Visegrad Countries and Education Challenges : An Efficiency Analysis

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Abstract

Education is the backbone of long-term economic prosperity. Thus, studying the educational landscapes of different countries for comparative reasons allows researchers to derive best practices that can be moulded into policies for the benefit of the collective well-being of communities in the regions. In this context, we conduct a detailed examination of school efficiency across 1190 schools at the NUTS2 regions of the Visegrad countries, namely Hungary, Poland, the Czech Republic, and the Slovak Republic, utilizing the rich dataset provided by PISA 2019. The dataset compiled for this research consists of an integrated mix of data, where student-level performance metrics and scores are aggregated to reflect school-level outcomes. This comprehensive dataset includes detailed information about the internal environment of each school, as well as the external factors surrounding it. Our analysis is threefold: first, we employ Data Envelopment Analysis (DEA) that identifies key factors contributing to school effectiveness and best practices in terms of student performances; second, we employ a double-bootstrap procedure to estimate the contribution of various non-discretionary variables on school efficiency.

Introduction

Knowledge plays a pivotal role in shaping a nation's economic landscape, driving growth and prosperity (Hanushek and Woessmann 2020) and (Hanushek 2020). It is considered a major factor for enhancing productivity and influencing a nation's overall economic situation (Adams 1990). The increasing of a nation's knowledge stock is closely related to the increasing of its human capital, achieved through investments in technology and training (Inglesi-Lotz and Pouris 2013) and (Hanushek 2020). Additionally (Hanushek and Woessmann 2021) determined that the overall prevalence of patience and risk-taking practices across countries accounts for nearly two thirds of the variations that drives this investment in Human Capital, which is to say that there are specific dynamics that govern these mechanics of influence. This deliberate effort in investing in the Human Capital results in a multiplier effect for the economies in question, fostering innovation, encouraging healthy competition, and contributing to comprehensive growth and development (Inglesi-Lotz, Balcilar, and Gupta 2014) and (Romer 1989), this was also emphasized by (Cunha et al. 2006) who explicitly mentioned this multiplier effect of skill gains. The emphasis on knowledge (tacit knowledge, know-how, skills of different dimensions) has consistently been associated with a nation's education system and its quality, strongly linked to long-term economic growth development and overall prosperity, for instance (Hanushek and Woessmann 2012) derived a causal effect of cognitive skills of a population on the long-term economic growth rates across countries.However, sustaining this correlation becomes a challenge as the socio-economic contexts and conditions change and evolve (Hanushek 2016). Understanding the mechanics that drives investment in Human Capital, and the causal effect of cognitive skills on economic growth are both a great starting point to address what constitutes these skills, and how they are acquired, by whom, and more imortantly how can agents of interest in this context optimize their return on investment and make sure that the resources enabled for this process are fully utilized, hence the focus on education, and educational institutions. The literature provided various scopes on how to approach educational landscapes from this perspective, two main scopes are efficiency (doing the right things) and effectiveness (doing things right). Essentially effectiveness focus on the practices (resources, operations, pedagogy, etc) that yields a desired result in terms of output, whereas efficiency (the scope of this paper) focuses on the operational dimension of these practices and how to maximize a desired output given a status quo of inputs. (Witte and López-Torres 2017) in a comprehensive review criticizes the dychotomy between the literature on efficiency and effectiveness in the context of an educational landscape, arguing that both scopes have distinct contributions that must be connected together for a rather comprehensive understanding of the issues challenges and adavantages of a given system. For the purposes of this paper we will approach the problem of assessing an educational landscape from the efficiency perspective, essentially given the finite nature of resources that are versed into a given system and because of the public nature of a majority of the education instituion which require additional attention to the policies implemented and their results and consequences on the public. This justifies the study of education systems as it allows to pinpoints the advantages and challenges that countries face in terms of educational excellence. following this line of thought, (Worthington 2001) assumes that education institutions conduct a basic transformation of inputs into outputs, and this transformation can be proxied with a production function which can be estimated directly (parametrically) or indirectly (non-parametrically). Using Frontier estimation methods such as Data-envelopment-Analysis ((Charnes, Cooper,

and Rhodes 1978)) or Stochastic-Frontier-Analysis ((Aigner, Lovell, and Schmidt 1977)) (or other similar methodologies) expanded the analysis tools that researchers used to approach educational institutions from the input/output perspective. Building on this, frontier methodologies are often utilized in a two-stage set up to further assess how efficient Decision Making Units (or DMU) react with other non-discretionary variables, this methodology has been observed in various studies including (Mayston and Jesson 1988), (Ray 2004), and (Ruggiero 2004) among others. For this paper we decided to adopt this approach where we estimate (non-parametrically) the production function of our school sample with the means of Data-envelopment-analysis (or DEA, yielding efficiency scores) in the first stage then we use a a double-bootstrap process (following (Leopold Simar and Wilson 2007)) to estimate a truncated regression that enables inference on some non-discretionary factors within the DMUs and around it. In this study we will use a sample of schools spanning across the Visegrad countries (V4:) extracted from the PISA survey data of 2022. This data allows us to specify a set of inputs, outputs, and non discretionary factors that we will use to derive best practices, and to derive inference in the second stage of our analysis. The remaining of the paper is as follows: section 2 will introduce the methodology and data used in the study, section 3 will provide the results, section 4 will present a discussion, and finally we conclude in section 5.

Data and Methodology

The literature is rich with studies regarding assessing educational landscapes of regions or cities (example: (Butler and Monk 1985), (Sengupta and Sfeir 1986), (Barrow 1991), (Ruggiero 1996), (Fukuyama and Weber 2002), (Banker, Janakiraman, and Natarajan 2004), (Davutyan, Demir, and Polat 2010), and (Johnson and Ruggiero 2014)), as well as countries (example: (Gershberg and Schuermann 2001), (Hanushek 2003), (Afonso and Aubyn 2006a), (Kocher, Luptacik, and Sutter 2006), (Giménez, Prior, and Thieme 2007), (Agasisti 2011b), (Thieme, Giménez, and Prior 2012), and (Aristovnik 2013)). There are also studies that tackles the assessment process from other angles, for example (Cooper and Cohn 1997) (used data on classes in South Carolina) and (De Witte and Rogge 2011) (assessed teachers' performance across various college courses). Additionally other papers studied and assessed the student level performance, including (Thanssoulis 1999), (Colbert, Levary, and Shaner 2000), (Thanassoulis, Da Conceição, and Silva Portela 2002), (Dolton, Marcenaro, and Navarro 2003), (Johnes 2006), (Deutsch, Dumas, and Silber 2013), (Portela, Camanho, and Keshvari 2013), (Thieme, Prior, and Tortosa-Ausina 2013), (Crespo-Cebada, Pedraja-Chaparro, and Santín 2014), and (Podinovski et al. 2014) to cite a few. Another scope of analysis remains, and that's the school level assessment which can be found in (A. M. Bessent and Bessent 1980), (Charnes, Cooper, and Rhodes 1981), (A. Bessent et al. 1982), (Ray 1991), (Thanassoulis 1996), (Bradley, Johnes, and Millington 2001a), (Ouellette and Vierstraete* 2005), (Grosskopf, Hayes, and Taylor 2009), (Essid, Ouellette, and Vigeant 2010a), (Agasisti 2011a), (Johnes, Bradley, and Little 2012a), (Burney et al. 2013a), and (Brennan, Haelermans, and Ruggiero 2014) among others.

Moreover, in order to assess these educational institutions (at any level of analysis), different methodologies can be used and employed depending on the premis, the need, and the objective of the study. In the realm of frontier analysis, DEA is the most common methodology used in such papers, however, DEA is commonly combined with other methodologies as well such as Bootstrapping (Essid, Ouellette, and Vigeant 2010b, 2013a), or simply a regression procedure (be it ols, tobit or truncated) (Ruggiero 1998; Afonso and Aubyn 2006b; Agasisti and Salerno 2007; Johnes, Bradley, and Little 2012b) or even using the Malmquist index (Worthington and Lee 2008; Ouellette et al. 2010; Essid, Ouellette, and Vigeant 2014) to cite a few. (Witte and López-Torres 2017) provides one of the most comprehensive reviews of the literature in this regard.

In this paper we will adopt the school level analysis scope. The assumption that Educaitional institutions can be regarded as productive units that transforms inputs into outputs ((Worthington 2001)), enables researchers to scrutinize data on school level with flexibility regarding the scope of the study or the angle of investigation. For this reason, efficiency analysis, especially DEA, has been quite popular in the literature as it captures the mechanics of this said transformation by estimating the frontier of efficient DMUs (in which the deviation from the efficiency frontier is assumed to be entirely due to inefficiency). However, these institutions, schools in particular, are not isolated entities. In fact, there's multiple factors that affect a school's performance spanning from the individual circumstances of the students, teachers, and staff of that school, to the environmental factors surrounding it, from infrastructure, location, and other competing

schools.

In order to conduct the investigation on the influential environmental factors on the efficiency of the schools in the Visegrad countries, we will leverage the PISA survey data from 2022 in a two-stage analysis, where in the first stage we estimate the efficiency of our units in each country, then we run a double bootstrap procedure that estimates the influence of each environmental factor in a truncated regression. In this section we will delve into more details on the data we used, the approach we adopt, and the model specifications.

Data

The PISA survey data is commonly used by researcher as it contains comprehensive information on many levels for multiple countries within the OECD and outside it. The survey contains multiple response files, on Student level, School level, and Teacher level (among others). The popularity of the use of this PISA survey data is reflected by the amount of papers published containing 'PISA data' or 'PISA survey' as a keyword which amounts to 322 papers from the Web of Science database and 414 from the Scopus database, between 2003 and 2024. In our study we combine a set a variables on school level and student level to build a comprehensive and aggregated school level data set that contain enough information that can be leveraged by the methodology we use to investigate the effect of non-discretionary variables on school efficiency for the Visegrad countries (Hungary (HUN), Poland (POL), Czech Republic (CZE), Slovak Republic (SVK)). Our final clean dataset contains 1180 observations originally, and 1085 observation after removing the missing values. The decomposition of the final dataset by country is described in table 1.

Table 1: Number of observation (schools) per country

CNT	count
CZE	399
HUN	206
POL	234
SVK	246

Table 2 provide a full description of the final data across all the visegrad countries.

Table 2: Descriptive statistics of all the variables for the entire sample

	min	max	mean	sd
Environmental Variables				
STUBI	1.000	4.000	1.854	0.548
TEABI	1.000	4.000	1.747	0.513
RESSI	1.000	4.000	1.919	0.759
STAFI	1.000	4.000	1.870	0.657
COMP	1.000	3.000	1.547	0.811
SCSIZE	9.000	1,910.000	461.549	261.138
LOC	0.000	1.000	0.629	0.483
TOTAT	4.000	126.500	39.494	21.189
Output Variables				
SCIENCE	237.794	675.767	488.679	70.216
READING	235.286	664.219	476.599	73.763
MATH	265.364	661.315	479.648	69.045
Input Variables				
CPERIODS	3.000	53.000	29.491	6.120

| STRATIO | 1.000 | 100.000 | 11.853 | 4.431 |

Table 3: Descriptive statistics of all the variables for each country

	Input Variables		Output Variables			Environmental Variables							
	CPERIODS	STRATIO	SCIENCE	READING	MATH	STUBI	TEABI	RESSI	STAFI	COMP	SCSIZE	LOC	TOTAT
CZE													
min	4.000	3.250	237.794	323.644	349.407	1.000	1.000	1.000	1.000	1.000	13.000	0.000	4.000
max	41.125	100.000	675.767	664.219	661.315	3.600	3.400	4.000	4.000	3.000	1,910.000	1.000	126.500
mean	30.157	13.042	503.257	493.412	492.427	1.895	1.862	1.886	1.954	1.617	459.782	0.569	36.267
sd	4.664	5.567	69.887	68.933	66.563	0.474	0.501	0.675	0.683	0.860	244.159	0.496	19.091
HUN													
min	3.000	1.000	322.458	241.531	265.364	1.000	1.000	1.000	1.000	1.000	9.000	0.000	9.000
max	53.000	25.409	659.594	628.476	636.929	3.800	4.000	4.000	3.750	3.000	1,461.000	1.000	123.000
mean	29.720	10.892	472.745	458.126	456.751	1.650	1.644	2.154	1.941	1.675	497.228	0.714	45.182
sd	7.139	3.212	76.142	83.917	77.683	0.572	0.501	0.823	0.604	0.836	272.114	0.453	21.831
POL													
min	3.000	1.000	358.259	235.286	305.966	1.000	1.000	1.000	1.000	1.000	23.000	0.000	4.500
max	42.840	20.192	638.343	627.149	632.535	3.600	3.400	3.750	4.000	3.000	1,428.000	1.000	124.500
mean	30.769	10.093	500.726	489.696	489.461	2.026	1.685	1.659	1.708	1.312	508.714	0.808	48.912
sd	7.057	3.438	63.010	71.327	62.903	0.526	0.531	0.669	0.630	0.636	297.766	0.395	23.701
SVK													
min	3.000	3.143	294.747	278.503	282.693	1.000	1.000	1.000	1.000	1.000	42.000	0.000	7.000
max	44.111	21.615	645.012	648.836	642.726	4.000	3.200	4.000	3.750	3.000	1,344.000	1.000	102.500
mean	27.001	12.403	466.918	452.341	468.762	1.793	1.704	2.024	1.827	1.549	389.675	0.488	31.006
sd	5.642	3.209	63.869	64.199	64.536	0.596	0.491	0.830	0.653	0.815	224.078	0.501	16.131

Inputs Choosing the inputs that will be used in our analysis is very important for few reasons. First, in the context of analyzing schools' efficiency, the inputs of schools are almost fixed, thus we have to use plausible inputs with enough variation. We decided to use as inputs the students to teacher ratio (STRATIO) which has been used in other studies such as (A. M. Bessent and Bessent 1980; Charnes, Cooper, and Rhodes 1981; Ray 1991; Johnes 1996; Cooper and Cohn 1997; Heshmati and Kumbhakar 1997; Afonso and Aubyn 2006a; Johnes and Li 2008; Cherchye et al. 2010; Agasisti 2011b, 2013a; Zoghbi, Rocha, and Mattos 2013) among others and the total number of class periods per week (CPERIODS) which has been used in similar studies such as (Rebai, Yahia, and Essid 2020; Yahia, Essid, and Rebai 2018) to cite a few. The data (per table 2) shoes that Czech Republic has an average of 30.157 class periods, similar to Poland's average of 30.769, although these are higher values compared to Hungary (29.720) and the Slovak Republic (27.001). Hungary exhibits the widest range with class periods extending up to 53, indicating significant variability in schooling intensity.

Outputs For the output we will adopt variables depicting aggregate (average) students' test scores by school, these aggregations describe the average scores students got for each school in MATH, READING, and SCIENCE. This is in accordance with multiple studies in this context such as(A. M. Bessent and Bessent 1980; Charnes, Cooper, and Rhodes 1981; Afonso and Aubyn 2006a; Cherchye et al. 2010; Essid, Ouellette, and Vigeant 2010a, 2013b; De Witte and Kortelainen 2013; De Witte et al. 2013; Rebai, Yahia, and Essid 2020; Yahia, Essid, and Rebai 2018) The descriptives in table 2 show that Poland and the Czech Republic present closely matched average scores in science (500.726 and 503.257 respectively), but Czech Republic seems to have an advantage compared to the rest of the countries in reading, and math as well, indicating that academic achievements vary widely across countries according to the survey. The Slovak Republic, with an average science score of 466.918, and Hungary, with 472.745, show lower performance levels in comparison, whereas Hungary shows the largest variations in all scores among the four countries with a standard deviation amounting to 76.142 in science, 83.917 for reading, and 77.683 for math.

Environmental variables The final piece of our data is the environmental (non-discretionary) variables which we will use to assess the contribution of environmental variables in the schools and around them on their efficiency. These variables are typically used in a two-stage analysis such as ours and provide insights that enable inference in order to understand what can be done (according to the sample of the study) to improve school efficiency that maximizes the output of test scores. We incorporated in the second stage of our analysis variables regarding behavior issues aggregated by means of other variables for students (STUBI, includes aspects such as truancy, disrespect towards teachers, substance abuse, and bullying), teachers (TEABI, reflecting the degree to which teachers meet individual students' needs, their absenteeism, resistance to change, strictness, and preparation for classes), and staff (STAFI, This variable measures the aspects related to the school's staff, encompassing the availability and quality of teaching staff and assisting personnel. It checks if there are enough teachers and assistants, and whether they are qualified and capable to meet educational demands.), as well as issues of available resources in the premises including personal and material resources (RESSI, this variable reflects the school's environment and resources, focusing on the availability of educational materials like textbooks and IT equipment, as well as the school's physical facilities such as buildings and heating/cooling systems. Essentially, it looks at whether students have the materials they need and a conducive learning environment). Both the STAFI and RESSI varaibles are observed in (Yahia, Essid, and Rebai 2018). Also we use the number of schools in the area (COMP, 3 none, 2 one school, 1 two or more schools) observed in studies like (Agasisti 2013b; Bradley, Johnes, and Millington 2001b; Rebai, Yahia, and Essid 2020), Community type where the school is located (LOC, 1 urban, 0 rural) observed in studies such as (Burney et al. 2013b; Mizala, Romaguera, and Farren 2002; Rebai, Yahia, and Essid 2020), school size depicted by the number of enrolled students in the school (SCSIZE), and the total number of all teachers at the school (TOTAT). In our data, Poland exhibits the highest mean in student behavioral issues (2.026), which may impact the teaching environment. However, its mean for teacher behavioral issues is relatively low (1.685), indicating that despite student behavior, teacher performance remains less affected. However Slovakia presents the highest maximum of student behavioral issues (4.0) despite having the second lowest average (1.793) after Hungary (1.650). Similarly shows the lowest teacher behavior issues (1.644) followed by Poland despite the latter having the highest maximum value in this variable across all countries (4.0). Moreover, for resources issues, Hungary stands at the top of the rank (2.177) followed by Slovakia

(1.975), which also have the highest variation in this variable (0.710), then Czech Republic (1.956) and finally Poland (1.868). Additionally, for staff-related issues, Slovakia and Hungary exhibit relatively high means (1.875 and 1.917 respectively), which suggests that there might be concerns regarding the availability or quality of assisting staff or teaching conditions. However, the Czech Republic (1.885) and Poland (1.5) show lower average values in staff issues, hinting at possibly better staff conditions or fewer concerns in these aspects. Notably, Slovakia and Czech Republic both have the highest maximum value (3.75) for staff issues, indicating some schools might face more significant challenges in this area.Regarding competition (COMP), the Czech Republic and Poland present lower average values (1.617 and 1.312 respectively), suggesting less competition among schools, which could mean fewer options for parents and potentially larger catchment areas for each school, especially for Poland which exhibits the lowest variation among the four countries (0.636). Hungary (1.675) and Slovakia (1.549) on the other hand show slightly higher averages, indicating higher competition among schools within these countries. When looking at school size by number of students (SCSIZE), Poland and Hungary exhibit the largest average sizes (508.714 and 497.228 respectively) and the highest variations as well (297.766 and 271.114 respectively). Conversely, the Czech Republic and Slovakia have smaller average school sizes (459.782 and 389.675 respectively). In terms of the community type where schools are located (LOC), Poland has the highest urban representation in term of mean (0.808), suggesting a greater proportion of schools in urban areas. Hungary follows with a mean value of (0.714), indicating a substantial urban presence as well. The Czech Republic and Slovakia have lower mean values, (0.569 and 0.488 respectively), suggesting a higher proportion of schools in rural areas in these countries. Lastly, the total number of teachers (TOTAT) shows Poland with the highest average (48.912) and the highest variation as well (23.701). Hungary follows with an average of (45.182), while the Czech Republic (36.267) and Slovakia (31.006) have lower averages, possibly indicating fewer resources in terms of teaching staff, which could impact the quality of education provided.

Methodology

The choice of the methodology is directly linked to the objective of this study. Since our aim is to investigate the environmental factors that influence the efficiency of schools in our sample we will first start by determining how we will estimate this efficiency, an then we will need to estimate the contributions of the other factors. Thus a two-stage analysis in plausible for this purpose. This two-stage analysis is based on an initial estimation of the efficiency using DEA, which will be regresses on other variable in the second stage.

To execute our approach, we start by scrutinizing DEA, the result of the pioneering work of (Charnes, Cooper, and Rhodes 1978) which was later popularized by (Banker, Charnes, and Cooper 1984), the idea is basically a linear program that estimates a set of parameters for each DMU that allows to rank these DMUs in order of their best practices or technical efficiency additionally depicting a frontier of best practice determined by efficient DMUs. DEA programs can be input oriented (minimize inputs at the same level of output, yielding efficiency scores between $]0,1]$ where a score of 1 indicate a fully efficient unit (FE)) or ouptut oriented (maximize outputs at the same level of inputs, yielding efficiency scores between $[1,+\infty[$, where a score of 1 indicate a fully efficient unit (FE)) while accounting for returns to scale as a constraint in the program. As for the second stage, it's also straight forward, as many authors advocate for the use of OLS or tobit regression such as (Chilingerian and Sherman 2004), (Ray 2004), and (Ruggiero 2004).

However, an interesting debate has took place regarding the statistical plausibility of second stage regression. On the one hand, advocates of this approach argue that the simplicity and versatility of the approach allows for valuable and practical insight. OLS or Tobit regressions are usually used in this context allowing for inference, in fact (Hoff 2007) provided a review of the use of tobit and OLS regression in a second stage, and advocated for the use of tobit. On the other hand opponents to the approach advocate for a more careful specifications, since a two-stage analysis doesn't stem for a data generating process (DGP), thus it's quite difficult to understand what is exactly being estimated in the second stage. One of the earliest critics of this approach was (Grosskopf 1996) who specified that other than the lack of a DGP, there's a possibility that these non-discretionary variables of the second stage can be correlated with the output efficiency of the first stage. Both (Grosskopf 1996) and (Ramalho, Ramalho, and Henriques 2010) argued against the use of linear models in the second stage. Building on this criticism, (Leopold Simar and Wilson 2007) was the first paper that coherently justified the use of a two-stage DEA proposing a DGP and two bootstrap algorithm

that enable inference in the second stage with a truncated regression. The basic idea behind (Leopold Simar and Wilson 2007) work, is that DEA efficiency scores are non-parametrically estimated, thus they are a non-observed estimate of an unkown efficiency frontier which means that these scores do not account for stochasticity (i.e: any deviation from the efficiency frontier is entirely due to inefficiency) which means that using non-parametric methods in the second stage is more appropriate as proven and discussed in (Léopold Simar and Wilson 2011), hence the bootstrap algorithms.

In this study, we adopt an output oriented model with the aim to maximize the average test scores' results of the schools in our sample data with variable returns to scales for the first stage, whereas for the second stage, we adopt the second algorithm (Double Bootstrap) from (Leopold Simar and Wilson 2007) to estimate the parameters of the second stage truncated regression, at 95% confidence interval, with the first bootstrap loop at L1=100, and the second one at L2=2000.

The DEA program is given by the following:

For a set of n Decision Making Units (DMUs), the inputs and outputs form matrices where each DMU is associated with m inputs $X = [x_1, x_2, ..., x_m]$ and s outputs $Y = [y_1, y_2, ..., y_s]$ we optimize the following:

$$
\begin{aligned}
\text{Maximize} \quad & \theta \\
\text{Subject to:} \quad & \sum_{j=1}^{n} \lambda_j y_{rj} \geq \theta y_{ro}, \quad \forall r = 1, ..., s, \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io}, \quad \forall i = 1, ..., m, \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j \geq 0, \quad \forall j = 1, ..., n.
\end{aligned}
$$

Where:

- θ is the efficiency score of DMU_0.
- x_{ij} and y_{rj} are the inputs and outputs of the jth DMU, respectively.
- λ_j are the weights assigned to each DMU, indicating the contribution of each DMU to the construction of the virtual DMU against which DMU_0 is being benchmarked.

Results

The results of the first stage DEA estimation (table 4) indicate that Poland is the most efficient country according to our specifications (1.183), followed by Slovakia (1.226). Then Hungary with a score of (1.253) who exhibits the largest variation in efficiency (0.172), while the Czech Republic ranks as the least efficient country (1.269).

Table 4: Average efficiencies for each country

	mean_efficiency	sd_efficiency	min_efficiency	max_efficiency
POL	1.183	0.116	1.000	1.575
SVK	1.226	0.141	1.000	1.734
HUN	1.253	0.172	1.000	1.788
CZE	1.269	0.150	1.000	1.774

Efficient units are has value closer to 1

In the table 5 and figure 1, we can see the distribution of schools across the efficiency quartiles. Poland present the biggest number of fully efficient schools (efficiency score = 1) with (5.46%) of the total number of schools,

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followed by Hungary (3.54%), Slovakia (3.32%), and lastly Czech Republic (1.92%). However, when we check the forth quartile of efficiency for each country we observe that Poland also has the most percentage of highly inefficient schools (24.79%) followed with close percentage by Czech Republic (23.98%). Additionally, in table 7, we calculated the frequency for null and non-null multiplier wights. These wights depict the importance that each DMU (school) give to each output when the efficiency score is being calculated for it. We can observe that science subjects have the most influence Polish and Czech schools' efficiency (55.56% and 48.62% respectively of schools have non-null weights) whereas mathematics is the influencing subject for Hungarian schools (39.81%) and Slovakian schools as well (73.98% highest among all countries)

Table 5: Distribution of Efficiency Scores by Country and Quartile

	FE	Q1	Q2	Q3	Q4
POL	13 (5.56%)	46 (19.66%)	58 (24.79%)	58 (24.79%)	59 (25.21%)
CZE	8 (2.01%)	92 (23.06%)	100 (25.06%)	99 (24.81%)	100 (25.06%)
SVK	9 (3.66%)	53 (21.54%)	61 (24.8%)	61 (24.8%)	62 (25.2%)
HUN	9 (4.37%)	43 (20.87%)	51 (24.76%)	51 (24.76%)	52 (25.24%)

Table 6: Frequency of null and non-null multiplier weights by output and country

	SCIENCE		READING		MATH	
	non-null	null	non-null	null	non-null	null
CZE	194 (48.62%)	205 (51.38%)	141 (35.34%)	258 (64.66%)	141 (35.34%)	258 (64.66%)
HUN	54 (26.21%)	152 (73.79%)	131 (63.59%)	75 (36.41%)	82 (39.81%)	124 (60.19%)
POL	130 (55.56%)	104 (44.44%)	121 (51.71%)	113 (48.29%)	97 (41.45%)	137 (58.55%)
SVK	105 (42.68%)	141 (57.32%)	99 (40.24%)	147 (59.76%)	182 (73.98%)	64 (26.02%)

For the second stage of our analysis the double-bootstrap procedure to estimate the parameters of the truncated regression are summarized in table 7.

Table 7: Regression coefficients and confidence intervals across countries

Variable	CZE	HUN	POL	SVK
Intercept	1.076^*	1.331^*	1.152^*	1.305^*
	(0.989, 1.161)	(1.209, 1.451)	(1.067, 1.233)	(1.198, 1.409)
STUBI	0.153^*	0.189^*	0.123^*	0.092^*
	(0.117, 0.188)	(0.142, 0.234)	(0.090, 0.157)	(0.058, 0.125)
TEABI	-0.062^*	-0.075^*	-0.052^*	-0.063^*
	(-0.093, -0.030)	(-0.132, -0.022)	(-0.085, -0.015)	(-0.105, -0.021)
RESSI	-0.020	-0.010	-0.032^*	-0.001
	(-0.043, 0.003)	(-0.043, 0.023)	(-0.057, -0.005)	(-0.028, 0.024)
STAFI	0.027^*	-0.033	-0.001	0.018
	(0.005, 0.050)	(-0.081, 0.013)	(-0.029, 0.025)	(-0.015, 0.054)
COMP	0.031^*	0.013	0.031^*	-0.019
	(0.014, 0.050)	(-0.015, 0.042)	(0.009, 0.055)	(-0.046, 0.007)
SCSIZE	0.0003^*	0.0001	-0.0001	0.0001
	(0.0002, 0.0004)	(-0.0001, 0.0002)	(-0.0002, 0.0000)	(-0.0001, 0.0003)
LOC	-0.010	-0.130^*	-0.056^*	-0.070^*
	(-0.043, 0.022)	(-0.191, -0.068)	(-0.094, -0.018)	(-0.119, -0.027)
TOTAT	-0.004^*	-0.002^*	0.0001	-0.003
	(-0.005, -0.002)	(-0.004, -0.0001)	(-0.001, 0.001)	(-0.006, 0.0001)

For The baseline efficiencies (when all variables are at zero) for the schools in all countries are statistically significant, suggesting a positive starting point for school efficiency. The intercepts vary across countries,

with Hungary having the highest baseline efficiency (1.331) followed by Slovakia (1.305), Poland (1.152), and Czech Republic (1.076). For Student Behavioral Issues the coefficients (STUBI) indicate the impact of student behavioral issues on school efficiency. All countries show a positive and significant relationship, suggesting that as student behavioral issues increase, so does the efficiency, which may seem counterintuitive indeed and could indicate that there might be omitted variables that may influence the relationship. Hungary has the highest coefficient (0.189), suggesting student behavioral issues have a more pronounced impact there compared to other countries. This might also suggest that in these four countries the schools manage to improve their efficiency despite the student related issues. In all countries, teacher behavior issues coefficients (TEABI) are negative and significant, meaning that teacher behavioral issues reduce school efficiency. The impact is greatest in Hungary (-0.075), indicating that teacher behavioral issues are a more significant problem for school efficiency there than in other countries. Hungary is followed by Czech Republic (-0.062) and closely Slovakia (-0.063) and lastly Poland (-0.052.) who also has the second lowest average value of this variable across its schools. Poland is also the only country that shows a significant negative coefficient (-0.032) for resource issues (RESSI), meaning that in Poland, lacking resources significantly reduces its schools' efficiency, this is also aligned with its average value regarding this variable with the lowest average issues among the rest of the countries. In other countries, this relationship is not statistically significant. Regarding staff issues (STAFI) Czech Republic is the only country where this variable have a statistically significant positive effect on school efficiency (0.027). This could suggest that in Czech Republic, schools manage to maintain or even improve efficiency despite staff-related challenges. Moreover, School competition seems to significantly improve efficiency only in Czech Republic and Poland, both with coefficients of (0.031), this could indicate that the presence of more schools in a given area positively influence the efficiency of these schools. The impact in Slovakia is negative but not significant whereas in Hungary it's positive but also not significant. School size (SCSIZE) impacts efficiency positively and significantly only in Czech Republic (0.0003), indicating that larger schools tend to be more efficient there. In the rest of the other countries, the effect of school size varies in sense (positive for Hungary and Slovakia and negative for Poland) and is not significant. Although despite its significance in Czech Republic the coefficient is very small for an actual effect on its efficiency. Additionally, The location of the school (LOC) shows significant negative coefficients for Hungary (-0.130), Poland (-0.056), and Slovakia (-0.070), as well as Czech Republic (-0.01) but insignificant, indicating that schools in rural areas (LOC = 0) are more efficient than those in urban areas (LOC = 1), especially in Hungary where the influence of this variable is notably larger. Lastly, for the number of teachers (TOTAT), its impact on school efficiency is negative and significant in Czech Republic and Hungary, suggesting that having more teachers than necessary could reduce efficiency. In Poland, the coefficient is positive but not significant, while in Slovakia, it's negative but not significant.

Discussion and concluding remarks

The results we discussed in the previous section, despite its usefulness provide counter intuitive insights in some cases, this might be due to several factors especially one concern of ours regarding the data used for the second stage. In fact, behavioral variables (STUBI and TEABI) are aggregated from different levels, the student behavioral issues were first aggregated from different other variables as discussed in section 2, then aggregated by school, wherhas for the teacher behavior issues, it was a simple horizontal aggregation from different variable, as the data in this context is already at school level. Moreover, these two variables along with resources issues and staff issues might not properly fit as environmental variables for a second stage. However, they might be considered as undesirable inputs and can be used in the DEA estimation in the first stage using a Directional Distance Function ((Chambers 1996)). Additionally and more importantly, the double-bootstrap truncated regression procedure of (Leopold Simar and Wilson 2007) requires the satisfaction of multiple assumption of its DGP. This has been explicitly discussed and argued in the initial paper and in (Léopold Simar and Wilson 2011) by emphasizing on the separability condition mentioned in assumptions 1 and 2 in (Leopold Simar and Wilson 2007), this condition simply mean that the second stage variables should not depend on the first stage variables (outputs). To properly use the double-bootstrap, this condition must be first tested, which can be a major area of improvement for our study. To summarize, we conducted a two-stage DEA analysis with a double-bootstrap truncated regression in the second stage to investigate the influence a set of non-discretionary variables affect the efficiency of a sample of schools in the four Visegrad countries. Our results showed that each country has its own strengths and weaknesses in terms of

their efficiencies, what drives them, and how they are influenced by the seconds stage variables. Given the specifications we used in our analysis Poland is the most efficient country with science related subject driving this efficiency (similar to Czech schools), which means that their schools' efficiency can be improved if more effort is made to improve the quality of teaching and the results in math and reading, Polish schools are also sensitive to resources issues as shown by the second stage results. Additionally, math is the most important subject for Hungarian and Slovakian schools, which also means that there is an area of improvement in terms of efficiency if more effort in other subjects in terms of quality of education and resources.

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