0.000624	0.000607	0.000577	0.000555	0.000364
	capital	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QM for LQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QM for MQ labor	0.000837	0.000816	0.000721	0.000743	0.000660	0.000688	0.000688	0.000676	0.000663	0.000626	0.000624	0.000607	0.000577	0.000555	0.000364
10 %	LQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	MQ labor	0.000000	0.000000	0.000000	0.000000	0.000155	0.000153	0.000152	0.000151	0.000000	0.000000	0.000000	0.000141	0.000000	0.000136	0.000133
	HQ labor	0.000837	0.000816	0.000721	0.000743	0.000155	0.000153	0.000152	0.000151	0.000663	0.000626	0.000624	0.000141	0.000577	0.000136	0.000133
	capital	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QM for LQ labor	0.000000	0.000000	0.000000	0.000000	0.000155	0.000153	0.000152	0.000151	0.000000	0.000000	0.000000	0.000141	0.000000	0.000136	0.000133
	QM for MQ labor	0.000837	0.000816	0.000721	0.000743	0.000000	0.000000	0.000000	0.000000	0.000663	0.000626	0.000624	0.000000	0.000577	0.000000	0.000000
20 %	LQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	MQ labor	0.000166	0.000163	0.000162	0.000160	0.000155	0.000153	0.000152	0.000151	0.000146	0.000144	0.000143	0.000141	0.000138	0.000136	0.000133
	HQ labor	0.000166	0.000163	0.000162	0.000160	0.000155	0.000153	0.000152	0.000151	0.000146	0.000144	0.000143	0.000141	0.000138	0.000136	0.000133
	capital	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QM for LQ labor	0.000166	0.000163	0.000162	0.000160	0.000155	0.000153	0.000152	0.000151	0.000146	0.000144	0.000143	0.000141	0.000138	0.000136	0.000133
	QM for MQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
30 %	LQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	MQ labor	0.000166	0.000163	0.000162	0.000160	0.000155	0.000153	0.000152	0.000151	0.000146	0.000144	0.000143	0.000141	0.000138	0.000136	0.000133
	HQ labor	0.000166	0.000163	0.000162	0.000160	0.000155	0.000153	0.000152	0.000151	0.000146	0.000144	0.000143	0.000141	0.000138	0.000136	0.000133
	capital	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QM for LQ labor	0.000166	0.000163	0.000162	0.000160	0.000155	0.000153	0.000152	0.000151	0.000146	0.000144	0.000143	0.000141	0.000138	0.000136	0.000133
	QM for MQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
40 %	LQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	MQ labor	0.000166	0.000163	0.000162	0.000160	0.000155	0.000153	0.000152	0.000151	0.000146	0.000144	0.000143	0.000141	0.000138	0.000136	0.000133
	HQ labor	0.000166	0.000163	0.000162	0.000160	0.000155	0.000153	0.000152	0.000151	0.000146	0.000144	0.000143	0.000141	0.000138	0.000136	0.000133
	capital	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QM for LQ labor	0.000166	0.000163	0.000162	0.000160	0.000155	0.000153	0.000152	0.000151	0.000146	0.000144	0.000143	0.000141	0.000138	0.000136	0.000133
	QM for MQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50 %	LQ labor	0.000131	0.000130	0.000130	0.000129	0.000127	0.000125	0.000124	0.000122	0.000000	0.000000	0.000119	0.000000	0.000000	0.000115	0.000000
	MQ labor	0.000131	0.000130	0.000130	0.000129	0.000127	0.000125	0.000124	0.000122	0.000146	0.000144	0.000119	0.000141	0.000138	0.000115	0.000133
	HQ labor	0.000131	0.000130	0.000130	0.000129	0.000127	0.000125	0.000124	0.000122	0.000146	0.000144	0.000119	0.000141	0.000138	0.000115	0.000133
	capital	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QM for LQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000146	0.000144	0.000000	0.000141	0.000138	0.000000	0.000133
	QM for MQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
60 % and higher	LQ labor	0.000131	0.000130	0.000130	0.000129	0.000127	0.000125	0.000124	0.000122	0.000120	0.000119	0.000119	0.000117	0.000116	0.000115	0.000114
	MQ labor	0.000131	0.000130	0.000130	0.000129	0.000127	0.000125	0.000124	0.000122	0.000120	0.000119	0.000119	0.000117	0.000116	0.000115	0.000114
	HQ labor	0.000131	0.000130	0.000130	0.000129	0.000127	0.000125	0.000124	0.000122	0.000120	0.000119	0.000119	0.000117	0.000116	0.000115	0.000114
	capital	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QM for LQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QM for MQ labor	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Table 35

Luenberger productivity indicator for the EU 27 and UK (part 1), social DDF model, base year 2000 (unless otherwise specified)

2000 –>	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
AT														
ProdCh	0.0030	-0.0155	0.0018	-0.0051	0.0161	0.0233	0.0237	0.0464	0.0220	0.0418	0.0446	0.0409	0.0391	-0.0493
TechCh	0.0030	-0.0149	0.0046	0.0043	0.0256	0.0313	0.0300	0.0481	0.0290	0.0477	0.0497	0.0455	0.0481	-0.0393
EffCh	-0.0001	-0.0005	-0.0028	-0.0094	-0.0095	-0.0080	-0.0063	-0.0017	-0.0070	-0.0060	-0.0052	-0.0046	-0.0090	-0.0100
BE														
ProdCh	-0.0050	-0.0005	0.0050	0.0172	0.0281	0.0358	0.0555	0.0774	0.0554	0.0614	0.0822	0.0785	0.0836	0.0951
TechCh	-0.0043	0.0036	0.0119	0.0252	0.0349	0.0425	0.0583	0.0790	0.0618	0.0678	0.0843	0.0820	0.0920	0.1024
EffCh	-0.0008	-0.0040	-0.0070	-0.0080	-0.0068	-0.0067	-0.0028	-0.0016	-0.0064	-0.0064	-0.0021	-0.0035	-0.0084	-0.0073
BG														
ProdCh	-0.0097	0.0215	0.0674	0.1001	0.1292	0.1832	0.2235	0.2455	0.2038	0.2216	0.2570	0.2593	0.2615	0.2412
TechCh	0.0025	0.0283	0.0591	0.0840	0.1036	0.1549	0.1862	0.2060	0.1688	0.1980	0.2367	0.2440	0.2492	0.2187
EffCh	-0.0122	-0.0069	0.0082	0.0161	0.0256	0.0283	0.0373	0.0395	0.0350	0.0236	0.0202	0.0153	0.0122	0.0225
CY (2008)														
ProdCh	-	-	-	-	-	-	-	-	-0.0468	-0.0342	-0.0448	-0.0544	-0.0750	-0.0857
TechCh	-	-	-	-	-	-	-	-	-0.0356	-0.0186	-0.0232	-0.0108	-0.0095	-0.0209
EffCh	-	-	-	-	-	-	-	-	-0.0113	-0.0156	-0.0216	-0.0436	-0.0655	-0.0648
CZ														
ProdCh	0.0260	0.0420	0.0680	0.0955	0.1275	0.1509	0.1852	0.1825	0.1493	0.1715	0.1842	0.1705	0.1673	0.1929
TechCh	0.0228	0.0353	0.0623	0.0900	0.1209	0.1415	0.1670	0.1611	0.1371	0.1622	0.1729	0.1588	0.1550	0.1792
EffCh	0.0032	0.0067	0.0057	0.0055	0.0066	0.0094	0.0181	0.0214	0.0122	0.0093	0.0113	0.0117	0.0123	0.0137
DE														
ProdCh	0.0137	0.0140	0.0040	0.0062	0.0084	0.0341	0.0451	0.0560	0.0312	0.0691	0.0896	0.0882	0.0886	0.1079
TechCh	0.0137	0.0168	0.0104	0.0149	0.0203	0.0419	0.0463	0.0530	0.0285	0.0635	0.0796	0.0771	0.0775	0.0975
EffCh	0.0000	-0.0028	-0.0064	-0.0087	-0.0119	-0.0078	-0.0012	0.0030	0.0026	0.0057	0.0101	0.0111	0.0111	0.0104
DK														
ProdCh	0.0227	0.0218	-0.0186	-0.0075	0.0038	0.0195	0.0602	0.0618	0.0383	0.0438	0.0442	0.0396	0.0429	0.0423
TechCh	0.0238	0.0227	-0.0137	-0.0015	0.0055	0.0161	0.0552	0.0544	0.0401	0.0514	0.0542	0.0481	0.0499	0.0501
EffCh	-0.0011	-0.0009	-0.0049	-0.0060	-0.0017	0.0034	0.0050	0.0074	-0.0017	-0.0076	-0.0100	-0.0085	-0.0070	-0.0078
EE														
ProdCh	0.0461	0.1012	0.1080	0.1144	0.1453	0.1793	0.1996	0.1891	0.1244	0.1077	0.1340	0.1735	0.1785	0.1980
TechCh	0.0460	0.0952	0.1026	0.1014	0.1235	0.1505	0.1635	0.1577	0.1168	0.1220	0.1341	0.1629	0.1646	0.1758
EffCh	0.0001	0.0060	0.0054	0.0131	0.0219	0.0288	0.0361	0.0313	0.0077	-0.0143	-0.0001	0.0106	0.0139	0.0221
EL														
ProdCh	0.0193	0.0336	0.0660	0.0738	0.0747	0.0690	0.0792	0.0683	0.0433	0.0017	-0.0486	-0.0893	-0.1098	-0.0916
TechCh	0.0202	0.0312	0.0601	0.0752	0.0719	0.0621	0.0694	0.0574	0.0404	0.0130	-0.0114	-0.0246	-0.0334	-0.0176
EffCh	-0.0009	0.0024	0.0059	-0.0013	0.0028	0.0069	0.0098	0.0109	0.0029	-0.0112	-0.0372	-0.0647	-0.0764	-0.0741
ES														
ProdCh	0.0070	0.0014	-0.0021	0.0021	0.0128	0.0211	0.0300	0.0125	-0.0236	-0.0243	-0.0236	-0.0439	-0.0471	-0.0315
TechCh	-0.0091	-0.0092	-0.0133	-0.0121	-0.0097	-0.0058	-0.0007	-0.0121	-0.0284	-0.0203	-0.0106	-0.0168	-0.0137	-0.0058
EffCh	0.0161	0.0106	0.0112	0.0142	0.0225	0.0269	0.0307	0.0247	0.0048	-0.0040	-0.0129	-0.0271	-0.0334	-0.0257
FI														
ProdCh	0.0164	0.0222	0.0239	0.0486	0.0666	0.0794	0.1026	0.1077	0.0806	0.1046	0.1169	0.1235	0.1276	0.1295
TechCh	0.0141	0.0172	0.0192	0.0456	0.0621	0.0705	0.0925	0.0944	0.0729	0.0988	0.1081	0.1146	0.1212	0.1271
EffCh	0.0024	0.0050	0.0047	0.0030	0.0044	0.0089	0.0101	0.0133	0.0077	0.0058	0.0088	0.0089	0.0063	0.0024
FR														
ProdCh	-0.0089	-0.0115	-0.0061	0.0049	0.0102	0.0144	0.0296	0.0405	0.0225	0.0404	0.0504	0.0472	0.0651	0.0760
TechCh	-0.0129	-0.0125	-0.0046	0.0096	0.0124	0.0148	0.0273	0.0337	0.0218	0.0390	0.0489	0.0471	0.0684	0.0821
EffCh	0.0040	0.0009	-0.0015	-0.0048	-0.0022	-0.0004	0.0023	0.0067	0.0007	0.0013	0.0014	0.0001	-0.0033	-0.0061
HR (2008)														
ProdCh	-	-	-	-	-	-	-	-	-0.0507	-0.0846	-0.0677	-0.0551	-0.0568	-0.0650
TechCh	-	-	-	-	-	-	-	-	-0.0460	-0.0668	-0.0405	-0.0142	-0.0134	-0.0307
EffCh	-	-	-	-	-	-	-	-	-0.0047	-0.0177	-0.0272	-0.0410	-0.0433	-0.0342
HU														
ProdCh	0.0287	0.0526	0.0651	0.0896	0.0898	0.1174	0.1231	0.1320	0.0967	0.0982	0.1058	0.0913	0.1157	0.1264
TechCh	0.0260	0.0516	0.0629	0.0898	0.0937	0.1210	0.1265	0.1352	0.1086	0.1156	0.1203	0.1070	0.1273	0.1303
EffCh	0.0027	0.0010	0.0022	-0.0003	-0.0039	-0.0037	-0.0034	-0.0032	-0.0119	-0.0174	-0.0145	-0.0156	-0.0116	-0.0039

Table 36

Luenberger productivity indicator for the EU 27 and UK (part 2), social DDF model, base year 2000 (unless otherwise specified)

2000 –>	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
IE														
ProdCh	-0,0118	-0,0220	-0,0453	-0,0485	-0,0448	-0,0356	-0,0270	-0,0144	-0,0226	-0,0119	-0,0028	0,0065	0,0035	0,0642
TechCh	-0,0089	-0,0152	-0,0373	-0,0426	-0,0390	-0,0289	-0,0202	-0,0011	0,0129	0,0283	0,0385	0,0465	0,0399	0,0970
EffCh	-0,0029	-0,0068	-0,0080	-0,0059	-0,0058	-0,0067	-0,0068	-0,0134	-0,0355	-0,0401	-0,0414	-0,0400	-0,0364	-0,0328
IT														
ProdCh	0,0035	-0,0081	-0,0240	-0,0124	-0,0168	-0,0141	-0,0126	-0,0340	-0,0539	-0,0474	-0,0476	-0,0835	-0,0924	-0,0952
TechCh	-0,0016	-0,0159	-0,0307	-0,0216	-0,0273	-0,0291	-0,0313	-0,0503	-0,0648	-0,0556	-0,0576	-0,0850	-0,0894	-0,0884
EffCh	0,0051	0,0078	0,0066	0,0092	0,0105	0,0150	0,0187	0,0163	0,0109	0,0082	0,0101	0,0015	-0,0029	-0,0068
LT														
ProdCh	0,1010	0,1446	0,1893	0,2227	0,2695	0,3201	0,3728	0,4137	0,3433	0,3881	0,4110	0,4264	0,4396	0,4308
TechCh	0,1040	0,1395	0,1814	0,2090	0,2383	0,2793	0,3267	0,3737	0,3284	0,3855	0,3973	0,4072	0,4154	0,4005
EffCh	-0,0030	0,0052	0,0080	0,0137	0,0313	0,0408	0,0462	0,0400	0,0149	0,0025	0,0137	0,0192	0,0242	0,0303
LU														
ProdCh	-0,0208	-0,0023	0,0692	0,0203	0,0074	0,0473	0,0501	0,0268	-0,0051	0,0315	0,0131	0,0146	0,0363	0,0467
TechCh	-0,0230	-0,0036	0,0738	0,0297	0,0134	0,0556	0,0550	0,0324	0,0012	0,0371	0,0186	0,0230	0,0447	0,0562
EffCh	0,0021	0,0013	-0,0047	-0,0094	-0,0060	-0,0083	-0,0049	-0,0056	-0,0063	-0,0055	-0,0055	-0,0084	-0,0084	-0,0096
LV														
ProdCh	-0,0140	0,0566	0,0917	0,0981	0,1460	0,1825	0,2055	0,1885	0,1277	0,1593	0,1901	0,2277	0,2475	0,2712
TechCh	-0,0205	0,0421	0,0750	0,0803	0,1232	0,1511	0,1714	0,1584	0,1311	0,1803	0,1878	0,2195	0,2311	0,2507
EffCh	0,0064	0,0145	0,0167	0,0178	0,0227	0,0314	0,0342	0,0301	-0,0034	-0,0210	0,0023	0,0082	0,0164	0,0205
MT (2003)														
ProdCh	-	-	-	-0,0266	-0,0404	-0,0095	0,0005	0,0311	0,0127	0,0219	0,0337	0,0617	0,0743	0,0741
TechCh	-	-	-	-0,0280	-0,0429	-0,0130	-0,0047	0,0089	0,0071	0,0146	0,0250	0,0511	0,0620	0,0608
EffCh	-	-	-	0,0014	0,0025	0,0035	0,0052	0,0222	0,0056	0,0073	0,0087	0,0105	0,0123	0,0133
NL														
ProdCh	0,0231	0,0006	-0,0107	-0,0087	-0,0014	0,0098	0,0175	0,0198	0,0114	0,0250	0,0305	0,0267	0,0310	0,0447
TechCh	0,0206	0,0005	-0,0069	-0,0019	0,0088	0,0155	0,0201	0,0209	0,0161	0,0318	0,0373	0,0353	0,0444	0,0577
EffCh	0,0024	0,0001	-0,0038	-0,0069	-0,0102	-0,0057	-0,0027	-0,0011	-0,0047	-0,0067	-0,0068	-0,0086	-0,0135	-0,0130
PL														
ProdCh	-0,0157	-0,0011	0,0217	0,0328	0,0410	0,0831	0,1249	0,1418	0,1253	0,1330	0,1471	0,1476	0,1580	0,1818
TechCh	-0,0087	0,0151	0,0367	0,0414	0,0409	0,0661	0,0921	0,0998	0,0869	0,0994	0,1139	0,1162	0,1268	0,1435
EffCh	-0,0071	-0,0162	-0,0150	-0,0086	0,0001	0,0170	0,0328	0,0420	0,0384	0,0336	0,0332	0,0314	0,0312	0,0383
PT														
ProdCh	-0,0049	-0,0096	-0,0347	-0,0494	-0,0475	-0,0468	-0,0434	-0,0487	-0,0569	-0,0533	-0,0786	-0,1039	-0,0947	-0,0890
TechCh	-0,0027	-0,0010	-0,0194	-0,0365	-0,0282	-0,0269	-0,0186	-0,0265	-0,0358	-0,0275	-0,0409	-0,0488	-0,0329	-0,0423
EffCh	-0,0022	-0,0086	-0,0153	-0,0128	-0,0193	-0,0199	-0,0248	-0,0221	-0,0211	-0,0257	-0,0377	-0,0551	-0,0618	-0,0466
RO (2001)														
ProdCh	-	0,0554	0,0948	0,1385	0,1426	0,1636	0,1584	0,2017	0,1601	0,1733	0,1831	0,1666	0,1868	0,1760
TechCh	-	0,0711	0,1009	0,1574	0,1543	0,1791	0,1666	0,2061	0,1739	0,1796	0,1955	0,1789	0,1991	0,1881
EffCh	-	-0,0158	-0,0061	-0,0189	-0,0117	-0,0155	-0,0082	-0,0044	-0,0138	-0,0063	-0,0124	-0,0123	-0,0123	-0,0121
SE														
ProdCh	0,0108	0,0079	0,0137	0,0414	0,0594	0,0447	0,0591	0,0552	0,0317	0,0595	0,0673	0,0665	0,0691	0,0699
TechCh	0,0089	0,0084	0,0185	0,0491	0,0688	0,0536	0,0631	0,0596	0,0438	0,0727	0,0770	0,0768	0,0793	0,0796
EffCh	0,0019	-0,0004	-0,0048	-0,0077	-0,0094	-0,0090	-0,0040	-0,0044	-0,0122	-0,0132	-0,0097	-0,0103	-0,0102	-0,0097
SI														
ProdCh	0,0274	0,0285	0,0191	0,0461	0,0528	0,0718	0,0887	0,0954	0,0506	0,0511	0,0724	0,0509	0,0337	0,0412
TechCh	0,0275	0,0303	0,0232	0,0492	0,0571	0,0731	0,0885	0,0928	0,0505	0,0570	0,0831	0,0673	0,0507	0,0572
EffCh	-0,0001	-0,0017	-0,0041	-0,0031	-0,0043	-0,0014	0,0002	0,0025	0,0001	-0,0059	-0,0107	-0,0164	-0,0170	-0,0160
SK														
ProdCh	0,0108	0,0296	0,0233	0,0367	0,0598	0,1145	0,1591	0,1733	0,1536	0,1396	0,1377	0,1274	0,1344	0,1411
TechCh	0,0087	0,0277	0,0123	0,0285	0,0381	0,0763	0,1186	0,1269	0,1172	0,1153	0,1095	0,1036	0,1125	0,1120
EffCh	0,0021	0,0019	0,0110	0,0082	0,0217	0,0382	0,0406	0,0464	0,0364	0,0243	0,0282	0,0238	0,0219	0,0290
UK														
ProdCh	0,0086	0,0171	0,0279	0,0520	0,0708	0,0882	0,1005	0,0993	0,0831	0,1026	0,1051	0,1108	0,1101	0,1230
TechCh	0,0066	0,0168	0,0274	0,0513	0,0699	0,0888	0,0997	0,1001	0,0916	0,1114	0,1151	0,1204	0,1174	0,1255
EffCh	0,0020	0,0003	0,0005	0,0007	0,0009	-0,0005	0,0008	-0,0008	-0,0085	-0,0088	-0,0100	-0,0096	-0,0073	-0,0025

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