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The Determinants of Economic Competitiveness

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This paper aims at identifying relevant indicators for TFP growth in EU countries during the recovery phase following 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 technique from the realm of statistical learning – in order to identify relevant predictors of TFP and its components from the Global Competitiveness Reports.

We find that only a few indicators prove to be stable predictors. In particular, 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 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. Concerning the bigger picture, it becomes obvious that advanced machine learning techniques might not be able to replace sound economic theory but they help separating the wheat from the chaff when it comes to selecting the most relevant indicators of economic competitiveness.

Keywords: Competitiveness, TFP growth, Stochastic Frontier Analysis, BART

JEL classification: C23, E24, O47

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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.* (1994) 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 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

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

the International Monetary Fund (IMF) as well as the Executive Opinion Survey (EOS) conducted by the World Economic Forum (2017).

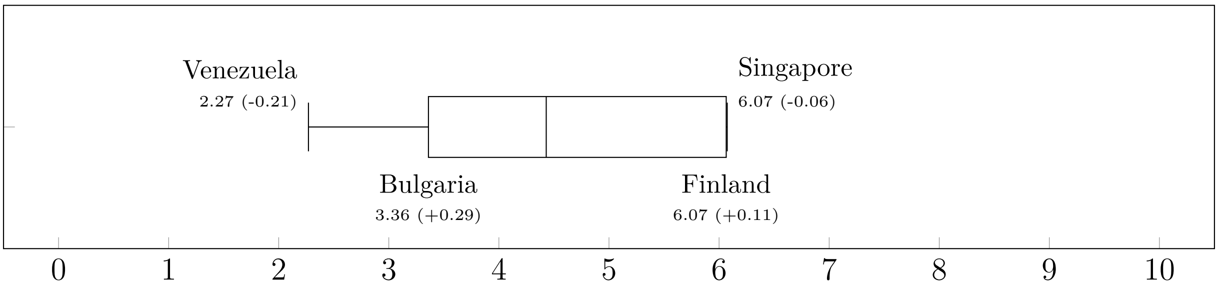
The GCI pillars are formulated in such a way, that higher scores are always "better"; hence, we would expect positive signs for each one of them when regressed on any measure of economic development. The methodological challenge will be to disentangle the effects from one another and to find the indicators 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

Sound institutions facilitate transactions and help reducing production costs and uncertainty. Institutions are – according to North (1990, p. 3) – *"the rules of the game in a society or, more formally, are the humanly devised constraints that shape human interaction."* Formal institutions, such as laws or contracts, are defined by official authorities, while informal institutions are usually unwritten sets of habits, customs or traditions.

The GCI pillar *institutions* is composed of 21 indicators for both public and private institutions, 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. Most of those indicators are sourced from the EOS. As the box plot in Figure 1 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 1
Institutions (1^{st} *Pillar)*



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses).

North (1987) states that complex economic structures and the trend towards specialization and division of labor lead to a growing importance of low transaction costs and confidence in contract enforcement. Acemoglu *et al.* (2005) also elaborate on how uncertainty about the observance of contracts and insecure property rights reduce incentives to invest and innovate.

A substantial empirical literature has examined and confirmed a tight relationship between institutions and economic variables such as GDP growth and productivity: Rodrik *et al.* (2004) identify institutions as a major contributing factor of income levels around the world, making use of a composite indicator that includes the protection of property rights and the strength of the rule of law. Knack and Keefer (1995) analyze the impact of property rights on economic growth and investment. They 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. They assume that the benefits of better institutions become effective through the channel of incentives for R&D spending. Égert (2016) analyzes 34 OECD countries and also observes that a higher rule of law and better law enforcement increase the effect of R&D on TFP. Hall and Jones (1999) find that institutions and government policies are the main driver of differences in capital accumulation and productivity. Mauro (1995) uses indicators of subjective indices of bureaucratic honesty and efficiency and finds that corruption leads to lower investment and consequently lowers economic growth. The empirical results by Alcalá and Ciccone (2004) point out that institutional quality has a major influence on the capital-output ratio and the average level of human capital but not on TFP. According to them, institutional quality works through the channel of capital accumulation. Chong and Calderón (2000) conduct a causal analysis to study whether institutional quality affects economic growth or vice versa. Their results indicate that institutional reforms need a long time to become effective and that in particular less developed countries benefit from institutional reforms; they also find some evidence that economic growth may lead to an improvement of institutions. The empirical results by Glaeser *et al.* (2004) suggest that human capital leads to improvements of institutions which in turn foster economic development. Acemoglu *et al.* (2014) react to these findings and confirm their own previous results that institutions are the real driver of economic development.

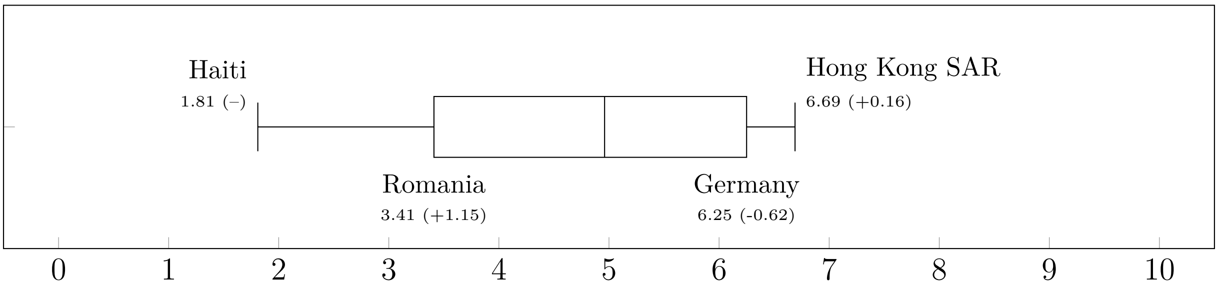
Since institutions in the EU are highly developed in comparison to other parts of the world and as there is only little variation over time, we do not expect this pillar to be a major predictor of TFP growth in the EU. Also, any improvements would need a long time to become effective (see, e. g., Chong and Calderón (2000)); hence, our feasible observation period would probably be too short to find any effects.

2.2.2 2^{nd} Pillar: Infrastructure

Electricity, telecommunication, water and transport infrastructure are used as inputs in most production processes. Good infrastructure reduces transport times and production costs, facilitates technology diffusion, the mobility of labor, plays a key role for trade and even impacts location decisions of households and firms.

The GCI pillar *infrastructure* consists of nine indicators, whereby the focus is on quality based on the EOS. Among the quantitative indicators are available airline seat kilometers, mobile-cellular telephone subscriptions and fixed-telephone lines. The highest average score in the EU holds Germany with 6.2, the lowest score has Romania with 3.4 (see Figure 2). In Germany and other EU15 countries, the indicator has decreased; some of the new members, however, have made major improvements, e. g. Poland with +1.8.

Figure 2
Infrastructure (2^{nd} Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses).

The main mechanisms through which infrastructure affects productivity are included in models of the New Economic Geography (see, e. g., Krugman (1991b) 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.

Aschauer (1989) initiated a debate on the relationship between public spending on infrastructure and productivity. He identified a positive relationship between the public capital stock on core infrastructure and TFP with high returns to public infrastructure investments. Since then, 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., Välilä (2020)). While Aschauer (1989) used the public capital stock and public expenditures for measuring infrastructure, Égert *et al.* (2009) argue that – especially in the EU – privatization and market liberalization make them unreliable measures of infrastructure. Calderón *et al.* (2015) take the same view and emphasize the importance of institutions in this context. Poor institutions and the resulting inefficient spending or even corruption can hinder infrastructural development (see also Esfahani and Ramírez (2003)). This is why public spending alone is not a good proxy for infrastructure. Accordingly, Gramlich (1994) considers the results presented by Aschauer (1989) implausibly high.

Using physical measures for infrastructure, Calderón *et al.* (2015) conclude that neither the level of development nor the level of infrastructure has an effect on the output elasticity of infrastructure. This result is in contrast to other studies that find higher impacts for countries with lower levels of infrastructure. Röller and Waverman (2001), for instance, identify higher effects of telecommunication infrastructure on growth for OECD countries than for non-OECD, arguing that a critical mass for telecommunication is needed for positive effects. However, at the margin, investments in infrastructure may not be productive, as shown by Fernald (1999) for road investments. He argues that a second identical road network would not lead to productivity growth. A panel analysis by Canning and Pedroni (2008) shows as well that infrastructure long-run effects on per capita income vary across countries and types of infrastructure, since some countries are above and others below their optimum level of infrastructure. Melo *et al.* (2013) conduct a meta-analysis of 33 studies and conclude that productivity effects of roads seem to be higher than of other transport modes and that the productivity effect of roads seems to be higher for the U.S. economy than in European countries. 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.

In recent years, an increasing number of empirical studies in regional, spatial, urban and transportation economics can be observed (see, e. g., Bronzini and Piselli (2009), Crescenzi and Rodríguez-Pose (2012), or Farhadi (2015)). Also, as endorsed by Redding and Turner (2014), causal analyses using different types of IV approaches have become more important (see, e. g., Donaldson and Hornbeck (2016), Baum-Snow *et al.* (2017), Hornung (2015) or Ghani *et al.* (2016)).

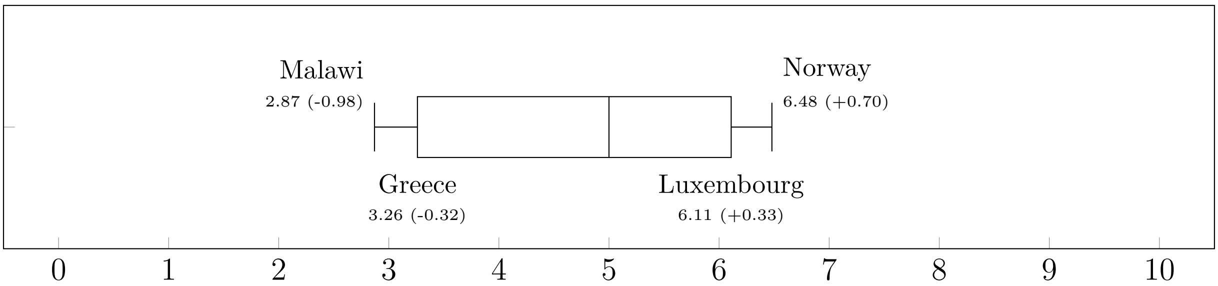
Since the quantity of infrastructure seems to be more important than its quality (see, e. g., Calderón and Servén (2004)), but the focus of this pillar is on quality, we do not expect it to be a major predictor of TFP growth in the EU.

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. It defines how economic decisions are made both by consumers and companies. According to Fischer (1993), a stable macroeconomic environment relies on, first and foremost, a predictable and low inflation rate and a sustainable and stable fiscal policy. Economic stability and predictability, in particular, are considered drivers of investments and productivity.

Accordingly, 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 3, 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 3
Macroeconomic Environment (3rd Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses).

Government spending has an impact on how an economy develops and can be important in times of crisis. A countercyclical fiscal policy might offset at least parts of the recessionary impact on an economy. However, the scientific results on deficit spending are rather mixed (see, e. g., Atoyan *et al.* (2012), Jha *et al.* (2014) or Guerguil *et al.* (2017)). In any case, however, deficit spending will increase public debt which, if it gets out of hand, could lead to a decreased financial and political independence. 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)). Another factor to consider is how the debts are composed. Afonso and Jalles (2013), for instance, investigate debt maturity (short-term or long-term debt above five years) and find a positive correlation between the maturity of sovereign debts and economic growth in OECD countries. In other words, longer average maturity appears to positively affect growth. Moreover, some literature suggests that the impact on the national economy is worse if the debt is owed to foreigners (foreign governments, private lenders or organizations), due to the fact that they cannot be taxed by the respective government (see, e. g., Gros (2013) or Doğan and Bilgili (2014)).

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)). Chen *et al.* (2016) investigate the impact of changes in credit ratings on economic growth and find that upgrades/downgrades may increase/decrease GDP growth via capital flows and interest rates.

Another crucial component of the macroeconomic framework is inflation. The relation between inflation and growth has been subject of controversial debates. A substantial number of studies on the matter, for instance by Mundell (1965) or Fischer (1993), agree that high inflation is not compatible with sustained growth. However, the empirical evidence is not as conclusive as often presented. Empirical studies, such as those by Fischer (1993) or Omay and Kan (2010), often discover a nonlinear relationship between inflation and growth. The effect on growth rates appears to depend on the rate of inflation. Clear negative effects on growth and investment, Barro (1995) suggests, might be limited to countries with exceedingly high inflation rates over a period of time. Moderate inflation does not appear to have a notable impact. Bruno and Easterly (1998) find no evidence of inflation having a long-term negative effect on growth: While inflation strongly impacts economic growth during a high inflation crisis, they argue, growth rates tend to recover quickly afterwards. 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, 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)).

As this pillar might well contain important prerequisites of economic development, we expect it to be a relevant predictor of TFP growth in EU countries.

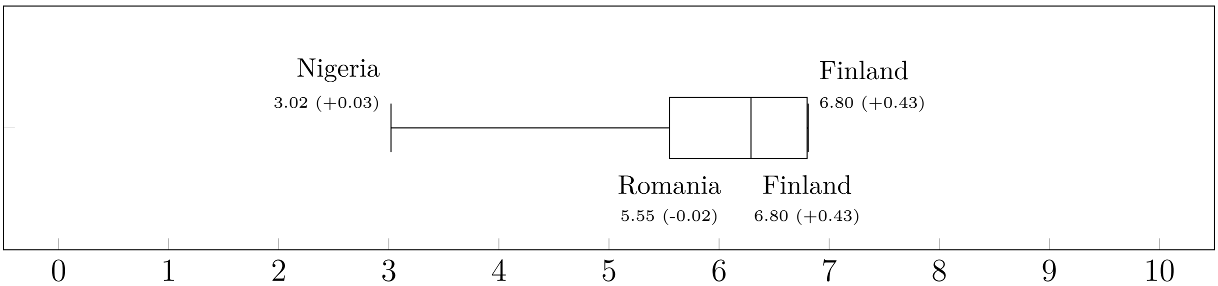
2.2.4 4^{th} Pillar: Health and Primary Education

The GCI places *health* and *primary education* in one pillar as both of them are among the most basic preconditions for an economy. A healthy working population is crucial for productivity as high absenteeism causes considerable costs and often results in decreasing efficiency and overall productivity. Furthermore, high prevalence rates of chronic diseases may also lead to lower labor force participation. The quality of primary education, in turn, is essential to allow access to any qualifications needed in the labor market.

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. Therefore, the focus of this section will be on life expectancy. In terms of *primary education*, the GCI focuses on the quality of primary education (based on the EOS) and primary education enrollment.

Figure 4 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.

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



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses).

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. The theory has come under criticism for falling short to explain wage and productivity differences. Despite the emergence of alternative approaches, for instance by Spence (1973), human capital theory remains a cornerstone of research on the economic effects of schooling.

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. 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)). Research also suggests a clear link between educational quality and individual income (see, e. g. Murnane *et al.* (2000) or Hanushek and Wößmann (2007)). Due to increasing global competition, Sahlberg (2006) urges schools to further embrace a culture of flexibility, creativity, risk-taking and networking.

An analysis by Papageorgiou (2003) on the contribution of human capital accumulation to economic growth explicitly differentiates between primary and post-primary education and finds that the major role of basic education lies in the *"production of final output"* (Papageorgiou, 2003, p. 622). Hence, primary education simply enters a country's production function as an input for the production of end products, while secondary and tertiary education are seen as contributors to the development of innovative ideas as well as the adoption and advancement of technology. While widespread primary education is certainly a prerequisite of competitiveness and therefore productivity, further improvements will most likely not affect the performance of high-tech oriented economies.

The second part of the pillar is dedicated to health. A common indicator of health is life expectancy. Higher life expectancy combined with lower fertility rates lead to a lasting transformation of the age structure in many developed countries, which could result in a decline in productivity due to lower labor market participation (see, e. g., Gordon (2017) or Baumgartner *et al.* (2006)). Interestingly, however, some studies find no negative impact of aging on GDP growth (see, e. g., Acemoglu and Restrepo (2017)). Cuaresma *et al.* (2014) try to assess the long-run effect of prospective aging on income dynamics in Europe. The results differ across countries and suggest a stronger negative effect for poorer countries. Prettner (2013) even shows that the positive effect of longevity outweighs the impact of a falling birth rate. Acemoglu and Restrepo (2017) provide a possible explanation: They conclude that ongoing automation might be the prime reason for their findings. Though the authors do not claim to have causal evidence, they argue for a balancing effect of robots on economic growth, especially in more developed countries.

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.

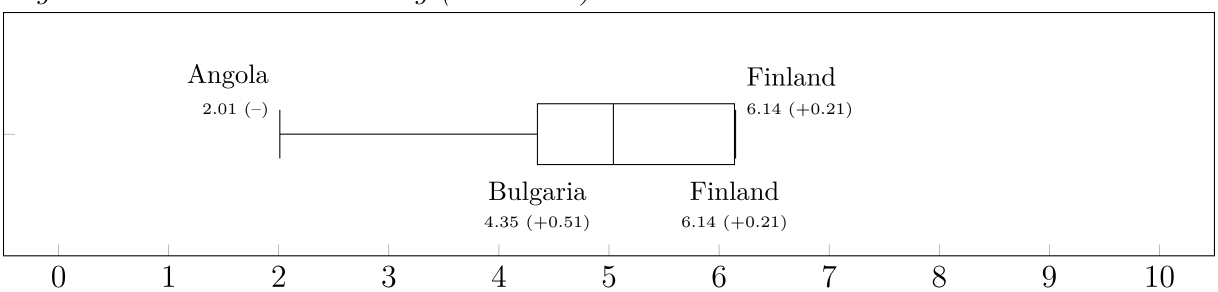
2.2.5 5th Pillar: Higher Education and Training

While basic education primarily enters the production process, higher education makes a substantial contribution to innovation and technology, as Papageorgiou (2003) notes. A pool of well-educated and skilled individuals is a vital condition for conducting R&D. This includes secondary and tertiary education as well as vocational training.

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 5 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.

Figure 5
Higher Education and Training (5th Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses).

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 – 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)).

Some researchers, however, stress that post-secondary education – simply measured in years of schooling or the number of graduates – will not inevitably lead to a growing economy. Hanushek (2016), for instance, highlights that increasing the quantity of higher education only leads to more growth if it comes with improved cognitive skills. He recommends a stronger focus on the quality of education instead of simply adding years. Similar recommendations have been put forward for primary education (see subsection 2.2.4).

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.

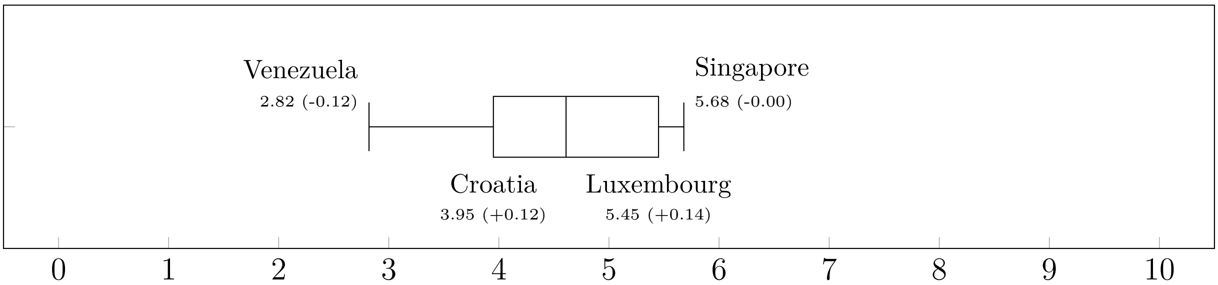
2.2.6 6^{th} Pillar: Goods Market Efficiency

Well-functioning goods markets ensure efficient production and trade. Countries establish efficient goods markets by choosing the right degree of competition and market access regulation. They also set incentives to invest and to maintain the confidence of both investors and consumers.

The GCI pillar *goods market efficiency* is composed of 16 indicators, combining several topics. It includes, i. a., barriers to market entry measured by the required procedures and time to start a business, indicators for the measurement of domestic and foreign competition, and the prevalence of foreign ownership. Figure 6 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)). Djankov *et al.* (2002) investigate 85

Figure 6
Goods Market Efficiency (6^{th} Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses).

countries and find that market entry is expensive in most of them and that higher barriers of entry are associated with a higher degree of corruption and an informal economy; hence, they can lead to inefficient rent-seeking. At the same time, countries with heavier regulations do not produce a higher quality of private or public goods. The findings by Coe *et al.* (2009) indicate that countries with a high ease of doing business are associated with higher levels of TFP. Nicoletti and Scarpetta (2003) find in their analysis of 23 industries in 18 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 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: Holmes and Schmitz (2010) review a series of studies on changes in competitive environments in industries; almost all of these studies conclude that an increase in competition results in productivity growth. Buccirossi *et al.* (2013) find in their empirical analysis for twelve OECD countries a positive relationship between competition policy and TFP growth. Fernandes *et al.* (2018) look at the effect of firm entry deregulation in Portugal, where a program (*"On the Spot Firm"*) was introduced in 2005 in order to reduce bureaucracy to register a new business. According to their findings, this program led to an increase in firm creation across industries and municipalities. Égert (2016) identifies for a panel of OECD countries for a period of three decades a negative association between anti-competitive product market regulations and TFP levels. Nickell (1996) finds some evidence of a positive link between competition and TFP growth in the UK manufacturing sector. His conjecture is, however, that growing competition does not raise the efficiency of firms, but allows many firms to operate in the market, of which only the best survive in the long run.

Aghion *et al.* (2005) show that the relationship between competition and innovation is complex. They develop a model that predicts the effect of product market competition on innovation and find an inverted U-shape relationship. They explain their findings by the fact that depending on the market situation, competition can encourage or discourage firms to innovate. If two or more competitors are level with each other, competition will animate them to innovate with the aim to outperform their rivals (*"escape competition effect"*). In contrast, in industries with a higher technological gap, increased product market competition may deter innovation by laggard companies since their expected profit from catching-up with the technological leader decreases with the intensity of competition (*"Schumpeterian effect"*). Griffith *et al.* (2010) confirm the escape competition effect in their empirical analysis of the introduction of the EU Single Market Programme (SMP).

Finally, the prevalence of foreign ownership can be a decisive factor for innovation activities and thus productivity, as stated by Guadalupe *et al.* (2012). They show for Spanish manufacturing companies that foreign owners acquire only the most productive firms and invest more in innovation, machinery and new organization structures than firms that stay domestic. The authors suggest that foreign ownership gives a firm access to larger markets and therefore incentives to innovate. Furthermore, knowledge spillovers through foreign-owned establishments may raise TFP, as stated by Haskel *et al.* (2007).

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.

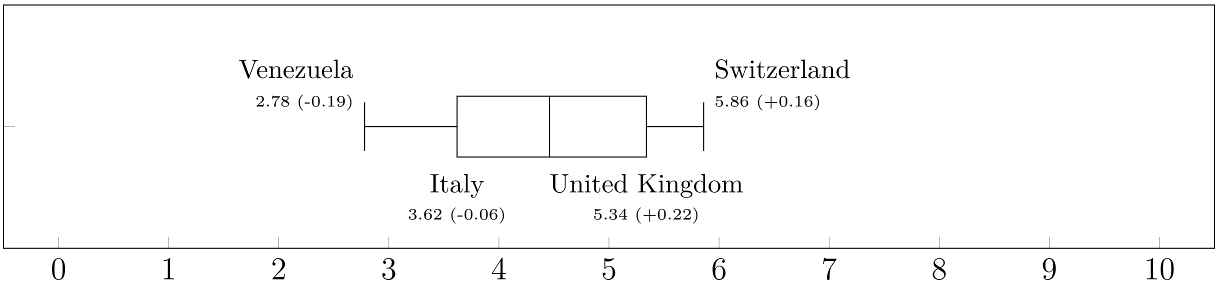
2.2.7 7^{th} Pillar: Labor Market Efficiency

Efficient labor markets allow the optimal allocation of labor. Ideally, productivity is boosted by matching workers with a fitting position in a swift and cost-efficient manner, especially in the face of rapidly changing market conditions. 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 7). With a score of 3.6, Italy is located at the bottom of the EU table.

Figure 7
Labor Market Efficiency (7th Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses).

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 (1990), Hopenhayn and Rogerson (1993), Nickell (1997), Fitoussi *et al.* (2000) or, more recently, Cunat and Melitz (2012)). Too much regulation, many argue, often leads to a decrease in overall productivity as well as higher unemployment. Hamermesh and Trejo (2000), for instance, show that the labor demand for overtime hours decreases when a high penalty is introduced. 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. Moreover, Haaland and Wooton (2007) show how country differences in hiring and firing costs strongly affect the investment decisions of multinational enterprises and therefore a country's capacity to attract foreign direct investment (FDI).

A flexible labor market goes hand in hand with the flexibility of wage determination. In this context, Nickell (1997) emphasizes the crucial role of labor unions, which indicate the degree to which wages are negotiated collectively. Strong unions are seen as a feature of an inflexible labor market and often raise unemployment. However, Nickell (1997) summarizes, the repercussions are negligible if wage negotiations are well coordinated with employers. 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. Higher prospective unemployment benefits, Burda *et al.* (2016) add, also lead to shirking and thereby to reduced productivity.

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. This is a crucial issue as job reallocation can be time-consuming and resource-intensive, which is captured in the renowned model of equilibrium unemployment and job matching by Mortensen and Pissarides (1994). Similarly, Acemoglu and Shimer (2000) draw attention to the positive effects of unemployment insurance on productivity: Workers who benefit from moderate insurance in case of unemployment are more likely to take the time to search for better-paid jobs that match their qualification, which in turn encourages employers to create these jobs.

Another aspect of a competitive labor market is its openness towards women. Although the correlation between female labor force participation and GDP has been subject to controversial discussions, the vast majority of researchers agree on a long-term positive impact on economic growth (see, e. g, Çağatay and Özler (1995), Gaddis and Klasen (2014) or Lechman and Kaur (2015)).

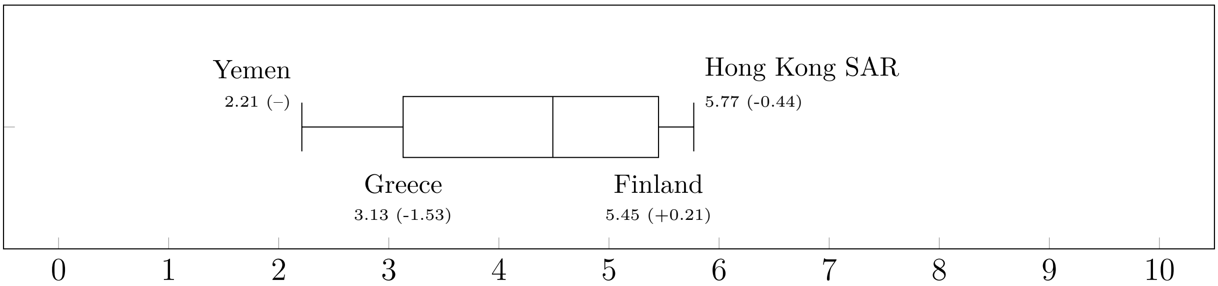
As some of the indicators in this pillar directly relate to labor productivity, we expect it to be a considerable predictor for TFP growth in the EU.

2.2.8 8th Pillar: Financial Market Development

A well-functioning financial market helps reducing transaction and information costs. It needs policies and institutions that allow the efficient allocation of capital. The GCI pillar *financial market development* includes eight indicators and contains, i. a., the availability and affordability of financial services for businesses, indicators for the stability of the financial sector, and an indicator that measures the degree of legal protection of borrowers' and lenders' rights. Seven of these indicators stem from the EOS.

In the EU, the average score for this pillar varies between 3.1 for Greece and 5.5 for Finland as depicted in Figure 8. The scores deteriorated in many EU countries after the 2009 crisis; the decline was particularly high in Greece and Cyprus.

Figure 8
Financial Market Development (8^{th} Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses).

King and Levine (1993b) stress four types of mechanisms through which financial markets affect productivity: The first one is to make capital available to entrepreneurs in order to convert their inventions into innovation. However, innovation activities are associated with uncertainty. Financial institutions help to diversify risks, which is the second mechanism. Third, financial institutions evaluate entrepreneurs and provide resources to the most productive ones. As this evaluation entails high fixed costs, it should be carried out by specialized organizations. The fourth channel refers to the ability of financial institutions to estimate the expected profits from innovations.

Many authors (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) or Madsen and Ang (2016)) conclude that financial market development boosts economic growth. King and Levine (1993a) find a set of indicators for financial development to have positive effects on growth, the efficiency of capital allocation and the rate of physical capital accumulation. Beck *et al.* (2000) show that financial intermediary development affects economic growth mainly via its positive effect on resource allocation and thus TFP growth.

However, not all authors take the positive effects of financial market development on economic development as proven. Calderón and Liu (2003), for instance, identify a bidirectional causality: The impact of financial development on TFP growth is stronger in developing countries than in industrial economies, whereas the reverse relationship is stronger for the latter. Zang and Kim (2007) find no evidence of causal effects of financial services on economic growth. However, they identify effects in the opposite direction and argue that a growing economy fosters greater demand for financial services.

According to Arestis and Demetriades (1997), institutional structures and governance of financial systems play a major role. Based on the example of Germany and the U.S., they show how different financial systems have varying effects on economic growth. Their results mirror the findings by Demetriades and Hussein (1996), Arestis *et al.* (2001) or Shan *et al.* (2001). De Gregorio and Guidotti (1995) suggest that the relationship between financial and economic development may vary across countries, stages of development and over time. Rioja and Valev (2004) confirm a non-linear relationship. They show that only in countries with intermediate levels of financial development, improvements will have a large, positive effect on economic growth. In highly developed financial systems, the effect is much smaller; the effects in countries with low levels of financial systems are unclear.

De Gregorio and Guidotti (1995) even find evidence for negative effects of financial intermediation on economic growth in a sample of twelve Latin American countries from 1950-1985. They argue that the extreme financial liberalization with a poor regulatory environment led to a collapse of financial markets in the region with negative effects on the efficiency of investment. Ghani and Suri (1999) also conclude that the banking sector can have negative effects on TFP growth. They show how rapidly growing bank lending in Malaysia negatively influenced the project selection process, risk analysis and monitoring. The consequence is that capital is allocated inefficiently. Also in Europe, credit misallocation can cause TFP loss, as shown by Gopinath *et al.* (2017) for Spain, Italy and Portugal. Acharya *et al.* (2019) observe that the prevalence of "zombie" firms and "zombie" lending during the financial crisis was high in some Southern European countries. According to them, credit misallocation through zombie lending can affect non-zombie firms in various ways: First, due to problems of zombie firms to service their debt, interest rates also grow for productive firms in the same industry. Second, zombie firms artificially kept alive have adverse effects on market competition. Schivardi *et al.* (2017) also explore the effects of credit misallocation on productivity during the financial crisis. They observe for Italy that zombie firms survived better in the environment of weaker banks while failures of healthy non-zombie firms simultaneously increased. Duval *et al.* (2020) show that worsening credit conditions played a crucial role in the European financial crisis and led vulnerable firms to reduce their innovation activities and thus affected TFP growth, especially in Southern Europe.

The relationship between financial and economic development is complex. As high scores of this pillar can, nonetheless, be connected to inefficient lending – in particular during the 2008/09 crisis in Southern Europe – we expect a negative relationship for those countries but assume a positive association for the more developed ones.

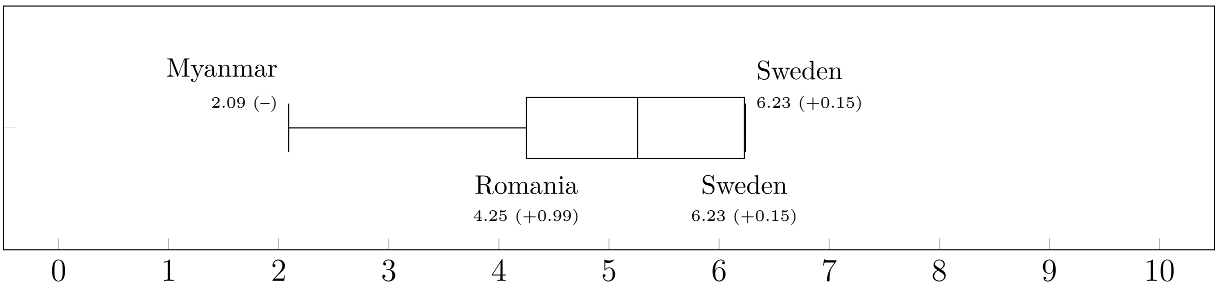
2.2.9 9th Pillar: Technological Readiness

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)). This pillar aims at capturing a country's capacity for adopting existing technologies in order to increase competitiveness.

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 9, 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 9
Technological Readiness (9th Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses).

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)). The relation between technological change, often measured by ICTs, and productivity growth is complex and has been subject of debates for decades. In his seminal paper, Solow (1957) analyzed long-term growth in the U.S. between 1909 and 1949 and found that close to 90 % of labor productivity growth could be traced back to technological advances. His analysis, however, might have been built on data from a historically unique time period and have led to findings that are not easily applicable to a different context. Solow (1987) himself concluded that the emergence of computer technology can be seen *"everywhere but in the productivity statistics"*. The resulting *productivity paradox*, also titled *IT paradox*, refers to a neutral or negative impact of investments in ICTs on firm performance and was affirmed by a number of studies (see, e. g., Berndt and Morrison (1995), Carr and Carr (2004), Lee and Connolly (2010) or Gilbert Jr *et al.* (2012)). Various researchers, such as Brynjolfsson (1993) and Crafts (2010), have challenged the validity of the productivity paradox with respect to methods and data, measurement issues, mismanagement of new technologies and the time lag between investment and measurable productivity growth. Although initial effects tend to be rather small, several researchers indeed 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)).

Although the availability of technological innovations is an essential precondition, it alone does not guarantee a successful firm level absorption, which refers to the ability to utilize, replicate and, if necessary, adapt external technologies. Sustained efforts and considerable investments are required to allow for a sufficient diffusion and adoption of the latest technologies. A variety of studies search for the conditions of an effective absorption (see, e. g., Qosasi *et al.* (2019), Boateng *et al.* (2011), Crafts (2010), Arogyaswamy and Elmer (2005) or Cohen and Levinthal (1989)). 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)). Goldberg *et al.* (2008) emphasizes that investor-friendly policies might aid in maximizing technology transfers. Glass and Saggi (1999) and Goldstein (2004), however, draw attention to the need to select policy interventions very carefully and strategically when it comes to FDI, as they could also exacerbate difficulties. Multinational companies and host countries may have diverging interests (see, e. g., Fu *et al.* (2011)). According to van der Straaten *et al.* (2019), MNEs tend to widen gender wage gaps in less-developed countries. They also shed light on the importance for host countries to have a strong property rights protection, as it strongly affects the behavior of MNEs in terms of wages.

Nevertheless, 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, especially in less developed EU countries.

2.2.10 10th Pillar: Market Size

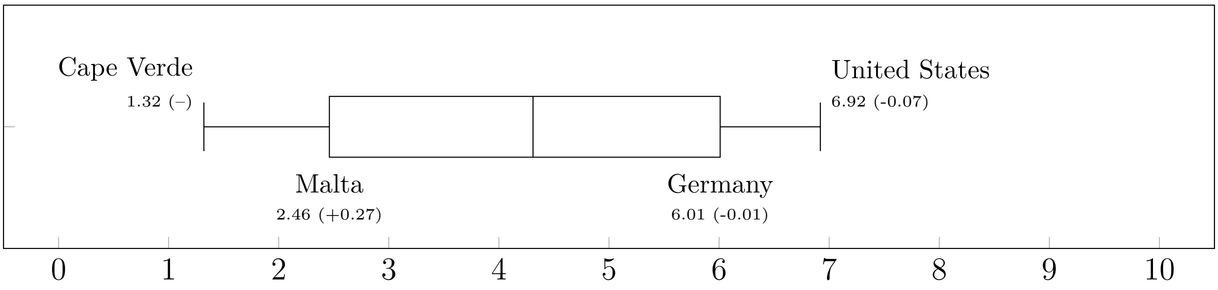
The overall market size of a country is determined by its domestic market capacity and its integration into the world economy. The size of a country (usually measured as a combination of population, land area or GDP) comes with costs and benefits.

The GCI pillar *market size* contains only a 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 10); Malta's average of 2.5 is the lowest. It is not surprising that – contrary to other pillars – the values of the pillar *market size* have remained mostly constant over time.

As noted by 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 the manufacturing sector (see, e. g., Krugman (1991b) or MacDonald (1994)). Briguglio (1998) confirms this hypothesis empirically. According to

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



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses).

his results, there is a positive relationship between country size and increasing returns to scale. Alcalá and Ciccone (2004) find positive effects of scale of production on average labor productivity through the channel of TFP. In contrast, Bartelsman *et al.* (2013) assume in their model slightly decreasing but almost constant returns to scale based on the findings by, i. a., Syverson (2004).

Market size further influences productivity through the availability and the formation of human capital. The restricted availability of working force can be a critical factor for small countries. According to Romer (1990), a large population does not necessarily generate higher economic growth; rather, the stock of human capital is important. In his model, the integration into international markets with high human capital stocks can foster economic growth. 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. Such specialization, however, might increase the exposure to exogenous shocks (see, e. g., Armstrong and Read (2003)). Easterly and Kraay (2000) confirm this empirically. Even though they do not find a significant difference in economic growth between large and small countries, they observe that small ones are more volatile than larger ones and are affected more by economic trade shocks.

Trade and market size often go hand in hand, but the findings concerning this relationship are mixed. Trade increases competition which, in turn, is suggested as one of the main mechanisms how market size can affect productivity. Melitz and Ottaviano (2008), for example, predict that larger markets trigger tougher competition, with the consequence that least productive firms exit the market. Thereby, resources are reallocated to more productive firms, which in turn raises the aggregate level of efficiency. Moreover, Grossman and Helpman (1991) assign a major role to the integration into global markets, arguing that it increases the exchange of information and makes spillover effects possible. While Alcalá and Ciccone (2004) identify a positive effect of trade and population size on TFP, the results by Badinger (2007) do not suggest that market size is related to productivity effects of trade.

Rose (2006) argues that trade openness has a negative relationship with country size and thus identifies trade openness as real determinant for economic outcomes, while he identifies the country size as insignificant. Easterly and Kraay (2000) conclude as well that small countries are more open to international trade, which in turn has positive growth effects. Ramondo *et al.* (2016) emphasize that trade models often underestimate domestic trade costs and that the consideration of this can weaken scale effects.

Market size also generates incentives for innovation, as shown by Acemoglu and Linn (2004). Even after correcting for endogeneity issues (as better products find larger markets), they find a high effect of potential market size on innovation in the pharmaceutical industry. They state that the driving forces behind innovation are profit incentives that grow with market size. Other authors support the view that larger markets encourage greater investment in innovation (see, e. g., MacDonald (1994) or Guadalupe *et al.* (2012)).

Briguglio (1998) and Armstrong and Read (2003) mention further disadvantages of small countries that could hinder their productivity. Small countries usually have poor natural resources, depend on imported technologies that are designed for larger productions, have limited connections to sea and air transport, have low domestic inter-industry linkages and are dependent on imports for production inputs and final demand. They also lack market power. On the other hand, it is assumed that social cohesion is stronger in smaller countries, which Alesina *et al.* (2005) consider to be an advantage for a country's economic development. In very large countries, administrative costs might exceed the benefits of size pointed out above.

All observed countries in our study are EU members (or joined the EU during the observation period), ensuring them access to the single market. In 2019, only Ireland and Cyprus exported more goods to partners outside the EU than inside (Eurostat (2020)). Hence, as all countries face more or less the same market, we do not expect this pillar to predict major differences in TFP growth in the EU.

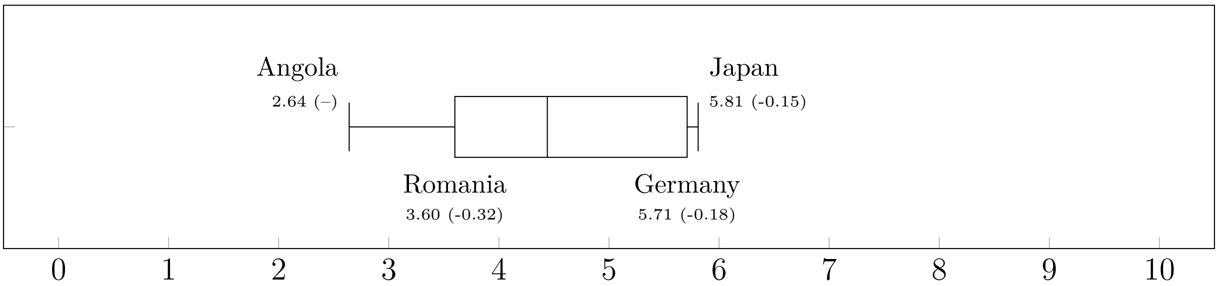
2.2.11 11^{th} Pillar: Business Sophistication

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). Dima *et al.* (2018, p. 11) label business sophistication one of the "soft" pillars, which are often related to the extent of R&D activities and, in turn, enable efficiency and productivity improvements. Therefore, the final two pillars – *business sophistication* and *innovation* (pillar 12) – are considered defining aspects for highly developed economies at an *innovation-driven* stage of development.

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



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses).

Globalization has given rise to a significant amount of literature dealing with the question how to stay competitive in light of greater competition. 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. Geographical proximity of interacting firms within and between industries has been much discussed, especially within the framework of the New Economic Geography (starting with Krugman (1991a,b)). The promotion of further cluster development might act as a foundation for countries to increase productivity. 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)). The definition of upgrading differs in the literature, just like the expected value and limitations for individual firms (for a critical discussion, see, e. g., Morrison *et al.* (2008)). Humphrey and Schmitz (2002) distinguish between four different categories of upgrading: Moving towards a technologically more advanced production process, shift to more complex products, adopt new functions or drop unnecessary ones and/or moving into a new economic sector. The authors also suggest that different types of relationships between actors within a value chain (e. g. loose business connections, co-dependent networks or varying degrees of hierarchies) also allow for different upgrading chances. Accordingly, Gereffi *et al.* (2005) and Elola *et al.* (2013) stress that chain governance needs to be sensitive to the respective relationships within a value chain and the upgrading prospects that come with it.

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.

Furthermore, business sophistication is frequently analyzed in combination with a country's or a firm's capacity to innovate. Razavi *et al.* (2012) use the GCI of 2011/12 to investigate the link between innovation and business sophistication and find a significant positive relation between these two pillars. Kirikkaleli and Ozun (2019) confirm the positive connection between business sophistication and innovation, along with benefits for the macroeconomic environment.

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.

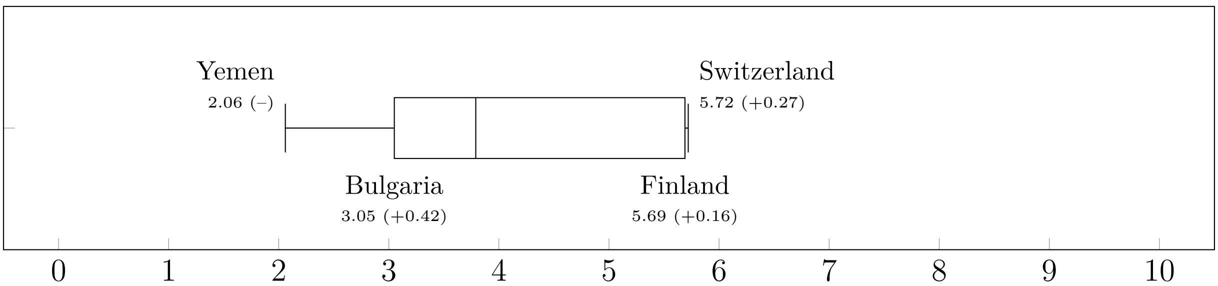
2.2.12 12^{th} Pillar: Innovation

The last pillar of the GCI is dedicated to innovation. The implementation of new goods, services and processes enables firms to produce more efficiently by reducing production costs and to create and occupy new markets. As stated by Schumpeter (1961), the incentive to innovate comes from the expectation of monopoly rents. However, uncertainty is a major characteristic of innovation.

The GCI pillar *innovation* is composed of seven indicators (i. a. company spending on R&D, availability of scientists and engineers and the number of patent applications under the Patent Cooperation Treaty (PCT)) and includes various actors of innovation, such as governments, companies, research institutions, universities and scientists. Most of the indicators are based on the EOS.

As depicted in Figure 12, Finland achieves the highest average score (5.7) within the EU; Bulgaria the lowest (3.0). Since 2009, most countries have improved their scores; only five have declined (i. e. Croatia, Cyprus, Czechia, Hungary and Romania).

Figure 12
Innovation (12^{th} Pillar)



Note: The plot shows average scores between 2009 and 2017 (and absolute changes in parentheses).

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, profit incentives are the driving force for technological progress. However, choosing the right indicators for the measurement of innovation is challenging (see, e. g., Hall *et al.* (2013)). Mainly two measures have been used to capture innovative activities: R&D expenditures as innovation input and patent counts as innovation output.

Griffith *et al.* (2004) find that R&D expenditures foster productivity growth directly through innovation and indirectly through technology transfer. Their results also suggest that the further away a country is from the technological frontier, the higher are the rates of productivity growth through R&D. Similarly, Coe *et al.* (2009) observe that domestic and foreign R&D capital are key determinants of TFP. But their results do not confirm the view that the distance to the frontier matters. More recently, Égert (2016) finds a strong positive link between overall R&D spending and TFP. This positive effect is only attributable to business funded R&D. Interestingly, R&D funded by the government has no positive effects. These findings are consistent with the results by Coe *et al.* (2009) and Pegkas *et al.* (2019); the latter find that business R&D expenditure has the highest positive effect on innovation in EU countries. According to the results by Griffith *et al.* (2006), however, central government funding for innovation projects increases the probability that a firm becomes active in R&D at all.

Furman *et al.* (2002) examine factors that have a direct effect on international patenting activities of foreign countries in the U.S. They identify various determinants of this relationship and find that public policy (e. g. incentives for innovation through protection of intellectual property, investment in human capital or creation of supportive environments for industrial clusters) affects R&D productivity. They state further that there has been a slow but steady convergence among the observed countries regarding the measured innovative capacity.

It must be noted in this context that innovation and its expected impact on productivity are not only embedded in institutional environments, but also 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)). Griffith *et al.* (2006), for instance, explore the link between innovation and labor productivity for manufacturing firms in France, Germany, Spain and the UK and find varying results in those four countries. Furthermore, the type of innovation must be considered: Lee and Kang (2007) examine Korean manufacturing firms and find that process innovation leads to higher productivity in the short run while they expect product innovation to be more important in the long run.

Also, the stage of development plays a crucial role for the effect of innovation on productivity. Most countries of the EU are – according to the Global Competitiveness Report – *innovation-driven* or on their way from *efficiency-* to *innovation-driven* economies; only Bulgaria is classified as *efficiency-driven* (see World Economic Forum (2017)). Innovation and technological change are seen as drivers of productivity, particularly for *innovation-driven* economies. 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*. In contrast, the imitation of well-established technologies plays a more important role for countries far below the frontier. The capability to do so is rather a question of *technological readiness* (see pillar 9 in subsection 2.2.9). Accordingly, Akçomak and Ter Weel (2009) suggest that backward economies should first invest in education and only in a second step in R&D, since the private sector cannot invest efficiently in innovation without the required social capital. 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 1 shows descriptive statistics.

Table 1
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 ($N(0, \sigma_\upsilon)$) 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.

[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.

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

$$
\begin{aligned}
\underbrace{ln\left(\frac{TFP_{i,1}}{TFP_{i,0}}\right)}_{\text{TFP growth}} = &\underbrace{\frac{1}{2}\cdot\left(\sum_{t=0}^{1}\frac{\partial ln(Y_{i,t})}{\partial t}\right)}_{\text{CTP}} \\
&+\underbrace{ln\left(\frac{e^{-u_{i,1}}}{e^{-u_{i,0}}}\right)}_{\text{CTE}} \\
&+\underbrace{\frac{1}{2}\cdot\left(\left(\sum_{t=0}^{1}S_t\cdot\varepsilon_{k,t}\right)\cdot(K_{i,1}-K_{i,0})+\left(\sum_{t=0}^{1}S_t\cdot\varepsilon_{l,t}\right)\cdot(L_{i,1}-L_{i,0})\right)}_{\text{CSC}} \\
&+\underbrace{\frac{1}{2}\cdot\left(\left(\sum_{t=0}^{1}\lambda_{k,t}-(1-c_{l,t})\right)\cdot(K_{i,1}-K_{i,0})+\left(\sum_{t=0}^{1}\lambda_{l,t}-c_{l,t}\right)\cdot(L_{i,1}-L_{i,0})\right)}_{\text{CAE}}
\end{aligned}
\tag{5}
$$

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

[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.

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 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.

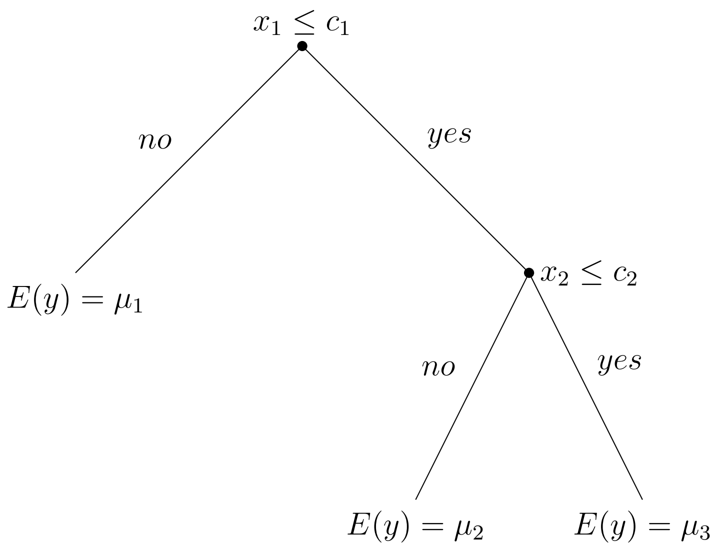
Hence, the inclusion of the twelve pillars in the SFA model lets us get rid of the methodological problems outlined in the last subsection, but it will not help us in truly identifying what – apart from capital and labor – drives economic growth. This issue is much more of a model selection problem which 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 13. The terminal nodes (i. e. the "leaves") contain the predictions of y in their respective partitions.

Figure 13
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 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.

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

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 2.[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 2. 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).

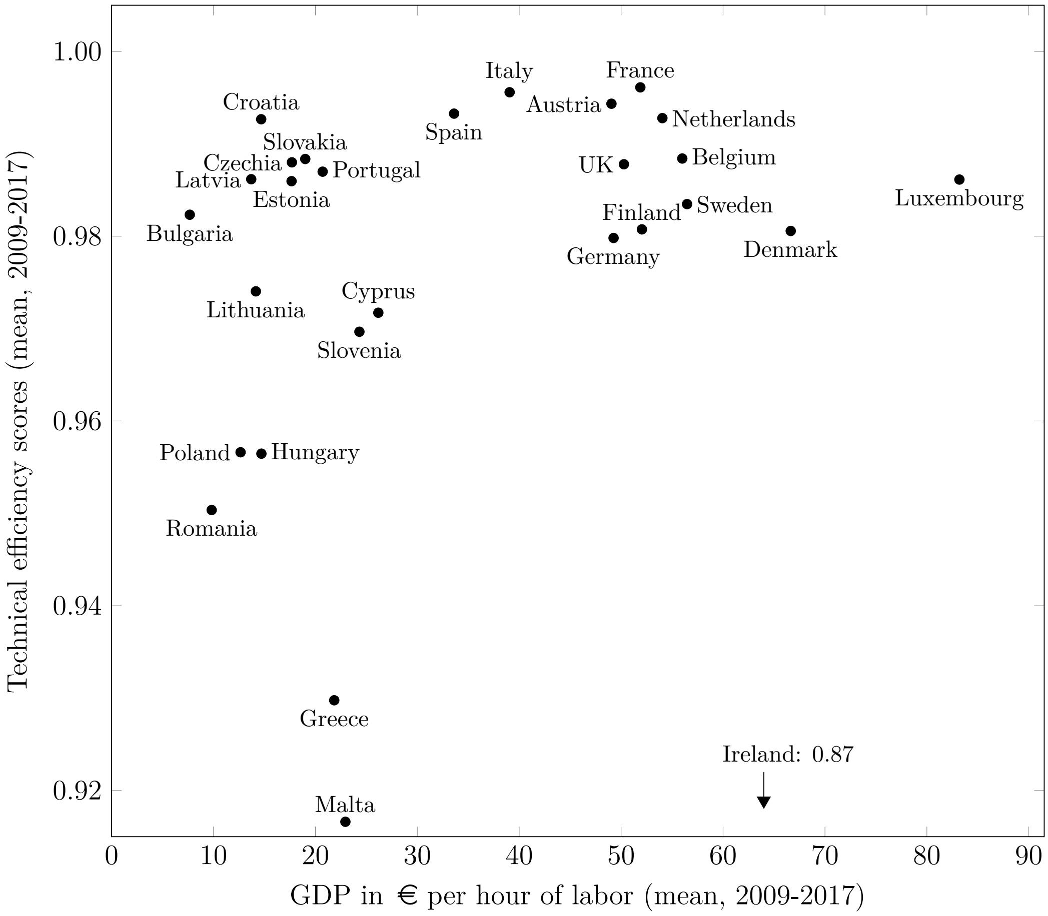
Table 2
Results from Stochastic Frontier Analysis (SFA) with "true" fixed-effects

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 14. 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 14
Results from Stochastic Frontier Analysis (SFA) with "true" fixed-effects



4.2 TFP decomposition results

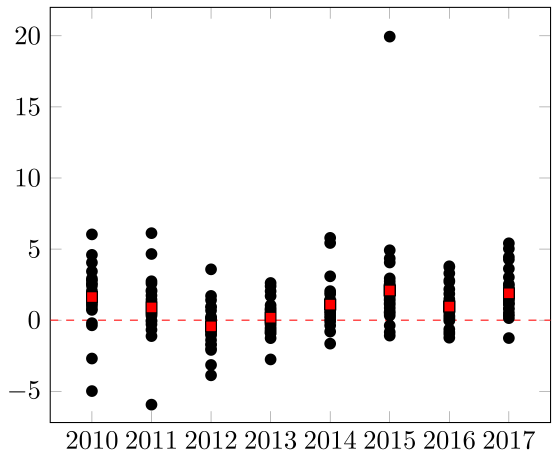
The SFA results will now be used to construct a measure for TFP growth and to decompose it into changes in technical progress (CTP), technical efficiency (CTE), scale efficiency (CSC) and allocative efficiency (CAE) as shown in Equation 5.

Figure 15 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

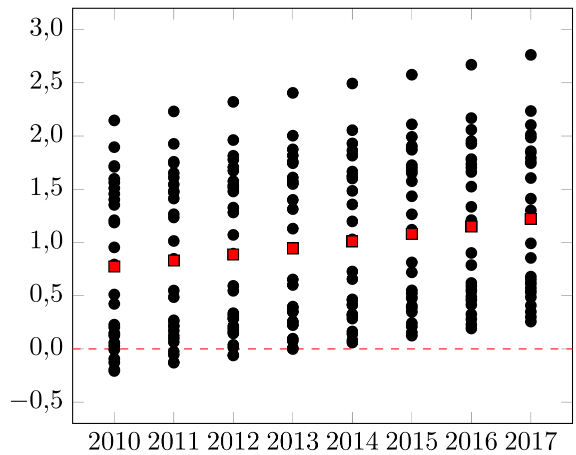
[6] The country was hit severely by the economic crisis in 2008/09 but has managed massive GDP growth rates since 2014. The key to success was to attract international enterprises with very low corporate tax rates. As their contribution to GDP is accounted for in Ireland but the actual production activities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

Figure 15
Results from TFP decomposition

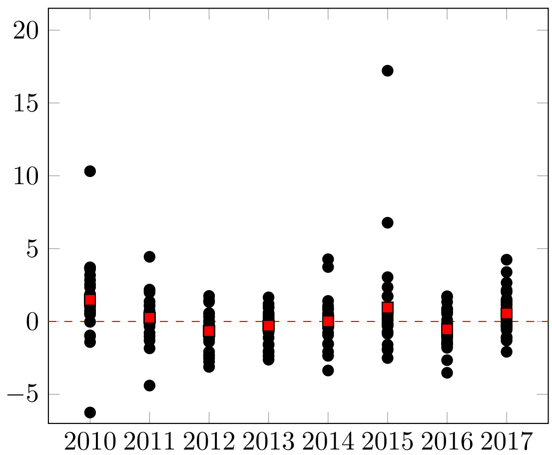
(a) *Changes in TFP (gTFP) in %*



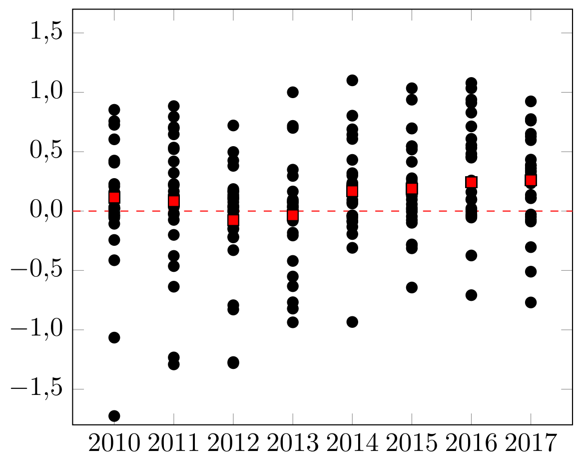
(b) *Changes in Technical Progress (CTP) in %*



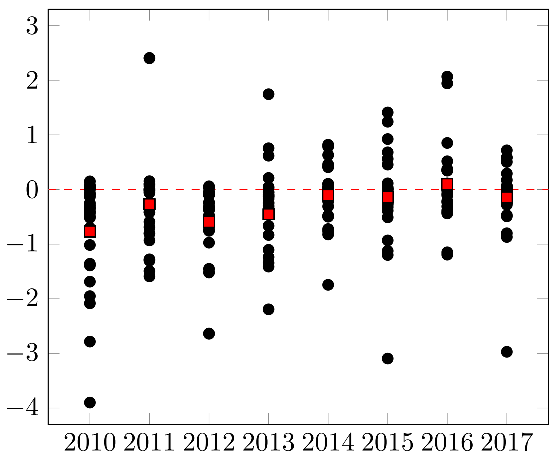
(c) *Changes in Technical Efficiency (CTE) in %*



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



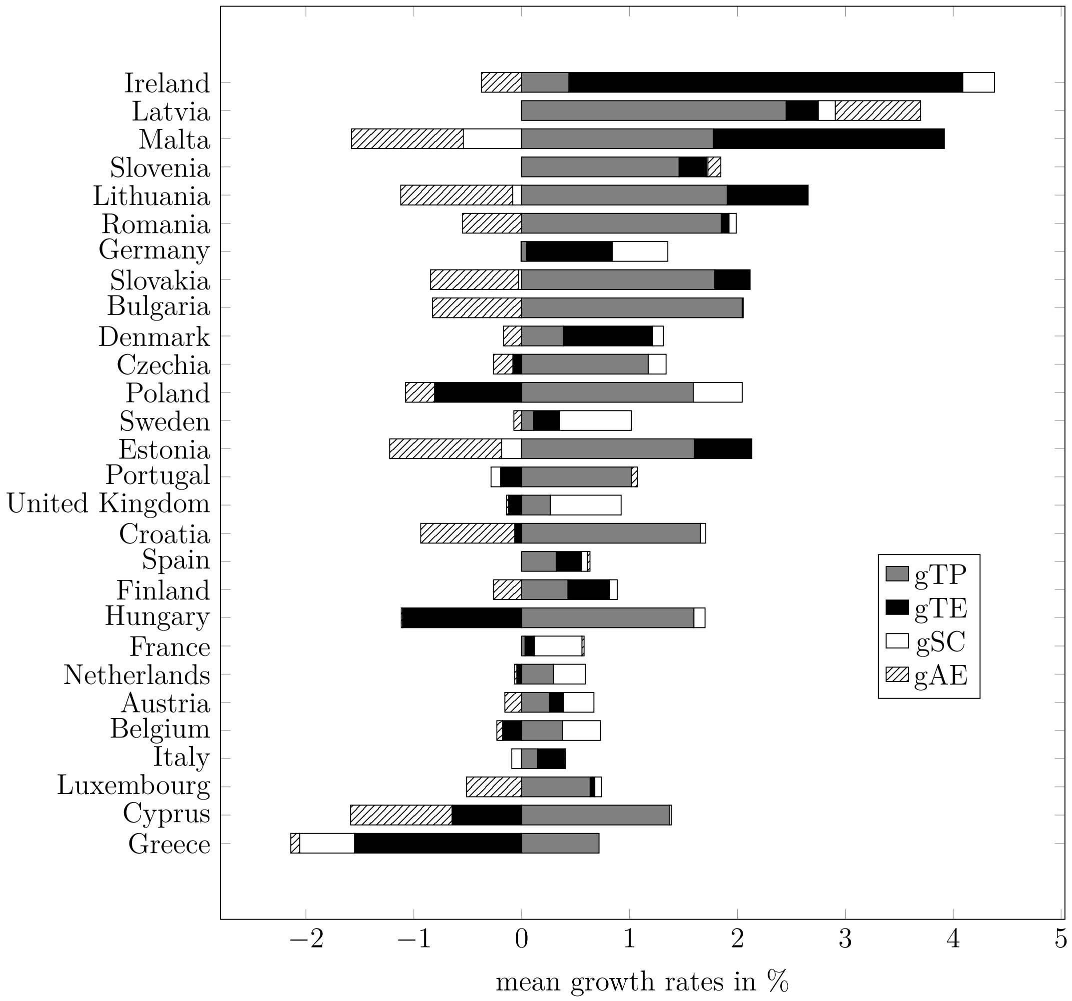
(e) *Changes in Allocative Efficiency (CAE) in %*



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 16.

Figure 16
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 17 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 3.

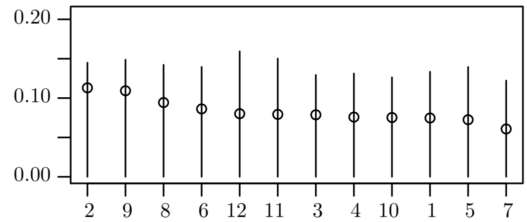
The plots indicate that increasing scores in pillars 6 and 9 indeed predict faster technical progress. Both results seem highly plausible as pillar 9 captures technology availability and absorption whereas pillar 6 measures how well the goods market is regulated and is attractive for FDI and competition.

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

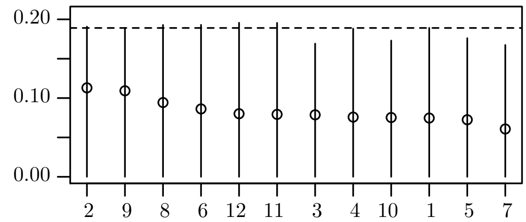
[7] We deploy the R package *bartmachine* by Kapelner and Bleich (2016). All variables have been centered.

Figure 17
Variable selection

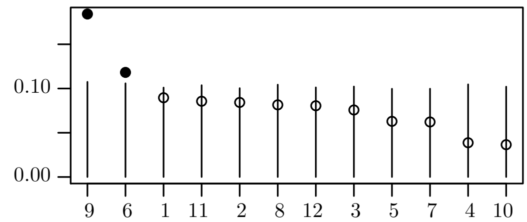
(a) *Local Procedure – TFP growth*



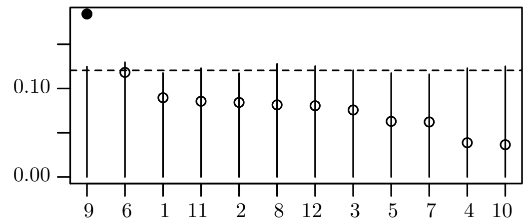
(b) *Global Procedures – TFP growth*



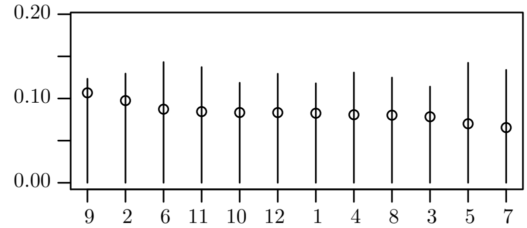
(c) *Local Procedure – CTP*



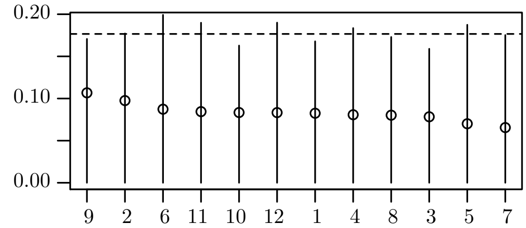
(d) *Global Procedures – CTP*



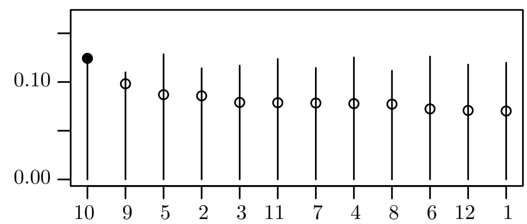
(e) *Local Procedure – CTE*



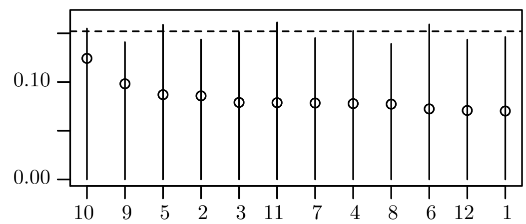
(f) *Global Procedures – CTE*



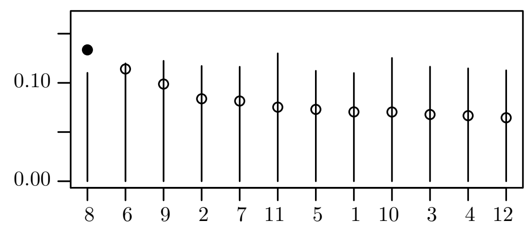
(g) *Local Procedure – CSC*



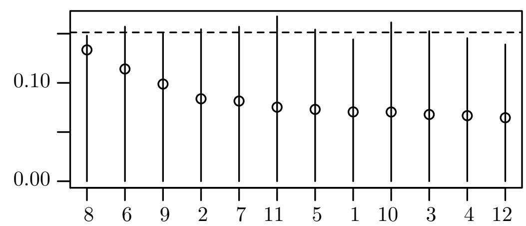
(h) *Global Procedures – CSC*



(i) *Local Procedure – CAE*

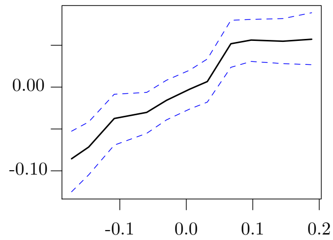
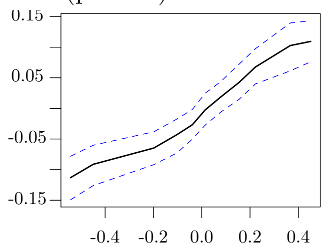
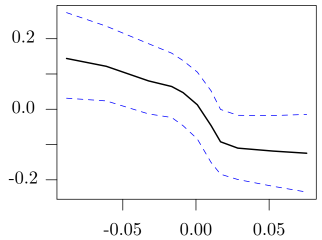
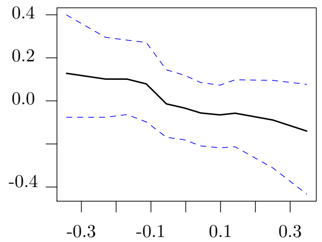


(j) *Global Procedures – CAE*



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 3
Partial dependence plots

TFP growth	No relevant variables identified (see Figure 17).
CTP	"Goods market efficiency" (pillar 6)  "Technological readiness" (pillar 9) 
CTE	No relevant variables identified (see Figure 17).
CSC	"Market size" (pillar 10) 
CAE	"Financial market efficiency" (pillar 8) 

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 18 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 4 (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 19 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 19 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 5 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 20 in the Appendix;[9] Table 6 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.

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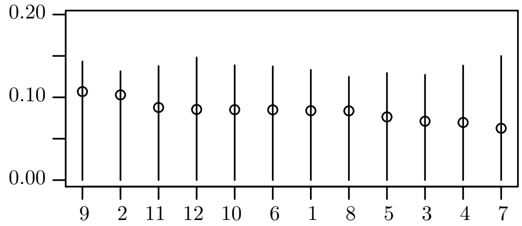
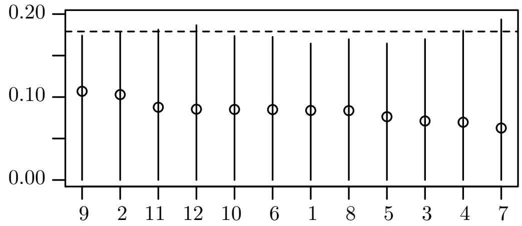
6 Appendix

Figure 18
Variable selection – set of higher-income economies

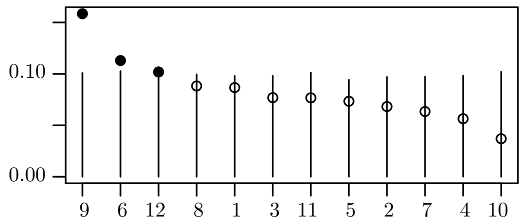
(a) *Local Procedure – TFP growth*



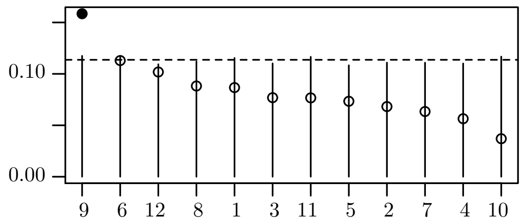
(b) *Global Procedures – TFP growth*



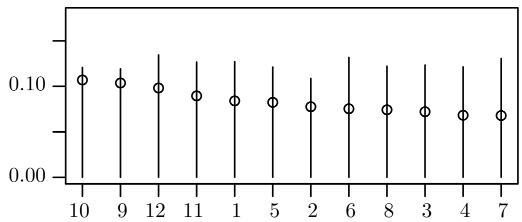
(c) *Local Procedure – CTP*



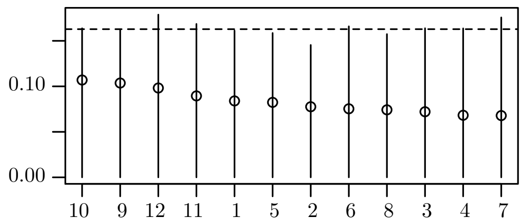
(d) *Global Procedures – CTP*



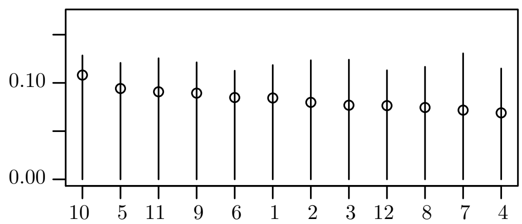
(e) *Local Procedure – CTE*



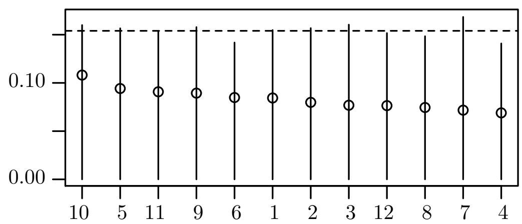
(f) *Global Procedures – CTE*



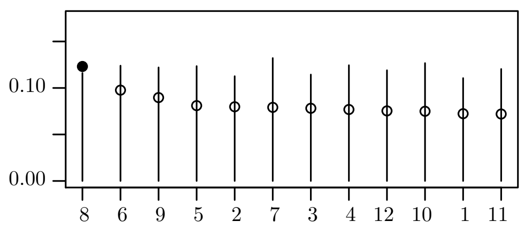
(g) *Local Procedure – CSC*



(h) *Global Procedures – CSC*



(i) *Local Procedure – CAE*



(j) *Global Procedures – CAE*

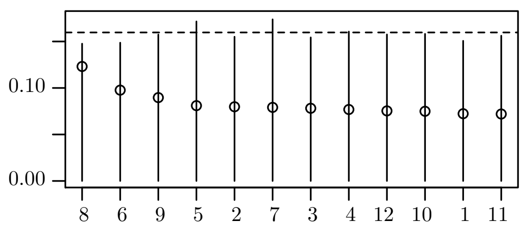


Figure 19

Variable selection – set of lower-income economies

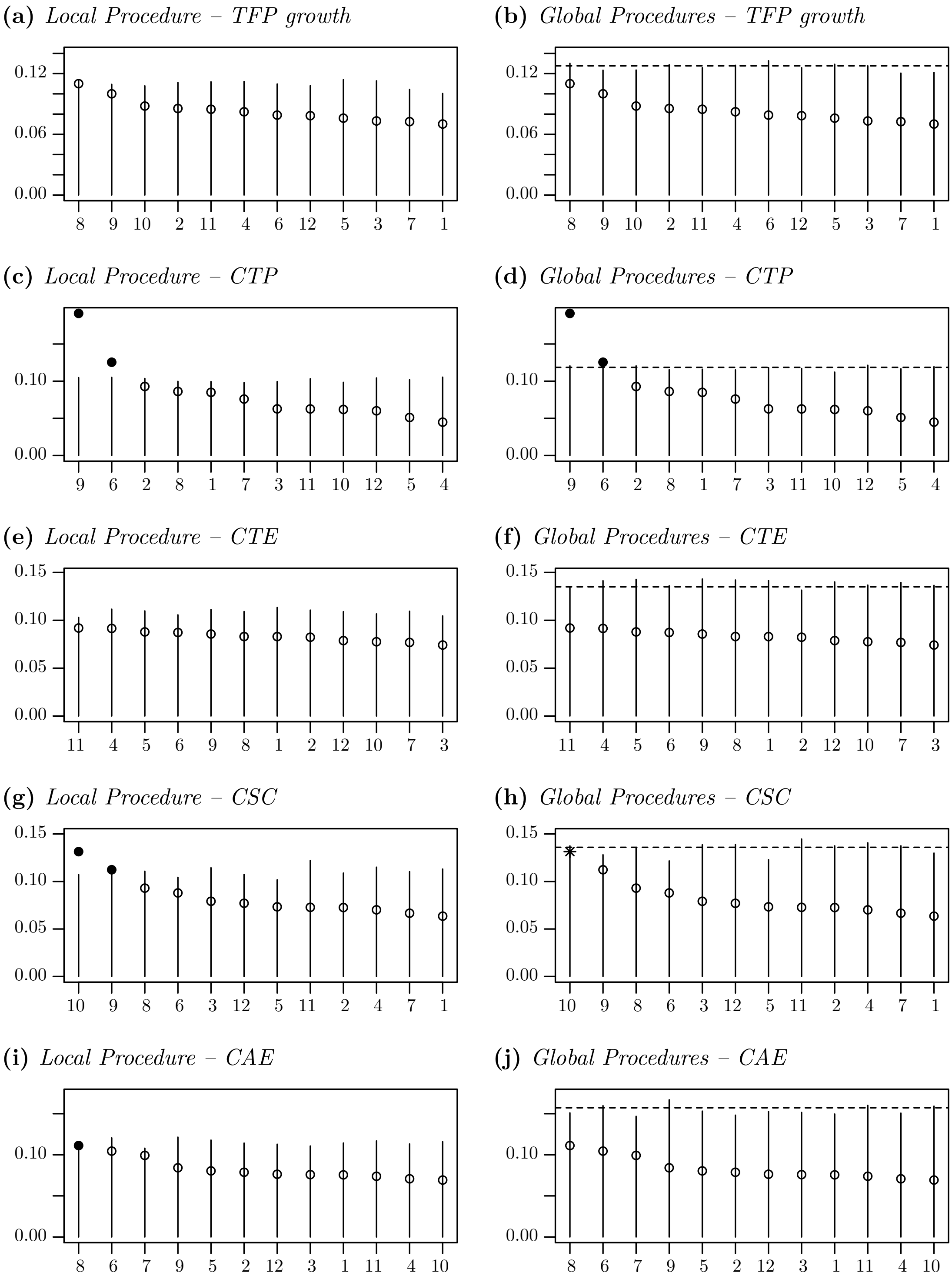
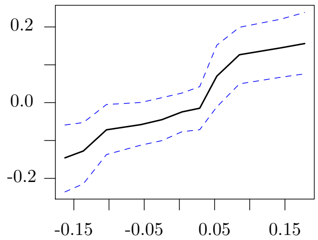
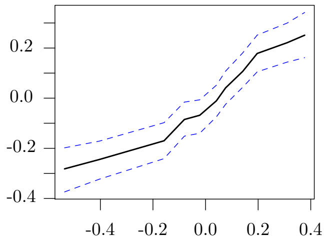
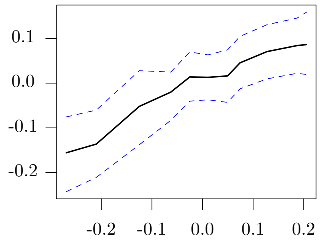
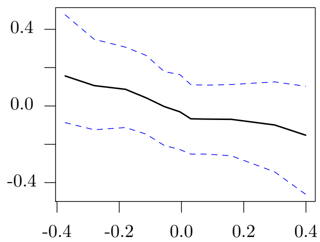
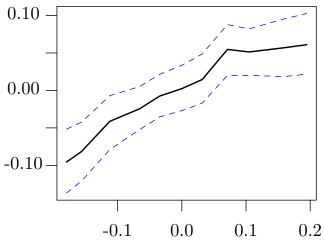
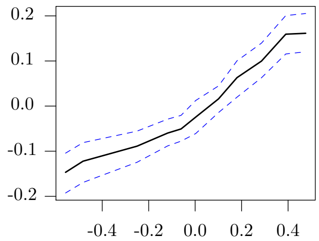
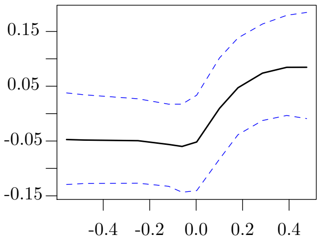
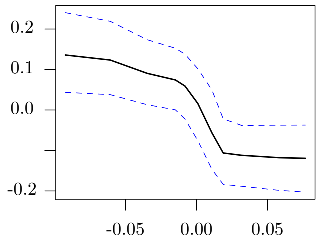
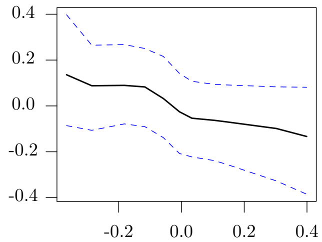


Table 4
Partial dependence plots – set of higher-income economies

TFP growth	No relevant variables identified (see Figure 18).		
CTP	"Goods market efficiency" (pillar 6)  	"Technological readiness" (pillar 9)  	"Innovation" (pillar 12) 
CTE	No relevant variables identified (see Figure 18).		
CSC	No relevant variables identified (see Figure 18).		
CAE	"Financial market" efficiency (pillar 8)  		

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

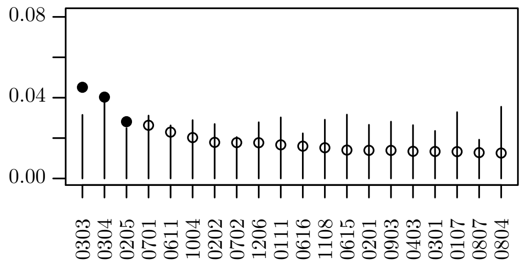
Table 5
Partial dependence plots – set of lower-income economies

TFP growth	No relevant variables identified (see Figure 19).
CTP	"Goods market efficiency" (pillar 6)  "Technological readiness" (pillar 9) 
CTE	No relevant variables identified (see Figure 19).
CSC	"Technological readiness" (pillar 9)  "Market size" (pillar 10) 
CAE	"Financial market efficiency" (pillar 8) 

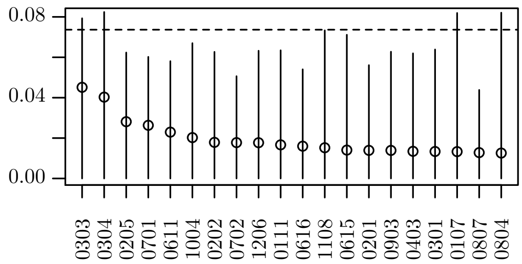
Note: The vertical axis depicts the partial effects. Blue lines represent 95 % credible intervals.

Figure 20
Variable selection – indicators

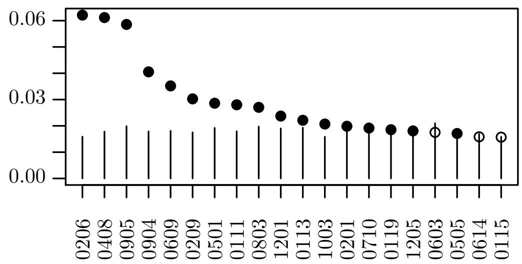
(a) *Local Procedure – TFP growth*



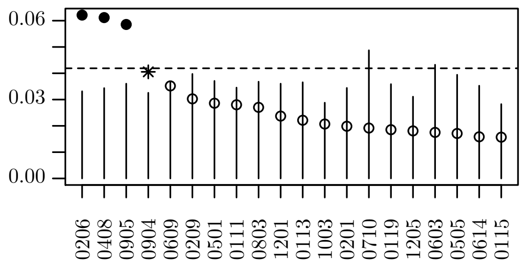
(b) *Global Procedures – TFP growth*



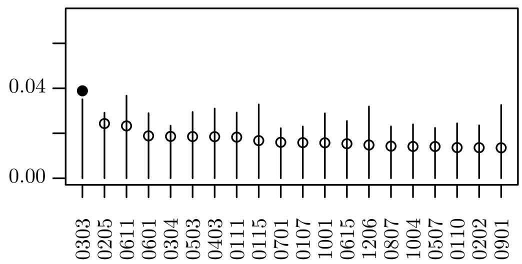
(c) *Local Procedure – CTP*



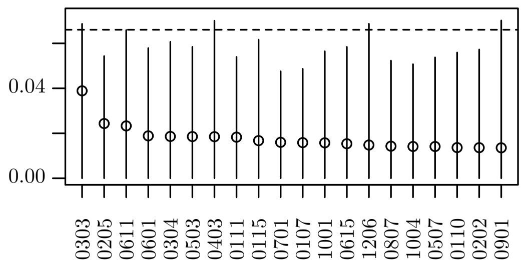
(d) *Global Procedures – CTP*



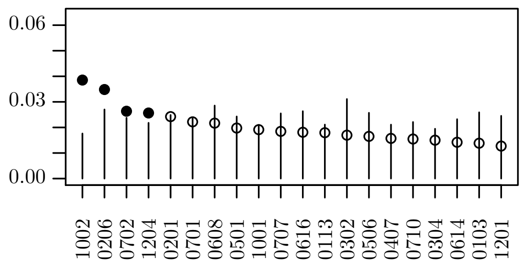
(e) *Local Procedure – CTE*



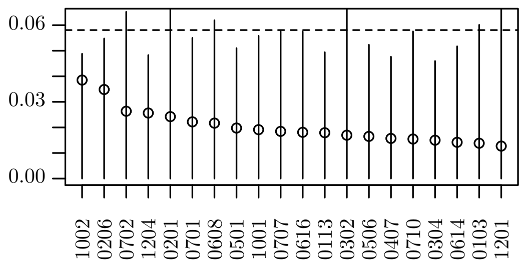
(f) *Global Procedures – CTE*



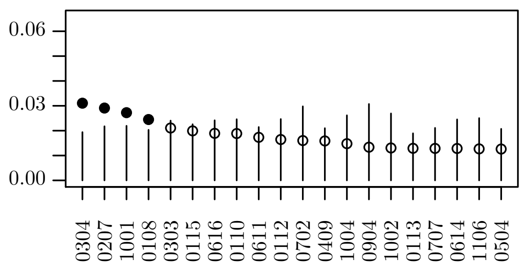
(g) *Local Procedure – CSC*



(h) *Global Procedures – CSC*



(i) *Local Procedure – CAE*



(j) *Global Procedures – CAE*

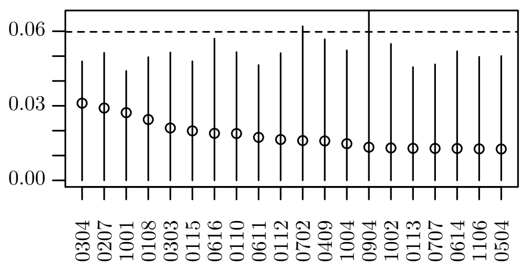
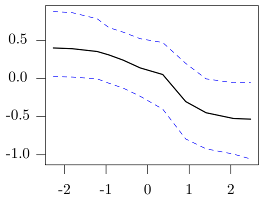


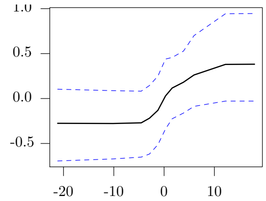
Table 6
Partial dependence plots – indicators

TFP growth

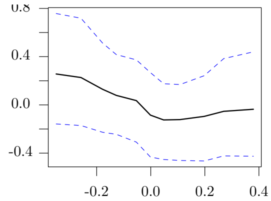
3.03: Inflation, in %



3.04: General government debt (in % of GDP)

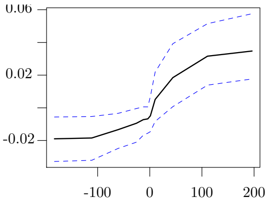


2.05: Quality of air transport infrastructure, 1-7

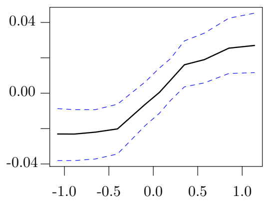


CTP

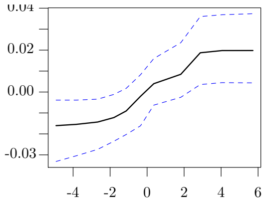
2.06: Available airline seat km/week



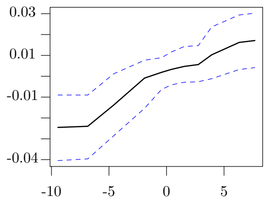
4.08: Life expectancy (in years)



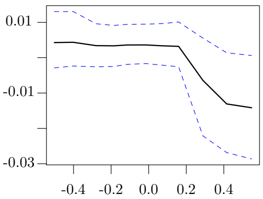
9.05: Fixed broadb. internet subscript. / 100 pop.



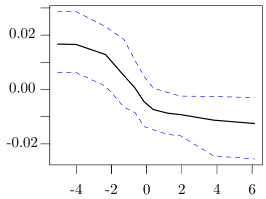
9.04: Individuals using internet, in %



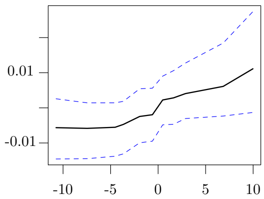
6.09: Prevalence of trade barriers, 1-7



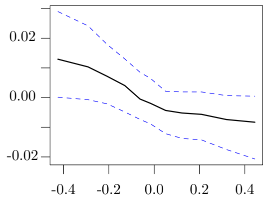
2.09: Fixed telephone lines / 100 pop.



5.01: Secondary education enrollment, in %

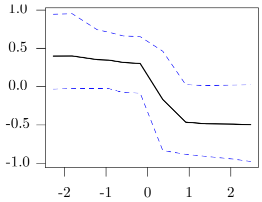


1.11: Eff. of legal framew. in challeng. regs., 1-7



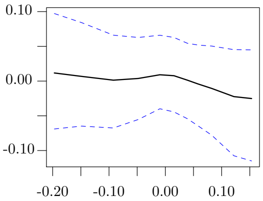
CTE

3.03: Inflation, in %

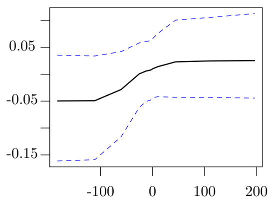


CSC

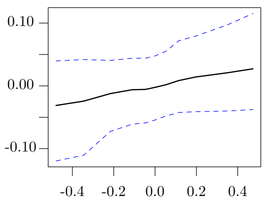
10.02: Foreign market size index, 1-7



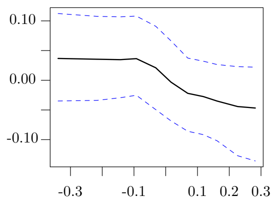
2.06: Available airline seat km/week



7.02: Flexibility of wage determination, 1-7

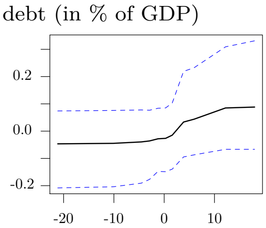


12.04: University-industry collaboration in R&D, 1-7

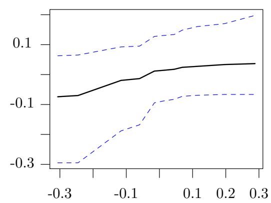


CAE

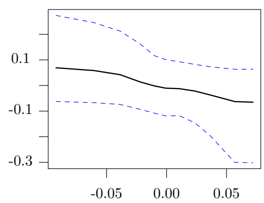
3.04: General government debt (in % of GDP)



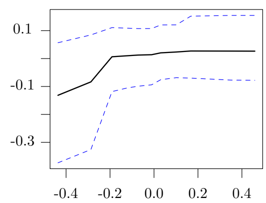
2.07: Quality of electricity supply, 1-7



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.