Assessing the performance of Peruvian education system from a governance perspective

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Abstract

This paper delves into the complexities of assessing educational performance and efficiency in the context of education governance. We propose a novel perspective on how governing features of educational systems influence their efficiency, focusing on the key features of public bodies responsible for local education management in Peru, known as UGELs. We characterize the educational production function using three inputs: planning conditions, human resources, and accountability mechanisms; and two outputs: student achievement and educational progress. Our efficiency estimation utilizes Robust Free Disposal Hull, Robust Data Envelopment Analysis, and Stochastic Non-parametric Envelopment approaches, leveraging unique government data from 2014. Additionally, we explore potential factors like infrastructure and internet access that could improve UGELs' efficiency through conditional DEA analysis. Our findings highlight the need for nuanced methodologies in evaluating educational performance and reveal a significant gap in existing literature. This paper addresses this gap by offering a comprehensive evaluation framework, emphasizing the importance of thorough assessments for gauging educational institution efficiency. As policymakers increasingly rely on evidence-based decision-making, our research provides valuable insights that can inform and shape education policy decisions, making it a significant contribution to the field of education policy and governance.

keywords: Governance, Education, Performance, Data Envelopment Analysis, Free Disposal Hull, Stochastic Non-Parametric Envelopment of Data.

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1 Introduction

Understanding how efficient education systems are is crucial for ensuring the effective delivery of educational services. Often the emphasis on governing public education's performance is on delivering an efficient service, i.e., maximizing the educational outcomes (typically student achievements) while minimizing inputs (a combination of educational means such as teachers, classroom size, technological assets, etc.), as highlighted in Witte and Lopez-Torres (2017)'s review. While the focus is warranted, scholars agree that a remaining challenge is taming the complexity of the administrative systems, including variations in policies and managerial models (Rao and Ediger, 2007; Sykes and Elmore, 1989). For example, inspired by post-bureaucratic models (e.g., networks, market models), some governments establish decentralized agencies to enrich education services and deliver administrative solutions. Other settings favor centralized models with less administrative diversification and tighter control over governmental bodies' performance (Bray, 1999; Mok, 2004). That divergence imposes an immediate challenge to public administrations to determine ways of better-approaching performance in the education administrative systems' complexity.

Public administration stands as one of the most significant application areas of productive efficiency analysis, both in terms of policy relevance and social implications (Buleca and Mura, 2014). A predominant focus in research involves leveraging data from international standardized tests, such as PISA (Programme for International Student Assessment), TIMSS (Trends in International Mathematics and Science Study), PIRLS (Progress in International Reading Literacy Study), and TALIS (Teaching and Learning International Survey). However, much of this research tends to emphasize students and schools rather than administrative systems (see for example Arbona et al., 2022; Fu et al., 2019; Guironnet and Peypoch, 2018; Lopez-Torres and Prior, 2022; Martìnez-Campillo and Fernàndez-Santos, 2020; Witte and Lopez-Torres, 2017). Empirical analysis within this literature typically focuses on how educational inputs translate into student achievements.

In this context, an emerging parallel stream advocates for alternative models to comprehensively understand educational results. The rationale is that educational efficiency is not confined to education inputs but necessitates a nuanced examination of the administrative and organizational aspects within education systems. This recognition prompts a broader exploration of governing performance theories and the adoption of more sophisticated methods to gauge their impact on education systems. Notably, scholars such as Agasisti and Pohl (2012) have emphasized the utility of performance and management models in assessing policy interventions aimed at improving educational outcomes. Furthermore, a growing body of literature, including works by Altamirano-Corro and Peniche Vera (2014), Andor and Hesse (2011), Bogetoft and Otto (2010), and Stensaker (2021), and recent contributions like Bertoletti et al. (2022), Bruno et al. (2016), Contini and Salza (2020), and Fusaro and Scandurra (2023), interrelates performance metrics with the political environment and diverse institutional capacities (e.g., mixed market and state, private law-based systems, public law-based structures, and state-controlled models), illustrating the multifaceted nature of the relationship between administrative indicators and educational performance. Such interplay underscores the importance of incorporating administrative indicators to gain a more comprehensive understanding of educational performance dynamics.

Education systems worldwide face the challenge of continuously enhancing efficiency to ensure the effective delivery of educational services. In this context, our study brings a unique and valuable perspective by examining the governance features of primary rural education in Peru and addressing pivotal methodological concerns. Unlike purely empirical or conceptual approaches, our paper combines both aspects to provide nuanced insights into the evaluation of educational efficiency. Specifically, this paper contributes to the existing literature by posing three complementary research questions: (1) What is the efficiency of the administrative local bodies (UGELs) responsible for education in Peru? (2) What specific nuances are revealed by three different frontier efficiency estimations — Robust Free Disposal Hull (FDH), Robust Data Envelopment Analysis (DEA), and Stochastic Non-parametric Envelopment (StoNED) — in evaluating the efficiency of UGELs? (3) What channels emerge as potential drivers to enhance the efficiency of UGELs in delivering educational services?

This paper makes significant contributions to the existing literature through four key aspects. First, it introduces a governance perspective to the evaluation of educational efficiency by presenting administrative indicators as inputs in production frontier models. Despite the abundance of literature on evaluating education systems, the administrative dimension remains largely overlooked. Our study stands out as the pioneer in considering administrative capacity as a crucial input in the efficiency estimation process. This unique contribution addresses a longstanding gap in the literature where the intricate dynamics of administrative systems have not been adequately explored in the context of educational efficiency at the local level. By investigating the governance perspective, the paper establishes the conceptual rationale for selecting administrative indicators, showcasing their significance in shaping educational outcomes. Second, our study utilizes a unique database, offering a quantitative examination of education provision in rural areas of Peru. The data inform about the governing features of the Local Management Units (Unidades de Gestion Educativa Local - UGELs) in Peru in 2014. The UGELs are the public bodies responsible for managing and providing educational services at the local level. This distinctive dataset enables us to provide empirical evidence in areas that are typically explored through qualitative research only.

Third, we provide a unique contribution by discussing three different frontier approaches: robust DEA (Data Envelopment Analysis), robust FDH (Free Disposal Hull), and StoNED (Stochastic Non-parametric Envelopment of Data). The adoption of frontier approaches ensures a paradigm of equity and fairness in the evaluation process. These approaches employ endogenous and customized weighting systems, assigning weights that optimize the final evaluation for all units. Within this framework, each unit is evaluated under the best possible light, while respecting the objectivity and impartiality of the evaluation. Unlike conventional studies that rely on a single model formulation, our research compares and contrasts alternative techniques. This comparative analysis is particularly crucial when applied to a novel setting, such as the local bodies managing education in Peru (UGELs). By doing so, we uncover the patterns and variations that might remain concealed in a singular model formulation, providing a richer understanding of efficiency dynamics in this unique context. Fourth, to shed light on the mechanisms that affect the efficiency of UGELs from a governance perspective, a conditional analysis is implemented. By doing so, we contribute to a more comprehensive understanding of the challenges and opportunities faced by UGELs.

In the following sections, we introduce the issue of evaluating governing performance and discuss the selection of appropriate variables for this purpose. Section 3 presents the methodological approach for estimating the functions and parameters of interest. Section 4 briefly describes the data derived from the Peruvian case study. Section 5 discusses the results, and Section 6 concludes the paper with reflections on efficiency estimations in education.

2 Governing performance in education

2.1 What does governing performance entail?

In the context of education, performance governance refers to the analysis of key elements within the public sector that ensure the delivery of public commitments. These elements include openness to administrative accountability, reasonable returns to public investments, and acceptable planning of education policies (Ranson, 2008; Soguel and Jaccard, 2008; Wilkins and Olmedo, 2018). Assessing performance governance is not necessarily a straightforward task. First, performance governance varies between countries, drastically shaping the focus of its meaning. In some cases, performance governance is associated with administrative evaluations; in other cases, governance assessments are considered as a means to increase the administrative accountability of the country specificity (Hanberger, 2016). Second, the concept differs between government levels, and thus it assumes different nuances according to the specific assessments. Third, at the heart of performance governance, there is a set of administrative traditions and management theoretical premises that open different perspectives on the topic (Lewis and Pettersson Gelander, 2009; Simons, 2015).

The specificity that characterizes the term performance governance in education can be analyzed from three perspectives. The first perspective focuses on citizen engagement in public action to address questions on effectiveness and can be summarized by the expression 'engaging citizens, measuring results, and getting things done'. This expression suggests that a high degree of participation is needed to evaluate performance and understand society's priorities (Denhardt et al., 2009; Epstein et al., 2006; Schmidthuber et al., 2019). The second perspective addresses the interface between the public apparatus and the national governance systems. More specifically, the ways public administration is governed by performance mechanisms (Ferlie et al., 2008; Tolofari, 2005). The third perspective concerns the re-balance of performance governance around service delivery. Here scholars agree that performance governance in education inherently connects with societal features and the ways of governing (and creating) the operating conditions for governments (e.g., intra-governmental structures) without losing the accent on the effectiveness of the education system, i.e. service provision (Saguin, 2019).

While these strands alone are insufficient to comprehensively conceptualize all elements of performance governance, they serve as entry points for reflecting on the themes that configure it. Terms like society's engagement, governmental relationships, and public services intertwine and cut across these themes, creating a dynamic framework. These insights situate our next exploration— a more nuanced analysis that involves the deliberate selection of inputs and outputs, from a perspective deeply rooted in governance principles.

2.2 Education efficiency from the governing standpoint: the selection of inputs and outputs

This section presents the rationale for selecting the variables used in our empirical models to describe the educational production function from a governance perspective. First, we discuss the choice of inputs categorized into three macro areas: planning conditions, human resources, and accountability. The intention is to capture these areas as essential governing features of UGELs. Note that efficiency literature in education has long overlooked the governing aspect, therefore the input choice is mostly driven by literature on education governance (Section 2.3). Second, we introduce test scores and the ability to progress in school as our chosen educational outcomes. Lastly, we consider contextual variables that may influence UGELs' capacity to utilize their governing features effectively in achieving the desired outcomes. Specifically, our focus extends to the quality of school infrastructure and internet access.

The first important aspect is ***planning conditions***, which refers to the ability to encourage effective planning practices and innovations guiding administrative processes that impact educational outcomes (Blaug, 1967). Planning is essential in public bodies where interconnected processes and, often constrained, resources generate a diverse array of educational services (Woodhall et al., 2004). In complex governance settings, where interdependence is high, the absence of planning may lead to conflicting objectives among internal bodies and disjointed rules and plans. In response, governments attempt to shape the conditions and pathways for implementing and monitoring strategic decisions in public action (e.g., management practices, planning methods, and optimizing resources). That lays the groundwork for a range of attributes when referring to planning capacities, including consultation and articulation of plans, timely and adequate planning aligned to education service requirements, and integrative planning to support the management of schools (Frank, 2006).

Another crucial aspect present in the literature is ***human resources*** and their role in the service value chain. They are essential for a well-performing public sector, requiring administrators to possess qualities such as competence, professionalism, and a service-oriented mindset (Khalil et al., 2017). The rationale is that civil servants are the operators of education policies, driving educational reforms through systems, procedures, and practices to ensure the effectiveness of public bureaucracy and the delivery of high-quality education services. This, in turn, demands robust governance mechanisms (e.g., financial strategies, organizational culture, coordination networks) that organize conducive working conditions, clear accountability structures, equitable and flexible employment arrangements, a strong organization culture, and ongoing professional development (Pollitt and Bouckaert, 2017).

The last input to consider is variations in efforts related to ***accountability***. In public administration, this often involves different approaches to connect with both citizens and government bodies, contributing to effective decision-making and the overall performance of public institutions. In practical terms, accountability manifests in various forms, particularly in education (e.g., teachers' self-evaluations, school inspections, international assessments), aiming to establish consistent arrangements that inform and shape public education (Tolofari, 2005). For instance, through an interconnected web of accountability mechanisms, multiple stakeholders and different government levels can address performance demands across schools. Additionally, diverse accountability levels (involving school boards, open institutional information, etc.) have the potential to validate indicators of education quality and incorporate/monitor school-system-level feedback (Behn, 2003). Therefore, accountability goes beyond merely inspecting schools; it involves creating a stable environment of shared standards with a focus on efficient management, organizational structure, inspection frameworks, and communication of standards, among other elements (Ozga, 2020).

Defining outputs in studies on education efficiency poses a challenge, given its connection with various notions and levels within the public sector, including government effectiveness and school performance. Previous literature has explored educational outcomes from three distinct perspectives. The first, a narrow-sense view of education effectiveness, centers on short-term goals and objectives. This involves measures such as the quantity and quality of educational services, encompassing factors like dropout rates, standardized test achievements, and attendance rates (e.g., Childs and Lofton, 2021; Goldhaber and Ozek, 2019; Mazrekaj and De Witte, 2020). The second perspective delves into the 'informal' and collective rules shaped by the policy environment, considering local practices, the organizational climate of public bodies, and governmental dynamics (see

Ackah-Jnr, 2020). The third perspective focuses on students' life conditions, including employability, financial security, and political participation, as well as societal changes such as social equity, reduced welfare program expenses, and increased tax revenue (e.g., Aars and Christensen, 2020; Kuusipalo et al., 2021; Lauder and Mayhew, 2020). In this paper, we adopt the first perspective, treating outputs as measurements of the results of educational services, and define the provision of educational services in terms of achievements. Specifically, our study considers two educational outcomes: i) the proportion of students with satisfactory performance in national test scores (Educational Census Evaluation - ECE, for 2nd grade of primary education, 7-8 years-old students) in Mathematics comprehension during the 2014-2015 academic year, and ii) the non-retention rates in 2nd level primary school.

Conducting a comprehensive evaluation and exploring potential risk factors and mechanisms to enhance efficiency requires the inclusion of contextual or environmental variables in the analysis. These variables shape the operational conditions within which public apparatus processes unfold (Ruggiero, 2019). The operating environment influences government decisions and practices in education, often through policy measures, regulations, and other conditions external to local governmental practice (De Witte and Kortelainen, 2013). Contextual determinants can manifest in various forms, including schools' composition (student population, program/levels), urbanity levels, educational attainment of the population in the area, and family characteristics, among others. Witte and Lopez-Torres (2017) classified contextual variables into four categories: student variables (such as gender, background, etc.); family variables (parental education, resources at home); education institution variables (funding, ownership, teachers' characteristics); and community variables (such as GDP per capita, migration, urban/rural area). In this study, we focus on contextual variables falling into the community category, specifically selecting two variables that collectively describe the level of development in the areas where schools operate: (1) Quality of Infrastructure and (2) Internet Access.

2.3 Research gaps and highlights

In this section we position our paper to recent literature, aligning it at the intersection of education, efficiency, and governance literature.

The literature widely acknowledges the importance of education as a pivotal sector for fostering national growth and upward social mobility (see, for example, Bertoletti et al., 2022; Montalvo-Clavijo et al., 2023). From a governance perspective, education involves the creation and enforcement of policies that shape the objectives, standards, and practices of the education system (Verger and Skedsmo, 2021). It includes overseeing resources, regulating institutions, developing curriculum, assessing outcomes, and ensuring inclusivity and equity (Nandi, 2022). Education governance aims to provide a framework for effective teaching and learning that meets societal needs and standards (Soares Furtado Oliveira et al., 2023). The literature on governance in education has driven the selection of the input, as illustrated in the previous section. However, the governance perspective in education has traditionally focused on conceptualization rather than quantitative investigation of efficiency and performance assessment in the context of governing education.

The importance of the efficiency perspective in education has been underscored, among others, by the review of (Witte and Lopez-Torres, 2017). Their study identifies commonly used categories of inputs, outputs, and environmental variables, in education efficiency evaluations using DEA and DEA-like approaches. Evaluating education from an efficiency perspective is especially relevant nowadays, given the high budget constraints faced by governments and decreased purchasing power for education budgets due to inflation (Bruno et al., 2016; Fusaro and Scandurra, 2023; Martìnez-Campillo and Fernàndez-Santos, 2020). However, most studies are focused on higher and secondary education (see for example Barra et al., 2018; Contini and Salza, 2020; Fu et al., 2019; Guironnet and Peypoch, 2018; Navas et al., 2020; Sulis et al., 2020; Sun et al., 2023; Wang, 2019), while primary education is especially neglected. One plausible explanation is the lack of international standardized test scores for young pupils and the overall challenges in defining educational performance among the youngest. Studies exhibit geographical limitations, with a predominant focus on specific regions. The majority of efficiency studies concentrate on the Chinese context (Fu et al., 2019; Sun et al., 2023; Wang, 2019), the United States (Aparicio et al., 2019; Guironnet and Peypoch, 2018), and Europe (Barra et al., 2018; Martìnez-Campillo and Fernàndez-Santos, 2020), as highlighted in the review by Mergoni and De Witte, 2022. Within Latin America, efficiency approaches are notably prevalent in Colombia (see for example Arbona et al., 2022; Navas et al., 2020), while no evidence is provided for the Peruvian situation.

From a methodological perspective, DEA-based approaches are widely accepted in the efficiency and education literature for their flexibility and ability to account for multiple dimensions (Arbona et al., 2022). Despite ongoing developments in DEA approaches, (including the models for fuzzy data by Aparicio et al., 2019, and the Conditional panel data DEA model by Lopez-Torres and Prior, 2022), the stochastic frontier approaches, DEA, and the Malmquist index remain the predominantly used frontier methods (Arbona et al., 2022; Fu et al., 2019; Guironnet and Peypoch, 2018; Martìnez-Campillo and Fernàndez-Santos, 2020; Navas et al., 2020). However, a limited number of studies compare the performance of different models. Exceptions are De Borger and Kerstens (1996), Drake and Simper (2003), and Liu et al. (2022), which compare DEA and FDH; and Andor and Hesse (2014) who compare DEA, StoNED, and Stochastic frontier analysis (SFA). Our study addresses these gaps by providing evidence on primary education in Peru, introducing the notion of frontier estimation in assessing the performance of governance in education, and comparing the efficiency performance of DEA, FDH, and StoNED.

In our study, we address gaps in the existing literature through a three-pronged approach. Firstly, we provide new evidence regarding primary education in Peru, an area that has been overlooked despite numerous studies on education efficiency. Secondly, we introduce the concept of frontier estimation to evaluate the performance of governance in education, filling a void in the previous literature that largely neglected quantitative assessments of efficiency in educational governance. Lastly, we conduct a comparative analysis of the performance of DEA, FDH, and StoNED, providing valuable insights by contrasting the features of these distinct approaches to efficiency. This comparative aspect is notably absent in prior literature, where these approaches have typically been employed independently.

3 Methodological approaches selected

This section introduces the selected methodological approaches for implementing efficiency estimation: robust and conditional DEA, robust FDH, and StoNED techniques. All these approaches belong to the frontier category, aiming to estimate efficiency by quantifying the deviation or distance from the frontier represented by the best-performing units.

Frontier approaches find wide acceptance in literature for evaluating the efficiency (and in general the performance) of decision-making units, such as the UGELs. Performance assessment in a multidimensional context is particularly challenging as the choice of an aggregating method is not straightforward. Non-parametric frontier models like DEA and FDH offer an endogenous set of weights that maximize the performance of all units. This approach brings various advantages: firstly, units are assessed under optimal conditions, enhancing equity, fairness, and acceptance among stakeholders; secondly, weights are assigned through an optimization problem, ensuring objectivity and well-defined criteria; thirdly, the optimization problem formulation accommodates multiple dimensions, enabling evaluations from various perspectives.

Another strength of non-parametric frontier approaches is their flexibility and applicability across different public sectors, from education to health, transportation, and energy. A drawback lies in their deterministic nature, considering all deviations from the best-performing frontier as inefficiency without accounting for an error term. The robust and conditional versions of DEA and FDH introduce stochasticity, while semi-parametric approaches like StoNED explicitly address measurement errors. StoNED, in particular, minimizes assumptions regarding the production function, incorporating error terms and allowing consideration of contextual variables. Alternatively, well-accepted parametric approaches in the literature, particularly Stochastic Frontier Analysis (SFA), offer better accounting for random variations in the data and employ more established methods for statistical inference. Nevertheless, a major drawback is the assumption of a specific functional form for the production function, often challenging to justify given the complex nature of real-world production processes.

The main differences between the approaches selected for this analysis lie in how they estimate the benchmarking frontier and how they measure the distance of the units from the frontier. In the non-parametric setting of DEA, the frontier is constructed as the smallest convex envelop encompassing all units (UGELs, in our case) in the sample. In contrast, FDH does not require convexity but simply the monotonicity of the production function and the free disposability of inputs. In the semi-parametric StoNED setting, the frontier is estimated relying on assumptions about the distribution of inefficiency and error terms. A detailed description of these methods is presented below.

3.1 Robust and Conditional DEA and FDH

Data Envelopment Analysis (DEA - Charnes et al., 1978) and Free Disposal Hull (FDH - Deprins et al., 2006) are the most popular non-parametric frontier approaches to estimating efficiency. The ability to account for multiple input and output dimensions and the few assumptions on which they rely make DEA and FDH particularly suited for performance evaluations in contexts where the production function is unknown (such as in education). Being non-parametric, these approaches do not assume a functional form for the production function, instead, evaluate each unit taking as a reference an empirical production function (also called the benchmarking frontier), given by the smallest envelop of the observed data (from here the name Data Envelopment Analysis). As DEA assumes convexity, the resulting production function is pice-wise, FDH relaxes the assumption of convexity and therefore characterizes a step-wise production function. Formally, under constant return to scale assumptions, the DEA production possibility set (i.e. the combination of all the achievable input-output bundles) is defined as:

$$\Psi^{DEA} = \{(x, y) \in R_+^{m+r} | y \leq \Sigma_{j=1}^{n} \gamma_j Y_j, x \geq \Sigma_{j=1}^{n} \gamma_j \ X_j \ for \ (\gamma_1, ..., \gamma_n) > 0\} \tag{1}$$

where x is the set of inputs ($x \in R^m$), y is the set of outputs ($y \in R^r$), and γ_j is the weight assigned to unit j. A different weight assignment distinguishes DEA and FDH production functions:

$$\Psi^{FDH} = \{(x, y) \in R_+^{m+r} | y \leq \Sigma_{j=1}^{n} \gamma_j Y_j, x \geq \Sigma_{j=1}^{n} \gamma_j \ X_j \ for \ (\gamma_1, ..., \gamma_n) \in (0, 1)\} \tag{2}$$

In both cases, the efficiency of each unit is measured in terms of distance from the efficient (or benchmarking) frontier. For a unit j_0 the output-oriented efficiency score is defined as $1/\lambda^{DEA}(x_{j_0}, y_{j_0})$, where:

$$\lambda^{DEA}(x_{j_0}, y_{j_0}) = sup\{\lambda | (x_{j_0}, \lambda y_{j_0}) \in \Psi^{DEA}\} \tag{3}$$

FDH efficiency score for unit j_0 can be defined similarly.

Robust versions of DEA and FDH have been presented among others, by Daouia and Gijbels (2011) - (robust order alpha approach) and Cazals et al. (2002) - (robust order m) approach to introduce some stochasticity in the standard deterministic efficiency DEA and FDH measures (Charnes et al., 1978; Deprins et al., 2006). In this paper we follow the approach by Cazals et al. (2002), which is based on a bootstrap approach to introduce stochasticity in the estimation process and to make statistical inference and hypothesis testing available. For each bootstrap replicate, m units out of the initial sample of n units are randomly selected and used as a reference set. The procedure is repeated B time and the average score is considered. Regarding the choice of m there are no theoretical studies, but Daraio and Simar (2007a) proposed the following rule of thumb as an upper bound: $m = \frac{\sqrt{n}}{n}$. In our analysis we selected $m = 40$. To choose this number we implemented an empirical approach, testing for different numbers of m, and selecting the one at the elbow in a graph with the number of super efficient units on the y and m on the x (see Daraio and Simar, 2005).

To formally introduce robust DEA and FDH scores, $\lambda^m(x_{j_0}, y_{j_0})$, we rely on the bootstrap procedure proposed by Daraio and Simar (2007b):

[1] For a given observation (x_{j_0}, y_{j_0}), draw a random sample of size m.

[2] Obtain standard DEA/FDH score for unit (x_{j_0}, y_{j_0}) considering the m units extracted to form the production function corresponding to the b^{th} bootstrap replicate ($\Psi^{m,b,DEA/FDH}$):

$$\lambda^{m,b}(x_{j_0}, y_{j_0}) = \sup\{\lambda | (x_{j_0}, \lambda y_{j_0}) \in \Psi^{m,b,DEA/FDH}\} \tag{4}$$

[3] Redo [1] and [2] for $b = 1, ..., B$.

[4] Consider $\lambda^m = \frac{1}{B} \sum_{b=1}^{B} \lambda^{m,b}(x_{j_0}, y_{j_0})$.

The conditional approach is based on the work of Daraio and Simar (2007b), who extended the work by Cazals et al. (2002). The advantages of this approach can be summarized in two main points. First, the conditional DEA and FDH allow accounting for the contextual characteristics z (also known as external-environmental factors) that might influence the production function and explain how these affect the performances (Daraio and Simar, 2007b). Second, standard and robust DEA and FDH are based on the often unrealistic assumption of separability, i.e., the assumption that all the units in the sample share the same production function, independently to their contextual characteristics. Conditional DEA, instead, delivers consistent results also in the case separability is not fulfilled (Daraio et al., 2018).

The underlying idea of conditional approaches is similar to the one of robust estimations, but in this case, the m units selected during each bootstrap replicate are not extracted randomly, but according to their similarity with the unit under evaluation along the contextual variables z. Typically, similarity is computed using a kernel estimation, in particular, the weight assigned to a unit j, when evaluating j_0, is the value of the kernel density function around point z_{j_0}, evaluated on the value of z of unit j (z_j), i.e., $s(j, j_0) = K_h(z_j, z_{j_0})$. Kernel functions are characterized by the choice of the functional form of the kernel (Epanechnikov ($K(u) = 3/4(1-u^2)$ if $|u| \leq 1$, 0 otherwise), Gaussian ($K(u) = \sqrt{2\pi} e^{-1/2u^2}$), Triangular ($K(z_j, z_{j_0}) = (z_j - z_{j_0})/h$) are typical functional forms) and by the choice of the smoothing parameter h, which is known as the bandwidth, i.e., the 'width' of the kernel function. Given the relevance of the bandwidth's selection, previous literature developed advanced methodology to implement optimal bandwidth selection (Buadin et al., 2010, 2019); while the choice of the functional form is left to the authors' subjective choice (in our case we used the Gaussian kernels, as it is the most used in case of continuous variables).

In this conditional context, the DEA production possibility set of an activity characterized by (x, y, z) is defined as:

$$\Psi^{DEA|z} = \Big\{(x,y) \in \mathbb{R}_+^{p+q} | y \leq \sum_{i|z-h \leq z_i \leq z+h} \gamma_i y_i ; x \geq \sum_{i|z-h \leq z_i \leq z+h} \gamma_i x_i, \quad \text{for non negative } \gamma \text{ such that } \sum_{i|z-h \leq z_i \leq z+h} \Big\} \tag{5}$$

Where h is the bandwidth of a kernel estimation (for more details about the bandwidth selection see Buadin et al., 2010). The conditional DEA score is defined as:

$$\lambda^{DEA|z} = \sup\{\lambda | (x, \lambda y) \in \Psi^{DEA|z}\}. \tag{6}$$

Conditional scores can be estimated using a bootstrap procedure similar to the one described for the computation of robust scores.

3.2 Stochastic nonparametric envelopment of data - StoNED method

The StoNED approach was first introduced by Kuosmanen and Kortelainen (2012) and has gained popularity as an alternative technique to evaluate performance in the context of frontier efficiency estimation. The method combines the advantages of the non-parametric Data Envelopment Analysis (DEA) with Stochastic Frontier Analysis (SFA). On the one hand, it does not require assumptions on the functional form of the production frontier (e.g., Translog, Cobb-Douglas) as SFA, but instead relies on axiomatic assumptions as DEA (CRS, convexity and Free disposability). On the other, StoNED admits deviations from the production attributed to both inefficiency (stochastic) and the noise term.

In our empirical setting, we examine two models. The first model focuses on educational output, specifically the ECE test scores denoted as y_1 (model 1). Meanwhile, the second model considers the rate of students able to progress in school, represented by y_2 (model 2). In both cases, the governing features considered are planning capacity (x_1), human resources (x_2), and accountability (x_3). Formally, the production frontier of a unit i is described by Kuosmanen and Kortelainen (2012) as:

$$y_{1,i} = \ln f(x_{1,i}, x_{2,i}, x_{3,i}) + u_i + v_i \tag{7}$$

$$y_{2,i} = \ln f(x_{1,i}, x_{2,i}, x_{3,i}) + u_i + v_i \tag{8}$$

Where u_i and v_i represent the asymmetric inefficiency term and the random noise term of unit i respectively. Drawing from SFA studies, the model assumes that inefficiency follows a half-normal distribution ($u_i \sim N^+(0, \sigma_u^2)$, and the noise term follows a normal distribution $v_i \sim N(0, \sigma_v^2)$. For the frontier f, no specific functional form is assumed, except for classical non-parametric DEA constraints (monotonicity, convexity, and the shape of the return to scale). The StoNED method involves two steps. In the first step, the average-production function is estimated through convex non-parametric least-squares (CNLS), using the following quadratic formulation (Kuosmanen and Johnson, 2010):

$$\begin{aligned}
\min_{\gamma,\beta,\varepsilon} \quad & \Sigma_{i=1}^{n}(\varepsilon_i^2) & \\
s.t. \quad & \gamma_i = \alpha_i + \beta_i' x_i + \epsilon_i & \forall i = 1, ..., N \\
& \gamma_i = \alpha_i + y_i \beta_i' \geq \alpha_h + Y_i \beta_h' & \forall i, h = 1, ..., N \\
& \beta_i \geq 0 & \forall i = 1, ..., N
\end{aligned} \tag{9}$$

Where γ_i is the expected value of production for unit i; α_i represents the intercept, i.e., the expected value of production when the inputs are 0; and β_i is the vector of the marginal productivity level for UGEL i. The first constraint is similar to linear regression equation, but here the parameters α and β are not constant across all observations. The second and third constrain are introduced, following Altamirano-Corro and Peniche Vera (2014), to guarantee that the regression lines are not downwards sloping and therefore ensure the convexity and monotonicity of the production function.

In the second step, the StoNED method uses the CNLS residuals to estimate the expected value of unit-inefficiency, considering the distribution assumptions of the model (half-normality or exponentially distributed with variance δ_v^2) along with variance of inefficiency and error terms. To estimate the variance of these parameters we use methods of moments while maintaining assumptions on half-normal inefficiency and normal distribution of noise term (Andor and Hesse, 2011).

The estimators of the second and third central moments of the composite error term distribution are expressed as:

$$\hat{M}_2 = \Sigma_{i=1}^{n}(\hat{\varepsilon}_i - \overline{\varepsilon})^2/n \quad \text{and} \quad \hat{M}_3 = \Sigma_{i=1}^{n}(\hat{\varepsilon}_i - \overline{\varepsilon})^3/n \tag{10}$$

As a reference, the estimators σ_u and σ_v are obtained from the equations below, where $\hat{\sigma}_u$ depends on the standard deviation of the inefficiency distribution:

$$\hat{\sigma}_u = \sqrt[3]{\hat{M}_3/(4/\pi - 1)\sqrt{2/\pi}} \quad \text{and} \quad \hat{\sigma}_v = \sqrt{\hat{M}_2 - [(\pi - 2)/\pi]\hat{\sigma}_u} \tag{11}$$

The UGELs specific inefficiency estimates are calculated using Jondrow et al. (1982) approach as follows:

$$E(u_i/\varepsilon_i) = \mu_* + \sigma_*[\phi(-\mu_*/\sigma_*)/1 - \theta(-\mu_*/\sigma_*)] \tag{12}$$

Where θ is the standard normal cumulative distribution function, ϕ denotes the standard normal density function, and following Kuosmanen and Kortelainen (2012), $\mu_* = -\varepsilon_i\sigma_u^2/(\sigma_u^2 + \sigma_v^2)$ and $\sigma_u^2 = \sigma_u^2\sigma_v^2/(\sigma_u^2 + \sigma_v^2)$. From eq 12, UGELs specific inefficiency estimates ($\hat{u}_i$) can be used to obtain the specific efficiency estimates with the equation: $E_i = exp(\hat{u}_i)$, where efficiency score value of 1 means that the UGELs performance on the respective output (learning achievements or enrollment rates) is on the efficient frontier, and a value less than 1 means the UGELs is inefficient.

While the original StoNED approach is limited to incorporating a single output, an extension has been developed that enables the simultaneous evaluation of two outputs (Kuosmanen and Johnson, 2017). However, we opted to maintain the two outputs in separate models to enhance interpretability and flexibility. This decision facilitates a more straightforward and comprehensible analysis, while also allowing for the potential benefits of employing distinct modeling approaches tailored to the unique characteristics of each output.

4 Empirical Specification

4.1 UGELs: Key Actors in Peru's Education System

The Peruvian education system encompasses various levels, including early childhood, primary, secondary, and higher education. The Local Education Management Units, known as UGELs (Unidades de Gestión Educativa Local), are at the heart of this system and have substantial influence in overseeing and coordinating educational activities. Acting as intermediaries between the Ministry of Education and schools, UGELs are pivotal entities responsible for the effective implementation of educational policies and programs.

The organizational framework of UGEL, delineated in RM 176-2021-MINEDU, reflects political and administrative divisions. Unlike Regional Directions of Education (DREs), which operate under regional governments, UGELs work closely with schools, acting as implementing bodies for educational initiatives. This unique structure aims to facilitate a localized approach to education administration, ensuring policies align with the specific needs and characteristics of diverse regions and schools. In this setting, the UGELs are the articulators of the system, and play a pivotal role in shaping education service delivery. Their responsibilities range from managing financial resources and personnel to overseeing infrastructure and operational elements.

Operating within a semi-decentralized state structure, UGELs maintain fiscal dependency on central bodies while holding constitutional status as local administration entities. This distinctive positioning empowers them to influence educational service provision at the local level. Evaluating their performance offers a unique opportunity to understand the effectiveness of administrative capacities (e.g., actions, policies) in achieving educational goals. Given the challenges of educational inequality, particularly between urban and rural areas, assessing UGELs' performance in rural areas becomes imperative for unraveling how administrative indicators contribute to addressing disparities and promoting equitable educational outcomes. This targeted examination ensures a nuanced understanding of the impact of administrative practices on the broader educational landscape in Peru.

4.2 Data

Our empirical approach avails of the data generated in 2014 by the Peruvian Minister of Education in the framework of the Public Investment Project: 'Improving the Decentralized Education Management in Rural Schools in the 24 Regions of Peru' (PIP-GED Rural). These data contain unique information about UGELs' institutional capacities.

While we acknowledge the constraints of using cross-sectional data, limited to the year 2014, we also highlight the distinctive attributes of our data and the untapped potential they offer for quantitative analysis. Leveraging the complex data from PIP-GED Rural provides essential advantages in the context of our study. This dataset includes rich descriptive information about Peru's background, facilitating the triangulation of insights from various methods, given its multi-purpose nature (Roy and Acharya, 2016). Studying performance governance requires valid and reliable information about the public sector. In this regard, the PIP-GED Rural data for 2014 represented a pioneering effort to quantify the administrative dimension of education in Peru (Tenopir, 2014).

Minedu is the governing body of national educational policies and exerts its stewardship through its executive decentralized bodies at the regional and local levels. UGELs are the public entities in charge of delivering education services at the local level (e.g. supervising the application of national educational policy, schools' institutional management, and evaluation of programs under their purview). In 2014, Minedu implemented the project PIP-GED-Rural to improve rural schools and collected rich and unique data on UGELs' institutional capacities (Valdivia et al., 2018). Each dimension encompasses different aspects of the 'National Plan for Modernization of the Public Management' passed by the Ministerial Resolution N° 004-2013-PCM (Tapia, 2022). The national plan presents the approaches, indicators, and leading entities responsible for implementing and monitoring the modernization process (Moron et al., 2022). The following section describes in detail the construction of the institutional capacity indicators.

Operationalization of Indicators in PIP GED Rural

Under the PIP-GED Rural project, the Ministry of Education gathered data on six macro-indicators that assess the administrative performance and institutional capacity of UGELs (Local Educational Management Units). These macro-indicators are (i) planning capacities, (ii) human resources, (iii) accountability, (iv) organization and service value chain, (v) information systems management, and (vi) intersectoral and participation management. This study primarily focuses on the first three indicators, considering them as the input of our production functions, as extensively discussed in Section 2.2.

Each macro-indicator was constructed as the average of three sub-indicators, ranging from 0 to 100, where 0 indicates poor performance and 100 indicates the ideal scenario. The sub-indicator scores were assigned by a committee of experts. *Planning capacities* considers the ability of UGELs to (1) develop local educational projects and institutional operative planning processes, (2) timely prepare acquisition and contracting plans, and (3) implement the planning agreed with rural education networks. *Human resources* were assessed based on (1) the organization and assignment of HR, (2) the training of staff in fundamental concepts, and (3) the specialization of staff in key areas. *Accountability* is constructed based on (1) the management of virtual spaces (institutional transparency portal), (2) the effective response to requests for access to public information, and (3) the installation and operation of committees to ensure the program aligns with the needs of rural education communities, and it fosters collaboration between stakeholders.

In the context of this study, the selected inputs are the three macro-indicators planning capacities, human resources, and accountability. Under the theme of *planning capacities*, the metrics delve into the articulation between Planning mechanisms, the adequacy of planning mechanisms to education services (e.g., timely preparation of Acquisitions and Contracting Plans), and management principles (e.g., Rural Education Networks' supervision and evaluation). Moving to *Human resources*, the metrics assess the organization and assignment of HR, training of staff in fundamental concepts, and specialization of staff in key areas. Finally, within the realm of *accountability*, the metrics gauge the management of Institutional Transparency Portals, the effective response to requests for access to public information, and the installation and operation of COPROA. Each of these metrics addresses specific challenges and priorities within the respective domains of planning capacities, human resources, and accountability.

Two outputs in the production frontier were defined: (1) level of student learning achievement (2nd grade) in Mathematics according to ECE results - used in Model 1; and (2) percentage of students passing to the next grade (enrollment rates) - used in Model 2. As for the first output, the *testscores in math* are collected by ECE, the Evaluacion Censal de Estudiantes. The ECE standardized tests are conducted every year in primary and secondary schools and collect information on students' achievement in mathematics and reading (Rossignoli, 2021).

As for the second output, the *percentage of successful students*, is constructed considering students evaluation. In particular, the students getting a 'Satisfactory' or 'In process' evaluation are grouped in one category, leaving out the students assigned to the category 'Beginning'. Therefore, the output variable considered in this paper indicates whether the students reached the learning achievements expected for the 2nd grade or are on the way to achieving them. The class remaining 'Beginning' suggests students did not achieve the expected learning and can only perform basic tasks for the 2nd grade. The choice of the outputs is in line with previous literature Altamirano-Corro and Peniche Vera, 2014; Witte and Lopez-Torres, 2017).

To ensure fairness in the evaluation, we also include in the analysis two environmental variables: (1) Internet access and (2) quality of infrastructure, collected from the census data at UGEL level, relative to the year 2014. *Internet access* is measured as the percentage of schools with internet access in the UGEL. The *quality of infrastructure* is assessed considering a number of subindicators: buildings needing reparation, building with no access to water, drainage, and electric energy. The idea is that by combining these two variable we have an idea of the quality of the environment where the school operate.

The descriptive statistics for the variable used in the study are displayed in Table 1 and the correlation is presented in Table 2. Note that the averages are reported at regional level, despite the units of observations are the UGELs. From the correlation table, we can observe that the inputs have weak linear relationships with each other and with the outputs, except for accountability, which has a moderate negative linear relationship with ECE test scores. The outputs have a weak positive linear relationship with each other, indicating that schools that perform well on one output tend to perform well on the other. The environmental variables have weak to moderate positive linear relationships with each other and with the second output, indicating that schools with better Internet access and infrastructure tend to have higher rates of students able to progress in school. However, they have weak negative linear relationships with the first output, indicating that schools with better Internet access and infrastructure tend to have lower ECE test scores.

Table 1: Descriptive Statistics of the inputs, outputs and environmental variables.

	Inputs			Outputs		Environmental Var.	
	x1	x2	x3	y1	y2	z1	z2
AMAZONAS	16.400	20.900	16.400	60.450	86.450	27.048	21.350
ANCASH	12.367	15.767	12.367	34.667	86.564	23.428	20.867
APURIMAC	14.050	16.750	14.050	32.250	88.803	9.318	17.325
AREQUIPA	5.067	16.933	5.067	62.467	89.510	17.824	11.333
AYACUCHO	27.375	17.625	27.375	51.575	90.093	22.081	12.375
CAJAMARCA	14.100	19.033	14.100	41.600	89.866	20.180	29.467
CUSCO	12.750	17.475	12.750	32.200	87.720	20.742	4.250
HUANCAVELICA	9.767	17.933	9.767	51.900	88.481	12.848	15.067
HUANUCO	19.733	20.133	19.733	37.767	85.052	12.113	14.267
ICA	26.450	19	26.450	56	94.367	22.334	51.450
JUNIN	2.300	13.700	2.300	28.900	90.300	11.840	2.300
LA LIBERTAD	18.780	16.480	18.780	61.460	85.734	24.510	26.080
LIMA	19.100	17.700	19.100	39.100	90.020	15.429	31.667
LORETO	2.300	20.100	2.300	64	77.419	6.818	15.300
MOQUEGUA	27.300	15.400	27.300	80	88.300	12.500	10.800
PASCO	25.700	21.200	25.700	77.800	95.912	16.964	29.100
PIURA	10.400	18.525	10.400	25.675	88.477	28.346	44.050
PUNO	21.560	19.680	21.560	55.940	94.290	7.224	19.580
SAN MARTIN	19	17.700	19	12.300	87.383	16.250	21.300
TACNA	3.400	16.900	3.400	25	93.108	31.797	72
TUMBES	5.700	20.200	5.700	56.600	88.931	27.273	52.900

Table 2: Correlation between the inputs (x1 - planning capacities, x2 - human resources, x3 - accountability), outputs (y1 - ECE test scores, model 1, y2 - rate of students able to progress in school, model2), and environmental variable (z1 - Internet access , z2 - quality of infrastructure).

	x1	x2	x3	y1	y2	z1	z2
x1	1	0.001	0.252	-0.028	0.195	0.089	0.018
x2	0.001	1	-0.103	0.089	0.153	-0.006	0.109
x3	0.252	-0.103	1	-0.282	0.182	-0.174	0.063
y1	-0.028	0.089	-0.282	1	0.162	-0.081	-0.139
y2	0.195	0.153	0.182	0.162	1	0.138	0.220
z1	0.089	-0.006	-0.174	-0.081	0.138	1	0.300
z2	0.018	0.109	0.063	-0.139	0.220	0.300	1

5 Results and discussion

This section organizes results in a dual reading. Section 5.1 presents the results for robust DEA, robust FDH, and StoNED estimations of models 1 and 2 (see Cazals et al., 2002; Kuosmanen and Johnson, 2010). This section descriptively discusses the technical efficiency of units and includes a geographical visualization of the efficiency scores. Section 5.2 compares the distribution scores from models 1 and 2 across the three estimations, providing further insights into their differences. This comparison is complemented by non-parametric tests.

In Section 5.3, our focus shifts to understanding the determinants of efficiency, highlighting the effects of selected environmental characteristics (Z variables) on UGELs' ability to transform inputs into outputs. To achieve this, we present results from conditional DEA estimation (Daraio and Simar, 2007a) and explore, quantile by quantile, how the conditional scores change concerning the robust scores along the Z variables. This analysis allows us to characterize efficiency for conditional features identified in previous sections, providing the groundwork for policy recommendations on promoting efficiency, such as investing in infrastructure and Internet access, and strategically targeting per quantiles.

5.1 Mapping Efficiency of UGELs from the governing perspective: findings from alternative approaches

Table 3 reports the results of Robust FDH, Robust DEA, and STONED estimations at the regional level (UGEL-level results can be found in the Appendix, Table 6). Classical DEA and FDH scores (Charnes et al., 1978; Deprins et al., 2006) possess a deterministic nature, making statistical inference and testing unfeasible. However, the implementation of robust approaches introduces variability and enables statistical testing, accounting for the presence of outliers (Cazals et al., 2002).

In our findings, the majority of UGELs have higher (or equal) FDH efficiency scores compared to DEA and StoNED, providing evidence supporting the benevolent interpretation of FDH (additional details on the comparison of DEA and FDH estimations can be found in Lovell and Eeckaut, 1993). According to theory, FDH estimation is expected to produce a smaller production possibility set due to it does not rely on convexity, describing a stepwise technology as opposed to the piecewise nature of DEA. However, through the implementation of robust estimations, we observed that DEA and FDH yield similar scores. The higher efficiency scores in Model 2 signify a more homogeneous performance among Decision Making Units (DMUs) concerning the rate of students passing the first grade compared to the test scores of students. This observation is not unexpected, considering that the two models focus on different aspects of educational outcomes, and the efficiency scores reflect the relative performance of DMUs in these distinct dimensions.

In Model 1 (where the output is estimated using the ECE test scores), robust FDH identifies 12 efficient UGELs (Bongara, Antonio Raymondi, Antabamba, Condesuyos, Huancasancos, Espinar, Rio Tambo, Gran Chimu, Sanchez Carrion, Putumayo, Sanchez Cerro, and Puno), while robust DEA designates 11 units as efficient in Model 1. The units identified as efficient are the same for both technologies, except for Sanchez Cerro. Table 3 presents the aggregated efficiency scores by regions. In the FDH technology, the regions maintaining an efficient performance position (concerning UGEL results) are Junin, Loreto, and Moquegua. For robust DEA, the regions maintaining the top ranking position (i.e., efficiency score of 1) are Junin and Loreto. Other regions with consistently high-efficiency scores include Amazonas, La Libertad, and Moquegua, encompassing efficient or highly ranked UGELs (e.g., UGELs Otuzco, Sanchez Carrion, Santiago de Chuco in La Libertad).

Model 2 (where the output is estimated using the rate of students progressing in school) provides a similar interpretation, with 22 efficient UGELs identified by robust FDH and 18 by DEA technology. The UGELs marked as efficient for both technologies include: Bongara, Antonio Raymondi, Antabamba, Castilla, Condesuyos, Huancasancos, Espinar, Chincha, Palpa, Rio Tambo, Sanchez Carrion, Viru, Huarochiri, Pasco, Azangaro, Puno, Sandia, and Tacna. Efficient regions in Model 2 encompass Ica, Junin, Pasco, and Tacna. The Ica region aligns with the units marked as efficient

(UGELs Chincha and Palpa), while Pasco and Tacna each consider one UGEL in the computation.

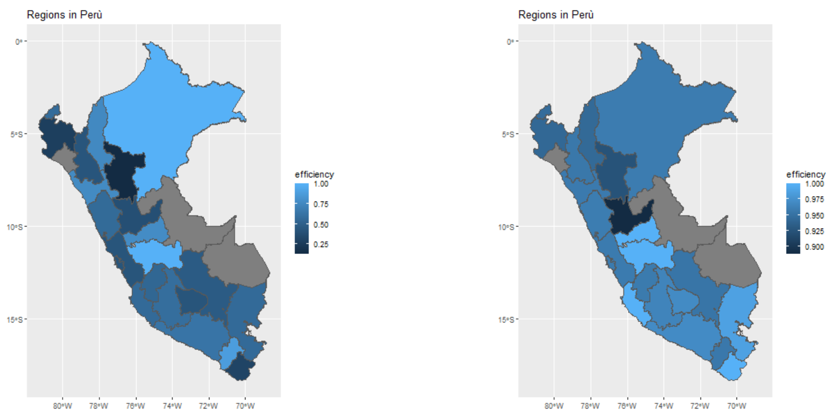
Table 3: Results from Robust FDH, Robust DEA, and StoNED approach for models 1 and 2.

	Model1			Model2		
Regions	FDH	DEA	StoNED	FDH	DEA	StoNED
AMAZONAS	0.759	0.760	0.443	0.964	0.944	0.939
ANCASH	0.599	0.568	0.483	0.975	0.959	0.952
APURIMAC	0.463	0.426	0.392	0.994	0.971	0.970
AREQUIPA	0.636	0.631	0.477	0.977	0.971	0.899
AYACUCHO	0.625	0.588	0.473	0.989	0.965	0.962
CAJAMARCA	0.423	0.430	0.392	0.971	0.955	0.969
CUSCO	0.516	0.467	0.360	0.973	0.953	0.937
HUANCAVELICA	0.533	0.543	0.475	0.977	0.958	0.963
HUANUCO	0.380	0.387	0.367	0.899	0.888	0.911
ICA	0.566	0.567	0.466	1	1	0.875
JUNIN	1	1	0.525	1	1	0.955
LA LIBERTAD	0.826	0.769	0.526	0.966	0.957	0.933
LIMA	0.445	0.426	0.441	0.985	0.958	0.937
LORETO	1	1	0.467	0.948	0.959	0.908
MOQUEGUA	1	0.883	0.592	0.994	0.955	0.965
PASCO	0.778	0.778	0.480	1	1	0.836
PIURA	0.270	0.278	0.309	0.968	0.943	0.956
PUNO	0.568	0.568	0.438	0.996	0.988	0.884
SAN MARTIN	0.136	0.131	0.238	0.968	0.925	0.944
TACNA	0.284	0.311	0.380	1	1	0.861
TUMBES	0.570	0.578	0.445	0.959	0.946	0.965

Interestingly, despite StoNED relying solely on classical non-parametric DEA constraints (monotonicity, convexity, and CRS) without assuming a specific functional form, the results from this approach are significantly lower than its non-parametric counterparts (DEA and FDH). We conjecture that the partition between asymmetric inefficiencies and the noise term makes StoNED a more nuanced approach. In our models, StoNED does not assign a score of 1 to any UGELs; however, the units classified as efficient according to DEA and FDH also obtain the highest scores in StoNED efficiency scores. This is except model 1, where UGELs Huaylas, Chincheros, La Union, Parinacochas, La Convencion, Huamalies, Chulucanas, Huancabamba, Sullana, and Lamas are excluded from achieving the highest score. Descriptive analyses of model 2 reveal that the efficient units for DEA and FDH do not necessarily have the highest scores in StoNED (see Annexes). For instance, UGEL Puno is marked as efficient in FDH and DEA, whereas in StoNED, it ranks the lowest (0.763). UGELs in similar scenarios include Tacna (0.861), Palpa (0.821), Sandia (0.814), and Pasco (0.836).

Figure 1: Regional differences in efficiency

(a) DEA - model 1 (b) DEA - model 2



Note: the results from the FDH estimations deliver similar maps

From a geographical standpoint, units maintaining efficient positions according to DEA and FDH in model 1 (totaling 11) are located in the regions of Amazonas (UGEL Bongara), Ancash (Antonio Raymondi), Apurimac (Antabamba), Arequipa (Condeuyos), Ayacucho (Huancasancos), Cusco (Espinar), Junin (Rio Tambo), La Libertad (Gran Chimu, Sanchez Carrion), Loreto (Putumayo), and Puno (Puno). In contrast, for model 2 (with a total of 18), the regions containing UGELs with an efficiency score of 1 for both DEA and FDH are Amazonas (UGEL Bongara), Ancash (Antonio Raymondi), Apurimac (Antabamba), Arequipa (Castilla, Condesuyo), Ayacucho (Huancasancos), Cusco (Espinar), Ica (Chincha, Palpa), Junin (Rio Tambo), La Libertad (Sanchez Carrion, Viru), Lima (Huarochiri), Pasco (Pasco), Puno (Azangaro), Puno (Puno, Sandia), and Tacna (Tacna). An important consideration is that, except for Arequipa, these regions have traditionally obtained low ranks in national test scores. Presenting preliminary evidence of a more comprehensive evaluation of efficiency scores.

For better visualization, the figure below elaborates on this idea by presenting the aggregated efficiency scores by region. In model 1, regions that typically exhibit low achievement levels (e.g., Loreto, Amazonas, Moquegua, Junin) dominate the cluster of regions with higher performance. Conversely, regions that are often better ranked in Peruvian educational trends (e.g., Lima, San Martin) show evidence of low-efficiency scores. Model 2 presents a more uniform interpretation, except for Loreto and Huanuco (which exhibit the lowest scores). This suggests that UGELs with a high level of educational achievements can still be inefficient, underscoring the importance of incorporating multiple dimensions in performance studies.

To the best of our knowledge, no prior studies have quantitatively studied the performance of UGELs, considering multiple dimensions. Consequently, a direct comparison with previous literature is unfeasible. Earlier works, like Valdiviezo et al., 2021 and Saavedra and Gutierrez, 2020, present a comprehensive overview of the Peruvian education system, shedding light on the continuous dilemmas and tensions within the public education system from the second half of the twentieth century up to the present day. The challenges of serving a nation with a majority of indigenous and Hispanic roots, alongside African, Asian, and Middle Eastern minorities, are also discussed by Garcia, 2004 and Ames, 2012. However, this perspective does not align with our findings, as we observed that regions with a majority of indigenous and Hispanic roots, such as Amazonas and Ayacucho, maintain efficient positions in our models.

Other studies have presented an overview of the current state of educational provision in Peru, with a predominant focus on higher education (Arrieta & Avolio, 2020; Sanchez & Singh, 2018), the promotion of science and technology (Calistro Rivera et al., 2022; So & Seo, 2020; Velarde et al., 2023), and inclusion (Cabello et al., 2023; Goico, 2019). Our paper complements these studies by providing an evaluation at the UGEL level of education provision, considering both administrative and educational variables. The evidence presented in these studies offers a comprehensive and critical perspective on the Peruvian education system, enabling us to compare its results with those of other literature on education in Latin America and beyond.

5.2 Comparing efficiency score distributions

In this section, we provide further insights into the comparison among different estimations. Figure 2 presents a comparative analysis of the density distribution of Robust FDH, Robust DEA, and StoNED. In the graphical examination of model 1, we observe that DEA and FDH exhibit a similar distribution with a 'fat tail' (indicating high variance), while StoNED scores present a lower variance and a more symmetric distribution. Despite the visual difference in variance for StoNED scores, the three models share a similar mean efficiency. The similarity between Robust DEA and FDH estimations implies that, in model 1, the convexity assumption is satisfied, as the only feature differentiating DEA and FDH is the relaxation of the convexity assumption in the FDH estimation.

The results from the Wilcoxon test affirm the observations made in the graphical analysis. It's essential to note that the Wilcoxon test is a non-parametric method for assessing differences in medians (Neter et al., 1993). The null hypothesis posits that the median efficiency scores obtained from various estimation approaches are equal. This test, applied in the context of non-parametric efficiency estimations, as demonstrated by Haas and Murphy (2003), Ma et al. (2020), and Riccardi et al. (2012), is utilized to compare efficiency scores derived from different models. In our study, a p-value of 0.45 confirms that robust DEA and FDH approaches yield similar results, while the significant differences observed in DEA-StoNED and FDH-StoNED comparisons are highlighted by p-values smaller than 0.001.

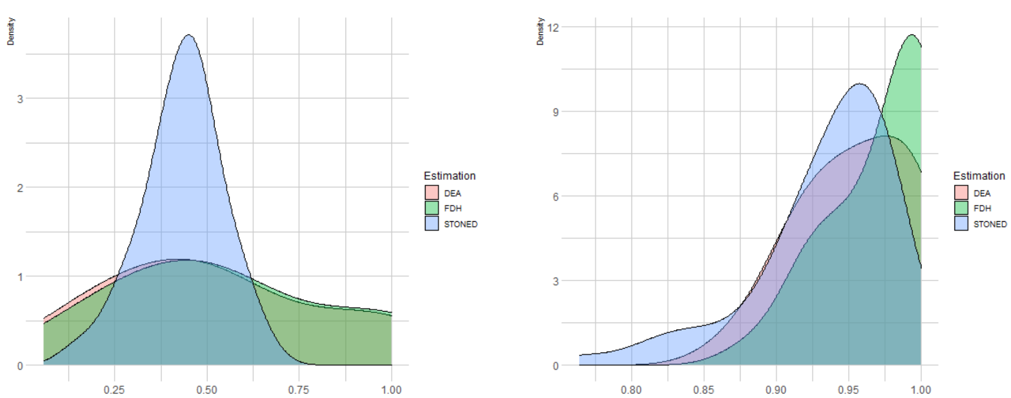
For model 2, we observe average efficiency scores closer to 1 for the three estimations, indicating higher homogeneity in the performances of UGELs. Due to the higher average and the upper boundary of efficiency scores capped at 1, the distribution of the efficiency scores in model 2 results asymmetric. Interestingly, unlike model 1, the three models exhibit a similar variance but a different mean efficiency. This contrast is also reflected in the Wilcoxon test results, which indicate a non-significant difference between Robust DEA and FDH estimation (p-value of 0.02), but a significant difference between Robust DEA and StoNED estimation (p-value of 0.013) and Robust FDH and StoNED estimation (p-value < 0.001).

As a robustness check, we also implemented the non-parametric test proposed by Li et al., 2009. This test detected no significant difference between Robust DEA and FDH for model 1 (p-value of 0.1). However, it revealed significant differences between Robust DEA and StoNED, as well as FDH and StoNED for model 1 (0.01858 and 0.001258 p-values). Additionally, the test indicated significant differences among the three estimations for model 2 (p-values smaller than 0.0003).

Figure 2: Density plots for DEA, FDH and StoNED estimations of model 1 (a) and 2 (b).

(a) Density distributions for model 1

(b) Density distributions for model 2



5.3 Investigating determinants of efficiency: results from conditional analysis

To explore the determinants of inefficiency and identify potential channels for enhancing the efficiency levels of UGELs, we conducted a Conditional DEA and FDH analysis. The regional-level results are presented in Table 4. To investigate the determinants of inefficiency and the possible channels to boost the efficiency levels of UGELs, we also conducted a Conditional DEA and FDH analysis. Results at the regional level are reported in Table 4, and the conditional efficiency scores for each UGEL can be found in Table 7 in the Appendix.

In Table 4, we observe that conditional scores, on average, are higher than robust scores. This outcome aligns with expectations, as the robust analysis evaluates each unit with respect to a random sample (of size m), assuming a common production function among all units. In the conditional case, this assumption is relaxed, allowing for different production functions for units characterized by distinct environmental features (i.e., different values of Z). In particular, the units to be included in the reference set (of size m) are selected according to their similarity along the conditional variables (Z). While conditional efficiency scores tend to be higher than robust scores, a notable discrepancy between the two estimations indicates potential significant effects of environmental variables. Another noteworthy point is that FDH and DEA scores exhibit similar rankings, despite the average conditional FDH scores being higher than the average DEA scores.

To further investigate the determinants of efficiency scores, the contextual variables are regressed against the conditional DEA scores using the non-parametric regression smoothing framework proposed by Daraio and Simar (2007a). The non-parametric regression does not require distributional assumptions and therefore is the most accurate approach to explain conditional DEA scores (since they do not follow standard distributions). In Daraio and Simar (2007a) paper, the authors consider the ratio of conditional over robust efficiency scores as the dependent variable in the non-parametric estimation. In this study, following the suggestion of Rogge et al. (2017), we inverted the ratio (i.e., robust over conditional efficiency) to facilitate a more direct graphical interpretation. According to Rogge et al. (2017), a negative slope of the regression line (higher value of conditional with respect to robust) signifies a negative influence of the conditional variable on the UGELs' possibility of being efficient, while a positive slope characterizes favorable environmental conditions.

The graphical representation of the non-parametric regression results is presented in Figure 3, illustrating the relationship between UGELs' efficiency scores and the quality of infrastructure and internet access (Daraio and Simar, 2007a and Buadin et al., 2010). A first insight is that contextual characteristics play an important role in determining the performance of model 1, as evidenced by the steeper non-parametric regression lines associated with this model.

Furthermore, Graph (a) illustrates the non-linear impact of infrastructure on UGELs' capac-

Table 4: Results from Conditional DEA and Conditional FDH for models 1 and 2.

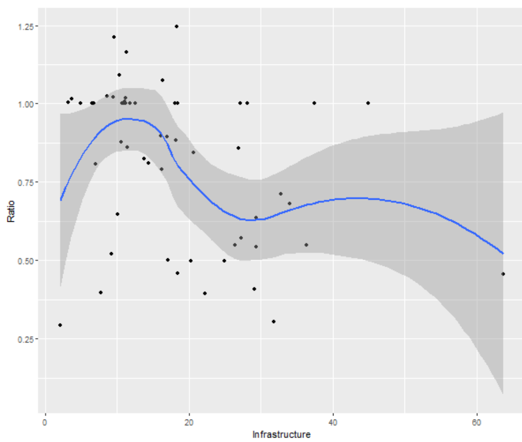
	Model1		Model2	
Regions	DEA	FDH	DEA	FDH
AMAZONAS	0.807	0.806	0.958	0.990
ANCASH	0.696	0.891	0.965	0.994
APURIMAC	0.554	0.561	0.985	1.000
AREQUIPA	0.721	0.724	0.971	0.975
AYACUCHO	0.756	0.876	0.987	0.998
CAJAMARCA	0.642	0.866	0.979	0.979
CUSCO	0.444	0.609	0.961	0.982
HUANCAVELICA	0.690	0.702	0.992	0.991
HUANUCO	0.417	0.454	0.918	0.940
ICA	0.841	1	1	1
JUNIN	1	1	1	1
LA LIBERTAD	0.974	0.996	0.983	0.992
LIMA	0.801	0.802	0.970	0.993
LORETO	1	1	1	1
MOQUEGUA	0.883	1	0.968	1
PASCO	0.874	0.923	1	1
PIURA	0.435	0.446	0.968	0.981
PUNO	0.600	0.622	1	1.000
SAN MARTIN	0.165	0.316	0.967	0.991
TACNA	1	1	1	1
TUMBES	1	1	1	1

ity to enhance schools' learning achievements (model 1). Extreme values of infrastructure quality, whether exceptionally high or low, correspond to unfavorable contextual conditions and restricted production possibilities. However, values within the 7 - 15 intervals encompass units with the broadest production possibility set. It's important to note that this effect is not significant based on the bootstrap test conducted by Racine, 1997. Graph (c) indicates that UGELs with lower infrastructure tend to exhibit higher conditional efficiency scores. This effect is statistically significant according to the bootstrap test. Although this result may seem counterintuitive initially, it can be explained by the notion that UGELs with limited infrastructure concentrate their efforts on maximizing the available inputs. Moreover, this outcome aligns with the evaluation focus on UGELs' ability to transform inputs into outputs. In some cases, conditions such as limited infrastructure, which are correlated with lower output, may also be associated with lower input, thereby favoring efficiency.

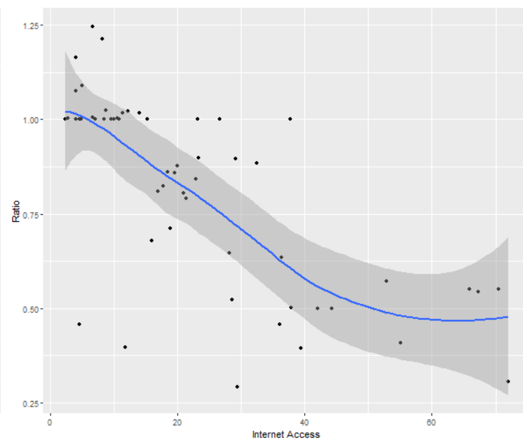
As for the effect of Internet access, the bootstrap test by Racine, 1997 showed that the influence of Internet access is significant for both models. Graph (b) illustrates a monotonic negative regression line, suggesting that higher levels of Internet access are associated with unfavorable conditions and are detrimental to UGELs' ability to produce learning achievements (model 1). On the other hand, the effect of Internet Access on model 2 - as depicted in Graph (d) - follows a U-shape, with extremely low and high values proving more favorable for efficiency scores than values within the interval of 15 - 30. Similar to the interpretation of graphs (a) and (c), spending on Internet Access beyond the capacity or existing conditions of an education system (e.g., teachers' abilities, school attendance) might divert institutions' focus from better managing their inputs. These findings suggest that spending on infrastructure and Internet Access is effective only up to the point where the education system can fully capitalize on the efficiency gains from additional developments in these areas.

Figure 3: Non-parametric regression explaining the ratio of the Robust DEA over the Conditional DEA.

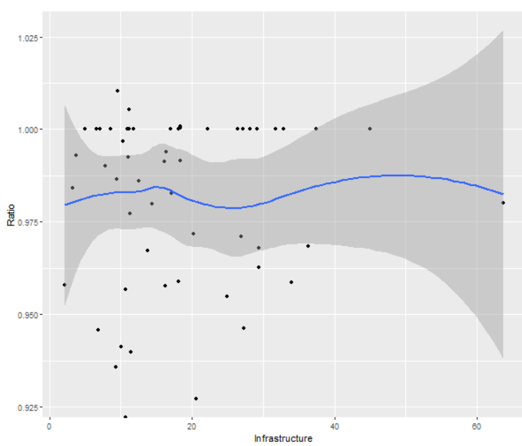
(a) Model 1 - Effect of Infrastructure on Eff.



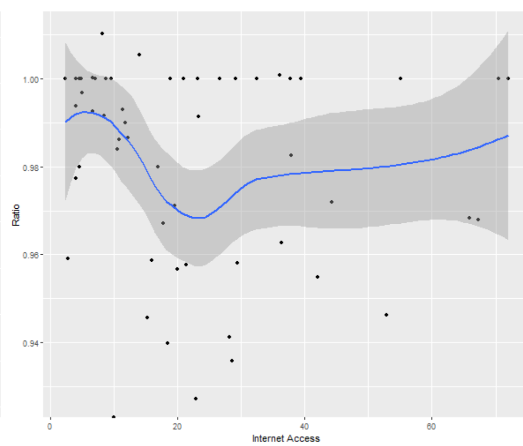
(b) Model 1 - Effect of Internet Access on Eff.



(c) Model 2 - Effect of Infrastructure on Eff.



(d) Model 2 - Effect of Internet Access on Eff.



5.4 Sensitivity and Robustness of Results

In this section, we examine the sensitivity of our findings by considering various factors, including the composition of units in the study, the selection of input and output variables, and potential impacts of measurement errors and outliers. Efficiency within the Data Envelopment Analysis (DEA) framework is defined as the ability to convert inputs into outputs relative to other units in the sample. Therefore, while our results demonstrate high internal validity, their sensitivity is contingent on the units included in the sample. The choice of input and output variables is equally crucial as it directly shapes the definition of efficiency. One notable limitation of DEA and Free Disposal Hull (FDH) is that they yield deterministic scores, thereby failing to account for potential measurement errors and outliers. However, by employing robust (and conditional) versions of DEA and FDH, we introduce an element of stochasticity into the computation of DEA/FDH scores, mitigating the impact of outliers and errors. Stochastic Non-smooth Envelopment of Data (StoNED) is a semi-parametric approach explicitly considering error terms, enhancing its robustness. Nevertheless, it still yields an efficiency score relative to other units in the sample. To summarize, our results are highly sensitive to the units included in the sample and the variables chosen for unit evaluation. These sensitivities are inherent to the DEA framework and are common considerations in DEA literature.

In this study, we employ conditional DEA and FDH analysis to examine the impact of environmental variables on efficiency. With this respect, the StoNEZD approach proposed by Johnson and Kuosmanen, 2011 is not directly comparable with the other two as it estimates the effect of Z using a single-stage process. In contrast, both DEA and FDH require a two-stage process: the first stage estimates the conditional efficiency scores, and the second stage estimates the impact of the environmental variables on efficiency. Between the two approaches (two stages DEA/FDH and one stage StoNEZD), we chose the first one due to its wider acceptance in the literature. Nevertheless, to ensure a comprehensive robustness check, we also implemented the StoNEZD estimation. This additional estimation confirmed the minimal effects of Internet Access and the level of Infrastructure on efficiency. Specifically, the effects were -0.006853947 and -0.006817778 for Model 1, and 0.0062946511 and 0.0009603033 for Model 2, respectively.

6 Conclusion

In this paper, we evaluated the performance of educational governance in Peru at the UGELs level. Performance evaluation literature has traditionally focused on the levels of students, teachers, and schools, neglecting the administrative aspects of educational systems. Recent studies have highlighted that good governance and administration practices in education systems promote effective and efficient delivery of education services. In particular, appropriate standards, incentives, information, accountability, and transparency are crucial for the high performance of public providers (Kennedy, 2003).

Our analysis availed of the data generated in 2014 by the Peruvian Ministry of Education about the administrative capacity of UGELs'. The data are used to evaluate UGELs' ability to use human resources, planning conditions, and accountability to create valuable educational outcomes, namely students' test scores in math (model 1) and the rate of students able to pass the grade with no retention (model 2). By comparing different estimation techniques, we provided an overarching perspective on UGELs' performances and presented insights on the impact of the technologies selected to induce fairer assessments of performance.

Six main lessons can be learned from this paper:

i) Efficiency approaches allow assessing UGELs' performance in their complexity and considering the multiple aspects (inputs and outputs) of education service delivery, ensuring a fairer classification. Typical econometrics approaches focus on associations between variables but fail in accounting for the complexity of the system as they consider only one dependent variable at the time (Barra et al., 2018; Montalvo-Clavijo et al., 2023). Efficiency estimation, on the contrary, is multidimensional and therefore offers more global (and fairer) evaluations (Aparicio et al., 2019; Navas et al., 2020; Sulis et al., 2020; Sun et al., 2023; Wang, 2019). The results from our efficiency estimations show that the ranking of UGELs drastically changes when accounting for the governing features of the education system (*Human Resources*, *Planning Capacities* and *Accountability*) and UGELs in regions that have traditionally scored lower in ECE Test scores are tagged as efficient (e.g., Loreto, Moquegua, Junin in model 1, and Ica, Junin, Pasco in model 2).

ii) By comparing the results from DEA, FDH and StoNED, we demonstrate that the choice of technology is relevant when ranking UGELs' performance. Therefore, policymakers ought to be aware of the efficiency score differences in performance estimations. Despite the importance of comparing different models, only limited papers implemented similar comparisons (e.g., see Andor and Hesse, 2011; De Borger and Kerstens, 1996; Drake and Simper, 2003; Liu et al., 2022). Non-parametric approaches (DEA and FDH) are the most accurate when the production function is unknown, as they rely on fewer assumptions. However, their scores are deterministic if robust approaches are not implemented. It is recommended to introduce stochasticity (e.g., bootstrapping) when performance estimations aim to present panoramic comparisons among UGELs that are robust to outliers in complex production settings (with the caveat of attributing all deviations from the frontier of efficiency).

iii) Semi-parametric approaches like StoNED, instead, are more subtle in detecting measurement errors and outliers but rely on distributional assumptions about the error and the inefficiency terms. Their use is preferable when data are subject to random noise. For instance, landslides blocking access to schools, and interruption of electricity service, which influence education service provision are better accounted for in stochastic frontier models.

iv) In general, FDH is the most benevolent (i.e., the one delivering the higher efficiency scores) and flexible approach, since it relies on a smaller number of assumptions. However, in our case, the Wilcoxon test shows that the difference between DEA and FDH estimations is not significant, indicating that both estimations deliver accurate results and that the convexity assumption on which DEA relies is fulfilled. That puts FDH as a good alternative to account for the heterogeneity of UGELs and provides reliable assessments of their efficiency (relative to pertinent variables detected).

v) When assessing performance, it is important to account for the environment in which the units operate. Conditional analysis allows us to compare UGELs with similar environmental characteristics, and therefore to discount for potential biases stemming from the evaluations of factors that are not under their control. Moreover, conditional production technology enables the exploration of (environmental) conditions associated with higher and lower efficiency scores. From a policy perspective, this has a twofold advantage: it enables identifying the areas that are most at risk of inefficiency and indicates possible mechanisms to boost efficiency gain.

vi) Finally, policymakers ought to be more attentive and refine their strategies when attempting to improve educational performance. Efficiency gains do not immediately happen by increasing the resources available (e.g., technology, staff training), and are subject to variations from heterogeneous environmental conditions. In our results, environmental variables (Infrastructure and Internet access) are associated with ambivalent effects on UGELs' production possibility set. These findings are consistent with the existing literature on educational performance, confirming that investments (resources) offer opportunities for efficiency gains provided education systems can capitalize on them.

This study has several limitations that suggest directions for future research. Firstly, the data used in this study covers only one year (2014), which limits the possibility of examining the temporal dynamics of the relationship between administrative resources and educational outcomes. A longitudinal analysis using panel data would be more informative and robust. Secondly, this study focuses on the case of Peru, which may not be generalized to other countries with different contexts and challenges in terms of governing systems. A comparative analysis across countries or regions would be useful to identify the factors that influence the effectiveness and efficiency of internet access and the quality of infrastructure in improving educational outcomes. Thirdly, this study investigates only two mechanisms that may mediate the impact of administrative resources on educational outcomes: internet access and quality of infrastructure. Other characteristics, such as teacher quality, pedagogical practices, curriculum design, and student motivation, may also play a role and deserve further exploration. Moreover, it would be interesting to disentangle between the shift of the frontier in the output direction and the effects of the distribution of efficiencies. Finally, from a methodological perspective, it would be interesting to compare different frontier approaches, such as stochastic frontier analysis, data envelopment analysis, and free disposal hull, to validate the results and assess the robustness of the efficiency estimates.

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Appendix

Table 5: Description of the inputs (x1 - planning capacities, x2 - human resources, x3 - accountability), outputs (y1 - ECE test scores, model 1, y2 - rate of students able to progress in school, model2), and environmental variable (z1 - Internet access , z2 - quality of infrastructure).

		Inputs			Outputs		Environmental	
Regions	UGEL	x1	x2	x3	y1	y2	z1	z2
AMAZONAS	BAGUA	30.300	19.900	48.700	51.700	84.795	26.912	19.600
AMAZONAS	BONGARA	2.500	21.900	18.200	69.200	88.104	27.184	23.100
ANCASH	HUAYLAS	30	15.900	52	20.200	84.478	18.391	36.100
ANCASH	PALLASCA	2.500	19.400	46	42.500	86.900	14.394	16.900
ANCASH	ANTONIO RAYMONDI	4.600	12	27.900	41.300	88.315	37.500	9.600
APURIMAC	ANTABAMBA	6.900	14.800	12.300	71.400	86.068	11.236	4.800
APURIMAC	CHINCHEROS	5.300	17.300	55.300	25.700	89.460	2.098	29.400
APURIMAC	COTABAMBAS	15.500	14.500	61.200	11.400	89.064	7.808	11.800
APURIMAC	GRAU	28.500	20.400	47.800	20.500	90.619	16.129	23.300
AREQUIPA	CASTILLA	8.300	17.200	63.400	71.200	94.220	32.857	18.800
AREQUIPA	CONDESUYOS	2.300	16.800	25	100	90.883	10.976	7
AREQUIPA	LA UNION	4.600	16.800	39.200	16.200	83.425	9.639	8.200
AYACUCHO	HUANCASANCOS	34.700	15.800	36.500	80.800	91.121	5	4.500
AYACUCHO	HUANTA	9.800	19.800	46.600	38.700	87.297	10.120	28.200
AYACUCHO	PARINACOCHAS	39.200	19.400	50.200	36.800	92.965	63.721	4.600
AYACUCHO	VICTOR FAJARDO	25.800	15.500	59.700	50	88.989	9.483	12.200
CAJAMARCA	CUTERVO	3.400	19.400	27.200	47.200	89.583	17.143	37.900
CAJAMARCA	JAEN	19.300	18.400	46.500	16.700	90.415	25	42
CAJAMARCA	SAN IGNACIO	19.600	19.300	59.200	60.900	89.599	18.399	8.500
CUSCO	ACOMAYO	6.400	19.900	16	35.800	89.340	11.321	4
CUSCO	ESPINAR	4.800	18.500	15.100	62.500	91.815	45	4
CUSCO	LA CONVENCION	30.800	14.800	58.500	5	85.973	16.351	4
CUSCO	PAUCARTAMBO	9	16.700	67.800	25.500	83.753	10.294	5
HUANCAVELICA	CASTROVIRREYNA	23.600	18.500	50.300	54.500	91.277	18.090	2.700

HUANCAVELICA	CHURCAMPA	2.300	17.200	51.100	56.800	88.194	11.152	14
HUANCAVELICA	TAYACAJA	3.400	18.100	50.900	44.400	85.972	9.302	28.500
HUANUCO	HUAMALIES	16.600	19.900	63.400	21	84.739	13.830	17.700
HUANUCO	LAURICOCHA	21.300	21.200	58.400	44.800	88.745	11.111	6.700
HUANUCO	PACHITEA	21.300	19.300	43.400	47.500	81.671	11.399	18.400
ICA	CHINCHA	35.600	18.300	30.300	53.200	92.717	26.486	70.500
ICA	PALPA	17.300	19.700	55.400	58.800	96.016	18.182	32.400
JUNIN	RIO TAMBO	2.300	13.700	64.700	28.900	90.300	11.840	2.300
LA LIBERTAD	GRAN CHIMU	27.500	14.200	69	82.500	85.115	10.667	9.900
LA LIBERTAD	OTUZCO	21.300	17.500	30.600	84.300	85.274	20.615	22.900
LA LIBERTAD	SANCHEZ CARRION	2.300	17.500	21.400	56.600	84.768	28.152	26.600
LA LIBERTAD	SANTIAGO DE CHUCO	19	18.600	27.500	55.800	84.601	34	15.900
LA LIBERTAD	VIRU	23.800	14.600	43.700	28.100	88.914	29.114	55.100
LIMA	CAJATAMBO	12.300	20.500	45.800	38.500	88.953	3.774	11.400
LIMA	HUAROCHIRI	28.400	15	54	30	92.264	22.222	39.400
LIMA	OYON	16.600	17.600	54.600	48.800	88.841	20.290	44.200
LORETO	PUTUMAYO	2.300	20.100	22.300	64	77.419	6.818	15.300
MOQUEGUA	SANCHEZ CERRO	27.300	15.400	59	80	88.300	12.500	10.800
PASCO	PASCO	25.700	21.200	44.300	77.800	95.912	16.964	29.100
PIURA	CHULUCANAS	10.500	19.700	53.300	25.500	88	29.350	36.400
PIURA	HUANCABAMBA	3.300	17.600	44.200	17.700	84.947	18.319	6.600
PIURA	TAMBOGRANDE	6.700	17.700	32	52.400	89.300	29.350	67.300
PIURA	SULLANA	21.100	19.100	53.800	7.100	91.660	36.364	65.900
PUNO	AZANGARO	24.700	19.700	49	34.300	93.496	7.051	21
PUNO	CARABAYA	37.900	19.600	42.800	56.300	90.943	10.645	20
PUNO	MOHO	24.200	20.700	50.100	48.500	94.678	3.268	10.500
PUNO	PUNO	10.500	19.200	58.200	100	96.633	6.582	37.700
PUNO	SANDIA	10.500	19.200	53.100	40.600	95.698	8.571	8.700
SAN MARTIN	LAMAS	19	17.700	51.200	12.300	87.383	16.250	21.300
TACNA	TACNA	3.400	16.900	57.700	25	93.108	31.797	72
TUMBES	ZARUMILLA	5.700	20.200	70.700	56.600	88.931	27.273	52.900

Table 6: Results from the Robust FDH, Robust DEA, and StoNED for model 1 and model 2, reported at UGEL level.

			Model1			Model2		
	Regions	UGEL	FDH	DEA	StoNED	FDH	DEA	StoNED
1	AMAZONAS	BAGUA	0.519	0.520	0.436	0.929	0.888	0.908
2	AMAZONAS	BONGARA	1	1	0.451	1	1	0.970
3	ANCASH	HUAYLAS	0.338	0.236	0.375	0.957	0.913	0.924
4	ANCASH	PALLASCA	0.458	0.469	0.412	0.969	0.965	0.958
5	ANCASH	ANTONIO RAYMONDI	1	1	0.661	1	1	0.974
6	APURIMAC	ANTABAMBA	1	1	0.595	1	1	0.966
7	APURIMAC	CHINCHEROS	0.274	0.295	0.374	0.987	0.956	0.972
8	APURIMAC	COTABAMBAS	0.366	0.194	0.333	1	0.983	0.975
9	APURIMAC	GRAU	0.212	0.214	0.267	0.988	0.945	0.966
10	AREQUIPA	CASTILLA	0.712	0.712	0.537	1	1	0.852
11	AREQUIPA	CONDESUYOS	1	1	0.587	1	1	0.927
12	AREQUIPA	LA UNION	0.197	0.182	0.307	0.932	0.913	0.917
13	AYACUCHO	HUANCASANCOS	1	1	0.584	1	1	0.966
14	AYACUCHO	HUANTA	0.407	0.406	0.388	0.957	0.920	0.940
15	AYACUCHO	PARINACOCHAS	0.380	0.379	0.387	1	0.981	0.970
16	AYACUCHO	VICTOR FAJARDO	0.713	0.569	0.532	1	0.961	0.971
17	CAJAMARCA	CUTERVO	0.481	0.502	0.430	0.988	0.983	0.976
18	CAJAMARCA	JAEN	0.180	0.179	0.272	0.995	0.955	0.972
19	CAJAMARCA	SAN IGNACIO	0.609	0.609	0.473	0.929	0.928	0.958
20	CUSCO	ACOMAYO	0.588	0.524	0.373	0.975	0.979	0.973
21	CUSCO	ESPINAR	1	1	0.492	1	1	0.918
22	CUSCO	LA CONVENCION	0.080	0.065	0.186	0.974	0.938	0.945
23	CUSCO	PAUCARTAMBO	0.398	0.281	0.390	0.942	0.896	0.911
24	HUANCAVELICA	CASTROVIRREYNA	0.554	0.548	0.471	0.994	0.959	0.976
25	HUANCAVELICA	CHURCAMPA	0.573	0.583	0.506	0.977	0.981	0.972
26	HUANCAVELICA	TAYACAJA	0.473	0.498	0.447	0.960	0.933	0.942
27	HUANUCO	HUAMALIES	0.214	0.221	0.280	0.881	0.881	0.907
28	HUANUCO	LAURICOCHA	0.448	0.452	0.388	0.920	0.921	0.947
29	HUANUCO	PACHITEA	0.479	0.489	0.433	0.894	0.863	0.879
30	ICA	CHINCHA	0.538	0.547	0.472	1	1	0.930
31	ICA	PALPA	0.595	0.588	0.460	1	1	0.821

32	JUNIN	RIO TAMBO	1	1	0.525	1	1	0.955
33	LA LIBERTAD	GRAN CHIMU	1	1	0.627	0.952	0.945	0.940
34	LA LIBERTAD	OTUZCO	0.843	0.843	0.553	0.945	0.926	0.931
35	LA LIBERTAD	SANCHEZ CARRION	1	1	0.498	1	1	0.895
36	LA LIBERTAD	SANTIAGO DE CHUCO	0.564	0.568	0.473	0.931	0.917	0.922
37	LA LIBERTAD	VIRU	0.722	0.435	0.480	1	1	0.974
38	LIMA	CAJATAMBO	0.392	0.400	0.374	0.972	0.935	0.956
39	LIMA	HUAROCHIRI	0.448	0.378	0.474	1	1	0.896
40	LIMA	OYON	0.494	0.500	0.474	0.983	0.940	0.959
41	LORETO	PUTUMAYO	1	1	0.467	0.948	0.959	0.908
42	MOQUEGUA	SANCHEZ CERRO	1	0.883	0.592	0.994	0.955	0.965
43	PASCO	PASCO	0.778	0.778	0.480	1	1	0.836
44	PIURA	CHULUCANAS	0.277	0.272	0.317	0.930	0.919	0.944
45	PIURA	HUANCABAMBA	0.194	0.224	0.301	0.961	0.930	0.933
46	PIURA	TAMBOGRANDE	0.533	0.542	0.482	0.984	0.967	0.972
47	PIURA	SULLANA	0.076	0.073	0.138	0.998	0.954	0.976
48	PUNO	AZANGARO	0.355	0.358	0.369	1	1	0.952
49	PUNO	CARABAYA	0.567	0.572	0.455	0.982	0.956	0.972
50	PUNO	MOHO	0.489	0.494	0.411	1	0.984	0.917
51	PUNO	PUNO	1	1	0.546	1	1	0.763
52	PUNO	SANDIA	0.429	0.417	0.408	1	1	0.814
53	SAN MARTIN	LAMAS	0.136	0.131	0.238	0.968	0.925	0.944
54	TACNA	TACNA	0.284	0.311	0.380	1	1	0.861
55	TUMBES	ZARUMILLA	0.570	0.578	0.445	0.959	0.946	0.965

Table 7: Results from the Conditional FDH and Conditional DEA, for model 1 and model 2, reported at UGEL level.

			Model1		Model2	
	Regions	UGEL	DEA	FDH	DEA	FDH
1	AMAZONAS	BAGUA	0.615	0.613	0.979	0.914
2	AMAZONAS	BONGARA	1	1	1	1
3	ANCASH	HUAYLAS	1	0.512	1	0.912
4	ANCASH	PALLASCA	0.624	0.588	0.983	0.980
5	ANCASH	ANTONIO RAYMONDI	1	1	1	1
6	APURIMAC	ANTABAMBA	1	1	1	1
7	APURIMAC	CHINCHEROS	1	1	1	1
8	APURIMAC	COTABAMBAS	1	0.457	1	0.988
9	APURIMAC	GRAU	0.246	0.243	1	0.953
10	AREQUIPA	CASTILLA	1	1	1	1
11	AREQUIPA	CONDESUYOS	1	1	1	1
12	AREQUIPA	LA UNION	0	0.163	0.919	0.910
13	AYACUCHO	HUANCASANCOS	1	1	1	1
14	AYACUCHO	HUANTA	0.920	0.627	0.992	0.978
15	AYACUCHO	PARINACOCHAS	0.886	0.827	1	1
16	AYACUCHO	VICTOR FAJARDO	0.745	0.552	1	0.974
17	CAJAMARCA	CUTERVO	0.988	0.994	1	1
18	CAJAMARCA	JAEN	1	0.353	1	1
19	CAJAMARCA	SAN IGNACIO	0.609	0.609	0.938	0.936
20	CUSCO	ACOMAYO	1	0.449	1	1
21	CUSCO	ESPINAR	1	1	1	1
22	CUSCO	LA CONVENCION	0.071	0.061	0.999	0.946
23	CUSCO	PAUCARTAMBO	0.361	0.257	0.933	0.899
24	HUANCAVELICA	CASTROVIRREYNA	0.545	0.547	1	1
25	HUANCAVELICA	CHURCAMPA	0.568	0.578	0.973	0.976
26	HUANCAVELICA	TAYACAJA	0.978	0.967	1	0.999
27	HUANUCO	HUAMALIES	0.321	0.258	0.921	0.908
28	HUANUCO	LAURICOCHA	0.448	0.448	0.928	0.928
29	HUANUCO	PACHITEA	0.563	0.566	0.956	0.919
30	ICA	CHINCHA	1	1	1	1
31	ICA	PALPA	1	0.668	1	1

32	JUNIN	RIO TAMBO	1	1	1	1
33	LA LIBERTAD	GRAN CHIMU	1	1	0.966	0
34	LA LIBERTAD	OTUZCO	1	1	1	1
35	LA LIBERTAD	SANCHEZ CARRION	1	1	1	1
36	LA LIBERTAD	SANTIAGO DE CHUCO	0.987	0.848	0.998	0.953
37	LA LIBERTAD	VIRU	1	1	1	1
38	LIMA	CAJATAMBO	0.410	0.398	0.981	0.942
39	LIMA	HUAROCHIRI	1	1	1	1
40	LIMA	OYON	1	1	1	0.967
41	LORETO	PUTUMAYO	1	1	1	1
42	MOQUEGUA	SANCHEZ CERRO	1	0.883	1	0.968
43	PASCO	PASCO	0.923	0.870	1	1
44	PIURA	CHULUCANAS	0.471	0.415	0.985	0.955
45	PIURA	HUANCABAMBA	0.186	0.182	0.940	0.933
46	PIURA	TAMBOGRANDE	1	1	1	1
47	PIURA	SULLANA	0.135	0.134	1	0.985
48	PUNO	AZANGARO	0.504	0.440	1	1
49	PUNO	CARABAYA	0.639	0.650	1	0.999
50	PUNO	MOHO	0.488	0.489	1	1
51	PUNO	PUNO	1	1	1	1
52	PUNO	SANDIA	0.406	0.406	1	1
53	SAN MARTIN	LAMAS	0.283	0.165	0.992	0.965
54	TACNA	TACNA	1	1	1	1
55	TUMBES	ZARUMILLA	1	1	1.000	1