Full research paper

A STATE-LEVEL ANALYSIS OF MEXICAN EDUCATION AND ITS IMPACT ON REGIONAL, ECONOMIC, AND SOCIAL DEVELOPMENT: TWO-STAGE NETWORK DEA APPROACH

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ABSTRACT

Education has been considered a cornerstone for human and economic development. Although there is a national educational strategy in most countries, various implementations are at the state level. This paper studies academic efficiency at the primary and secondary levels and the human development dimensions – long and healthy life, being knowledgeable, and enjoying a decent standard of life – at the state level. For this purpose, a network data envelopment analysis (NDEA) with two stages was proposed. The first stage studies the educational process efficiency, while the second evaluates its impact in the form of the human development index. The study found significant differences between the evaluated states in the education stage, where the lowest efficiencies are mainly in the southwest of Mexico. The results also indicate that better education quality leads to greater regional, economic, and social development at the state level. This study contributes to the NDEA applications on the understanding of the impact that education has in improving the development of the regions holistically.

KEYWORDS

Data Envelopment Analysis, human development index, Mexico, regional development, educational efficiency

HOW TO CITE

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Highlights

- *A Network Data Envelopment Analysis model was constructed to evaluate the impact of education on regional, economic, and social development in Mexico.*
- *The best-evaluated states in education reported lower Teacher/Student and School/Student ratios compared to the less efficient states.*
- *The best-evaluated states in education have better regional, economic, and social development.*

INTRODUCTION

The education system in Mexico faces several problems mainly related to social and regional gaps. The system lacks teaching staff, educative materials, innovation of study programs and plans, and insufficient school infrastructure and services. In 2018, 25% of teaching positions at primary and secondary levels were not contracted, which resulted in an average of 34 students per teacher (García, 2018). This situation improved during the last years, and by 2022 the student-teacher ratio was 23.71 in primary education, 15.55 in secondary education, and 11.77 in the high school level (SEP, 2022). Still, the OECD average is around 13 students per teacher (OECD, 2022).

This goes in hand with the government expenditures on education. In OECD countries, expenses per student in primary to tertiary education grew by an average of 1.7% between 2012 and 2019. However, in Mexico, average spending per student fell by 0.3-0.5% per year as students' numbers grew faster than educational expenditures (OECD, 2022). Consequently, nationwide, primary school teachers are paid around 40% less than the OECD average during the first

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ten years of teaching experience and approximately 26% lower at the secondary level (OECD, 2022). Furthermore, as García (2018) stated, 40% of teachers did not complete required training programs, and 3 out of 10 teachers in primary education do not have a higher education degree.

The lack of quality education and, consequently, inadequate social development and shortage of economic opportunities have led to a higher migration to more prosperous and more developed regions (Eggert et al., 2010). Access to education is lower for vulnerable groups, especially in the rural areas. Limited access to schools due to a long distance is considered a significant barrier to education (Ama et al., 2020; Falch et al., 2013; Liu and Xing, 2016), as lower population density and longer distances can make education investments costly (Cattaneo et al., 2022). Regarding Mexico and rural communities, 6 out of 10 persons from 15 to 17 years old live isolated and without nearby schools, 13.2% of children and youth in extreme income poverty do not attend compulsory education, and 3 out of 10 students drop out the school due to lack of money (García, 2018).

Limited access to education is crucial in primary school completion and transition to the secondary school level. According to SEP (2022), the net enrollment rate in Mexican primary education dropped from 94.8% in 2014 to 89.8% in 2022. In addition, the terminal efficiency in primary education was 96.7% nationwide, 91.0% in secondary education, and 64.9% in high school. In this case, allocating more resources to educational programs may mitigate such interregional migration and increase regional economic performance (Eggert et al., 2010).

This study aims to evaluate Mexican education's efficiency and its impact on regional, economic, and social development. For this purpose, a two-stage network Data Envelopment Analysis (NDEA) model is proposed. The analysis uses data from the Mexican National Educative system and data related to Human Development Index in Mexico, both for all 32 Mexican states. This analysis targets to respond to the following research questions:

- *RQ1: What is the efficiency level of education process regarding the analyzed academic levels?*
- *RQ2: Can significant differences in educational efficiency be observed regarding the academic level?*
- *RQ3: What factors lead to higher educational efficiency?*
- *RQ4: Does higher educational efficiency lead to better regional, economic, and social development in the Mexican states?*

The rest of the article is divided as follows: In the next section, we present a brief literature review of Data Envelopment Analysis (DEA) applications in education and regional and economic development; in Materials and methods, we describe the two-stage DEA methodology and introduce the model structure and dataset; in Results, we calculate the efficiency scores and investigate a relationship between education and regional, economic and social development; in Discussion, the obtained results are analyzed, we suggest possible implications of the results and mention several limitations of the analysis; finally, we conclude the article with future research directions.

Literature review

Non-parametric efficiency evaluations

Data Envelopment Analysis (DEA) is a non-parametric technique used to evaluate efficiency and productivity with a comprehensive record of successful applications in numerous sectors (Emrouznejad and Yang, 2018; Liu et al., 2013; Mahmoudi et al., 2020). For example, Avilés-Sacoto et al. (2020) used DEA methodology to investigate the regional efficiency of innovation systems; Ferro and Romero (2021) constructed a DEA model to determine countries' efficiency in producing codified knowledge. Flegl and Hernández Gress (2023) applied DEA to evaluate the efficiency of public security in Mexico; Moghaddas et al. (2022) assessed a resource allocation in a sustainable supply chain based on DEA modeling; Wu and Lin (2022) applied a DEA model to measure the performance of cultural tourism of several Asian tourist destinations.

The value of the DEA methodology is its capability to evaluate the individual efficiency or performance of a Decision-Making Unit (DMU) within a set of homogeneous DMUs operating in a specific application domain (Liu et al., 2013). DEA requires very few assumptions about the variables´ selection, and it is a methodology directed to frontiers rather than central tendencies. Instead of trying to fit a regression plane through the center of the data, DEA tries to stay on top of the observations by calculating an efficiency frontier (Cooper et al., 2011).

Efficiency evaluations in education

The DEA methodology has a long history of applications in education. These applications differ regarding the educational, institutional, and/or regional level point of view. For example, considering recent publications, many authors evaluated the efficiency at an institutional level. Ben Yahia et al. (2018) assessed the educational efficiency of 105 public secondary schools in Tunisia. Chen et al. (2021) employed a two-stage DEA model to measure the operating efficiency of 52 universities in China regarding teaching and research activities. Halásková et al. (2022) investigated the efficiency of 26 private and public secondary education schools in Slovakia through the DEA analysis. Sagarra et al. (2017) investigated the research and teaching efficiency at 55 universities in Mexico. Santos Tavares et al. (2021) used a network DEA model to evaluate the financial, undergraduate, and graduate-level performance of 45 Brazilian federal universities. Shamohammadi and Oh (2019) employed a two-stage network DEA to evaluate the efficiency of 57 Korean private universities.

From a cross-regional/country perspective, Delprato and Antequera (2021) applied a DEA model to evaluate private-public schools' efficiency gap at the secondary level in Latin America. Minuci et al. (2019) used a DEA analysis to estimate the technical efficiency of West Virginia school districts, whereas Ramzi et al. (2016) analyzed the efficiency of primary and secondary education in 24 governorates in Tunisia. See et al. (2022) applied the hierarchical DEA model to assess the quality of higher education systems in 50 countries listed in the U21 National Higher Education Systems 2020 ranking. Williams et al. (2013) evaluated the performance of national higher education systems in 48 countries included in the National Science Foundation ranking.

Regarding study programs or course satisfaction applications, Fuentes et al. (2016) composed a three-stage DEA model to assess teaching efficiency in higher education to optimize the quality of the teaching process. Mendoza-Mendoza et al. (2023) used a DEA model to evaluate industrial engineering programs offered at Colombian higher education institutions.

Data Envelopment Analysis and Education Quality

Education quality is a measure of the efficiency of an educational process. It can be viewed from different perspectives, as quality is a complex multi-dimension concept (Ahmad, 2015), including multiple factors. These factors should synergize to satisfy all stakeholders (Velásquez Rodríguez et al., 2022). These factors usually include educational resources and infrastructure, students, teachers, administrative employees, and teaching and learning outcomes (Flegl and Andrade Rosas, 2019; Gambhir et al., 2016; Jalongo et al., 2004; Sahu et al., 2013; Udouj et al., 2017; Velásquez Rodríguez et al., 2022).
From the perspective of the DEA models, education quality can be understood as a process of transforming the available resources into teaching and learning outcomes. In this way, school quality can be grasped as a capability to prepare students to perform well on standardized tests and the labor market during their professional life (Flegl and Andrade Rosas, 2019; Hanushek and Woessmann, 2008). Considering this definition, the common set of inputs in DEA models consists of expenditures in education or Research & Development (Santos Tavares et al., 2021; See et al., 2022;); funding (Chen et al., 2021; Shamohammadi and Oh, 2019; Williams et al., 2013); Number of students and international students (Chen et al., 2021; See et al., 2022;); Number of academic and non-academic employees (Chen et al., 2021; Minuci et al., 2019; Sagarra et al., 2017; Shamohammadi and Oh, 2019).
On the other hand, the outputs usually cover enrollment rates (Santos Tavares et al., 2021; See et al., 2022); number of graduates (Sagarra et al., 2017; Williams et al., 2013); standardized test results (Delprato and Antequera, 2021; Minuci et al., 2019; Ramzi et al., 2016); dropout levels (Ben Yahia et al., 2018); graduates' employment (See et al., 2022); scientific outcomes, such as published scientific articles (See et al., 2022; Shamohammadi and Oh, 2019; Williams et al., 2013); granted research funds (Chen et al., 2021); generated patents (Chen et al., 2021; Santos Tavares et al., 2021; Shamohammadi and Oh, 2019); or international scientific collaboration (Williams et al., 2013).

Efficiency evaluations of regional and economic development

DEA has also been successfully applied for evaluating regional developments from various perspectives. For example, Chen (2017) deployed a DEA model to measure efficiency in Taiwan's counties regarding economic development, public security, social welfare, and education. Giménez et al. (2017) used a DEA model with desirable and undesirable outputs to evaluate the efficiency of generating social welfare regarding Mexico's Human Development Index (HDI). Marshall and Shortle (2016) used a DEA model to evaluate the quality of life within Mid-Atlantic states in the USA. Min et al. (2020) investigated regional technology development and commercialization efficiencies in South Korea using a two-stage DEA model. Moreno and Lozano (2016) measured public finance management efficiency concerning social welfare in 29 European governments. Qu et al. (2022) used a three-stage DEA model to observe regional sustainability performance regarding economic growth, waste disposal, and health protection.
Considering the impact of education on regional developments, Berbegal-Mirabent et al. (2013) assessed the efficiency of Spanish universities regarding knowledge transfer activities to enhance local industry systems. Rodionov and Velichenkova (2020) observed the link between universities and regional innovation system development in 85 regions in Russia. Vliamos and Tzeremes (2006) applied a DEA model to evaluate the efficiency of higher education systems in 20 OECD countries regarding their contribution to economic development.

Materials and methods

Data Envelopment Analysis

Charnes et al. (1978) developed the mathematical methodology known as Data Envelopment Analysis (DEA). It is used to compare the relative efficiency of a group of entities, commonly referred to Decision Making Units (DMUs). DEA lets compute the performance of each DMU in relation to every other DMU in the set by using mathematical programming tools. After calculating the efficiency ratings, DEA establishes an efficient frontier where the top-performing DMUs are situated. The remaining units outside the efficiency frontier are referred to as inefficient. However, DEA offers the frontier a chance to identify how the inefficient DMUs should modify in order to become efficient by radial projection (Cooper et al., 2011).
DEA is a linear programming technique that can handle multiple measures in a single integrated model. The measures are inputs, which are resources or factors that one aims to diminish, or outputs, which are outcomes or results that one seeks to maximize (Avilés-Sacoto et al., 2021). Two "return to scale" strategies are provided by DEA - the Constant Return to Scale (CRS) and the Variable Return to Scale (VRS). According to Avilés-Sacoto et al. (2020), the VRS is an extension of the CRS. Either the input orientation or the output orientation can be used to view CRS and VRS. The input orientation is used when evaluating how much input for a DMU can be decreased while maintaining performance. The output orientation is used when the output side needs to be improved and the inputs are difficult to control (Avilés-Sacoto et al., 2021).
Through time, the DEA's initial idea has been expanded in literature, covering a variety of theoretical and applied research fields. One is the Network DEA (N-DEA), particularly a two-stage DEA process. For example, the studies of Liang et al. (2006), Kao (2009), Tone and Tsutsui (2009), Cook and Zhu (2014), and Cook et al. (2010) present a review of network models, including a two-stage process or multi-stage situations in DEA. Among the different two-stage structures analyzed in DEA is the serial process. In this type of setting, the outputs from the first stage serve as the inputs

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to the second stage; this is the most frequent two-step setting examined in the DEA literature. Other two-stage systems are closed -in that nothing enters or exits the system in between the stages. Some variations of this allow outputs from Stage 1 to leave the system and inputs to Stage 2 to enter the system at that point (Avilés-Sacoto et al., 2015).

For the paper herein, it was considered a serial process, where the outputs from the first stage serve as the inputs to the second stage.

Model structure and research questions

The structure of the DEA model is presented in Figure 1. The analysis uses a two-stage network process design divided into the education and development stages. The first stage aims to evaluate the educational process regarding three academic levels: Primary school (ISCED level 1, equivalent of *primaría* level in Mexico), Junior high school (ISCED level 2, equivalent of *secundaría* level in Mexico), and High school (ISCED level 3, equivalent of *preparatoría* level Mexico) (UNESCO, 2012).

Considering the common DEA model structures in education and the evaluated three academic levels, the teacher-student ratio (TSR) represents the first input. Educational analyses and statistics usually utilize a student-teacher ratio (e.g., Brunello and Checchi, 2005; Vliamos and Tzeremes, 2006). However, reflecting the DEA methodology, the bigger the TSR is, the more time a teacher can devote to each student's needs, and less amount of class time is needed to deal with disruptions, which should be reflected in higher outcomes and school attainment (Kedagni et al., 2021), i.e., securing better education quality. Similarly, the second input constitutes the school-student ratio (SSR), which reflects the accessibility of education. A similar approach was also used by Ramzi et al. (2016) and Halásková et al. (2022), who used the number of teachers per 100 students, the number of classes per 100 students, and the number of schools per million inhabitants as measures describing schools' quality.

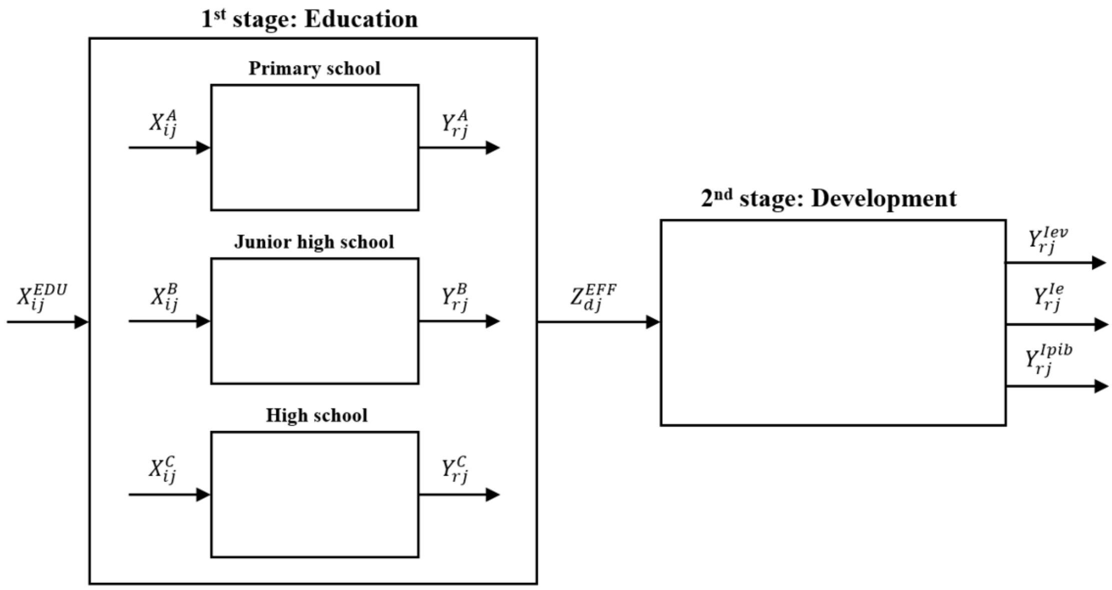

Figure 1: Two-stage model structure (own elaboration)

On the other hand, the outputs of the 1st stage consist of terminal efficiency (TE), enrollment rate (ER), and dropout rate (DR). The TE represents a percentage of students who completed an academic level on time according to the number of years programmed, i.e., a proportion of a cohort that finishes the academic level in the established time. The ER is the proportion of the total enrollment of a determined academic level, with respect to the population of official age to study the level. This indicator shows the percentage of the potential demand for a given academic level being met. A higher gross enrollment rate for an academic level is interpreted as a higher school attendance by the population in the statutory ages[1]. Finally, the DR is the percentage of students who drop out of school activities during the school year and at the end of it, compared to the total number of students enrolled in the school year[2]. The dropout rate represents an undesirable output (Chen et al., 2018; Flegl and Hernández Gress, 2023; Seiford and Zhu, 2002) of each academic level. Each sub-model (primary school, junior high school, and high school) has the same input-output structure with data linked to its corresponding academic level.

The second stage of the DEA model aspires to investigate the impact of education on regional, economic, and social development. In this scope, excluding the above-mentioned educational variables, the DEA models incorporate variables linked to the unemployment rate (Chen, 2017; Murias et al., 2006; Vliamos and Tzeremes, 2006); income (Murias et al., 2006; Vliamos and Tzeremes, 2006); gross domestic product

1 It is important to mention that this indicator is sensitive to the migration of the population and figures greater than 100% can be reached if students from neighboring states register as new students.

2 When the indicator is positive, it is probable that dropout will only occur to a degree in a given school cycle; sometimes the percentage can be negative, due to the fact that during the school year under study there were more students who enrolled as ''admitted'' than those who stated that they were ''withdrawn'' from school.

(Giménez et al., 2017; Moreno and Lozano, 2016; Qu et al., 2022; Rodionov and Velichenkova, 2020); literacy (Giménez et al., 2017; Marshall and Shortle, 2016); life expectancy (Qu et al., 2022); innovative activities (Rodionov and Velichenkova, 2020); among others.

So, to intend capturing development in all three areas, we take the Human Development Index (HDI) as the outcome of this stage. The HDI measures the average achievement in several key dimensions of human development, such as (i) a long and healthy life, (ii) being knowledgeable, and (iii) having a decent standard of living. The HDI has been calculated as the geometric mean of the normalized indices for each of the three dimensions (UNDP, 2023):

$$\mathrm{HDI} = \frac{1}{3} I_{LEI} + \frac{1}{3} I_{EI} + \frac{1}{3} I_{GDP} \tag{1}$$

where I_{LEI} is the Life expectancy index (LEI), I_{EI} is the Education index (EI), which is calculated as 2/3 of Literacy level and 1/3 of Net enrollment rate, and I_{GDP} is Gross domestic product (GDP) per capita. To secure comparability between GDP and the other two outputs, we used an ideal normalization of GDP. In this case, the highest GDP equals 100, and the rest GDPs vary between 0 and 100 correspondingly. We assume that LEI represents regional development, EI represents social development, and GDP represents economic development. These three dimensions of the HDI are then used as independent outputs for the 2nd stage of the analysis.

This idea takes a similar approach as Murias et al. (2006), who decomposed a synthetic economic well-being index based on the Index of Economic Well-being (Osberg and Sharpe, 1998) to evaluate the economic situation of 50 Spanish provinces regarding consumption capacity, wealth stocks, inequality, and economic insecurity. The HDI as an output in DEA models has been used by several authors (e.g., Despotis, 2005; Giménez et al., 2017; Van Puyenbroeck and Rogge, 2020).

The obtained efficiency scores in the 1st stage from the three academic levels defined above were used as the inputs for the 2nd stage. Thus, considering a two-stage DEA process described, for example, by Kao and Hwang (2008) or Chen et al. (2018), these inputs were considered as intermediates variables.

Data

The state-level analysis includes records for all 32 Mexican states for 2021. More precisely, in the case of education, the data covers the school year 2020/2021 in all three academic levels- primary (PRI), junior high (JHS), and high school (HS). The TSR, TSS, TE, ER, and DR indicators for the first stage of the DEA model were collected or calculated from the Interactive education statistics consultation system of the Secretary of Public Education (Secretaría de Educación Pública) published by the Mexican National Institute of Statistics and Geography (INEGI, 2023a). Table 1 summarizes the descriptive statistics of the selected indicators.

Academic level	Indicators	Max	Min	Mean	Standard deviation
Primary school					
Input (*x*)	Teacher/Student Ratio (TSR)	0.124	0.068	0.089	0.015
	School/Student Ratio (SSR)	0.028	0.007	0.015	0.006
Output (y)	Terminal Efficiency (TE)	103.100	89.200	97.478	3.275
	Enrollment Rate (ER)	114.300	87.500	96.428	4.966
	Dropout Rate (DR)	2.000	-2.000	0.363	0.838
Junior high school					
Input (*x*)	Teacher/Student Ratio (TSR)	0.201	0.055	0.115	0.035
	School/Student Ratio (SSR)	0.035	0.002	0.012	0.008
Output (y)	Terminal Efficiency (TE)	96.800	78.500	90.950	3.577
	Enrollment Rate (ER)	111.200	73.500	83.797	6.795
	Dropout Rate (DR)	8.100	-0.900	2.944	1.707
High school					
Input (*x*)	Teacher/Student Ratio (TSR)	0.151	0.049	0.097	0.026
	School/Student Ratio (SSR)	0.008	0.002	0.005	0.001
Output (y)	Terminal Efficiency (TE)	76.200	55.300	64.922	4.566
	Enrollment Rate (ER)	98.400	50.200	62.163	8.711
	Dropout Rate (DR)	16.500	1.000	12.788	3.191

Table 1: Introduction of indicators and descriptive statistics of the data set for the education stage

For the second stage of the DEA model, the Life expectancy of the population was obtained from Demography and Society – Population statistics published by the Mexican National Institute of Statistics and Geography (INEGI, 2023b). The Literacy level and Net enrollment rate required for calculating the Education index (EI) were obtained from the Interactive Education Statistics Consultation System of the Secretary of Public Education (INEGI, 2023a). Finally, gross domestic product (GDP) per capita was acquired from the Mexican National Institute of Statistics and Geography (INEGI, 2023c). The GDP per capita was normalized to secure comparability between all three indexes (outputs) used in the second stage of the analysis. Table 2 presents the descriptive statistics of the indexes.

MaxDEA Ultra 7 software was used for all the efficiency calculations. In this case, a CCR output-oriented DEA model was performed in both stages; to eliminate possible drawbacks in determining the best efficient DMUs when $\varepsilon = 0$, as several

	Indicators	Max	Min	Mean	Standard deviation
Output (y)	Life Expectancy Index (LEI)	76.600	73.300	75.219	13.108
	Education Index (EI)	93.798	83.975	90.463	15.939
	Gross Domestic Product (GDP)	100.000	23.823	49.190	18.925

Table 2: Introduction of indicators and descriptive statistics of the data set for the development stage

inputs and outputs can be omitted from the model (Dyson et al., 2001; Toloo, 2014), the non-Archimedean element ε was set equal to 0.3 (i.e., an absolute weight restriction) after several simulations. IBM SPSS Statistics 26 was used for the statistical part of the analysis.

RESULTS

This study is divided into two parts. First, the educational process results are described; second, the education's impact on regional, economic, and social development is investigated.

1st stage: education

The first stage of the analysis is divided into three sub-models. Regarding the Primary school level, the average efficiency was 0.740 with a standard deviation (StDev) of 0.194. The highest efficiency was obtained by Ciudad de México (1.000), Yucatán (1.000), Baja California (0.962), Querétaro (0.925), and Quintana Roo (0.922). On the other hand, the worst efficiency can be observed in Michoacán (0.471), Veracruz (0.492), Durango (0.538), Chiapas (0.552), and Hidalgo (0.690). With greater detail, the Top 5 states registered 13.16% lower TSR and 33.94% lower SSR compared to the national average. However, on the other hand, these states reported 6.15% bigger ER, 254.48% lower DR, and 2.53% bigger TE. Comparing this with the five worst states, which registered +23.97% TSR, +54.27% SSR, -0.44% ER, +192.41% DR, and -2.44% TE compared to the national average. The complete results are summarized in Table 3.

Considering the Junior high school level, the average efficiency was 0.630 with a StDev of 0.200. This represents an efficiency drop of 0.110 compared to the previous education level (Table 3). The best-evaluated states are Ciudad de México (1.000), Yucatán (1.000), Nuevo León (0.964), Sonora (0.902), and Querétaro (0.791), whereas the worst-evaluated states are Oaxaca (0.353), Chiapas (0.389), Michoacán (0.430), Guerrero (0.462), and Durango (0.469). Using the same detail about the inputs and outputs of this sub-model, the best-evaluated states have TSR -33.94% and SSR -54.62% compared to the national average, with ER +8.26%, DR -66.71% and ET +3.79%. The worst-evaluated states record opposite tendencies: TSR was +45.44% and SSR +104.80%, ER -8.35%, DR +74.61%, and ET -5.66%.

Finally, the high school educational level obtained an average efficiency of 0.791 with a StDev of 0.175. This result indicates that the high school level is the best of the three sub-models, with the lowest variability among the states. The best-evaluated states are Chiapas (1.000), Ciudad de México (1.000), Jalisco (1.000), Tabasco (1.000), and Nuevo León (0.974). The worst-evaluated states are Morelos (0.626), Colima (0.635), Nayarit (0.675), Veracruz (0.684), and Chihuahua (0.693) (Table 3). In this case, the top 5 states registered -11.07% TSR, -34.23% SSR, +7.24% ER, -36.03% DR, and +0.89% TE compared to the national level. On the other hand, the worst five states registered +18.82% TSR, +37.07% SSR, -5.83% ER, +12.14% DR, and -4.35% TE.

Based on the obtained results and regarding the RQ3, the analysis revealed that although the best-evaluated states register more students per teacher and school ratios, they achieve higher enrollment rates, terminal efficiency, and lower dropout rates. This suggests that better educational results instead depend on quality than the quantity of teaching staff. In this case, teaching quality is linked to teachers' education, experience, and training (Canales and Maldonado, 2018; Clotfelter et al., 2007; Ome et al., 2017).

Considering the RQ2 and applying the Tuckey test, there are significant differences between the efficiencies of each academic level. More precisely, the JHS efficiencies are significantly lower compared to the HS efficiencies ($p < 0.001$) and the PRI efficiencies ($p = 0.008$).

2nd stage: development

The second stage of the analysis evaluates the impact of education on the regional, economic, and social development expressed by the HDI. For this, the obtained efficiency scores from the previous stage are used as the inputs, and HDI indicators are used as the outputs. The average efficiency of the development stage is 0.842 with StDev 0.098 (Table 3). These numbers indicate a high efficiency across all the analyzed states with a low variation. Both parameters are the highest/lowest considering the three sub-models in the 1st stage.

The highest efficiency was obtained by Colima (1.000), Michoacán (1.000), Oaxaca (1.000), Veracruz (1.000), and Durango (0.980). On the other hand, the lowest efficiencies were obtained by Yucatán (0.665), Estado de México (0.714), Ciudad de México (0.721), Tabasco (0.721) and Puebla (0.730). In most cases, we can see an inverse position of the states considering the first stage of the analysis (Table 3). For example, Ciudad de México was ranked within the top 5 in all three academic levels, Yucatán was in the top 5 in Primary and Junior high school levels, and Tabasco was within the best-evaluated in High school level. Similarly, Michoacán, Oaxaca, and Veracruz were ranked among the worst-evaluated at each level.

In more detail, the worst efficient states in the 2nd stage reported higher educational efficiencies in PRI (+15.75%), in JHS (+25.33%), and in HS (+19.76%) compared to the national average. Their education quality also resulted in higher HDI, +0.19% in regional development, +12.36% in economic development, and +1.01% in social development. However, these developments were not significantly higher than the most-efficient states in the 2nd stage. Putting this into context with the best-evaluated states in the 2nd stage, these states obtained 24.77% lower efficiency in PRI, -28.27% in JHS, and -10.60% in HS levels compared to the national average. Even though their HDI indicators are -0.48% in regional development, -3.36% in social development, and -12.38% in economic development, their impact of education on HDI is relatively higher than the worst-evaluated states.

So, considering the RQ4, we can conclude that higher education quality leads to higher regional, economic, and social development. However, this development is not reflected in higher efficiency in the development stage. This means that the impact of education on development should be much higher. Figure 2 summarizes the results of the three sub-models from the first stage and the efficiency results in the second stage. It can be seen that there is no clear relationship between educational quality and development stages.

State	Efficiency PRI	PRI position	Efficiency JHS	JHS position	Efficiency HS	HS position	Efficiency HDI	HDI position
Aguascalientes	0.889	6	0.633	16	0.709	23	0.806	19
Baja California	0.962	3	0.776	7	0.697	27	0.809	18
Baja California Sur	0.806	11	0.654	13	0.732	21	0.878	12
Campeche	0.620	26	0.538	22	0.783	15	0.863	15
Chiapas	0.552	28	0.389	31	1.000	1	0.943	6
Chihuahua	0.839	9	0.789	6	0.693	28	0.801	20
Ciudad de México	1.000	1	1.000	1	1.000	1	0.721	30
Coahuila	0.814	10	0.683	9	0.773	16	0.770	24
Colima	0.659	23	0.529	23	0.635	31	1.000	1
Durango	0.538	29	0.469	28	0.707	25	0.980	5
Estado de México	0.721	18	0.655	11	0.795	12	0.714	31
Guanajuato	0.748	16	0.558	19	0.705	26	0.782	22
Guerrero	0.514	30	0.462	29	0.847	9	0.791	21
Hidalgo	0.690	20	0.655	12	0.741	20	0.937	7
Jalisco	0.842	8	0.639	15	1.000	1	0.867	13
Michoacán	0.471	32	0.430	30	0.746	19	1.000	1
Morelos	0.688	21	0.556	20	0.626	32	0.912	9
Nayarit	0.678	22	0.507	24	0.675	30	0.916	8
Nuevo León	0.885	7	0.964	3	0.974	5	0.735	27
Oaxaca	0.623	25	0.353	32	0.763	17	1.000	1
Puebla	0.699	19	0.649	14	0.912	6	0.730	28
Querétaro	0.925	4	0.791	5	0.783	14	0.739	26
Quintana Roo	0.922	5	0.552	21	0.824	11	0.864	14
San Luis Potosí	0.608	27	0.478	26	0.848	8	0.906	10
Sinaloa	0.802	13	0.609	17	0.718	22	0.845	16
Sonora	0.804	12	0.902	4	0.763	17	0.760	25
Tabasco	0.741	17	0.657	10	1.000	1	0.721	29
Tamaulipas	0.765	14	0.722	8	0.708	24	0.829	17
Tlaxcala	0.757	15	0.565	18	0.857	7	0.770	23
Veracruz	0.492	31	0.477	27	0.684	29	1.000	1
Yucatán	1.000	1	1.000	1	0.825	10	0.665	32
Zacatecas	0.626	24	0.505	25	0.787	13	0.882	11
Average	**0.740**	-	**0.630**	-	**0.791**	-	**0.842**	-
StDev	**0.194**	-	**0.200**	-	**0.175**	-	**0.098**	-

Table 3: 1st stage and 2nd stage efficiency results (own elaboration)

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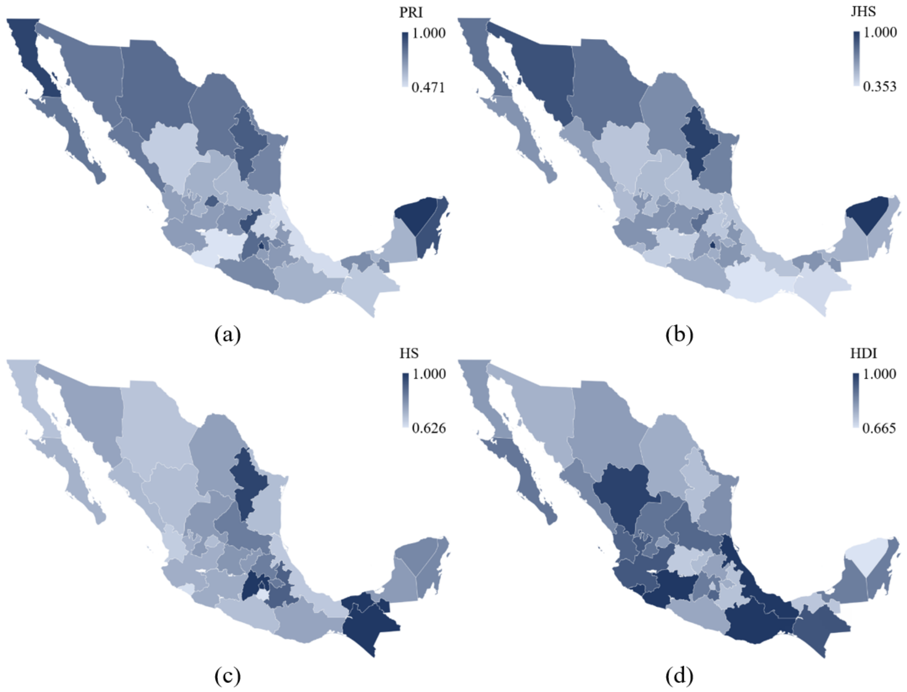

Figure 2: Results of the two-stage network process: (a) Primary school level efficiency; (b) Junior high school level efficiency; (c) High school level efficiency; (d) Human development index level efficiency (own elaboration using GeoNames, Microsoft, TomTom tool)

DISCUSSION

The article's main objective was to investigate Mexican education's efficiency and its impact on regional, economic, and social development. Regarding the first stage (RQ1), the analysis indicates a congruence in the obtained scores to some extent. In many cases, the best and worst-evaluated states remain similar in all three levels, and the differences between both sides of the ranking are significant. For example, at the PRI level, the two worst-evaluated states obtained an educational efficiency of 0.471 and 0.492, respectively. Similarly, at the JHS level, the worst-evaluated states had an efficiency of 0.353 and 0.389, whereas at the HS level, 0.626 and 0.653. So, we can conclude that significant differences in educational efficiency can be observed regarding the academic level (RQ2).

Considering the definition of education quality, the observed differences can be linked to the states' capability to transform available resources into teaching and learning outcomes. The DEA model supposed that a bigger teacher-student ratio and better access to education (expressed by the school-student ratio) would lead to better educational results. However, the analysis did not confirm this, as the best-evaluated states in all levels reported lower TSR and SSR compared to the less efficient states (RQ3). For example, at the JHS level, the best-evaluated states had TSRs of 33.94% and SSRs of 54.62% lower than the national average. This is in contradiction, for example, with Brunello and Checchi (2005) and Kedagni et al. (2021), who found that the lower students–teacher ratio (meaning higher teacher-student ratio) is positively correlated with higher educational attainment.

The results indicate that the quality of teaching and school infrastructure play a more critical role than the quantity of both. Regarding teaching quality, our results align with Clotfelter et al. (2007), who observed a positive effect of teacher experience, test scores, and regular licensure on students' achievements. Similarly, Buddin and Zamarro (2009) and Canales and Maldonado (2018) also found a positive effect of teachers' experience on students' learning outcomes. From the perspective of school infrastructure, Barragan Torres (2017) and No et al. (2016) investigated that school characteristics are an important factor in students' school attendance, dropout rates, and increased transition outcomes between educational levels. Similarly, Ben Yahia et al. (2018) observed that more resources should be spent on improving school buildings and materials to enhance educational efficiency and decrease dropout numbers.

Further, as shown in Figure 2, the lowest educational efficiencies are mainly in the southwest of Mexico, which may result in lower regional development and economic opportunities due to the higher concentration of highly skilled workers in other parts of the country (Eggert et al., 2010; Giménez et al., 2017). If we leave the efficiency point of view, then the best-evaluated states in the 1st stage of the DEA model have better HDI indicators. For example, Ciudad de México reached 1.000 efficiencies in all three sub-models in the first stage and has a 1.84% bigger life expectancy index, 3.38% bigger education index, and 103.29% bigger GDP per capita. Similarly, Estado de México has an LEI of +3.00%, EI of +10.14%, and GDP of +86.54%, whereas Puebla +2.18%, +6.22%, and +36.55%, respectively. This result corresponds with the research presented by Giménez et al. (2017), who demonstrated the highest efficiency in generating HDI in Aguascalientes, Baja California Sur, Campeche, Ciudad de México, Colima, Estado de México, and Nuevo León. In contrast, Coahuila, Durango, Hidalgo, Michoacán, Oaxaca, Sinaloa, and Veracruz were the least efficient states.

However, if the efficiency point of view of the 2nd stage is considered, the analysis did not prove the impact of better educational process on bigger regional, economic, and social development (RQ4). The results revealed that the least efficient states in the education stage were the most efficient states in the development stage. For example, Oaxaca and Veracruz reached a development efficiency of 1.000, although Oaxaca was ranked 25th in PRI, 32nd in JHS, and 17th in HS, and Veracruz ranked 31st, 27th, and 29th. On the other hand, the least efficiency in the development stage was obtained by Ciudad de México (0.770), Estado de México (0.714), and Yucatán (0.665), i.e., states with high efficiencies in PRI, JHS, and HS. Therefore, we can conclude that higher education quality leads to better regional, economic, and social development, but the difference is not significant, resulting in lower technical efficiency of Ciudad de México, for example.

Study limitations

The presented analysis has several limitations. First, the state-level analysis may be misleading as significant differences between municipalities in each state exist (expressed by marginality index, for example). So, it would be desirable to apply the DEA model on a municipality level to precise the obtained results. However, the availability of some indicators may limit the feasibility of such an analysis. Second, the analysis used only one school period (2020/2021). This may result in biased results in some cases due to extraordinary events (such as local pandemic closures of schools, natural disasters, etc.), resulting in worse educational outcomes. Therefore, the analysis should be extended to cover more periods. The Malmquist index or Window Analysis models could be used from the DEA methodology to evaluate the efficiency developments. Third, we were unable to incorporate government expenditures in education into the model due to its unavailability. The education expenditures may enhance the obtained results considering resource allocation.

CONCLUSION

This study developed a NDEA to answer four questions. The research found that the states with better education quality are not necessarily related to educational efficiency. We also found that the three academic levels are different in terms of educational efficiency. Lastly, we also found that educational efficiency is not improving the state's development. These findings suggest that education policymakers could allocate more resources to achieve academic quality rather than quantity and align academia with local needs. On the other hand, as politicians are allocating fewer resources to education, efficiency is a must, but effectiveness is needed first; effectiveness in this context has to do with improving the quality of life of the people in the state; efficiency in this context has to do with providing quality education with fewer resources.

Future research may go in several ways. Considering the mentioned limitations, the analysis can incorporate more school years into the evaluation to investigate the development of all parameters. Similarly, the other way can incorporate demographic parameters to assess the state's or regional specifics' impact on the efficiencies. A progression of this work also consists of measuring the NDEA robustness and considering a longitudinal study.

REFERENCES

Ahmad, S. Z. (2015) 'Evaluating student satisfaction of quality at international branch campuses', *Assessment & Evaluation in Higher Education*, Vol. 40, No. 4, pp. 488–507. https://dx.doi.org/10.1080/02602938.2014.925082

Ama, H. A., Morad, F. R. and Mukhopadyay, S. (2020) 'Assessment of stakeholders views on accessing quality and equity of basic education in rural communities of Abia State. Nigeria', *Educational Research and Reviews*, Vol. 15, No. 8, pp. 454–464. https://doi.org/10.5897/ERR2020.4018

Avilés-Sacoto, S. V., Cook, W. D., Güemes-Castorena, D. and Zhu, J. (2020) 'Modelling Efficiency in Regional Innovation Systems: A Two-Stage Data Envelopment Analysis Problem with Shared Outputs within Groups of Decision-Making Units', *European Journal of Operational Research*, Vol. 287, No. 2, pp. 572–582. https://doi.org/10.1016/j.ejor.2020.04.052

Avilés-Sacoto, S. V., Cook, W. D., Imanirad, R., and Zhu, J. (2015) 'Two-stage network DEA: When intermediate measures can be treated as outputs from the second stage', *Journal of the Operational Research Society*, Vol. 66, No. 11, pp. 1868–1877. https://doi.org/10.1057/jors.2015.14

Avilés-Sacoto, E. C., Avilés-Sacoto, S. V., Güemes-Castorena, D. and Cook, W. D. (2021) 'Environmental performance evaluation: A state-level DEA analysis', *Socio-economic Planning Sciences*, Vol. 28, 101082. https://doi.org/10.1016/j.seps.2021.101082

Barragan Torres, M. (2017) 'School and institutional effects on secondary education transitions in Mexico', *International Journal of Educational Research*, Vol. 85, pp. 68–86. https://doi.org/10.1016/j.ijer.2017.06.005

Berbegal-Mirabent, J., Lafuente, E. and Solé, F. (2013) 'The pursuit of knowledge transfer activities: An efficiency analysis of Spanish universities', *Journal of Business Research*, Vol. 66, No. 10, pp. 2051–2059. https://doi.org/10.1016/j.jbusres.2013.02.031

Ben Yahia, F., Essid, H. and Rebai, S. (2018) 'Do dropout and environmental factors matter? A directional distance function assessment of Tunisian education efficiency', *International Journal of Educational Development*, Vol. 60, pp. 120–127. https://doi.org/10.1016/j.ijedudev.2017.11.004

Brunello, G. and Checchi, D. (2005) 'School quality and family background in Italy', *Economics of Education Review*, Vol. 24, No. 5, pp. 563–577. https://doi.org/10.1016/j.econedurev.2004.09.001

Buddin, R. and Zamarro, G. (2009) 'Teacher qualifications and student achievement in urban elementary schools', *Journal of Urban Economics*, Vol. 66, pp. 103–115. http://dx.doi.org/10.1016/j.jue.2009.05.001

Canales, A. and Maldonado, L. (2018) 'Teacher quality and student achievement in Chile: Linking teachers' contribution and observable characteristics', *International Journal of Educational Development*, Vol. 60, pp. 33–50. https://doi.org/10.1016/j.ijedudev.2017.09.009

Cattaneo, A., Adukia, A., Brown, D. L., Christiaensen, L., Evans, D. K., Haakenstad, A., McMenomy, T., Partridge, M., Vaz, S. and Weiss, D. J. (2022) 'Economic and social development along the urban–rural continuum: New opportunities to inform policy', *World Development*, Vol. 157, 105941. https://doi.org/10.1016/j.worlddev.2022.105941

Charnes, A., Cooper, W. W. and Rhodes, E. (1978) 'Measuring the efficiency of decision making units', *European Journal of Operations Research*, Vol. 2, No. 6, pp. 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Chen, C. C. (2017) 'Measuring departmental and overall regional performance: applying the multi-activity DEA model to Taiwan's cities/counties', *Omega*, Vol. 67, pp. 60–80. https://doi.org/10.1016/j.omega.2016.04.002

Chen, L., Lai, F., Wang, Y.-M., Huang, Y. and Wu, F.-M. (2018) 'A two-stage network data envelopment analysis approach for measuring and decomposing environmental efficiency', *Computers & Industrial Engineering*, Vol. 119, pp. 388–403. https://doi.org/10.1016/j.cie.2018.04.011

Chen, Y., Ma, X., Yan, P. and Wang, M. (2021) 'Operating efficiency in Chinese universities: An extended two-stage network DEA approach', *Journal of Management Science and Engineering*, Vol. 6, No. 4, pp. 482–498. https://doi.org/10.1016/j.jmse.2021.08.005

Clotfelter, C. T., Ladd, H. F. and Vigdor, J. L. (2007) 'Teacher credentials and student achievement: Longitudinal analysis with student fixed effects', *Economics of Education Review*, Vol. 26, pp. 673–682. http://dx.doi.org/10.1016/j.econedurev.2007.10.002

Cook, W. D. and Zhu, J. (2014) *Data Envelopment Analysis: A Handbook on the Modeling of Internal Structures and Networks*, Springer: New York.

Cook, W. D., Liang, L., and Zhu, J. (2010) 'Measuring performance of two-stage network structures by DEA: A review and future perspective', *Omega*, Vol. 38, No. 6, pp. 423–430. https://doi.org/10.1016/j.omega.2009.12.001

Cooper, W., Seiford, L. and Zhu, J. (2011) *Handbook on data envelopment analysis*. New York: Springer. https://dx.doi.org/10.1007/978-1-4419-6151-8

Delprato, M. and Antequera, G. (2021) 'Public and private school efficiency and equity in Latin America: New evidence based on PISA for development', *International Journal of Educational Development*, Vol. 84, 102404. https://doi.org/10.1016/j.ijedudev.2021.102404

Despotis, D. K. (2005) 'Measuring human development via data envelopment analysis: the case of Asia and the Pacific', *Omega*, Vol. 33, No. 5, pp. 385–390. https://doi.org/10.1016/j.omega.2004.07.002

Dyson, R. G., Allen, R., Camanho, A. S., Podinovski, V. V., Sarrico, C. S. and Shale, E. A. (2001) 'Pitfalls and protocols in DEA', *European Journal of Operational Research*, Vol. 132, No. 2, pp. 245–259. http://dx.doi.org/10.1016/S0377-2217(00)00149-1

Eggert, W., Krieger, T. and Meier, V. (2010) 'Education, unemployment and migration', *Journal of Public Economics*, Vol. 94, No. 5–6, pp. 354–362. https://doi.org/10.1016/j.jpubeco.2010.01.005

Emrouznejad, A. and Yang, G.-L. (2018) 'A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016', *Socio-Economic Planning Sciences*, Vol. 61, pp. 4–8. https://doi.org/10.1016/j.seps.2017.01.008

Falch, T., Lujala, P. and Strøm, B. (2013) 'Geographical constraints and educational attainment', *Regional Science and Urban Economics*, Vol. 43, No. 1, pp. 164–176. https://doi.org/10.1016/j.regsciurbeco.2012.06.007

Ferro, G. and Romero, C. (2021) 'The Productive Efficiency of Science and Technology Worldwide: A Frontier Analysis', *Journal on Efficiency and Responsibility in Education and Science*, Vol. 14, No. 4, pp. 217–230. https://doi.org/10.7160/eriesj.2021.140402

Flegl, M. and Andrade Rosas, L. A. (2019) 'Do professor's age and gender matter or do students give higher value to professors' experience?', *Quality Assurance in Education*, Vol. 27, No. 4, pp. 511–532. https://dx.doi.org/10.1108/QAE-12-2018-0127

Flegl, M. and Hernández Gress, E. S. (2023) 'A two-stage Data Envelopment Analysis model for investigating the efficiency of the public security in Mexico', *Decision Analytics Journal*, Vol. 6, 100181. https://doi.org/10.1016/j.dajour.2023.100181

Fuentes, R., Fuster, B. and Lillo-Bañuls, A. (2016) 'A three-stage DEA model to evaluate learning-teaching technical efficiency: Key performance indicators and contextual variables', *Expert Systems with Applications*, Vol. 48, pp. 89–99. https://doi.org/10.1016/j.eswa.2015.11.022

Gambhir, V., Wadhwa, N. C. and Grover, S. (2016) 'Quality concerns in technical education in India A quantifiable quality enabled model', *Quality Assurance in Education*, Vol. 24, No. 1, pp. 2–25. https://doi.org/10.1108/QAE-07-2011-0040

García, A. K. (2018) *Educación en México: insuficiente, desigual y la calidad es difícil de medir [Education in Mexico: insufficient, unequal and the quality is difficult to measure]*, El Economista, [Online], Available: https://www.eleconomista.com.mx/politica/Educacion-en-Mexico-insuficiente-desigual-y-la-calidad-es-dificil-de-medir-20181225-0028.html [14 Jun 2023].

Giménez, V., Ayvar-Campos, F.J. and Navarro-Chávez, J.C.L. (2017) 'Efficiency in the generation of social welfare in Mexico: A proposal in the presence of bad outputs', *Omega*, Vol. 69, pp. 43–52. https://doi.org/10.1016/j.omega.2016.08.001

Halásková R., Mikušová Meričková B. and Halásková M. (2022) 'Efficiency of Public and Private Service Delivery: The Case of Secondary Education', *Journal on Efficiency and Responsibility in Education and Science*, Vol. 15, No. 1, pp. 33–46. http://dx.doi.org/10.7160/eriesj.2022.150104

Hanushek, E. A. and Woessmann, L. (2008) 'The role of cognitive skills in economic development', *Journal of Economic Literature*, Vol. 46, No. 3, pp. 607–668. http://dx.doi.org/10.1257/jel.46.3.607

INEGI (2023a) *Características educativas de la población [Educational characteristics of the population]*, Instituto Nacional de Estadística y Geografía, [Online], Available: https://www.inegi.org.mx/temas/educacion/ [10 Mar 2023].

INEGI (2023b) *Demografía y Sociedad – Población [Demography and Society – Population]*, Instituto Nacional de Estadística y Geografía, [Online], Available: https://www.inegi.org.mx/app/tabulados/interactivos/?pxq=Mortalidad_Mortalidad_09_61312f04-e039-4659-8095-0ce2cd284415 [10 Mar 2023].

INEGI (2023c) *Economía y Sectores Productivos – PIB y cuentas nacionales [Economy and Productive Sectors – GDP and national accounts]*, Instituto Nacional de Estadística y Geografía, [Online], Available: https://www.inegi.org.mx/temas/pib/ [10 Mar 2023].

Jalongo, M. R., Fennimore, B. S., Pattnaik, J., Laverick, D. M., Brewster, J. and Mutuku, M. (2004) 'Blended Perspectives: A Global Vision for High-Quality Early Childhood Education', *Early Childhood Education Journal*, Vol. 32, pp. 143–155. https://doi.org/10.1023/B:ECEJ.0000048966.13626.be

Kao, C. and Hwang, S.-N. (2008) 'Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan', *European Journal of Operational Research*, Vol. 185, No. 1, pp. 418–429. https://doi.org/10.1016/j.ejor.2006.11.041

Kao C. (2009) 'Efficiency measurement for parallel production systems', *European Journal of Operational Research*, Vol. 196, No. 3, pp. 1107–1112. https://doi.org/10.1016/j.ejor.2008.04.020

Kedagni, D., Krishna, K., Megalokonomou, R. and Zhao, Y. (2021) 'Does class size matter? How, and at what cost?', *European Economic Review*, Vol. 133, 103664. https://doi.org/10.1016/j.euroecorev.2021.103664

Liang L., Yang, F., Cook, W. D. and Zhu, J. (2006) 'DEA models for supply chain efficiency evaluation', *Annals of Operations Research*, Vol. 145, pp. 35–49. https://doi.org/10.1007/s10479-006-0026-7

Liu, J. S., Lu, L. Y. Y., Lu, W.-M. and Lin, B. J. Y. (2013) 'A survey of DEA applications', *Omega*, Vol. 41, No. 5, pp. 893–902. http://dx.doi.org/10.1016/j.omega.2012.11.004

Liu, J. and Xing, C. (2016) 'Migrate for education: An unintended effect of school district combination in rural China', *China Economic Review*, Vol. 40, pp. 192–206. https://doi.org/10.1016/j.chieco.2016.07.003

Mahmoudi, R., Emrouznejad, A., Shetab-Boushehri, S. N. and Hejazi, S. R. (2020) The origins, development and future directions of data envelopment analysis approach in transportation systems.', *Socio-Economic Planning Sciences*, Vol. 69, 100672. https://doi.org/10.1016/j.seps.2018.11.009

Marshall, E. and Shortle, J. (2016) 'Using DEA and VEA to Evaluate Quality of Life in the Mid-Atlantic States', *Agricultural and Resource Economics Review*, Vol. 34, No. 2, pp. 185–203. https://doi.org/10.1017/S1068280500008352

Mendoza-Mendoza, A., De La Hoz-Domínguez, E. and Visbal-Cadavid, D. (2023) 'Classification of industrial engineering programs in Colombia based on state tests', *Heliyon*, Vol. 9, No. 5, e16002. https://doi.org/10.1016/j.heliyon.2023.e16002

Min, S., Kim, J. and Sawng, Y.-W. (2020) 'The effect of innovation network size and public R&D investment on regional innovation efficiency', *Technological Forecasting and Social Change*, Vol. 155, 119998. https://doi.org/10.1016/j.techfore.2020.119998

Minuci, E., Ferreira Neto, A. B. and Hall, J. (2019) 'A data envelopment analysis of West Virginia school districts', *Heliyon*, Vol. 5, No. 7, e01990. https://doi.org/10.1016/j.heliyon.2019.e0199

Moghaddas, Z., Tosarkani, B. M. and Yousefi, S. (2022) 'Resource reallocation for improving sustainable supply chain performance: An inverse data envelopment analysis', *International Journal of Production Economics*, Vol. 252, 108560. https://doi.org/10.1016/j.ijpe.2022.108560

Moreno, P. and Lozano, S. (2016) 'Super SBI Dynamic Network DEA approach to measuring efficiency in the provision of public services', *International Transactions in Operational Research*, Vol. 25, No. 2, pp. 715–735. https://doi.org/10.1111/itor.12257

Murias, P., Martinez, F. and De Miguel, C. (2006) 'An Economic Wellbeing Index for the Spanish Provinces: A Data Envelopment Analysis Approach', *Social Indicators Research*, Vol. 77, pp. 395–417. https://doi.org/10.1007/s11205-005-2613-4

No, F., Taniguchi, K. and Hirakawa, Y. (2016) 'School dropout at the basic education level in rural Cambodia: Identifying its causes through longitudinal survival analysis', *International Journal of Educational Development*, Vol. 49, pp. 215–224. http://dx.doi.org/10.1016/j.ijedudev.2016.03.001

OECD (2022). *Education at Glance 2022: OECD Indicators*, Organisation for Economic Co-operation and Development, [Online], Available: https://www.oecd.org/education/education-at-a-glance/ [15 Jun 2023].

Ome, A., Menendez, A. and Elise Le, H. (2017) 'Improving teaching quality through training: Evidence from the Caucasus', *Economics of Education Review*, Vol. 61, pp. 1–8. https://doi.org/10.1016/j.econedurev.2017.09.003

Osberg, L. and Sharpe, A. (1998) 'An index of economic well-being for Canada', *CSLS Conference on the State of Living Standards and the Quality of Life in Canada*, Ottawa, Ontario.

Qu, J., Wang, B. and Liu, X. (2022) 'A modified super-efficiency network data envelopment analysis: Assessing regional sustainability performance in China', *Socio-Economic Planning Sciences*, Vol. 82 (Part B), 101262. https://doi.org/10.1016/j.seps.2022.101262

Ramzi, S., Afonso, A. and Ayadi, M. (2016) 'Assessment of efficiency in basic and secondary education in Tunisia: A regional analysis', *International Journal of Educational Development*, Vol. 51, pp. 62–76. https://doi.org/10.1016/j.ijedudev.2016.08.003

Rodionov, D. and Velichenkova, D. (2020) 'Relation between Russian Universities and Regional Innovation Development', *Journal of Open Innovation: Technology, Market, and Complexity*, Vol. 6, No. 4, pp. 118. https://doi.org/10.3390/joitmc6040118

Sagarra, M., Mar-Molinero, C. and Agasisti, T. (2017) 'Exploring the efficiency of Mexican universities: Integrating Data Envelopment Analysis and Multidimensional Scaling', *Omega*, Vol. 67, pp. 123–133. https://doi.org/10.1016/j.omega.2016.04.006

Sahu, A. R., Shrivastava, R. R. and Shrivastava, R. L. (2013) 'Critical success factors for sustainable improvement in technical education excellence: A literature review', *The TQM Journal*, Vol. 25, No. 1, pp. 62–74. https://doi.org/10.1108/17542731311286432

Santos Tavares, R., Angulo-Meza, L. and Parracho Sant'Anna, A. (2021) 'A proposed multi-stage evaluation approach for Higher Education Institutions based on network Data envelopment analysis: A Brazilian experience', *Evaluation and Program Planning*, Vol. 89, 101984. https://doi.org/10.1016/j.evalprogplan.2021.101984

See, K. F., Ng, Y. C. and Yu, M.-M. (2022) 'An alternative assessment approach to national higher education system evaluation', *Evaluation and Program Planning*, Vol. 94, 102124. https://doi.org/10.1016/j.evalprogplan.2022.102124

Seiford, L. M. and Zhu, J. (2002) 'Modeling undesirable factors in efficiency evaluation', *European Journal of Operational Research*, Vol. 142, No. 1, pp. 16–20. http://dx.doi.org/10.1016/S0377-2217(01)00293-4

SEP (2022) *Principales Cifras del Sistema Educativo Nacional 2021-2022 [Main Figures of the National Education System 2021-2022]*, Secretaría de Educación Pública – Dirección General de Planeación, Programación y Estadística Educativa, [Online], available: https://www.planeacion.sep.gob.mx/Doc/estadistica_e_indicadores/principales_cifras/principales_cifras_2021_2022_bolsillo.pdf [10 Jun 2023].

Shamohammadi, M. and Oh, D. (2019) 'Measuring the efficiency changes of private universities of Korea: A two-stage network data envelopment analysis', *Technological Forecasting and Social Change*, Vol. 148, 119730. https://doi.org/10.1016/j.techfore.2019.119730

Toloo, M. (2014) 'The role of non-Archimedean epsilon in finding the most efficient unit: With an application of professional tennis players', *Applied Mathematical Modelling*, Vol. 38, No. 21–22, pp. 5334–5346. https://doi.org/10.1016/j.apm.2014.04.010

Tone, K. and Tsutsui, M. (2009) 'Network DEA: A slacks-based measure approach', *European Journal of Operational Research*, Vol. 197, No. 1, pp. 243–252. https://doi.org/10.1016/j.ejor.2008.05.027

Udouj, G., Grover, K., Belcher, G. and Kacirek, K. (2017) 'An investigation of perceptions of programme quality support of adult basic education programmes', *Evaluation and Program Planning*, Vol. 61, pp. 106–112. https://doi.org/10.1016/j.evalprogplan.2016.11.015

UNDP (2023) *Human Development Index (HDI)*, United Nations Development Programme, [Online], Available: https://hdr.undp.org/data-center/human-development-index#/indicies/HDI [31 May 2023].

UNESCO (2012) *International Standard Classification of Education – ISCED 2011*, United Nations Educational, Scientific and Cultural Organization, Institute for Statistics, [Online], Available: https://uis.unesco.org/sites/default/files/documents/international-standard-classification-of-education-isced-2011-en.pdf [11 Jun 2023].

Van Puyenbroeck, T. and Rogge. N. (2020) 'Comparing regional human development using global frontier difference indices', *Socio-Economic Planning Sciences*, Vol. 70, 100663. https://doi.org/10.1016/j.seps.2018.10.014

Velásquez Rodríguez, J., Neira Rodado, D., Crissien Borrero, T. and Alexander Parody, A. (2022) 'Multidimensional indicator to measure quality in education', *International Journal of Educational Development*, Vol. 89, 102541. https://doi.org/10.1016/j.ijedudev.2021.102541

Vliamos, S. J. and Tzeremes, N. G. (2006) 'Education Efficiency and Labor Market Achievements: An Evaluation for Twenty OECD Countries', *The Journal of Economic Asymmetries*, Vol. 3, No. 2, pp. 103–124. https://doi.org/10.1016/j.jeca.2006.02.006

Williams, R., de Rassenfosse, G., Jensen, P. and Marginson, S. (2013) 'The determinants of quality national higher education systems', *Journal of Higher Education Policy and Management*, Vol. 35, No. 6, pp. 599–611. https://doi.org/10.1080/1360080X.2013.854288

Wu, Y.-C. and Lin, S.-W. (2022) 'Efficiency evaluation of Asia's cultural tourism using a dynamic DEA approach', *Socio-Economic Planning Sciences*, Vol. 84, 101426. https://doi.org/10.1016/j.seps.2022.101426