

# ACADEMIC PRODUCTIVITY DYNAMICS IN COLOMBIAN SOCIAL SCIENCE PROGRAMS: A PCA–MALMQUIST INDEX APPROACH (2020–2023)

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## ABSTRACT

Higher education institutions need timely, explainable tools to identify students at risk of low performance on large-scale examinations and to guide targeted academic support strategies. In response to this challenge, this study proposes an explainable machine learning framework to predict undergraduate students' performance levels in Colombia's SABER PRO examination. Using student background variables (e.g., gender, region, school type, parental education, and occupation) and SABER 11 standardised test scores (Critical Reading, Mathematics, Citizenship Skills, Science, and English), we formulate a binary classification problem that distinguishes desirable outcomes (levels 3–4) from non-desirable outcomes (levels 1–2). We benchmark baseline models against non-linear learners, including XGBoost, GLMNET, SVM, DT, and LDA, using a 10-fold cross-validation protocol with systematic hyperparameter tuning. Model performance is assessed through confusion matrices and AUC scores. To support educational decision-making, we complement predictive results with explainability analyses, including global feature importance and individual-level explanations via SHAP, enabling transparent identification of the key drivers behind performance levels. The proposed approach provides actionable learning analytics to guide early academic support, promote responsible and transparent educational decision-making, and improve the likelihood of desirable SABER PRO achievement.

## KEYWORDS

Academic efficiency, educational analysis, Malmquist Index, social sciences

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## Highlights

- PCA improved dimensionality reduction in academic productivity assessment.
- Regional disparities shaped productivity in Colombian Social Science programs.
- Technological change was the main driver of productivity growth.
- Productivity gaps reflect unequal regional capacity for academic modernization.

## INTRODUCTION

Higher education systems face growing pressure to demonstrate effectiveness and equity while operating under heterogeneous regional constraints (Baciu et al., 2025). In Colombia, academic outcomes and institutional capacities vary substantially across departments, partly reflecting differences in digital infrastructure, teaching resources, and financing. These disparities motivate the use of objective, reproducible methods to evaluate academic efficiency and to understand how productivity evolves at the regional level.

Most empirical efficiency studies in higher education rely either on static frontier estimates or on fragmented indicator

sets that limit comparability across time and space (Jain and Gulati, 2025). When the objective is to evaluate intertemporal performance, the Malmquist productivity index (MI) provides a well-established decomposition of productivity change into shifts in the best-practice frontier (technological change) and movements toward or away from that frontier (efficiency change). However, MI results are sensitive to input and output selection, and rich educational databases may introduce redundancy and multicollinearity among competency indicators. Consequently, estimating educational productivity enables the identification of gaps and opportunities that lead to better planning and resource allocation. Besides, academic

skills are not uniform across different university programs. For an educational decision-maker, it would be important to know how efficiency varies over time, allowing for the assessment of the quality of education transversally (Sánchez-Sánchez et al., 2024; Zuluaga-Ortiz et al., 2023).

In Colombia, higher education presents a multifaceted problem with at least three fundamental causes. First, institutional resources are not evenly distributed across regions. Several studies report academic gaps between regions, driven by factors such as technological infrastructure, teacher training, and financing, which generate significant differences in academic productivity (Metzger and Shenai, 2021; Sierra-González and Ramos-Pérez, 2021). Accordingly, Gallimore (2025) shows that peripheral regions like Chocó and La Guajira have 40% less access to digital platforms than metropolitan areas like Bogotá and Antioquia, restricting their capacity to implement educational innovations. Second, there are methodological and structural gaps in the evaluation of academic efficiency. The absence of standardised metrics for measuring productivity leads to inaccurate diagnoses. Several studies identify that 78% of Ibero-American institutions use incongruous indicators, distorting comparisons between Higher Education Institutions (HEIs) (Agaronnik et al., 2022; Segbenya et al., 2024).

Third, there is a low integration of the factors that drive high productivity. Recent research shows that educational strategies and policies often fail to integrate variables such as technology and human talent. Delahoz-Dominguez et al. (2020) state that considering only one dimension of productivity increases productivity by just 0.3%, whereas considering all factors could boost it by up to 12%. Finally, these challenges are intensified by regressive funding mechanisms. Authors quantify that departments with low productivity levels receive at least 34% fewer resources, thereby widening the aforementioned gap each year (Barbosa-Camargo et al., 2021; Cai and Lönnqvist, 2022).

Consequently, in the research by Agasisti and Johnes (2015), the methodology was applied to European universities, identifying technological change (TC) as the main driver of productivity gains, while pure technical efficiency (PECH) explains system stability. Gao et al. (2022) combined the Malmquist Index with Principal Component Analysis (PCA) to successfully identify groups with diverse performance levels.

Thus, the study contributes not only to the measurement of efficiency but also to the discussion of responsibility in higher education, particularly in relation to regional equity and accountable resource allocation. Therefore, this paper addresses these challenges by combining PCA with a DEA-based Malmquist framework to investigate how academic productivity in Colombian social science programmes changes across departments over the 2020–2023 period, and whether these changes are primarily explained by technological change or by shifts in efficiency. Its theoretical contribution lies in reducing “indicator fragmentation” in academic productivity assessment by explicitly linking (i) the latent structure of competencies identified through PCA with (ii) a parsimonious and reproducible Data Envelopment Analysis (DEA) production specification for dynamic productivity measurement.

## LITERATURE REVIEW

### Efficiency in higher education

Analysing several reviews of the higher education efficiency literature, non-parametric DEA emerges as the dominant methodological approach, accounting for roughly 50% to 70% of published studies, while Stochastic Frontier Analysis (SFA) constitutes most of the remainder (Naderi, 2022; Rella et al., 2025; Ye et al., 2025) and faculties within colleges of a comprehensive university in Iran, we simultaneously evaluate efficiency scores of departments, faculties, colleges, and the university. It has been shown that: (1. These studies typically rely on cross-sectional designs or short panel datasets and employ single-frontier models that provide a “snapshot” of technical or cost efficiency relative to a best-practice frontier at a given point in time (Alvarez-Sández et al., 2023; Dipierro and Witte, 2024; Jain and Gulati, 2025) like any organization, must attend to the needs of the environment to provide quality services. Among the various aspects related to educational quality, administrative efficiency management has gained interest in recent times. This is due to the need to optimize resources and streamline the daily operations of an educational institution. This scoping review examines how efficiency is being measured in HEIs. By contrast, dynamic productivity approaches, such as the Malmquist index, as well as models that distinguish persistent inefficiency, remain comparatively less common. However, more recent contributions suggest growing interest in capturing intertemporal changes in institutional performance (Ye et al., 2025) pure technical efficiency (PTE).

Reviews of the higher education efficiency literature show a marked reliance on single indicators or a limited set. In the teaching dimension, the most common outputs are degrees completed or the number of graduates, while value-added measures and learning quality indicators remain comparatively rare (Rella et al., 2025). In research, studies usually rely on either publication counts or grant income, with ongoing debate over which proxy is more appropriate; both tend to produce highly correlated efficiency rankings while capturing different dimensions of performance (Oliveira-Melo et al., 2025). Likewise, only a small minority of studies explicitly incorporate quality-related variables or third-mission outputs, such as patents or community engagement activities (Liu et al., 2024). Although the literature increasingly acknowledges the importance of multi-mission frameworks and institutional heterogeneity—for example, through multilevel frontiers, meta-frontiers, and strategic clustering—most empirical applications still operationalize efficiency through relatively narrow and fragmented combinations of inputs and outputs (Agasisti and Berbegal-Mirabent, 2020; Ferro and D’Elia, 2020; Liu et al., 2024).

### Malmquist and productivity estimation

The Malmquist Productivity Index (MPI) has become a widely used tool for analysing productivity change in HEIs, particularly in multi-output settings where teaching, research, and third-mission activities jointly define institutional performance. Evidence from diverse national contexts—including Europe,

China, Malaysia, New Zealand, Spain, and Colombia—shows that the MPI is well suited to tracking changes in total factor productivity over time and decomposing them into efficiency change and technological change components (Brintseva, 2024; Parteka and Wolszczak-Derlacz, 2013; Wang et al., 2020; Xiao et al., 2024). At the same time, the validity of MPI-based estimates depends critically on the careful specification of inputs and outputs, as well as on the treatment of potential sources of bias such as environmental conditions, technological heterogeneity, and statistical uncertainty (Guo and Ye, 2025; Thanassoulis et al., 2011). Recent studies using more advanced extensions, including the global Malmquist index, metafrontier approaches, bootstrapping procedures, and three-stage DEA models, suggest that these methods improve both robustness and comparability across time periods and institutional groups (Mehroolhassani et al., 2019). Overall, the literature supports the MPI as a valuable framework for dynamic productivity analysis in HEIs, provided that its application is grounded in strong methodological rigour.

### Inputs and Outputs in Malmquist Productivity Analysis

Malmquist Productivity Index (MPI)–DEA results in higher education are highly dependent on how the production process is specified: which inputs/outputs are chosen, how technology is modelled over time, and what assumptions are made about scale and the environment (Pourmahmoud and Bagheri, 2023). In western China’s higher education, Guo and Ye (2025) build a three-stage DEA + global Malmquist model using province-level inputs (faculty, expenditure structures, human capital) and outputs (student and research performance). They show that adjusting for environmental variables and random shocks in a threestage framework changes the level and decomposition of efficiency and TFP, revealing that unadjusted models overestimate efficiency and obscure the role of scale vs. pure technical efficiency. In a similar approach, Arbona et al. (2022) apply a metafrontier Malmquist–Luenberger to education systems, allowing for heterogeneous technologies and “good” and “bad” outputs (e.g., performance and inequality). They show that incorporating bad outputs and metafrontiers changes the interpretation: part of what would be labeled “technical change” in a simpler MPI becomes technologygap and qualityorientation effects across groups.

Consequently, outputs restricted to volume (graduates, enrolments) tend to show scale-driven efficiency change, while including research outputs, quality, or equity indicators often reallocates variation into the technological change term or reveals regression in quality despite expansion (Brintseva, 2024; Xue et al., 2021). In contrast, contemporaneous Malmquist (frontier by year) can yield noncircular and inconsistent productivity paths; shifts in the frontier between  $t$  and  $t + 1$  are very sensitive to sample composition and outliers (Afsharian and Ahn, 2015). Besides, Robust, uncertain, or bootstrapbased MPI extensions show that small perturbations in inputs/outputs can materially change efficiency and MPI scores, indicating sensitivity to data uncertainty and to the particular index formulation used to compute EC and TC (Peykani et al., 2025).

### Malmquist and Principal Component Analysis

(Bo-xin et al., 2007) propose an “improved DEAbased MPI” that explicitly incorporates PCA to deal with multicollinearity among variables and weak links between DMUs and input/output indices. Using panel data from 10 Chinese container ports, they show that the PCA-enhanced MPI provides a more practical dynamic performance evaluation. In contrast, conventional MPI suffers from correlated variables and poorly structured index sets.

More broadly, multiple DEA–PCA studies show that PCA improves discrimination (fewer spurious efficient units) and stabilises efficiency scores when dimensionality is high, which is precisely the same DEA frontier that underlies MPI. For instance, Adler and Golany (2002) reduce the “curse of dimensionality” by using PCA to derive assurance-region constraints on DEA weights; three PCA–DEA formulations are shown to “noticeably improve the strength of DEA models”. Alternatively, using Monte Carlo simulations, PCA–DEA consistently yields more accurate classification of efficient/inefficient units than variable-reduction methods, reducing misclassification across all basic DEA models (Adler and Yazhensky, 2010). Overall, empirical PCA–DEA applications (corporate performance, public services) find far fewer “efficient” units and lower average efficiency, interpreted as a more realistic measure of performance rather than inflated efficiency due to too many variables (Liang et al., 2009; Lim et al., 2018).

Since MPI is built from DEA scores over time, improving the frontier’s stability and discrimination via PCA is expected to yield more robust MPI trajectories, as illustrated by the improved DEA-based MPI (Bo-xin et al., 2007). This is direct evidence that PCA–DEA integration can improve the robustness of MPI-type productivity tracking.

### MATERIALS AND METHODS

The original database contained 11,099 individual student-level observations collected between 2020 and 2023. However, the decision-making units (DMUs) in the DEA–Malmquist analysis were not individual students, but 23 Colombian departments observed over time, as the study aimed to compare territorial dynamics in academic productivity. Accordingly, the microdata was aggregated by department and year, generating a balanced panel for the study period. For each department-year, the variables associated with prior academic conditions (Saber 11) and university outcomes (Saber Pro) were summarised using central tendency indicators consistent with the latent dimensions identified through PCA. This aggregation strategy preserved the informational richness of the original database while aligning the empirical specification with the study’s regional-comparative objective.

For the construction of the results, the public database of the Colombian Institute for the Evaluation of Education Quality (ICFES) is used (ICFES, 2022). This database relates the assessment of state competencies in high school (Saber 11) and university (Saber PRO) (See Table 1). Furthermore, it is important to note that the competencies assessed in Saber 11 are the inputs to the research’s academic production function, while those assessed in Saber PRO are its outputs. Finally, the DMUs in the study are the departments of Colombia.

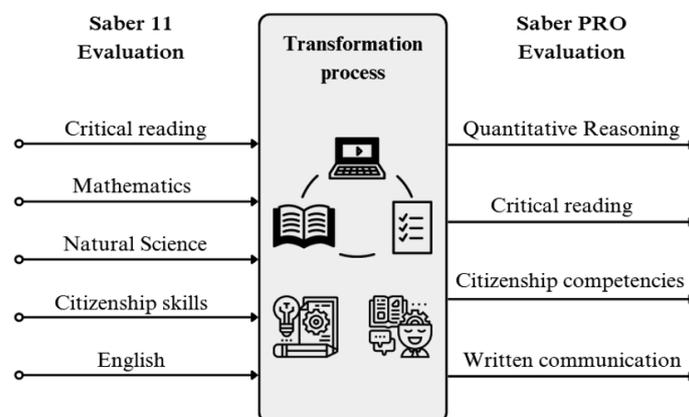
Component	Module	Brief description of what is assessed	Scale
Saber 11	Critical Reading	Ability to understand, interpret, and critically evaluate texts from everyday and academic contexts, including taking a critical position on their content.	0-300
	Mathematics	Ability to address situations that can be solved using mathematical tools, using them to understand situations, transform information, justify statements, and solve problems.	
	Social and Citizenship	Knowledge and skills to understand the social world, analyse events, arguments, concepts, and contexts, and issue critical judgments in civic and social situations.	
	Natural Sciences	Ability to understand and use concepts, notions, and theories from the natural sciences to solve problems, and to explain phenomena in nature based on observations, patterns, and scientific concepts.	
	English	Reading comprehension and communicative abilities in English, focused on language use at the reading level.	
Saber Pro	Critical Reading	Ability to understand, interpret, and critically evaluate written texts, including identifying explicit and implicit ideas, argumentative structure, and purpose.	0-100
	Quantitative Reasoning	Ability to interpret quantitative information, apply mathematical reasoning, and solve problems using numerical, graphical, and statistical representations.	
	Written Communication	Ability to produce a coherent and relevant written argument in response to a prompt, with attention to structure, clarity, and communicative purpose.	
	Citizenship Skills	Ability to analyse social situations and civic issues, reason about coexistence, rights, and democratic participation, and evaluate arguments in public-life contexts.	
	English	Reading comprehension and language use in English, aligned with CEFR/MCER proficiency levels (A1-B2).	

**Table 1: Variable's description**

The methodological design of the research is structured in two stages: first, a Principal Component Analysis (PCA) is carried out using an orthogonal linear transformation to identify performance profiles based on the DMUs' location in the quadrants. Second, a model is built using the Malmquist Index analysis methodology to evaluate academic efficiency between 2020 and 2023. This analysis is conducted using the production function shown in Figure 1.

The DEA model was specified with an output-oriented perspective, given that the analysis aimed to evaluate the extent to which departments transformed initial academic conditions into higher education outcomes. This orientation is appropriate in the educational context because territorial units have limited capacity to modify incoming students' characteristics in the short term. In contrast, institutional and regional policies are expected to improve academic outcomes by better leveraging available educational conditions and support structures. In this sense, the model assesses the potential expansion of academic results conditional on the observed input structure. Thus, the model was estimated under variable returns to scale (VRS) to account for structural heterogeneity across Colombian departments.

To preserve the discriminatory capacity of DEA, the dimensionality of the production function was kept parsimonious relative to the number of DMUs. In line with standard recommendations in the DEA literature, the number of observations must be sufficiently larger than the total number of inputs and outputs included in the model (Dyson et al., 2001; Khezrimotlagh, Cook and Zhu, 2021). For that reason, PCA was used as a preliminary step to organize the original indicators into coherent dimensions and avoid overparameterization. This procedure reduced redundancy among variables and contributed to a more stable and reproducible frontier estimation, preventing the excessive concentration of efficiency scores near unity that often arises when too many correlated indicators are introduced into the model (Cinca and Molinero, 2004). Therefore, in methodological terms, PCA was not used as a substitute for DEA, but as a complementary procedure to structure the information space, reduce redundancy among indicators, and support a more parsimonious specification of the academic production function. This improves the transparency and reproducibility of the subsequent DEA–Malmquist estimation.



**Figure 1: Academic production function**

## RESULTS

The first stage of the method involves data exploration through Principal PCA. For this, a graphical representation of the PCA in two dimensions is constructed (See Figure 2). The relationship of the variables with the principal components shows that they are grouped as follows: the first quadrant (Q1) groups the competencies Saber 11 Quantitative Reasoning (RC\_11), Saber 11 Citizenship Competencies (CC\_11), and Saber PRO Quantitative Reasoning (RC\_PRO). The second and third quadrants (Q2, Q3) have no academic competencies. Finally, the fourth quadrant (Q4) includes the competencies Saber 11 Mathematics (MAT\_11) and Natural Sciences (NAT\_11), Saber PRO Critical Reading (LC\_PRO), Citizenship Competencies (CC\_PRO), English (LC\_11), English (CE\_PRO), and English (ING\_11).

and Written Communication (CE\_PRO), and Saber 11 English (ING\_11). It is noteworthy that these competencies determine the characterization of the quadrants; thus, if an observation falls in the fourth quadrant, it indicates high performance related to the competencies there.

The distribution of observations across the quadrants is as follows: the second quadrant accounts for the majority (32%), followed by the first (25%), then the third (24%), and finally the fourth (20%). This distribution may reflect how competencies align based on their statistical similarities and their weight within the model. The lower percentage in the fourth quadrant could imply that the competencies in that quadrant show greater dispersion or lower weight in the first principal component.

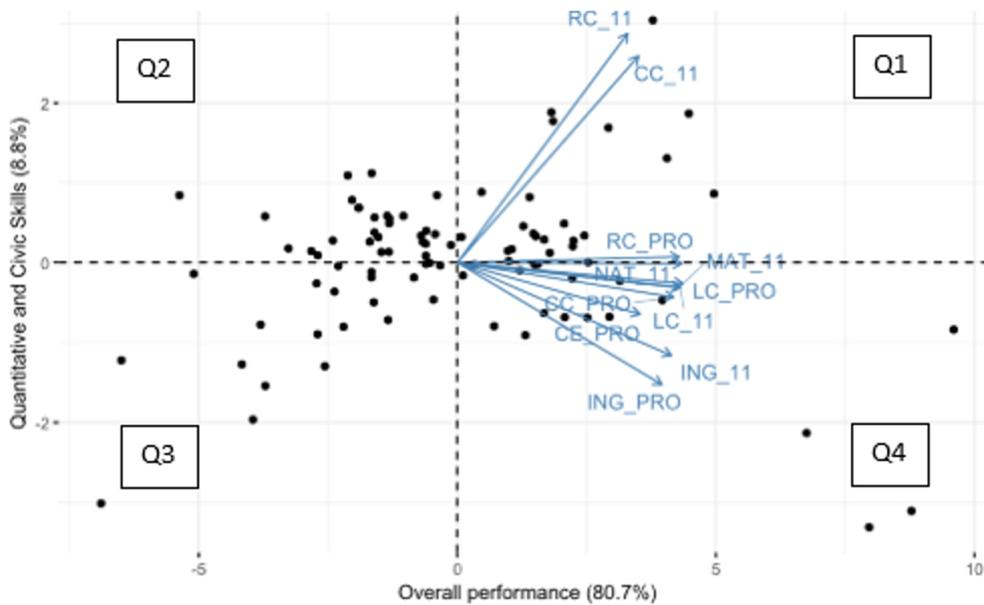


Figure 2: PCA two-dimensional biplot of academic competencies

Consequently, Table 2 is constructed to break down the PCA results by year. Consequently, in 2020, observations were concentrated in the third quadrant (43%), and combining this with the concentration in the second quadrant (14%) yields 57%, indicating that over half of the study’s observations showed low performance. In 2021, the concentration in the second and third quadrants was 61%, up from 2020, indicating a deterioration in performance. Similarly, in 2022

and 2023, the concentration in quadrants two and three was 52%, showing a decrease of 9% from 2021 to 2022, which then remained stable in the transition to 2023.

Furthermore, the behaviour in the fourth quadrant is important to note as it has the highest share of academic competencies. This quadrant had the lowest concentration of observations across all years. However, in 2022 and 2023, it increased to 27%, suggesting an improvement in the population’s overall performance.

Year	Quadrant			
	1	2	3	4
2020	7 (30%)	3 (14%)	10 (43%)	3 (13%)
2021	6 (26%)	6 (26%)	8 (35%)	3 (13%)
2022	5 (22%)	10 (43%)	2 (9%)	6 (26%)
2023	5 (22%)	10 (43%)	2 (9%)	6 (26%)

Table 2: Distribution of Observations by Year in the PCA 2D Biplot.

The second stage of the method involves analysing the academic production function using the Malmquist Index. Table 3 shows the results of the Malmquist Index indicators (MI: Malmquist Index; TC: technological change;

PECH: pure technical efficiency; SECH: scale efficiency). For the first period (2020-2021), the productivity indicator MI is less than 1 (MI = 0.96), indicating a decrease in overall system performance. This is associated with

the technological change indicator (TC = 0.95); however, pure technical efficiency (PECH = 1.01) showed a slight improvement, and its scale efficiency (SECH = 1.0) remained constant. For the second period (2021-2022), a recovery in productivity is observed (MI = 1.01), with an increase in the technological change indicator (TC = 1.01), and stability in both the technical efficiency indicator (PECH = 1.0) and

the scale efficiency indicator (SECH = 1.0). Finally, for the third period (2022-2023), the overall system productivity level remained constant (MI = 1.0). Meanwhile, there was an improvement in the technological change indicator (TC = 1.01), but a regression in the pure technical efficiency indicator (PECH = 0.99), while scale efficiency remained stable (SECH = 1.0).

Period	MI	TC	PECH	SECH
2020-2021	0.96	0.95	1.01	1.00
2021-2022	1.01	1.01	1.00	1.00
2022-2023	1.00	1.01	0.99	1.00

**Table 3: Overall Malmquist Index Results**

On the other hand, Table 4 presents the Malmquist indicators by department. Overall, departments with improvements in their academic productivity (MI > 1) are: Atlántico (1.01), Bolívar (1.01), and Magdalena (1.03). These three departments show progress in their technological indicator, and Bolívar also shows an increase in technical efficiency. Among departments with stable productivity (MI = 1.0) are Caldas, Cauca, Cundinamarca, La Guajira, and Risaralda. In contrast, departments with lower productivity levels (MI < 1) include Huila, Quindío, Tolima, Santander, Nariño, and Cesar. It is seen that in some cases, their technological change and pure technical efficiency indices are also below 1.

Consequently, significant differences between regions are evident. For instance, the department of Huila has the lowest overall productivity performance (MI = 0.95),

with regressions in its technological change indicator (TC = 0.96) and technical efficiency (PECH = 0.99), suggesting that efforts are insufficient to improve educational quality. In contrast, for the department of Magdalena, its productivity index (MI = 1.03) is the highest, supported by its level of technological change (TC = 1.03), while the other indicators remain constant. In the cases of Caldas and Cauca, we observe stable productivity indicators (MI = 1.00), while improvements occur in pure technical efficiency (PECH = 1.01) and technological change decreases (TC = 0.99). Lastly, in the case of Córdoba and La Guajira, despite the productivity levels (MI = 0.99; MI = 1.00), the respective scale efficiency values both indicate an upward trend (SECH = 1.01), suggesting that both may be employing effective quality improvement strategies.

DMU	MI	TC	PECH	SECH
Antioquia	0.99	0.99	1.00	1.00
Atlántico	1.01	1.01	1.00	1.00
Bogotá	0.99	0.99	1.00	1.00
Bolívar	1.01	1.00	1.01	1.00
Boyacá	0.99	0.99	1.00	1.00
Caldas	1.00	0.99	1.01	1.01
Cauca	1.00	0.99	1.01	1.00
Cesar	0.98	0.98	1.00	1.00
Choco	0.99	0.99	1.00	1.00
Córdoba	0.99	0.99	1.00	1.01
Cundinamarca	1.00	1.00	1.00	1.00
Huila	0.95	0.96	0.99	1.00
La guajira	1.00	0.99	1.00	1.01
Magdalena	1.03	1.03	1.00	1.00
Meta	0.99	0.99	1.00	1.00
Nariño	0.97	0.98	0.99	1.00
Norte Santander	0.99	0.98	1.00	1.00
Quindío	0.96	0.97	0.99	1.00
Risaralda	1.00	1.00	1.00	1.00
Santander	0.97	0.98	0.99	1.00
Sucre	0.98	0.99	0.99	1.00
Tolima	0.97	0.98	0.99	1.00
Valle	0.99	0.98	1.00	1.00

**Table 4: Malmquist Index Results by Department**

Table 5 presents the results of the Malmquist indicators by period and department. In the first period (2020-2021), most departments experienced a decline in productivity ( $MI < 1$ ), likely due to insufficient effort in the technological aspect ( $TC < 1$ ). On the contrary, in the second period (2021-2022), some departments improved their productivity levels ( $MI \geq 1$ ), and technological transition ( $TC > 1$ ) enabled them to do so. For instance, departments such as Antioquia, Atlántico, Bolívar, Caldas, Cauca, and especially Cundinamarca ( $TC = 1.12$ ) showed improvements, suggesting that more effective strategies were used. This recovery, which was present in the second period, allowed a consolidation and recovery in the third period (2022-2023), as the department of Magdalena presented an improvement in its overall productivity level ( $MI = 1.15$ ) and its technological transition indicator ( $TC = 1.15$ ), which

evidently positions this department as a benchmark in the region. The behaviours of each department are differentiated, finding marked trends. For instance, Magdalena shows sustained and exemplary growth in the last period. Cundinamarca shows a disruptive improvement in the second period (2021-2022), followed by a regression in the third period (2022-2023). Atlántico keeps a stable increasing behaviour with  $MI = 0.99$  in the first period, and then  $MI = 1.02$  in the second and third periods. The department of Bolívar shows sustained growth in all its indicators; similarly, the department of Boyacá moved from a decline in 2020 to positive behaviour in 2022. In contrast, the department of Huila shows low productivity performance in all periods. Departments like Risaralda and Caldas show continuous improvement, while Tolima shows an irregular trajectory. The department of Quindío keeps a constant level of productivity.

DMU	MI			TC			PECH			SECH		
	2020-2021	2021-2022	2022-2023	2020-2021	2021-2022	2022-2023	2020-2021	2021-2022	2022-2023	2020-2021	2021-2022	2022-2023
Antioquia	0.95	1.02	1.00	0.95	1.03	0.99	1.00	0.99	1.01	1.00	1.00	1.00
Atlántico	0.99	1.02	1.02	0.99	1.04	0.99	1.00	0.98	1.02	1.00	1.00	1.00
Bogotá	0.98	1.00	0.99	0.97	1.00	1.00	1.01	1.00	0.99	1.00	1.00	1.00
Bolívar	0.97	1.00	1.05	0.94	1.02	1.03	1.02	0.98	1.02	1.01	1.00	1.00
Boyacá	0.93	1.01	1.02	0.93	1.01	1.02	1.00	1.00	1.00	1.00	1.00	1.00
Caldas	0.98	1.02	1.01	0.94	1.02	1.01	1.02	1.00	1.00	1.01	1.00	1.00
Cauca	0.98	1.01	1.01	0.94	1.01	1.01	1.04	1.00	1.00	1.00	1.00	1.00
Cesar	0.94	1.00	1.00	0.94	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Choco	0.94	1.05	0.98	0.94	1.02	1.00	1.00	1.00	1.00	1.00	1.03	0.97
Córdoba	0.96	1.03	0.99	0.94	1.00	1.01	0.99	1.02	0.98	1.02	1.00	1.00
Cundinamarca	0.98	1.12	0.93	0.98	1.12	0.93	1.00	1.00	1.00	1.00	1.00	1.00
Huila	0.94	0.96	0.97	0.94	0.97	0.97	1.00	0.99	0.99	1.00	1.00	1.00
La guajira	0.98	0.98	1.02	0.96	0.98	1.02	1.00	1.00	1.00	1.03	1.00	1.00
Magdalena	0.94	1.02	1.15	0.94	1.02	1.15	1.00	1.00	1.00	1.00	1.00	1.00
Meta	0.97	0.99	1.00	0.97	0.99	1.00	1.00	1.00	1.00	1.00	0.99	1.01
Nariño	0.94	0.99	0.98	0.93	0.99	1.03	1.00	1.00	0.96	1.01	1.00	0.99
Norte Santander	0.99	0.98	0.98	0.95	1.00	1.00	1.04	0.99	0.98	1.01	0.99	1.00
Quindío	0.92	1.00	0.96	0.92	1.00	0.99	1.00	1.00	0.97	1.00	1.00	1.00
Risaralda	0.95	1.05	1.02	0.95	1.04	1.01	1.01	1.00	1.00	0.99	1.00	1.01
Santander	0.94	0.99	0.97	0.94	1.02	0.99	1.00	0.98	0.99	1.00	1.00	0.99
Sucre	0.99	0.97	0.98	0.98	0.97	1.00	1.00	1.00	0.98	1.01	1.00	1.00
Tolima	0.91	1.00	0.99	0.94	1.00	1.00	0.97	1.01	0.99	1.00	1.00	1.00
Valle	0.95	1.02	0.99	0.94	1.02	0.99	1.01	1.00	1.00	1.00	1.00	1.00

Table 5: Malmquist Index Results by Year and Department

## DISCUSSION

This research contributes to the frontier of knowledge in the field of efficiency analysis in education by using two data science tools to evaluate the dynamics of productivity in social science programs in Colombia. The combined use of the tools addresses two related drawbacks in the literature: the lack of indicators and the predominance of static assessments. In this order of ideas, the research is aligned with recent works that conclude that the analysis of academic productivity generates valuable information because it analyzes efficiency dynamically and not as isolated indicators (Arbona et al., 2022; Fu and See, 2022)

However, in terms of results, the most consolidated performance profile is in quadrant IV. This quadrant indicates that

the productivity of the evaluated programs is related to the areas of critical reading, English, and written communication. It is important to note that, although the concentration of DMUs in this quadrant increased in the last period analysed, the concentration of DMUs in the lower performing profiles was maintained. This result is supported by the literature, which evidences that academic performance is strongly related to environmental inequalities derived from the inequitable distribution of state resources (Arbona et al., 2022; Timmis and Valladares-Celis, 2025)

In line with the above, the results of the technological change indicator indicate that improvements in academic productivity depend on the ability to modernize teaching, learning, and

organizational conditions. This result aligns with recent studies that conclude that factors such as technical progress, digitalization of processes, and institutional modernization play a fundamental role in academic productivity indicators (Fu and See, 2022; Gao and Wang, 2023; Hieu and Niem, 2024; Liu et al., 2023).

On the other hand, in a global analysis, Magdalena stands out as a point of reference for the last period of analysis. In addition, Bolívar and Atlántico also presented favorable trajectories, while Quindío, Huila, and Nariño remained below the productivity frontier. In this sense, the results show that differences in performance are linked to unequal territorial capacity rather than only to institutional efforts.

Finally, this study has several limitations that should be acknowledged. First, although the DEA–Malmquist framework allows the analysis of productivity change over time, the results remain sensitive to the specification of inputs and outputs, even when PCA is used to reduce redundancy and improve parsimony. In line with standard DEA recommendations, the number of observations must be sufficiently larger than the total number of inputs and outputs included in the model, which requires maintaining a simplified production structure at the departmental level. Second, aggregating 11,099 student-level observations into 23 departments improves comparability across territories, but it may also mask within-department heterogeneity and institutional differences among higher education providers. Third, the study covers the 2020–2023 period, which is analytically relevant but still relatively short for capturing longer-term structural changes in academic productivity. Future research could address these limitations by extending the time horizon, incorporating additional contextual variables related to institutional quality and regional investment, and conducting complementary analyses at the university or program level to better capture intra-regional variation. Such extensions would help strengthen the explanatory power and policy relevance of the findings.

## CONCLUSION

This study examined academic productivity in Colombian Social Science programs as a dynamic and multidimensional

expression of educational performance. The findings show that productivity is not determined solely by final academic outcomes, but by the interaction among students' incoming competency profiles, the academic conditions of higher education institutions, and the broader regional context in which these processes occur. The increase in the high-performance quadrant over the study period suggests that some territories improved their academic positioning, while the Malmquist decomposition showed that technological change was the main driver of productivity growth. At the same time, the departmental analysis confirmed that academic productivity in Colombia is markedly heterogeneous, with some regions displaying stronger trajectories of innovation and adjustment than others. These results reinforce the idea that the quality of higher education should be assessed through dynamic, territorially sensitive approaches rather than isolated, static indicators.

From a methodological perspective, integrating Principal Component Analysis with Malmquist productivity analysis provides a coherent framework for addressing indicator fragmentation and evaluating changes in academic efficiency over time. In particular, PCA helped organize the dataset's information structure through an unsupervised learning approach. At the same time, the DEA–Malmquist framework enabled identification of whether productivity changes were associated with technological progress, pure efficiency gains, or scale effects. Beyond its technical contribution, the study also has implications for educational policy and responsibility in higher education. The results suggest the need to strengthen academic quality through differentiated regional strategies to improve digital infrastructure, pedagogical capacity, and institutional support systems, especially in departments facing less favorable productivity dynamics. In this sense, promoting academic productivity should not be understood only as an efficiency objective, but also as part of a broader commitment to equity, accountability, and balanced territorial development in higher education.

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