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Abstract

In this paper, we investigate sources of total factor productivity (TFP) growth in the Baltic States during the period of 1995-2013. In order to see which component, technological change or efficiency change, accounts for greater part of TFP growth, we apply three stochastic frontier panel data models with time-varying efficiency (true fixed effects model, random effects model and random effects decay model) based on macroeconomic data of European Economic Area (EEA) countries.

We find that technological change and efficiency change have been similarly important for TFP growth in Latvia and Lithuania. This reflects that both technological progress and catching-up to the EEA country technology level have been important contributors to TFP growth for Latvia and Lithuania. Estonia, according to our results, has relied almost entirely on the technological change. We argue that this could be explained by Estonia's relatively higher level of institutional quality already in the mid 1990s, limiting further efficiency increase.

Furthermore, we identify factors that may boost efficiency levels. Since technological progress can be considered as given for small counties, policy makers may be more interested in policies that help to improve efficiency. Our results suggest that institutional quality and R&D expenditure are important drivers of the efficiency improvements, while foreign direct investment inflows turn out to have an insignificant effect when controlled for institutional quality. We show that lower independence of the court system and efficient contract enforcement mechanisms, proxied by property rights component of Economic Freedom Index, is one of the key aspects of institutional quality that contributes positively to efficiency and therefore also to TFP.

Keywords: Total factor productivity, stochastic frontier

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1. Introduction

Empirical evidence shows that total factor productivity (TFP) is the main engine of economic growth (Easterly and Levine, 2001). This is especially important for the Baltic States, where the traditional production factors – capital and labour – are stagnating and declining, respectively. However, very little attention has been paid to the sources of TFP dynamics in this region. We contribute to the existing literature by exploring the determinants of TFP growth from 1995 to 2013 via the Stochastic Frontier Analysis (SFA) in the context of the European Economic Area (EEA).

TFP is the part of a country's output not explained by the capital and labour. The importance of TFP in explaining cross-country income differences is shown by a number of papers, such as Hsieh and Klenow (2010), Fare, Grosskopf, and Margaritis (2006), Caselli, Esquivel and Lefort (1996), Islam (1995), and others. We decompose TFP growth into technological change and efficiency change components, as suggested by Fare, Grosskopf, Norris and Zhang (1994). Technological change represents a shift in the production frontier, while EC corresponds to the catch-up effect towards the frontier.

In order to decompose TFP growth, we employ three alternative panel-data SFA models: true fixed effects model (Greene, 2005a), random effects inefficiency model (Battese and Coelli, 1995) and random effects decay model (Battese and Coelli, 1992). All assume that the sample countries have a common production frontier. We use EEA country sample to construct the frontier because the sample of the Baltic States is too small for estimation purposes and would not reflect the production possibility frontier as the Baltic States are not world technology leaders.

The first objective of the study is to compare the role of technological change and efficiency change in explaining TFP growth for the Baltic States in the context of EEA countries. In particular, we are interested in exploring how efficiency has changed in the Baltic States over time. Technological change has historically been assumed as the main driver of TFP growth; however, this assumption has been re-examined (Prescott, 1998). Given that efficiency gains explain a significant share of TFP growth, policy makers may be interested in the direct channels for improving efficiency.

Our second objective relates to examining possible efficiency determinants. Small and open economies like the Baltic States rarely have enough resources to boost world technology levels; policy makers may therefore be more interested in policies that enhance efficiency levels and help catch-up to the world technology level. The literature on TFP's efficiency determinants at a macro-level is sparse, especially on papers employing the SFA methodology. Most authors focus on either OECD sample countries (due to data availability) or differences between developed and developing countries (due to an interest for income convergence). Others (Deliktas and Balcilar, 2005) examine transition economies, such as the Baltic States, separately. However, up to our knowledge, none has analyzed efficiency determinants solely among the EEA countries, putting the old Western European economies and the transition economies on a single frontier. Krasnopjorovs (2012) put all EU countries on a single frontier, but does not look at efficiency determinants. We aim to attempt to fill this gap in the literature.

The research questions are the following:

(1) *Which source, technological change or efficiency change, accounts for a greater part of TFP growth within the Baltic States*?

(2) What, if any, determinants can boost efficiency (institution quality, R&D expenditure, FDI inflows)?

The remainder of the paper is structured as follows: section two integrates the development of hypotheses with the review of literature; section three describes the three SFA models we use along with the data; section four presents the results for both TFP decomposition and EC determinants, which are then discussed in section five; section six concludes.

2. Literature review

2.1. The role of total factor productivity in economic growth

Empirical data have consistently shown that a large fraction of income variance across countries cannot be explained solely by differences in physical and human capital. Under Solow residual approach, developed by Solow (1957), this fraction is attributed to total factor productivity (TFP) cross-country differences. . For example, Klenow and Rodriguez-Clare (1997) attribute 60% of income level differences across countries due to TFP, as opposed to just 40% for human and physical capital. In terms of growth rates, TFP's share in explaining cross-country income variation is even larger (Easterly and Levine (2001) report 90%). Literature has since provided a bulk of hypotheses as to what may cause deviations in TFP. 'Country-specific effects' are by far the most common explanation. Hsieh and Klenow (2010), Fare et al. (2006), Islam (1995), Caselli et al. (1996) and others have further attributed the country-specific effects to technology and efficiency components of TFP.

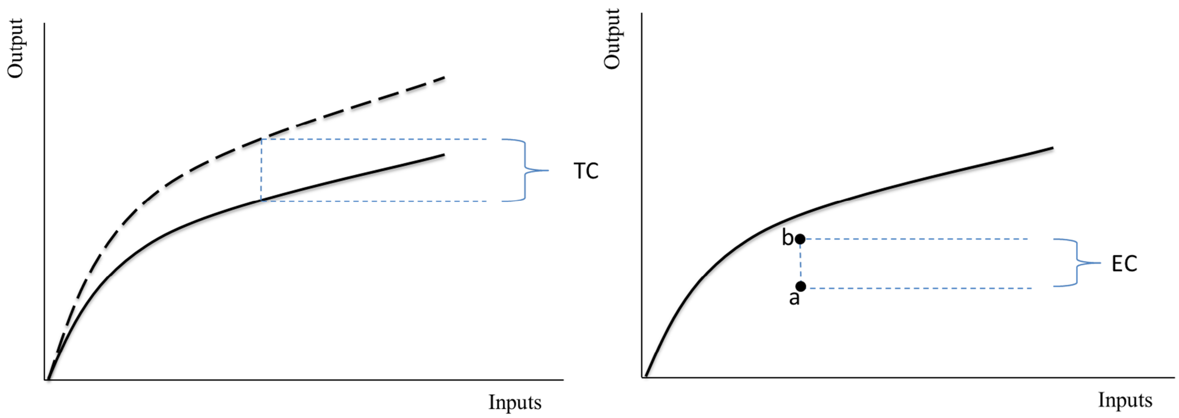
Although the consensus among authors establishes TFP's share in cross-country variation of incomes as significant, not everyone agrees. On the empirical side, the common critique asks to rather re-consider the calibration of physical and human capital; however, many influential authors, such as Prescott (1998), and Hall and Jones (1999) conclude that parameterization would only have a limited explanatory power. Examining the input-output relationship is beyond the scope of this paper; yet we agree that there is room for some alternative forms of the production function. A more theoretical critique points to the free-movement of knowledge across borders, which should make it easy to adopt the best-practice know-how; but this view is largely dismissed on practical grounds due to various barriers for know-how adoption, e.g. differences in legal systems (Barro, 1995) and technology models that may be appropriate for some countries but not for others (Basu and Weil, 1998).

As a result, despite some alternative explanations, we follow the consensus among authors that recognizes the pivotal importance of TFP and go further to compare the role of technology and efficiency components of TFP.

2.2. Decomposing total factor productivity

Decomposing TFP growth into a technological change (TC) component and a efficiency change (EC) component allows explaining economic growth via three factors, instead of just two: (1) capital accumulation represents movement along the curve; (2) technological change shows shifts of the curve; and (3) efficiency change allows for a movement towards the curve (see Figure 1).

Figure 1. Technological change and efficiency change



Note. The graph on the left shows a shift in the production frontier or technological change; a country with the same level of efficiency produces an additional level of output if the country fully absorbs new technology. The graph on the right depicts movement towards the frontier or efficiency change; a country produces an additional level of output given the same technology level.

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Literature shows mixed results as to whether technological change or efficiency change is the driving force of TFP. Traditionally, the focus on technology change has been much larger than on efficiency improvements, partly due to the influence of Solow (1957). However, as basic assumptions of the Solow model were re-examined, the role of efficiency was found to be even larger than that of technological change (Prescott, 1998). Weil (2005) supports the thesis that efficiency change may contribute as much, if not more, than technological change. Meanwhile Osiewalski, Koop and Steel (1997), who looked only at Western economies and Poland, found that technological change is much more significant than efficiency change. We recognize the various views on the sources of TFP growth, and present the **first hypothesis** as follows: <u>efficiency change and technological change are both significant sources of TFP growth among EEA countries during the 1995-2013 period.</u>

Two specific methods have been developed to measure the level of inefficiency: the non-parametric DEA and the parametric SFA. Both methods assume that all countries have a common production possibility frontier. Fare et al. (1994) took an already established DEA method and applied it to TFP measurement. It laid a foundation work that boosted the role of inefficiency to the front of the current TFP literature. The main pitfall of DEA lies in its deterministic nature: it introduces inefficiency, but also assumes that any deviation from the frontier must be explained in terms of it. Fellow researches, such as Cooper, Seiford and Zhu (2004), pointed out that deviations from the maximum output could also be explained by (a) measurement error or (b) random events, such as external shocks, luck, or unexpected disturbances. The stochastic frontier analysis (SFA) has solved the problem by introducing a random shock element. In contrast to DEA, SFA employs parametric estimation by specifying the functional form of the production function. Generally, authors stick to Cobb-Douglas or a more generalized translog production function form. Fried, Lovell and Schmidt (2007) provide an overview of the literature for both methods. They conclude that most authors find only minor differences between SFA and DEA under the Cobb-Douglas specification, with few exceptions (e.g. the financial sector, as discussed by Bauer, Berger, Ferrier and Humphrey, 1998).

2.3. Boosting efficiency: Channels for catching-up towards the frontier

Even though there is a vast literature that examines the determinants of TFP (e.g. trade openness, the financial system, etc., as summarized by Isaksson, 2007), only a few papers focus on analyzing the drivers of efficiency change. We aim to analyze efficiency change determinants specifically, because the determinants of TFP and its efficiency change component are not necessarily the same, as argued by Danquah, Moral-Benito and Ouattara, (2014). For example, trade openness may have opposing effects on technological change and efficiency change (Iyer, Rambaldi, & Tang, 2008). Important policy implications follow: given that efficiency gains explain a significant share of TFP growth, policy makers may be interested in the direct channels for improving efficiency.

The literature on efficiency determinants at a macro-level is sparse, especially on papers employing the SFA methodology. The bulk of works cover FDI and R&D stock as proxies for efficiency change. Iyer et al. (2008) use FDI and relative R&D stock in 22 OECD countries between 1982 and 2000, and employ human capital stock and financial market development as control variables. They make a distinction between various forms of FDI as proxies for trade openness, finding that all forms of FDI inflows, as well as R&D stock, improve efficiency, while FDI outflows diminish it. A recent work by Wijeweera, Villano and Dollery (2010), who looks at FDI flows for 45 countries from 1997 to 2004, points to the need for a skilled labour in enhancing efficiency from FDI. In sum, the consensus within the literature establishes an increase in R&D and FDI as the main drivers of efficiency improvements.

Human capital is often used for larger samples that include developing countries. One can thus show that human capital increases output not only as a factor of production, but also via the efficiency term. Yet for our sample of EEA countries, scores on the popular ‘average years of schooling’ proxy are very similar, and thus are highly unlikely to be empirically significant. Moreover, the proxy does not incorporate the quality of education. For a similar sample, Miller and Upadhyay (2000) find no significant effect for the popular human capital proxies. Iyer et al. (2008) and Kneller and Stevens (2006) show the significance, but either use non-European control countries (Canada) or allow human capital to vary across industries. Although we recognize the role of education, we do not believe the usual quantitative proxies are relevant for our sample.

Ghosh and Mastromarco (2013) extend the work of Iyer et al. by incorporating migration variables. They argue that new labour force can boost economic growth not only as a factor of production, but also through efficiency, given the unique know-how of immigrants. Whether immigrants contribute to the workforce know-how depends on their human capital endowment. Importantly, they find that migration decreases inefficiency only in countries that are richer in human capital. We recognize migration as a possible determinant of efficiency change, but do not focus on it in this paper largely due to a lack of reliable data.

Despite surprisingly little empirical evidence on the institutional quality channel, it has attracted a plethora of theoretical literature. North (1991) lists a variety of ways through which developed institutions can improve the efficiency of resource allocation by reducing uncertainty. This is especially true for property rights: in an environment of low property rights protection by the government, business is forced to spend part of its resources on security instead of investment (Hall & Jones, 1999). A recent European example is analysed by Blanchard and Kremer (1997), who describe how efficiency plummeted after the vital institutional aspects of production were dismantled in the ex-Communist countries. Moreover, different institutional groups affect efficiency through different mechanisms. In addition to property rights mechanism, authors examine the role of legal institutions (Levine, 1998); labour market institutions (Besley & Burgess, 2002); financial market development (Iyer et al., 2008); and others.

However, institutional aspects are notoriously difficult to measure, and perhaps even more difficult to interpret. If there is somewhat of a consensus that better institutional quality can boost efficiency of developing countries, its role for the developed Western world is unclear. For instance, Barro (1996) claims that institutions in the advanced countries are already so well developed that any changes are unlikely to have a significant effect on output. Meanwhile Merkina (2009), Klein and Luu (2003), and others conclude that institutional aspects remain a major source of improvements in efficiency and consequently in cross-country incomes. Brunetti and Weder (1998) show that better institutions can have positive spill-over effects in other areas, such as greater domestic investment.

Most of the proxies used for measuring institutional quality are survey-based. Specific indices, such as the Transparency International Corruption Index, are easier to interpret. Similarly, some authors calculate specific bottom-up indices. Botero, Djankov, Porta, López and Shleifer (2003) calculate their own indices for (a) employment laws, (b) collective relations laws and (c) social security laws. For example, the economic cost of firing a worker is constructed manually by making assumptions on the size of the firm and the average worker, combined with regulated payment requirements in case of a firing. However, such indices capture only one mechanism of the institutional spectrum within a country, such as the legal base. Compiled indices allow expanding the spectrum. For instance, Merkina (2009) uses the Economic Freedom Index (EFI) as a 'good proxy' for institutional quality. De Haan, Lundstrom and Sturm (2006) describe the EFI Index as ‘reliable and useful’. It compiles data for five major areas: government size, property rights, access to financial markets and to international trade, and state regulation of business. An alternative compiled index could be the World Bank’s survey-based corporate governance indices, used by Kaufman, Kraay and Mastruzzi (2006) to proxy institutional quality.

In sum, we find a gap in the literature with regard to the role of institutional quality as a driver of efficiency change, largely due to the difficulty of measuring it empirically. As a result, **our second hypothesis** is related to the <u>possible inefficiency determinants and the</u>

Table 1. Variables and expected effects

Variables	Notation	Expected effect
Production factor inputs		
Log of capital (capital stock in Euro	k	Positive
Log of labour	l	Positive
Time	time	Positive
Potential inefficiency determinants		
R&D expenses to GDP	RD	Negative
Net FDI to GDP	FDI	Negative
Institution quality	EFI	Negative

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direction of their expected effects, which include institutional quality (with different measures of institutional quality for robustness check purposes), as well as the traditional efficiency determinants R&D and FDI (summarized in Table 1).

In general, authors have tried to find new variables that explain efficiency chnage by balancing the issues of biasness and multicollinearity. On the one hand, Hejazi and Safarian (1999) pointed out that excluding some channels of outward orientation would overestimate the role of others, such as FDI or R&D. This has been the main motivation for Ghosh and Mastromarco (2013) to examine the effect of migration. On the other hand, including too many variables will eventually lead to multicollinearity issues. We look for a compromise, aiming to benefit from compiled indices that combine several effects, such as measures by EFI and the World Bank. We also prioritize some variables (FDI, R&D and the institutional quality) over others (migration), recognizing that too many variables will lower the reliability of our model.

2.4. Technological change, efficiency change and the Baltic States

A very small number of works decompose TFP into technological change and efficiency change for the Baltic States at a macro level. Deliktas and Balcilar (2005) is the closest to ours; they estimate TFP and its efficiency component within a sample of 25 transition economies, including the Baltics, from 1991 to 2000. Arazmuradov, Martini and Scotti (2011) employ a similar technique but for the sample of ex-Soviet countries, from 1995-2008. Arazmuradov et al. (2011) find that TFP change is positive and very similar for all Baltic States from 2000 onwards. Deliktas and Balcilar (2005) show decreasing TFPs but for the 1990s sample period.

In terms of technological change, all Baltic States show improvement, particularly so Estonia, according to Arazmuradov et al. (2011). Deliktas and Balcilar show a decline for Latvia during the 1990-2000 period. In terms of efficiency change (the average annual efficiency growth rate over the sample period), Deliktas and Balcilar (2005) show positive changes for all Baltic States, with Latvia and Lithuania performing the best. In contrast, Arazmuradov et al. (2011) find that efficiency for the Baltic States has on average decreased during the 1995-2008 period; yet the decrease is driven by the results of the late 1990s.

The literature on efficiency determinants for Baltic States is also surprisingly sparse. Arazmuradov et al. (2011) finds that machinery imports and human capital improve efficiency, while a set of other variables influence TFP growth in general. However, these results may be driven by non-Baltic countries of the ex-Soviet country sample. Liik, Masso and Ukrainski (2014) examine solely R&D in terms of its contribution to efficiency change for OECD countries, finding it has a positive role on efficiency change. They also show that R&D expenditure enhances productivity more in high-tech industries than others. These conclusions can be extended to the Baltics, according to Liik et al. (2014).

Several authors use industry-level data for the Baltic States. Tonini (2012) uses fixed-effect SFA to compare TFP growth between European Union and Candidate Countries in the agriculture sector, for the 1993-2006 period. He follows a slightly different specification, employing a two-stage method instead of simultaneously calculating frontier and efficiency determinants. In addition, he uses the translog functional form instead of Cobb-Douglas. Tonini finds that Lithuania performs considerably better than Latvia and Estonia in terms of efficiency. Yet in terms of overall TFP growth, Estonia excels by a margin. In contrast to Tonini, Košak & Zoric (2011) employ a random-effects model. They address the heterogeneity problem in banking efficiency research for Central and Eastern Europe, including the Baltics, for the 1998-2007 period. They argue that this choice contributed to relatively small differences in inefficiencies, revealing a homogenous group in terms of bank performance.

3. Methodology

Stochastic frontier analysis, firstly introduced by Aigner, Lovell, and Schmidt (1977), is a widely applied tool in efficiency studies due to its econometric nature unlike non-parametric alternative approaches. Our main model is the true fixed effects (TFE) panel data stochastic frontier model using the maximum likelihood dummy variable method, developed by Greene (2005a). In addition to the TFE model for robustness check purposes, we employ two alternative classical time-varying stochastic frontier models from Battese and Coelli (1995; 1992).

All these models have an important advantage over other stochastic frontier model specifications: they assume time varying inefficiency unlike some time-invariant models, such as the models by Pitt and Lee (1981) and Battese and Coelli (1988). This assumption helps to measure efficiency change over time. Another advantage specific to the TFE model is that it uses different intercepts for each country in the efficient frontier estimation, which accounts for time invariant country heterogeneity and thus excludes such bias from our inefficiency scores.

In the next sub-section, we introduce the functional form of the efficient frontier, describe the models and show a TFP decomposition method.

3.1. Functional form of the frontier and the model

Efficient frontier shows the maximum output level, Y, that could be achieved by country i at time t, given amount of capital stock, K, labour, L, and technology, A (eq. 1).

$$Y_{it} = f(A_{it}, K_{it}, L_{it}) \tag{1}$$

We employ the Cobb-Douglas production function specification for the efficient frontier (2), which is the most widely applied functional form of the production function in the literature. Some papers use a more general translog production function allowing input elasticities to differ across countries (e.g. Iyer et al., 2008). However, the translog form requires a large sample as it calculates more parameters than the Cobb-Douglas form. As our sample is relatively small (N<1000)[1], we stick to Cobb-Douglas (eq. 2) to avoid over-parameterization.

$$Y_{it} = A_{it}{K_{it}}^{\beta_1}{L_{it}}^{\beta_2}, \tag{2}$$

[1] N= number of countries × number of years

where β_1 and β_2 are output elasticities to capital stock and labour, respectively. Empirically the Cobb-Douglas function can be estimated in a log-linear from:

$$y_{it} = \beta_{it} + \beta_1 k_{it} + \beta_2 l_{it}\ , \tag{3}$$

where β_{it}=log(A_{it}) and lower case letters y_{it}, k_{it}, l_{it} are natural logarithms of Y_{it}, K_{it}, and L_{it} respectively. We ensure time-varying technology, $\beta_{it,}$ by inclusion of yearly time dummies, dyear, in addition to country specific intercepts β_i (eq. 4). In other words, β_{it} is estimated as sum of country specific intercept, β_i, and parameter of yearly time dummy variable, β_t.

$$y_{it} = \beta_i + \beta_1 k_{it} + \beta_2 l_{it} + \sum_{t=1996}^{2013} \beta_t \mathrm{dyear}_t \tag{4}$$

The efficient frontier, also referred to as the world production frontier, shows the output level that a country has the potential to achieve at given input levels. In reality, countries do not achieve their potential output levels and deviate from the production frontier. This effect is captured in the error component, ε_{it}:

$$y_{it} = \beta_i + \beta_1 k_{it} + \beta_2 l_{it} + \sum_{t=1996}^{2013} \beta_t \mathrm{dyear}_t + \varepsilon_{it} \tag{5}$$

The error component is divided into an inefficiency term, u_{it}, and a stochastic error term, v_{it}, by using Jondrow, Lovell, Materov and Schmidt's (1982) inefficiency estimation method. In general, the model looks as follows:

$$y_{it} = \beta_i + \beta_1 k_{it} + \beta_2 l_{it} + \sum_{t=1996}^{2013} \beta_t \mathrm{dyear}_t + v_{it} - u_{it} \tag{6}$$

Note that the total estimated deviation from the production frontier is$\varepsilon_{it} = v_{it} - u_{it}$. Inefficiency, $u_{it,}$ is a strictly positive number between 0 and 1, and it is identically, independently, half-normally distributed. If u_{it}=0, a country i at time t is fully efficient; in other words, it produces the maximum output level given its input level (Ghosh and Mastromarco, 2013). The second component of the total error term v_{it} captures unobserved random errors. The stochastic error term is assumed to be identically, independently and symmetrically distributed with a standard normal distribution.

A set of dummy variables for each year, as opposed to a single time trend dummy, reflects time-varying technological change and allows controlling for economic cycles that inefficiency estimates might pick up. In other words, any cyclical economic effects are captured in the time dummies instead of in the inefficiency estimates. While a single time trend variable estimates average yearly frontier shifts, the dummy approach yields estimates for annual shifts in comparison to a base year (in our case, 1995).

Note that we use country specific intercepts β_i as suggested by Greene (2005a) and Kumbhakar and Wang (2005). A single intercept may lead to a misspecification bias arising from unobserved country specific factors impact on output levels, but are not related to the production process itself. Greene (2005b) argues for the use of country specific intercepts, in addition to efficiency estimates, to account for the full heterogeneity of countries in the conventional fixed effects models. Thus, we employ Greene's true fixed effects model (2005a) that completely separates time invariant country heterogeneity from inefficiency estimates.

Belotti and Ilardi (2012) highlighted that maximum likelihood dependent variable method used in a true fixed effects model is appropriate only when the time period is long enough (T>15). Otherwise country specific intercepts are estimated inconsistently (incidental parameters problem). In our data set, time period is large enough (data of 19 years). Thus, the incidental parameter problem should not arise.

In the TFE model, time-invariant country heterogeneity is taken out from efficiency scores. For robustness check purposes, we estimated two additional alternative classical time-varying efficiency stochastic frontier models that capture country specific effects in the efficiency scores: the random effects model by Battese and Coelli (1995) and the time decay model by Battese and Coelli (1992). We denote these models by BC95 and BC92, respectively. Both are normal-truncated normal distribution models (meaning that stochastic error follows normal distribution, whereas inefficiency follows truncated-normal distribution) estimated via the maximum likelihood method. Compared to the TFE model, BC92 assumes a single intercept term for all countries in the frontier estimation. Note that we focus on efficiency dynamics, not the magnitudes, thus the possibility of different inefficiency scores is not a major issue. In addition to the single intercept assumption, Battese and Coelli (1992) also specifies inefficiency term as a function of time:

$$u_{it} = \exp(-\mu(t - T)u_i), \tag{7}$$

where T is the number of years in the sample period; μ is the parameter for a time trend, and u_i reflects country specific effects and has non-negative truncated normal distribution.

Compared to the BC92, the model proposed by Battese and Coelli (1995) specifies inefficiency as a function of other exogenous variables, instead of time. In our case, we follow the approach first proposed by Stevenson (1980) and allow inefficiency scores to simply vary around a constant mean.

The results of the TFE, BC95 and BC92 regression models can be used to estimate TFP growth, technological change and efficiency change, as shown in equation 8 (Khumbhakar & Wang, 2005; Kumar & Russell, 2002). Technological change (TC) represents a shift of the efficient frontier, while efficiency change (EC) shows a catch-up towards the frontier:

$$\Delta TFP = TC + EC, \tag{8}$$

where $TC = \beta_t$ from equation 6, $EC = -\frac{\partial u_{it}}{\partial time}$ may be calculated from our stochastic frontier models. The impact of technological change is the difference between the coefficients of the two time dummies from equation (6), or the dummy coefficient if 1995 is considered as the base year.

3.2. Adding exogenous efficiency factors

So far we have described how to decompose TFP growth into technological change and efficiency change. We go further by estimating potential factors driving efficiency change. Wang and Schmidt (2002) pointed out that one step and two step methods are used to estimate the effects of exogenous variables on efficiency. A one step method simultaneously estimates frontier parameters, efficiency terms and its exogenous determinants (for instance, by maximum likelihood). A two-step method estimates efficiency scores first, and only then regresses efficiency scores on exogenous variables. Wang and Schmidt (2002) show that the two-step procedure may lead to severely biased estimations. Therefore, we employ a one-step procedure and include efficiency determinants in Greene's true fixed effects model:

$$\begin{aligned} y_{it} &= \beta_i + \beta_1 k_{it} + \beta_2 l_{it} + \textstyle\sum_{t=1996}^{2013} \beta_t \mathrm{dyear}_t + v_{it} - u_{it} \\ u_{it} &= \delta_0 + \delta_1 R\&D_{it} + \delta_2 FDI_{it} + \delta_3 EFI_{it} + e_{it} \end{aligned} \tag{9}$$

We use (1) foreign direct investment inflows to GDP (FDI), (2) research and development expenditure to GDP (R&D) and (3) institutional quality proxies (EFI and WBI) as efficiency determinants. Efficiency determinants are estimated by parameterizing the variance of inefficiency scores ($\sigma_{uit} = \sigma_{ui} \cdot \exp(\delta^{`} Z_{it})$, where Z is a vector of inefficiency determinants, and δ is a vector of unknown parameters).

3.3. Data

We employ annual panel data of 30 EEA countries for the period of 1995-2013. The choice of the period was based on data availability for the Baltic States. Data sources are summarized in the Table 2, with descriptive statistics displayed in Appendix 1.

Table 2. Data sources

Variable	Description	Data source
Y	GDP in Euro PPP terms	Eurostat data for GDP in current prices and PPP index.
K	Capital stock in Euro PPP terms	European Commission AMECO database for capital to GDP ratios. Our calculations using GDP and PPP data from Eurostat.
L	Labour hours (hours worked)	Eurostat data for total labour hours worked.
R&D	R&D expenditure to GDP	United Nations Educational, Scientific, and Cultural Organization (UNESCO) Institute for Statistics database
FDI	Net foreign direct investment inflow to GDP	World Bank database
EFI	Economic freedom index (0-100)	The Wall Street Journal and The Heritage Foundation data.
WBI	World Bank Index (0-100)	Average score of 6 sub-indices from the Worldwide Governance Indicators data scaled to 0-100 range

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The dependent variable is GDP in current prices, modified in Euro PPP terms (purchasing power parity) in order to account for international price level differences and expressed in log terms. We use the total labour hours worked per year as our labour input rather than the total number of people employed, believing it is a closer approximation for the true labour input. Data on physical capital were calculated from capital-to-output ratios given in the European Commission AMECO database. Capital measures were expressed in monetary terms and thus were also adjusted to PPP.

The index of economic freedom (EFI) combines four pillars of institutions (rule of law, regulatory efficiency, market openness, limited government) into one index graded on a scale of 0-100. The index consists of ten equally weighted quantified factors: property rights, freedom from corruption, fiscal freedom, government spending, business freedom, labour freedom, monetary freedom, trade freedom, investment freedom, and financial freedom. We similarly constructed an alternative institutional quality index (WBI) from equally weighted six sub-indices from survey-based World Bank governance indicators (Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law, Control of Corruption).

4. Analysis of results

4.1. Results of regression models without exogenous efficiency determinants

In this section, we demonstrate the results of three frontier estimation models: TFE, BC92 and BC95.[2] The results are reported in Appendix 2. All the frontier input coefficients were positive and statistically different from 0 at the 1% level. The coefficients for capital ranged from 0.53 – 0.75, but the coefficients for labour from 0.17-0.38. These coefficients can be interpreted as input elasticities with respect to output. Time dummy coefficients were statistically different from zero, except two cases in the BC95 model and one case in the BC92 model. A total of 21 out of 30 country-specific intercepts (not reported here) in the true fixed effects model were statistically different from zero at least at the 10% level. The parameter μ in the BC92 model (in equation 7) was 0.02 significant at the 1% level, which rejects hypothesis of time invariant inefficiency and confirms declining inefficiency over time for the whole sample ($\mu>0$). Coefficients in all regressions are jointly significant at the 1% level.

We tested if the inefficiencies are not simply random errors. We calculated variance parameter γ for all the models: $\gamma = \sigma_u^2/(\sigma_u^2+\sigma_v^2)$. The closer the γ is to one, the greater part of country deviations from the frontier are attributed to the inefficiency. If the γ is zero, then all deviations from the frontier are due to noise (Ghosh and Mastromarco, 2013). Appendix 2 shows that γ value in our models varied from 0.911 to around 1. The hypothesis that $\gamma = 0$ was rejected in all three cases, indicating that inefficiency exists in the sample. Therefore, it is not reasonable to simply assume a conventional (fully efficient) production function for the whole Europe without accounting for inefficiency. Deliktas and Bacilar (2005) empirically show the same result.

Table 3. Summary statistics of inefficiency estimates of all countries

Inefficiency	TFE	BC95	BC92
Mean	0.065	0.197	0.314
SD	0.058	0.122	0.199
Min	0.000	0.021	0.012
Max	0.333	0.567	0.866

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2 We implemented all models in the statistical software package Stata, Stochastic Frontier Analysis package by Belotti et al. (2013).

Summary statistics of the inefficiency estimates of the three models are provided in the Table 3, but the inefficiency scores over time are plotted in Appendix 3. The average inefficiency differed across models; the mean scores were from 0.06 to 0.31. The inefficiency scores of the true fixed effects model were the lowest. This was expected as the true fixed effects model takes out time-invariant country specific effects out of inefficiency scores. Other two models consider country specific effects as a part of inefficiency, yielding higher inefficieny. The Battese and Coelli (1992) model showed particularly high inefficiency scores in the beginning of the sample period (see Appendix 3), possibly because the time trend the model imposes in the inefficiency equation is a very restrictive assumption for our long time period analysis.

4.2. Total factor productivity growth decomposition

Figure 2 shows annual TFP growth for all three Baltic States. All Baltic countries showed rapid annual TFP growth in the period of 1996-2007. The TFP declined by 10% to 15% in 2008 and 2009 due to substantial negative efficiency change and technological change that may arise from time dummies that capture economic cycle. Table 4 shows the summary of TFP growth decomposition for the Baltic States for the period 1995 – 2013.

Figure 2. Annual TFP growth in the Baltic States based on data from TFE model

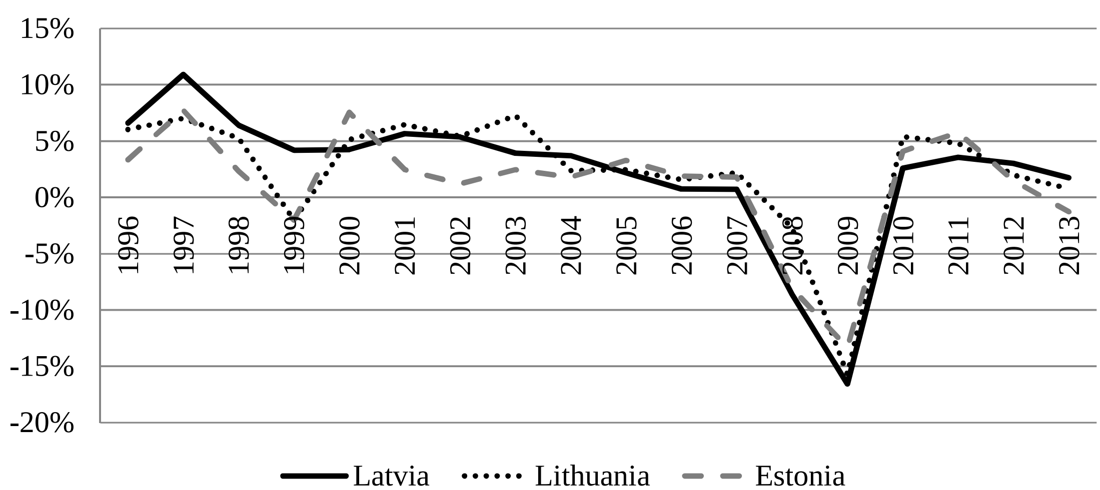

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Table 4. TFP growth decomposition for the Baltic States in the period 1995-2013

	Country	TFE	BC95	BC92
Efficiency change	Latvia	19%	16%	19%
	Estonia	1%	-4%	27%
	Lithuania	22%	18%	17%
	EEA Average	-0.13%	12%	0.47%
Technological change		21%	13%	19%
TFP growth	Latvia	40%	29%	38%
	Estonia	23%	9%	46%
	Lithuania	44%	31%	36%
	EEA Average	21%	25%	20%

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All models predict positive technological change between 13% - 21%, which indicates technology progress in Europe. All three models clearly show that Latvia and Lithuania have managed to increase efficiency during the 19 year period, supporting our expectations of declining inefficiency over time. The efficiency change for Latvia is estimated to be between 16% and 19%, while the results for Lithuania are between 17% and 22%. Estonia shows mixed results. The TFE and BC95 models shows that the efficiency rise is around zero, while the BC92 model shows a very different result of 27% increase in the efficiency, but one must note that this increase is enforced by the overall time trend assumption in this particular model. The TFE and BC95 models' estimates show that the inefficiency has returned to its 1995 level in Estonia only after 2008. It used to be lower from 2003 to 2007.

Efficiency changes in all the EEA countries for the 1995-2013 period based on the TFE and BC95 models are depicted in Figure 3 and Figure 4, respectively. Latvia and Lithuania are among leaders in terms of efficiency change. These countries had relatively low efficiency levels in 1995. Higher efficiency change among Eastern European countries that are also considered as transition economies may reflect their convergence towards more developed country efficiency levels, for example, via improvements in institutional quality.

Figure 3. Efficiency change in the EEA countries 1995-2013 from TFE model

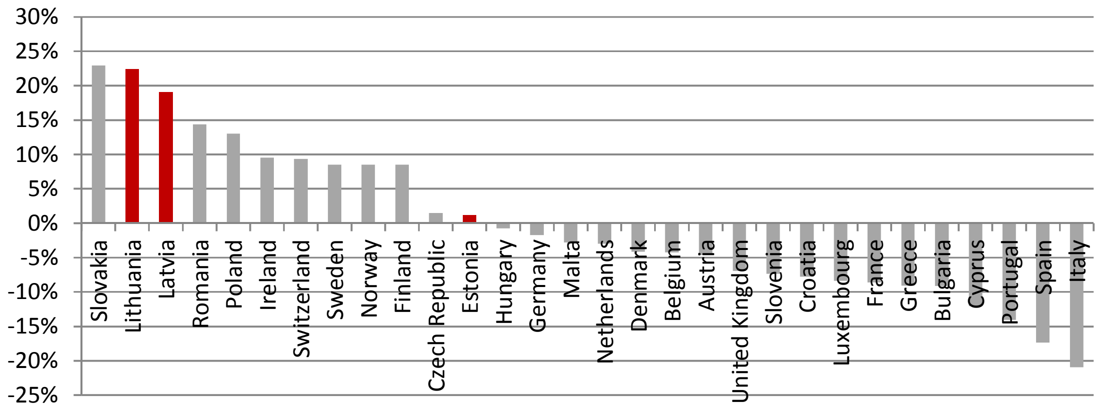

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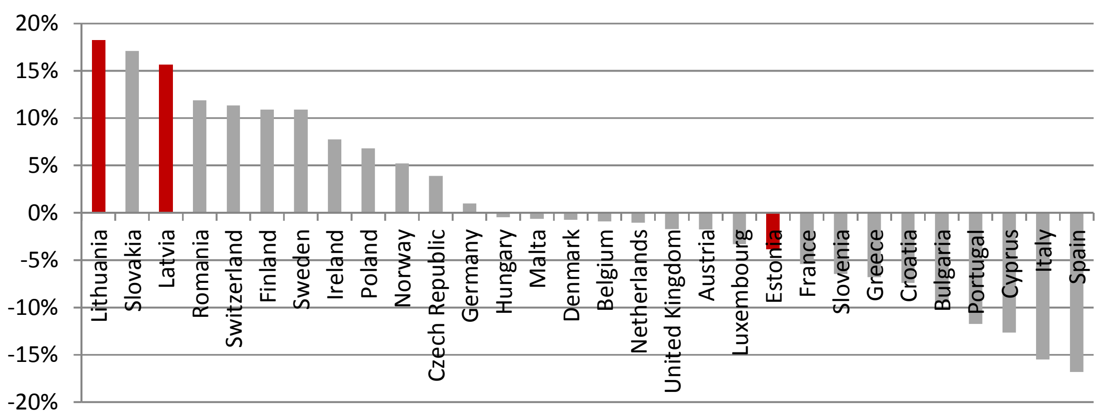
Figure 4. Efficiency change in the EEA countries 1995-2013 from BC95 model



Created by the authors.

To sum up, our estimations show that efficiency change has been as important source of growth as technological change for Latvia and Lithuania (in line with our first hypothesis), while Estonia has relied more on the technological change (rejects our first hypothesis). All three Baltic States still show some level of inefficiency, thus it is important to investigate the determinants that contribute to improvements in country efficiency. We analyse some of such determinants in the next sub-section.

4.3. Results of regression models with exogenous efficiency determinants

In this sub-section, we provide the results of the true fixed effects model with exogenous variables introduced in the inefficiency equation. Institutional aspects are regarded as notoriously difficult to measure, and authors disagree on the use of proxies, with Merkina

(2009) favouring EFI while Kaufman et al. (2006) using WBI. That is why we used both EFI and WBI indices for robustness check purposes. Results showed that both EFI and WBI are significant efficiency determinants at the 1% level (Appendix 4.1). Table 5 shows inefficiency equation part of regressions with EFI and WBI indices. We stick to EFI, generally the more popular proxy among authors, for reasons of comparability.

Table 5. Inefficiency equation with alternative institutional quality proxies

Inefficiency equation				
EFI	-0.076***	(0.008)		
WBI			-0.167***	(0.029)
constant	0.068	(0.526)	5.430***	(1.739)

Significance: ***: 1% level; **: 5% level; *: 10% level. Standard errors in parenthesis.
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Second, we tested three efficiency determinants combined – R&D, FDI and institutional quality – via three regressions by adding one additional inefficiency determinant, which allows for sensitivity analysis as well as to check for the omitted variable bias. The results of inefficiency equation are summarized in the Table 6 (full results in Appendix 4.2) Coefficient on R&D had a negative effect on inefficiency and was statistically different from zero at the 1% significance level in all three cases. FDI also had a negative effect on inefficiency at the 1% significance level. However, when controlled for EFI, FDI turned out as statistically insignificant.

Table 6. Inefficiency equation with institutional and non-institutional variables

Inefficiency equation						
R&D	-0.712***	(0.093)	-0.502***	(0.083)	-0.644***	(0.169)
FDI			-0.052***	(0.009)	-0.020	(0.014)
EFI					-0.108***	(0.016)
constant	-3.96***	(0.147)	-3.943***	(0.145)	2.613***	(0.988)

Note. Significance: ***: 1% level; **: 5% level; *: 10% level. Standard errors in parenthesis.
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Coefficients on capital and labour were consistent in terms of significance levels of 1% and the magnitude, around 0.56 for capital and 0.30 for labour. The regression with two factors in the inefficiency equation (R&D and FDI) showed twice as low coefficient for labour (0.15).The time dummies were statistically different from zero in almost all cases at the 1% significance level with three exceptions. As with the previous models, these three models also showed γ close to one, thus, rejecting hypothesis that inefficiencies are just random errors. Coefficients in all models are jointly significant at the 1% level.

Finally, we looked for the driving forces behind the significance of the institutional quality proxy by decomposing EFI into its components. Results are presented in Appendix 4.3 and in the Table 7 (excerpt from the regression results). We chose a sample of three indicators, each corresponding to one of the broader dimensions of institutional quality, namely property rights (within the rule of law dimension), labour freedom (regulatory efficiency), and investment freedom (open markets). Results showed that only EFI's property rights component had a statistically significant impact on efficiency change, yielding a negative effect. Coefficients on capital and labour, as well as time dummies were in line with previous results.

Table 7. Inefficiency equation with several EFI sub-indices

Inefficiency equation						
Property rights	-0.032***	(0.093)	-0.033***	(0.003)	-0.034***	(0.004)
Labour freedom			0.007	(0.005)	0.008	(0.005)
Investment freedom					0.004	(0.006)
constant	-2.749***	(0.147)	-3.170***	(0.370)	-3.387***	(0.524)

Note. Significance: ***: 1% level; **: 5% level; *: 10% level. Standard errors in parenthesis.

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5. Discussion of results

Frontier equation results confirm that capital and labour contribute positively to GDP level. Furthermore, our efficient frontier models show positive technological change with respect to 1995, reflecting an upward shift of the frontier over time. For example, the time dummy for the year 2013 estimated by the true fixed effects model is equal to 0.213. The interpretation is that GDP in all countries is by 21.3% higher with the same factors of production and the same efficiency levels compared to the 1995.

5.1. TFP growth, technological change and efficiency change in the Baltic States

Our first research objective was to estimate TFP growth in the Baltic States and divide it in the technological change and efficiency change components. We estimated that TFP has grown on average around 30% in the Baltic States during 1995-2013. It means that the Baltic States have managed to significantly improve their productivity levels within the period despite the substantial TFP decline in 2008.

Regarding the TFP growth decomposition, we observe positive technological change over the period of 1995-2013. Advanced countries with large research and development investments typically are considered as drivers of the technology level improvements. The Baltic States, for sure, benefit from the technological change. However, from policy maker perspective, a more important aspect for the Baltic States is the efficiency change component in the TFP growth because it reflects the technology catching-up effect.

Regarding the results of efficiency scores, the results of the TFE and the BC95 models seem to be more appropriate compared to the results from the BC92 model, as the time trend assumption in the BC92 model is too restrictive (see Appendix 3). The TFE model predicted that the average inefficiency is 0.065, which means that on average the sample countries produce 6.5% less output than they could. In other words, EEA countries on average could produce around 7%[3] more output without increasing capital or labour. The BC95 estimates 24.5%, but the BC92 model 45.2% more output potential. The true fixed effect model shows the lowest inefficiency scores because they exclude time invariant country heterogeneity from the inefficiency calculation.

All three models clearly showed that Latvia and Lithuania have also managed to increase efficiency during the 19 year period. The increase in the efficiency levels might

[3] Potential increase in output =inefficiency/(1-inefficiency)

reflect either more efficient use of existing technology (Rao & Coelli., 1998) or increased ability to adapt western European technology. Estonia showed very mixed results. The more reliable TFE and BC95 models showed that the efficiency change has been close to zero. This partly reflects that Estonia had high level of institutional quality already in 1995 which is an important determinant of efficiency level.

Deliktas and Balcilar (2005) showed improvements in the efficiency levels in the Baltic States that are offset by a decline in the technology levels, leading to an overall TFP decline in the 90s. Although we cover a completely different time period, we show a TFP increase even in the overlapping period of 1995-2000. Arazmuradov et al. (2011) show similar empirical findings as we do. As estimated by our BC95 and BC92 models, Arazmuradov et al. (2011) also finds larger inefficiency levels for Estonia compared to Lithuania and Latvia in the period 1995-2008. They find that the TFP growth in Estonia relies more on technological changes than on efficiency change, whereas Latvia and Lithuania relies on both efficiency change and technological change. They also showed an efficiency decline in 2008.

5.2. Analysis of factors that contribute to country efficiency increase

R&D and FDI. We find that a higher spending on R&D is associated with lower inefficiency, which is in line with previous research. We contribute to the literature by showing that innovation investments are important in explaining efficiency differences within Europe. Our results confirm the role of R&D from a different perspective than used by Iyer et al. (2008), who treats R&D as an inventory stock rather than an annual expense.

The initial results on FDI confirm the consensus established in the literature: higher foreign investment inflows may help to reduce domestic inefficiencies. However, when controlled for institutional quality variable, the impact of FDI inflows is no longer significant. We thus cannot confirm the results of Iyer et al. (2008), who examined FDI for a similar sample of advanced Western countries, and found a significantly positive relationship.

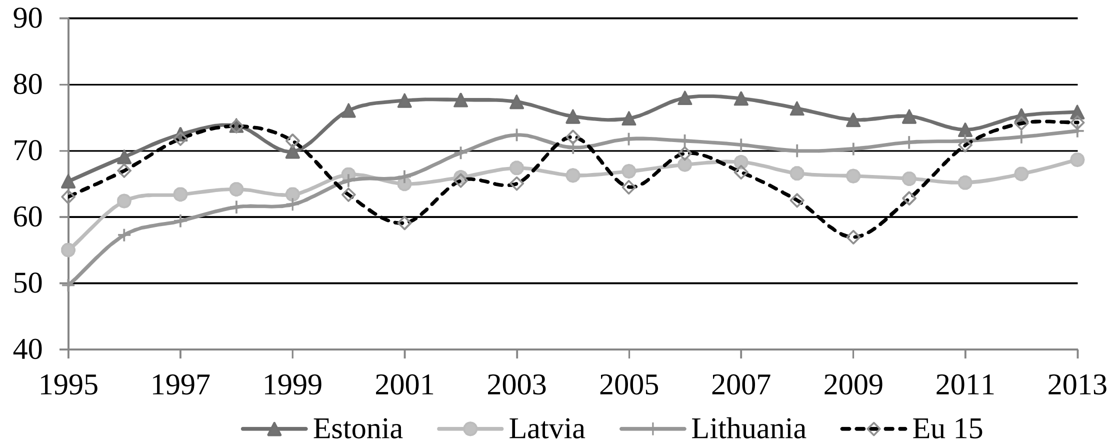
Institutional quality. Perhaps our greatest contribution is showing that institutional quality remains a very important factor behind efficiency levels even within Europe. Results are robust to different proxies of institutional quality (EFI and WBI). We therefore reject the hypothesis of Barro (1996), who claimed that institutions within Europe are so well developed that they should not have a large economic significance in the future. The main drivers of the finding are likely to be the Eastern European countries (for instance, Romania has improved its institutional quality the most within our sample).

Results are in line with the work of Merkina (2009) and Klein and Luu (2003), who also find a significant relationship between EFI and TFP's efficiency component. In addition, we extend their work by decomposing EFI into its categories. We show that property rights is the main mechanism through which institutional quality impacts inefficiency. Within the context of EFI, property rights measures the corruption levels within the court system, the independence of courts, as well as the ability of individuals and businesses to use courts as a way of enforcing contracts.

The importance of the court system entails different policy implications for Latvia and Lithuania, and Estonia. Latvia and Lithuania perform considerably worse in terms of property rights as compared to Estonia (Appendix 1), and to other countries within our sample. Moreover, scores on property rights for Latvia and Lithuania are generally lower than on other institutional categories. Results therefore indicate that the judiciary system, plagued by corruption, may have been one of the key drivers of inefficiency in the region, but more so for Latvia and Lithuania. Policy makers should take into account the room for improvement in court system that would enhance efficiency, as businesses would spend a lesser part of their resources on security, focusing instead on innovation and investment (Hall & Jones, 1999). Estonia has proven that institutional catch-up is possible: the country historically underperformed in the labour regulation category (in 2010, its score was around 12 percentage points lower than for Latvia and Lithuania), but it has reduced the gap to just 3 percentage points (likely as a result of the 2009 labour market reforms).

Admittedly, the historic importance of institutions in lowering inefficiency in the Baltic States says little about the policy implications for the future. Part of the problem is that most of the catch-up is likely to have already happened. The current institutional basis was largely developed during the first two decades after the collapse of the Soviet Union, especially during the process of joining various international groups or organizations (especially in the context of EU membership in 2004). Figure 5 shows the dynamics of EFI for the Baltic States, indicating a remarkable catch-up of close to 15 basis points in just one decade (1995-2005).

Figure 5. Economic freedom index change for the Baltic States and for an average of EU-15 in the period of 1995-2013.



Graph created by the authors using data from Heritage Foundation (2014).

Institutional developments during the last decade indicate that all Baltic States could be entering a stage of much lower improvements in institutional quality. As a result, we are cautious on stating that institutions will play as big a role in the upcoming decade in reducing inefficiencies, except for the court system, whose reform poses a significant potential for improving output, especially in Latvia and Lithuania.

6. Conclusions

This study decomposes total factor productivity (TFP) growth in the Baltic States during the period of 1995-2013. In our analysis, we apply three stochastic frontier panel data models with time-varying efficiency (true fixed effects model, random effects model and random effects decay model) based on macroeconomic data of EEA countries.In total, we answered two research questions:

Which source, technological change or efficiency change, accounts for a greater part of TFP growth within the Baltic States?

We find that TFP has grown on average around 30% in the Baltic States during 1995-2013. Our first hypothesis expected the role of technology and efficiency changes both to be significant sources of TFP growth. We accept our first hypothesis for Latvia and Lithuania, while the hypothesis does not hold for Estonia, where technological progress is the main driver of TFP growth.

In comparison to 1995, inefficiency in Latvia and Lithuania has declined by 16 to 20 percent, depending on the choice of the model. For Estonia, we do not find evidence for significant efficiency improvements. Higher efficiency change among Eastern European countries aka the transition economies reflects their convergence towards the efficient frontier or the efficiency levels of the developed European countries. A limitation to the frontier approach is that we cannot predict how many years it will take for the Baltic States to converge to the average level of productivity of EEA countries as it looks only at the productivity growth and not at absolute values.

What, if any, determinants explain efficiency differences in the EEA as a whole?

Our second hypothesis expected R&D, FDI and institutional quality as significant drivers of efficiency change. We confirm that R&D expenditures help to explain inefficiency differences among European countries, with more expenditure improving efficiency. Our results complement the work of Iyer et al. (2008), who treat R&D as an inventory stock rather than as an annual expense. In contrast to previous works, the impact of FDI inflows on TFP's efficiency component is shown to be insignificant when we account for institutional quality. We thus reject our second hypothesis with respect to FDI inflows having a negative effect on inefficiency.

Perhaps our greatest contribution is showing that institutional quality remains a very important factor for inefficiency differences even within Europe. Results are robust to alternative proxies for institutional quality (EFI and WBI), in support of our second hypothesis. Lower independence of the court system and a lack of efficient contract enforcement mechanisms, as proxied by EFI's property rights component, emerges as on of the key reasons for inefficiency differences among EEA countries. Even if most of the catch-up in the quality of institutions has already happened, policymakers must not turn a blind eye to the potential gains of reforming the court system.

We therefore find that TFP in the Baltic States and in Latvia in particular can be improved through the efficiency channel via higher R&D spending and reforming the court system.

As for further research, analysis could be more focused on a particular industry, taking into account that a country could transfer its resources from less productive (e.g. agriculture) to industries that are more productive (e.g. manufacturing, services). Admittedly, data availability would remain a challenge.

References

Aigner, D., Lovell, C., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. Journal Of Econometrics, 6(1), 21-37.

Arazmuradov, A., Martini, G., & Scotti, D. (2011). Determinants of total factor productivity in former Soviet Union economies: A stochastic frontier approach. *Economic Systems*, *38*(1), 115-135.

Balcilar, M., & Deliktas, E. (2005). A Comparative Analysis of Productivity Growth, Catch-Up, and Convergence in Transition Economies. *Catch-Up, and Convergence in Transition Economies (January 1, 2005).*

Barro, R. J. (1996). *Determinants of economic growth: a cross-country empirical study* (No. w5698). National Bureau of Economic Research.

Barro, R. J., Mankiw, N. G., & Sala-i-Martin, X. (1995). *Capital mobility in neoclassical models of growth* (No. w4206). National Bureau of Economic Research.

Basu, S. & Weil, D. N. (1998). Appropriate Technology and Growth. *The Quarterly Journal of Economics, 113(4), 1025-1054.*

Battese, G. E., & Coelli, T. J. (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of econometrics*, *38*(3), 387-399.

Battese, G. E., & Coelli, T. J. (1992). *Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India*. Journal of Productivity Analysis 3(1/2), 153-9.

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical economics*, *20*(2), 325-332.

Bauer, P. W., Berger, A. N., Ferrier, G. D., & Humphrey, D. B. (1998). Consistency conditions for regulatory analysis of financial institutions: a comparison of frontier efficiency methods. *Journal of Economics and Business*, *50*(2), 85-114.

Belotti, F., & Ilardi, G. (2012). Consistent Estimation of the 'True' Fixed-Effects Stochastic Frontier Model. *CEIS Research Papers*, 10(5).

Belotti, F., Daidone, S., Ilardi, G., & Atella, V. (2013). Stochastic frontier analysis using Stata. *The Stata Journal*, 13(5), 719-758.

Besley, T. J., & Burgess, R. (2002). Can labour regulation hinder economic performance? Evidence from India.

Blanchard, O., & Kremer, M. (1997). Disorganization. *The Quarterly Journal of Economics*, 1091-1126.

Botero, J. C., Djankov, S., La Porta, R., López de Silanes, F., & Shleifer, A. (2003). The regulation of labor. *NBER working paper*, (w9756).

Brunetti, A., & Weder, B. (1998). Investment and institutional uncertainty: a comparative study of different uncertainty measures. *Weltwirtschaftliches Archiv*, *134*(3), 513-533.

Caselli, F. (2004). Accounting for Cross-Country Income Differences. *NBER Working Paper*, No. 10828.

Caselli, F., Esquivel, G., & Lefort, F. (1996). Reopening the convergence debate: a new look at cross-country growth empirics. *Journal of Economic Growth*, *1*(3), 363-389.

Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). Multilateral comparisons of output, input, and productivity using superlative index numbers. *The Economic Journal*, 73-86.

Cooper, W., Seiford, L., Zhu, J. (2004). Handbook On Data Envelopment Analysis. Massachusetts: Kluwer Academic Publishers.

Danquah, M., Moral-Benito, E., & Ouattara, B. (2014). TFP growth and its determinants: a model averaging approach. Empirical Economics, 47(1), 227-251.

De Haan, J., Lundström, S., & Sturm, J. E. (2006). Market-oriented institutions and policies and economic growth: A critical survey. *Journal of Economic Surveys*, *20*(2), 157-191.

Deliktas, E., & Balcilar, M. (2005). A comparative analysis of productivity growth, catch-up, and convergence in transition economies. *Emerging Markets Finance and Trade*, *41*(1), 6-28.

Easterly, W., & Levine, R. (2001). What have we learned from a decade of empirical research on growth? It's Not Factor Accumulation: Stylized Facts and Growth Models. T*he World Bank economic review*, *15*(2), 177-219.

Fare, R., Grosskopf, S. & Margaritis, D. (2006). Productivity growth and convergence in the European Union. *Journal of Productivity Analysis, 25, 111-141.*

Fare, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *The American economic review*, 66-83.

Fried, H., Lovell, K. & Schmidt, S. (2007). The Measurement of Productive Efficiency and Productivity. *Oxford University Press.*

Ghosh, S., & Mastromarco, C. (2013). Cross-border Economic Activities, Human Capital and Efficiency: A Stochastic Frontier Analysis for OECD Countries. *World Economy*, 36(6), 761-785. doi:10.1111/twec.12010

Greene, W. (2005a). Fixed and random effects in stochastic frontier models. Journal of Productivity Analysis, 23(1), 7-32.

Greene, W. (2005b). Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model. *Journal Of Econometrics*, 126(2), 269-303.

Hall, R. E., & Jones, C. I. (1999). *Why do some countries produce so much more output per worker than others?*. No. w6564. National bureau of economic research, 1999.

Hejazi, W., & Safarian, A. E. (1999). Trade, foreign direct investment, and R&D spillovers. *Journal of International Business Studies*, 491-511.

Heritage Foundation, (2014). *Economic freedom index 1995-2013* [Data file]. Retrieved August 1, 2014, from http://www.heritage.org/index/explore

Hsieh, C. & Klenow, P. J. (2010). Development Accounting. *American Economic Journal: Macroeconomics 2010, 2(1), 207-223.*

Huang, T. H., & Wang, M. H. (2004). Comparisons of economic inefficiency between output and input measures of technical inefficiency using the Fourier flexible cost function. *Journal of Productivity Analysis*, *22*(1-2), 123-142.

Isaksson, A. (2007). Determinants of total factor productivity: A literature review. *Research and Statistics Branch, UNIDO*.

Islam, N. (1995). Growth empirics: a panel data approach. *The Quarterly Journal of Economics*, 1127-1170.

Iyer, K. G., Rambaldi, A. N., & Tang, K. K. (2008). Efficiency externalities of trade and alternative forms of foreign investment in OECD countries. *Journal of Applied Econometrics*, *23*(6), 749-766.

Jondrow, J., Lovell, C. K., Materov, I. S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of econometrics*, 19(2), 233-238.

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2006). Measuring governance using cross-country perceptions data. *International handbook on the economics of corruption*, *52*.

Klein, P. G., Luu, H. (2003). Politics and Productivity. Economic Inquiry, 41(3), 433-447.

Klenow, P., & Rodriguez-Clare, A. (1997). The Neoclassical Revival in Growth Economics: Has It Gone Too Far? *NBER Macroeconomics annual 1997*, pp. 73-103.

Kneller, R., & Stevens, P. A. (2006). Frontier Technology and Absorptive Capacity: Evidence from OECD Manufacturing Industries*. *Oxford Bulletin of Economics and Statistics*, *68*(1), 1-21.

Košak, M., & Zorić, J. (2011). Accounting for heterogeneity in cross-country bank efficiency comparisons. *Economics of Transition, 19*(3), 473-494.

Krasnopjorovs, O. (2012) Measuring the sources of economic growth in the EU with parametric and non-parametric methods. *Journal of Economics and Management Research*, 1,106-122.

Kumar, S., & Russell, R. R. (2002). Technological change, technological catch-up, and capital deepening: relative contributions to growth and convergence. *American Economic Review*, 527-548.

Kumbhakar, S. C., & Wang, H. J. (2005). Estimation of growth convergence using a stochastic production frontier approach. *Economics Letters, 88*(3), 300-305.

Levine, R. (1998). The legal environment, banks, and long-run economic growth. *Journal of money, credit and banking*, 596-613.

Liik, M., Masso, J., & Ukrainski, K. (2014). The contribution of R&D to production efficiency in OECD countries: econometric analysis of industry-level panel data. *Baltic Journal of Economics*, 1-23.

Malmquist, S. (1953). Index numbers and indifference surfaces. *Trabajos de Estadistica y de Investigacion Operativa*, *4*(2), 209-242.

Merkina, N. (2009). Technological catch-up or resource rents?. *International Economics and Economic Policy*, *6*(1), 59-82.

Miller, S. M., & Upadhyay, M. P. (2000). The effects of openness, trade orientation, and human capital on total factor productivity. *Journal of development economics*, *63*(2), 399-423.

North, D. C. (1991). Institutions, ideology, and economic performance. *Cato J.*, *11*, 477.

Osiewalski, J., Koop, G., & Steel, M. F. (1997). *A stochastic frontier analysis of output level and growth in Poland and western economies*. Center for Economic Research, Tilburg University.

Pitt, M. M., & Lee, L. F. (1981). The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of development economics*, *9*(1), 43-64.

Prescott, E. (1998). Needed: a theory of total factor productivity. International Economic Review 39 (3): 525–551.

Rao, D. S. P., & Coelli, T. J. (1998). A cross-country analysis of GDP growth catch-up and convergence in productivity and inequality. *Centre for Efficiency and Productivity Analysis (CEPA) Working Paper No. 5*, *98*.

Solow, R. M. (1957). Technical change and the aggregate production function. *The review of Economics and Statistics*, 312-320.

Stevenson, R. E. (1980). Likelihood functions for generalized stochastic frontier estimation. *Journal of econometrics*, *13*(1), 57-66.

Tonini, A. (2012). A Bayesian stochastic frontier: an application to agricultural productivity growth in European countries. *Economic Change and Restructuring*, *45*(4), 247-269.

Wang, M. H., & Schmidt, P. (2002). One-Step and Two-Step Estimation of the Effects of Exogenous Variables on Technical Efficiency Levels. *Journal Of Productivity Analysis*, 18(2), 129-144.

Weil, D. N. (*2005*). Accounting for the Effect of Health on Economic Growth. NBER Working Papers, No. 11455.

Wijeweera, A., Villano, R., & Dollery, B. (2010). Economic growth and FDI inflows: A stochastic frontier analysis. *The Journal of Developing Areas*, *43*(2), 143-158.

Appendix 1. Data

Table 1. Descriptive statistics of data 1995-2013

Mean Values (1995-2013)							
Country	**GDP**	**Capital**	**Labour hours**	**R&D**	**FDI**	**EFI**	**WBI**
Belgium	271,109	705,926	6,727	2.0	18.8	68.2	76.7
Bulgaria	60,610	139,400	5,792	0.5	8.7	57.9	52.2
Czech Republic	171,299	547,021	9,151	1.3	4.7	68.6	66.4
Denmark	146,000	333,332	3,999	2.5	3.0	73.4	86.7
Germany	2,073,351	6,154,433	56,982	2.5	2.0	69.6	80.0
Estonia	16,620	43,237	1,189	1.1	8.3	74.5	68.2
Ireland	116,380	331,891	3,344	1.4	13.6	78.3	80.3
Greece	198,698	751,227	9,054	0.6	0.8	59.6	62.7
Spain	906,357	3,192,429	29,594	1.1	3.2	67.1	69.5
France	1,476,066	4,508,949	39,081	2.2	2.2	61.3	74.1
Croatia	52,580	105,109	2,483	0.9	4.1	54.3	53.7
Italy	1,476,066	4,177,587	43,275	1.1	0.8	61.8	63.7
Cyprus	14,659	34,555	652	0.4	6.5	70.5	70.5
Latvia	22,909	36,448	1,873	0.5	4.6	65.3	60.3
Lithuania	37,284	63,836	2,643	0.7	3.4	67.2	62.5
Luxembourg	25,148	47,901	473	1.6	56.4	75.6	84.3
Hungary	130,709	266,776	8,203	0.9	9.5	63.7	67.0
Malta	7,109	12,434	289	0.5	8.6	63.7	73.0
Netherlands	448,138	1,231,194	11,576	1.9	5.3	73.5	84.7
Austria	222,964	740,317	6,728	2.3	3.7	69.2	82.1
Poland	441,196	867,175	30,963	0.7	3.3	61.2	63.5
Portugal	173,913	474,604	9,557	1.0	3.0	64.3	71.6
Romania	175,795	311,249	18,527	0.5	3.8	56.5	52.4
Slovenia	35,715	81,593	1,557	1.7	1.6	60.2	68.8
Slovakia	71,596	145,703	3,813	0.7	3.8	63.5	63.0
Finland	127,532	335,506	4,046	3.3	3.0	70.8	87.5
Sweden	240,161	746,479	7,097	3.6	5.1	68.9	85.0
United Kingdom	1,487,998	3,607,640	47,274	1.8	4.1	77.2	80.1
Norway	169,467	440,922	3,463	1.6	2.9	68.1	84.3
Switzerland	236,628	736,719	7,110	2.7	3.8	79.3	84.9
N	570	570	570	570	563	563	570

Note. GDP and capital are millions of EUR in PPP terms. Labour hours are millions. R&D expenditure, net foreign direct investment is expressed in percent of GDP. Economic freedom index (EFI) and World Bank governance indicator (WBI) are between 0 and 100.

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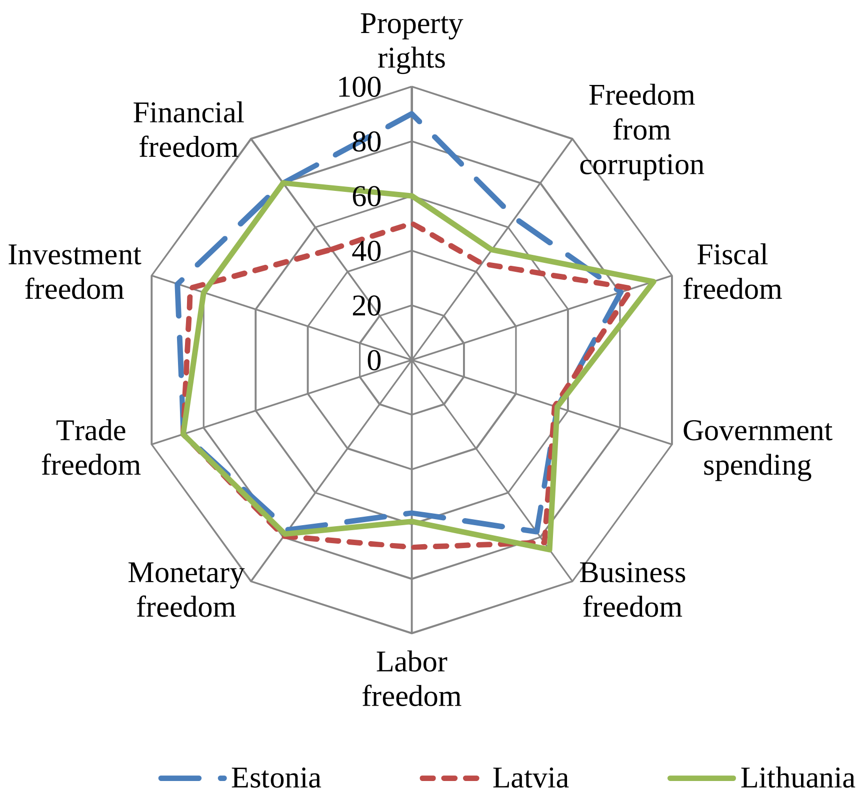
Figure 1. EFI components for the Baltic States in 2013



Graph created by the authors using data from Heritage Foundation (2014).

Appendix 2. Results of models without inefficiency determinants

	TFE		BC95		BC92	
Variable	Coefficient	SE	Coefficient	SE	Coefficient	SE
k	0.658***	(0.020)	0.751***	(0.008)	0.532***	(0.039)
l	0.171***	(0.026)	0.182***	(0.009)	0.385***	(0.038)
dyear1996	0.026***	(0.009)	0.014***	(0.033)	0.016	(0.013)
dyear1997	0.044***	(0.002)	0.039	(0.033)	0.046***	(0.013)
dyear1998	0.056***	(0.010)	0.066	(0.033)	0.067***	(0.013)
dyear1999	0.074***	(0.010)	0.073**	(0.033)	0.079***	(0.013)
dyear2000	0.100***	(0.005)	0.105**	(0.033)	0.119***	(0.014)
dyear2001	0.119***	(0.013)	0.119***	(0.033)	0.130***	(0.014)
dyear2002	0.138***	(0.015)	0.134***	(0.033)	0.155***	(0.015)
dyear2003	0.150***	(0.009)	0.142***	(0.033)	0.160***	(0.015)
dyear2004	0.177***	(0.009)	0.166***	(0.032)	0.189***	(0.016)
dyear2005	0.199***	(0.010)	0.180***	(0.032)	0.205***	(0.016)
dyear2006	0.218***	(0.012)	0.199***	(0.033)	0.227***	(0.017)
dyear2007	0.236***	(0.014)	0.205***	(0.033)	0.247***	(0.018)
dyear2008	0.237***	(0.018)	0.181***	(0.033)	0.231***	(0.019)
dyear2009	0.164***	(0.012)	0.108***	(0.033)	0.164***	(0.020)
dyear2010	0.173***	(0.013)	0.122***	(0.033)	0.184***	(0.021)
dyear2011	0.186***	(0.016)	0.134***	(0.033)	0.194***	(0.022)
dyear2012	0.201***	(0.017)	0.131***	(0.033)	0.198***	(0.023)
dyear2013	0.213***	(0.017)	0.128***	(0.033)	0.190***	(0.023)
constant			-0.501***	(0.077)	0.789***	(0.124)
λ	1091.319		3.208		40.6	
σ	0.087		0.189		0.208	
σ_u	0.087		0.181		0.203	
σ_v	0.000		0.056		0.005	
γ	1.000		0.911		0.999	
Log-likelihood	977.037		317.810		813.793	
N	570		570		570	

Note. The true fixed effects model's country specific intercepts are not included in the table to save space. Standard errors for variance parameters are not included.
$\lambda = \sigma_u/\sigma_v$. $\gamma = \sigma_u^2/(\sigma_u^2+\sigma_v^2)$
Significance: ***: 1% level; **: 5% level; *: 10% level.

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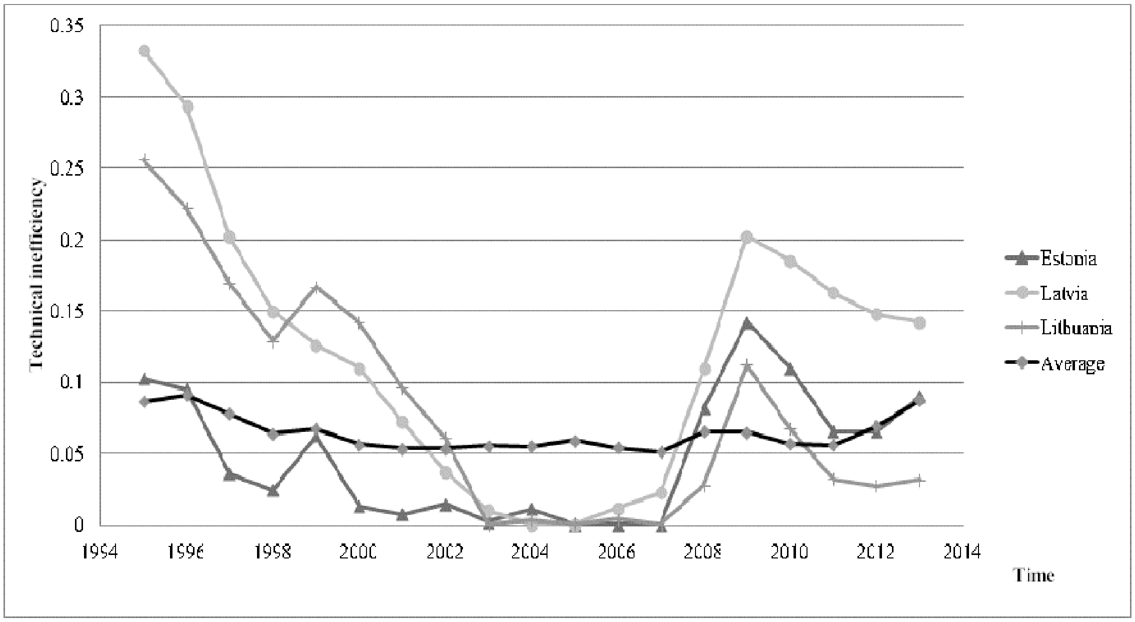
Appendix 3. Plots of inefficiency scores from TFE, BC95 and BC92 models

Figure 1.Inefficiency scores from the TFE model over time



Note. Only the scores for the Baltic States and the sample average are reported.

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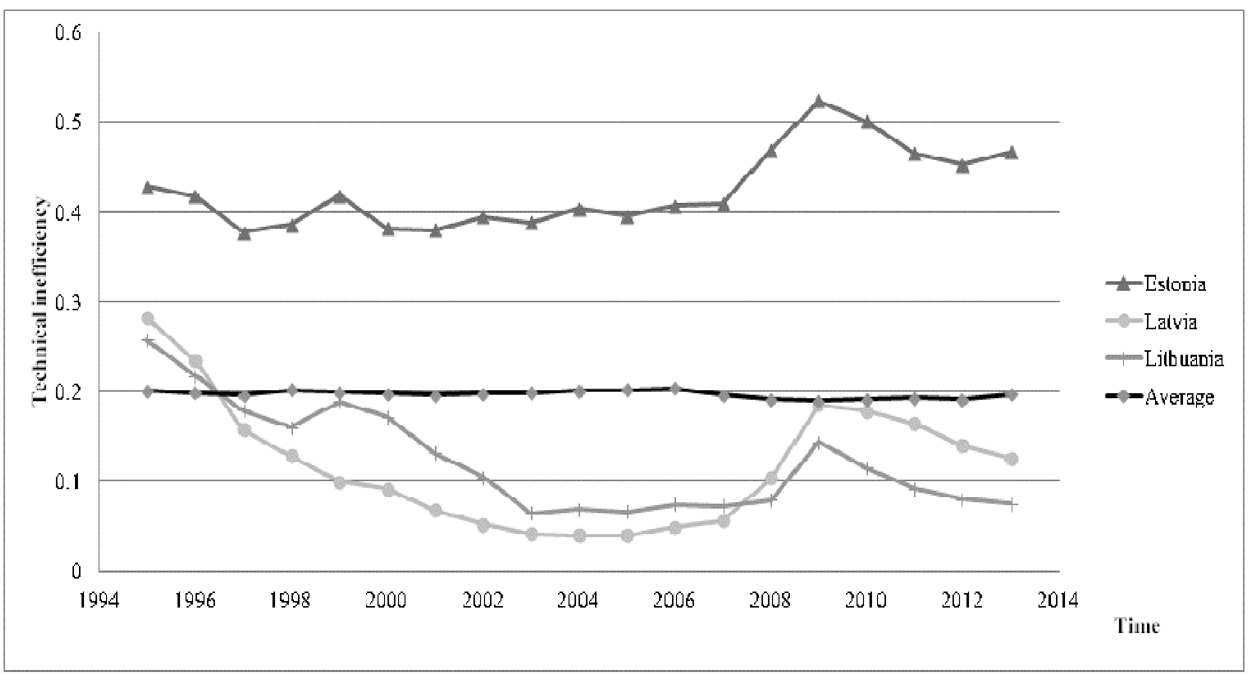
Figure 2. Inefficiency scores from the Battese and Coelli (1995) model over time



Note. Only the scores for the Baltic States and the sample average are reported.

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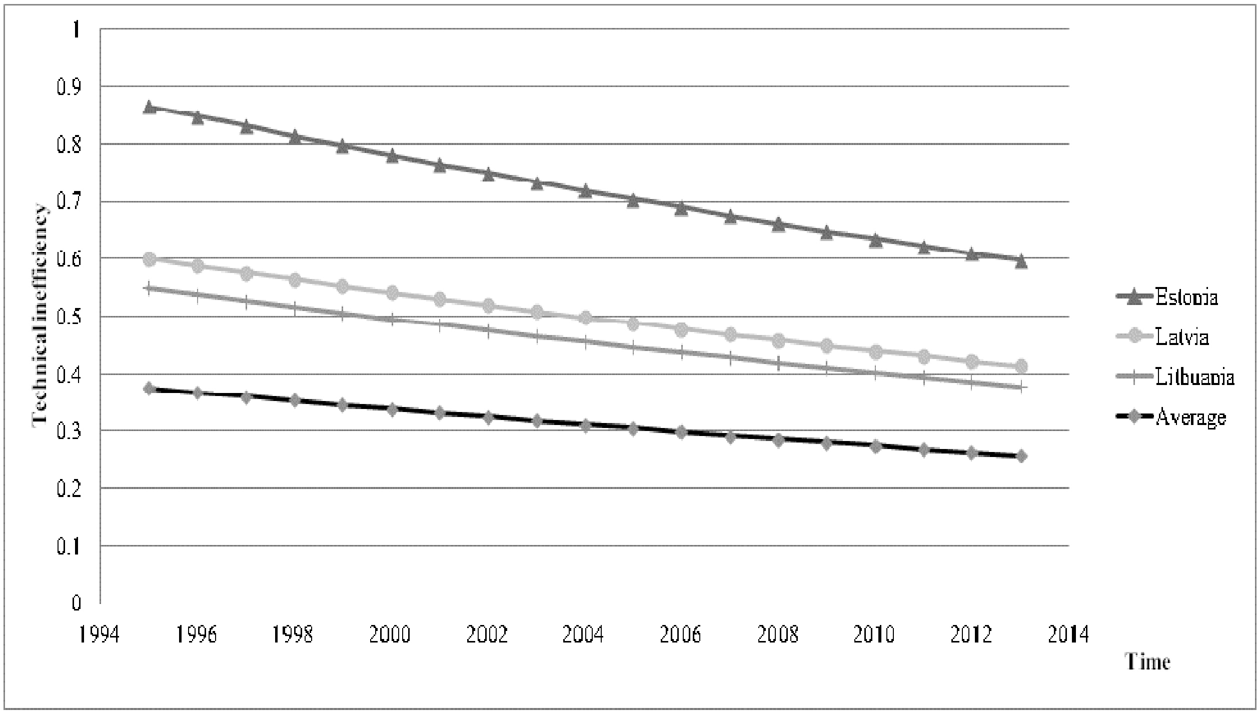
Figure 3. Inefficiency scores from the Battese and Coelli (1992) model over time



Note. Only the scores for the Baltic States and the sample average are reported.

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Appendix 4. Results of true fixed effects models with inefficiency determinants

Table 1. Regression results with institutional quality proxies in the inefficiency equation

	Reg 1	SE	Reg 2	SE
Frontier equation				
k	0.594***	(0.021)	0.586***	(0.018)
l	0.255***	(0.036)	0.284***	(0.033)
dyear1996	0.027***	(0.008)	0.020***	(0.010)
dyear1997	0.047***	(0.002)	0.052***	(0.010)
dyear1998	0.058***	(0.003)	0.080***	(0.010)
dyear1999	0.075***	(0.003)	0 .09***	(0.010)
dyear2000	0.126***	(0.005)	0.141***	(0.011)
dyear2001	0.132***	(0.006)	0.155***	(0.011)
dyear2002	0.149***	(0.006)	0.169***	(0.011)
dyear2003	0.161***	(0.007)	0.176***	(0.011)
dyear2004	0.185***	(0.007)	0.205***	(0.012)
dyear2005	0.213***	(0.009)	0.223***	(0.012)
dyear2006	0.240***	(0.014)	0.248***	(0.013)
dyear2007	0.258***	(0.011)	0.274***	(0.014)
dyear2008	0.247***	(0.014)	0.260***	(0.015)
dyear2009	0.185***	(0.015)	0.200***	(0.015)
dyear2010	0.200***	(0.015)	0.225***	(0.015)
dyear2011	0.212***	(0.015)	0.245***	(0.016)
dyear2012	0.231***	(0.015)	0.251***	(0.016)
dyear2013	0.243***	(0.015)	0.249***	(0.017)
Inefficiency equation				
EFI	-0.076***	(0.008)		
WBI			-0.167***	(0.029)
constant	0.068	(0.526)	5.430***	(1.739)
λ	30374343		1.913	
σ	0.083		0.063	
σ_u	0.083		0.056	
σ_v	0		0.029	
γ	1		0.785	
Log-likelihood	1026.549		998.861	
N	570		570	

Note. Country specific intercepts in frontier equation are not included in the table to save space. Standard errors for variance parameters are not included.
$\lambda = \sigma_u/\sigma_v$. $\gamma = \sigma_u^2/(\sigma_u^2+\sigma_v^2)$ Significance: ***: 1% level; **: 5% level; *: 10% level.

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Table 2. Regression results with several inefficiency determinants

	Reg 1	**SE**	**Reg 2**	**SE**	**Reg 3**	**SE**
Frontier equation						
k	0.561***	(0.029)	0.571***	(0.028)	0.568***	(0.018)
l	0.291***	(0.056)	0.147**	(0.026)	0.332***	(0.035)
dyear1996	0.031***	(0.008)	0.038***	(0.009)	0.018*	(0.010)
dyear1997	0.050***	(0.003)	0.048***	(0.010)	0.042***	(0.010)
dyear1998	0.061***	(0.008)	0.074***	(0.008)	0.069***	(0.010)
dyear1999	0.077***	(0.012)	0.084***	(0.010)	0.008***	(0.010)
dyear2000	0.117***	(0.005)	0.122***	(0.006)	0.117***	(0.010)
dyear2001	0.128***	(0.013)	0.140***	(0.012)	0.136***	(0.010)
dyear2002	0.145***	(0.011)	0.175***	(0.008)	0.156***	(0.011)
dyear2003	0.159***	(0.012)	0.181***	(0.014)	0.164***	(0.011)
dyear2004	0.185***	(0.011)	0.206***	(0.016)	0.219***	(0.011)
dyear2005	0.217***	(0.013)	0.237***	(0.010)	0.212***	(0.012)
dyear2006	0.240***	(0.016)	0.269***	(0.013)	0.237***	(0.013)
dyear2007	0.271***	(0.015)	0.300***	(0.015)	0.261***	(0.014)
dyear2008	0.262***	(0.016)	0.277***	(0.019)	0.245***	(0.014)
dyear2009	0.192***	(0.017)	0.203***	(0.018)	0.184***	(0.014)
dyear2010	0.218***	(0.017)	0.213***	(0.018)	0.211***	(0.015)
dyear2011	0.241***	(0.018)	0.240***	(0.021)	0.232***	(0.015)
dyear2012	0.249***	(0.018)	0.254***	(0.024)	0.241***	(0.016)
dyear2013	0.261***	(0.018)	0.268***	(0.024)	0.240***	(0.016)
Inefficiency equation						
R&D	-0.712***	(0.093)	-0.502***	(0.083)	-0.644***	(0.169)
FDI			-0.052***	(0.009)	-0.020	(0.014)
EFI					-0.108***	(0.016)
constant	-3.96***	(0.147)	-3.943***	(0.145)	2.613***	(0.988)
λ	3033140		36576291		3.153	
σ	0.086		0.088		0.072	
σ_u	0.086		0.088		0.068	
σ_v	0		0		0.022	
γ	1		1		0.909	
Log-likelihood	1010.93		997.307		985.77	
N	570		563		563	

Note. Country specific intercepts in frontier equation are not included in the table to save space. Standard errors for variance parameters are not included.
$\lambda = \sigma_u/\sigma_v$. $\gamma = \sigma_u^2/(\sigma_u^2+\sigma_v^2)$ Significance: ***: 1% level; **: 5% level; *: 10% level.

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Table 3. Regression results with economic freedom index sub-indices

	Reg 1	**SE**	**Reg 2**	**SE**	**Reg 3**	**SE**
Frontier equation						
k	0.623***	(0.021)	0.062***	(0.021)	0.615***	(0.020)
l	0.235***	(0.038)	0.229***	(0.032)	0.231***	(0.006)
dyear1996	0.019***	(0.009)	0.019***	(0.008)	0.021**	(0.009)
dyear1997	0.044***	(0.009)	0.044***	(0.008)	0.045***	(0.010)
dyear1998	0.054***	(0.012)	0.056***	(0.009)	0.057***	(0.010)
dyear1999	0.070***	(0.009)	0.072***	(0.009)	0.073***	(0.010)
dyear2000	0.120***	(0.012)	0.123***	(0.009)	0.124***	(0.124)
dyear2001	0.124***	(0.009)	0.124***	(0.008)	0.126***	(0.005)
dyear2002	0.142***	(0.009)	0.142***	(0.008)	0.143***	(0.007)
dyear2003	0.151***	(0.009)	0.152***	(0.009)	0.153***	(0.008)
dyear2004	0.174***	(0.010)	0.175***	(0.008)	0.177***	(0.008)
dyear2005	0.200***	(0.011)	0.201***	(0.010)	0.203***	(0.010)
dyear2006	0.222***	(0.015)	0.221***	(0.015)	0.223***	(0.011)
dyear2007	0.242***	(0.010)	0.244***	(0.013)	0.246***	(0.013)
dyear2008	0.232***	(0.016)	0.234***	(0.013)	0.236***	(0.013)
dyear2009	0.167***	(0.017)	0.169***	(0.016)	0.173***	(0.016)
dyear2010	0.179***	(0.015)	0.181***	(0.014)	0.185***	(0.016)
dyear2011	0.195***	(0.017)	0.197***	(0.015)	0.200***	(0.014)
dyear2012	0.209***	(0.015)	0.211***	(0.015)	0.215***	(0.016)
dyear2013	0.221***	(0.015)	0.223***	(0.015)	0.227***	(0.017)
Inefficiency equation						
Property rights	-0.032***	(0.093)	-0.033***	(0.003)	-0.034***	(0.004)
Labour freedom			0.007	(0.005)	0.008	(0.005)
Investment freedom					0.004	(0.006)
constant	-2.749***	(0.147)	-3.170***	(0.370)	-3.387***	(0.524)
λ	19047619		158056415		32704	
σ	0.084		0.084		0.084	
σ_u	0.084		0.084		0.084	
σ_v	0		0		0	
γ	1		1		1	
Log-likelihood	1028.423		1029.590		1029.569	
N	570		570		570	

Note. Country specific intercepts in frontier equation are not included in the table to save space.
Standard errors for variance parameters are not included.
$\lambda = \sigma_u/\sigma_v$. $\gamma = \sigma_u^2/(\sigma_u^2+\sigma_v^2)$ Significance: ***: 1% level; **: 5% level; *: 10% level.

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