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Article

Mathematics in Ecuadorian Professional Life: Quantitative Literacy and a Bayesian Analysis of Unemployment by Educational Level

Las matemáticas en la vida profesional ecuatoriana: alfabetización cuantitativa y un análisis bayesiano del desempleo por nivel educativo

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Abstract

Objective: To reflect on the role of mathematics in professional practice in Ecuador and to demonstrate, using open data, how quantitative reasoning (particularly Bayesian inference) supports decision-making. Methodology: A thematic review was combined with an empirical study based on open data from the World Bank (World Development Indicators, based on ILO estimates) on unemployment rates by educational level in Ecuador between 2005 and 2024 (n = 57 country-year observations). Two Bayesian models were estimated using PyMC—a comparison of means by educational level and a time trend—with weakly informative priors and Hamiltonian Monte Carlo (NUTS) sampling. Results: The average unemployment rate was higher among those with intermediate education (6.15%; 94% credibility interval: [5.73, 6.59]) and advanced education (4.95%; [4.57, 5.34]) than among those with basic education (2.49%; [2.20, 2.80]); the posterior probability that

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unemployment among those with advanced education would exceed that of those with basic education was 1.00, and unemployment among those with advanced education showed an upward trend (0.068 percentage points per year; [0.009, 0.128]; probability of a positive slope = 0.98). Conclusions: Far from denying the value of education, this pattern reflects informality and the wait for formal employment, and demonstrates why careful statistical interpretation is an indispensable professional skill in contemporary Ecuador.

Keywords: mathematics education; quantitative literacy; Bayesian inference; labor market; Ecuador.

Resumen

Objetivo: reflexionar sobre el papel de las matemáticas en el ejercicio profesional en el Ecuador y mostrar, con datos abiertos, cómo el razonamiento cuantitativo (en particular la inferencia bayesiana) sostiene la toma de decisiones. Metodología: se combinó una revisión temática con un estudio empírico basado en datos abiertos del Banco Mundial (Indicadores del Desarrollo Mundial, con base en estimaciones de la OIT) sobre las tasas de desempleo por nivel educativo en el Ecuador entre 2005 y 2024 (n = 57 observaciones país-año). Se ajustaron dos modelos bayesianos con PyMC —una comparación de medias por nivel educativo y una tendencia temporal— con priores débilmente informativos y muestreo de Monte Carlo hamiltoniano (NUTS). Resultados: la tasa media de desempleo fue mayor en la educación intermedia (6.15 %; intervalo de credibilidad del 94 %: [5.73, 6.59]) y avanzada (4.95 %; [4.57, 5.34]) que en la básica (2.49 %; [2.20, 2.80]); la probabilidad posterior de que el desempleo con educación avanzada supere al de educación básica fue de 1.00, y el desempleo con educación avanzada mostró una tendencia creciente (0.068 puntos porcentuales por año; [0.009, 0.128]; probabilidad de pendiente positiva = 0.98). Conclusiones: lejos de negar el valor de la formación, el patrón refleja la informalidad y la espera por un empleo formal, y evidencia por qué la interpretación estadística cuidadosa es una competencia profesional insoslayable en el Ecuador contemporáneo.

Palabras clave: educación matemática; alfabetización cuantitativa; inferencia bayesiana; mercado laboral; Ecuador.

Introduction

One need only take a close look at a typical workday in Ecuador to discover that mathematics is everywhere, even though it is almost never explicitly mentioned. The accountant balancing a ledger, the agricultural engineer calculating fertilizer doses per hectare on farms in Los Ríos, the doctor interpreting the sensitivity of a diagnostic test, the vendor estimating her profit margin from memory at the Quevedo market, or the technician adjusting the turbine at a hydroelectric plant: all of them reason with quantities, proportions, rates, and probabilities. Mathematics is, in this sense, a kind of invisible infrastructure of professional life—so commonplace that we rarely notice it until it fails.

Research on numeracy in the workplace has shown that the mathematics used in professional practice is not a simple replica of what is taught in the classroom. Wake (2015) documents that, to function effectively in a job, people need context-specific modeling—the ability to translate reality into useful representations and to return to reality with a decision. FitzSimons and Wedege (2024) emphasize that this workplace numeracy is both technical and social: it is interwoven with the tools, norms, and relationships specific to each trade. The gap between school mathematics and workplace mathematics does not mean that the former is useless, but rather that it requires a process of appropriation that vocational training should explicitly support.

This phenomenon has become more pressing with digitalization. Karaali (2023) warns that, in the age of artificial intelligence, quantitative literacy—far from becoming dispensable—is becoming the skill that allows one to discern when to trust an automated calculation and when to question it. Van Laar et al. (2019) and Rakowska and de Juana-Espinosa (2021), drawing on research into 21st-century competencies, agree that data skills and analytical thinking currently top the lists of skills most in demand by employers. And economic evidence suggests that these skills pay off: Lee and Wie (2017) estimate significant wage returns associated with cognitive and quantitative competencies in Asian labor markets—a finding consistent with a long tradition in the economics of education.

This article pursues two intertwined objectives. The first, of a reflective nature, is to argue why mathematics—and statistical reasoning in particular—constitute a core competency for professional practice in Ecuador. The second, of an empirical nature, is to demonstrate this with a concrete and reproducible example: to analyze, using Bayesian inference and open data, a feature of the

Ecuadorian labor market that directly challenges those who train professionals. The choice of the Bayesian approach is not coincidental; as will be seen, it allows uncertainty to be expressed in the plain language of probability—something a professional needs when making decisions without certainty.

The text is organized as follows: Section 2 reviews the literature on labor numeracy, statistical literacy, educational performance in the region, and the link between higher education and the labor market in Ecuador, as well as Bayesian reasoning as a professional practice. Section 3 describes the open data and models. Section 4 presents and discusses the results. Section 5 concludes with findings and implications for teaching and public policy.

From School Mathematics to Numeracy in the Workplace

The distinction between school-based mathematical knowledge and workplace numeracy underpins much of the literature. Wake (2015) proposes a modeling-based perspective: the competent professional does not mechanically apply formulas but rather constructs provisional models of their situation, uses them to make decisions, and revises them in light of the results. FitzSimons and Wedege (2024) complement this idea by showing that numeracy in the workplace is a social practice, shaped by the tools, formats, and conventions of each sector. A pedagogical implication emerges from both works: training numerically competent professionals requires authentic situations, not just decontextualized exercises.

Statistical and Quantitative Literacy as a Competency

If anything characterizes contemporary work, it is the ubiquity of data. Statistical literacy—the ability to read, interpret, and question quantitative information—has become an essential component of citizenship and professional performance. Sabbag et al. (2018) distinguish between and empirically measure statistical literacy and statistical reasoning, showing that they are related but not identical constructs. Gómez-Blancarte et al. (2021) document, at the Mexican secondary level, the gap that still separates the statistics curriculum from its effective teaching—a gap that resonates throughout the region. In the field of adult competencies, Tunstall (2020) analyzes how numeracy is measured within the framework of the Program for the International Assessment of Adult Competencies (PIAAC), and Curry (2019) translates that framework into concrete instructional guidelines. Karaali (2023) links these discussions to the current technological landscape: quantitative literacy is what enables us to engage critically with automation.

Performance, Attitudes, and Equity in Mathematics Education

Performance in mathematics and its social distribution have been extensively studied using international assessments. Gamboa and Waltenberg (2012) show, using data from PISA 2006–2009, that in Latin America a considerable portion of the inequality in outcomes is explained by circumstances beyond individual effort (socioeconomic background, family environment), which constitutes an inequality of opportunity. Gamboa and Krüger (2016) delve deeper into the role of early childhood education in later achievement. Using more recent data, Guerra et al. (2026) analyze PISA 2022 and highlight socioeconomic and digital gradients in mathematics performance across Latin America and the Caribbean. Martins and Veiga (2010) confirm the significance of parents' education in score gaps. Regarding school-related factors, Liu et al. (2024) demonstrate, across a decade of PISA data, the association between perceived instructional quality and mathematics achievement. These findings are important for Ecuador because they describe the background from which future professionals emerge.

Attitudes and emotions also matter. Lim and Chapman (2015) demonstrate that teaching interventions can simultaneously improve attitudes, anxiety, motivation, and performance, suggesting that the affective dimension is not merely an afterthought but a factor with measurable consequences. Finally, gender equity remains an unresolved issue: Beekman and Ober (2015) document how trends in math test scores may or may not position young women for careers in science, technology, engineering, and mathematics (STEM), and Martínez et al. (2023) analyze, from an interregional perspective, the persistently low representation of women in these fields. Without equity in access to mathematical proficiency, professional life reproduces existing inequalities.

Higher Education and the Labor Market in Ecuador

The link between education and employment in Ecuador has well-documented characteristics. In a recent econometric study, Rivera Ávalos (2026) finds that higher education is a determinant of formal employment; that is, a higher level of education increases the probability of obtaining a formal job. This finding coexists, however, with a structural history: MacIsaac and Rama (1997) had already shown that labor market regulations play a significant role in determining hourly wages in the country. The quality and governance of the university system have been the subject of successive reforms; Jameson (1997) described early on the tensions within a higher education system subject to multiple pressures, and Jiménez Cabrera (2021) analyzes how current regulations seek to ensure quality. Acosta and Stefos (2021) compare the quality assurance systems of Colombia and Ecuador, while Reinoso Avecillas (2023) examines dual programs in Ecuador's public technical higher education system—a model that directly link the classroom and the workplace. At the regional level, Ontaneda Jiménez and Mendieta Muñoz (2022) show that institutional factors influence subnational economic growth, reinforcing the idea that human capital formation operates within structures that either enhance or limit it. These institutional conditions partly explain why the returns on education—well established internationally by Lee and Wie (2017)—do not automatically translate into better employment outcomes, and why the digital and analytical skills highlighted by Van Laar et al. (2019) and Rakowska and de Juana-Espinosa (2021) take on strategic value.

Bayesian Reasoning as a Professional Practice

Bayesian statistics offers a framework particularly attuned to the way professionals reason: one starts with prior knowledge, updates it with evidence, and arrives at a conclusion expressed as a probability. Zellner (1995) contrasts the Bayesian and frequentist approaches to inference and decision-making, emphasizing the former's consistency for decision-making under uncertainty. Reilly (1976) represents the calculus tradition that made Bayesian inference operational long before modern computing. In professional practice, examples abound: Berry (2006) and Etzioni and Kadane (1995) demonstrate the role of Bayesian methods in medicine and public health; Kostoulas and Doi (2024) explain how likelihood ratios, interpreted Bayesianly, guide clinical diagnosis; and Takramah et al. (2022) apply hierarchical Bayesian models to estimate neonatal mortality with spatiotemporal variation. In engineering and management, Akhavan Niaki and Fallah Nezhad (2007) integrate Bayesian inference with stochastic dynamic programming to make decisions in production processes, and Ferrara et al. (2017) use robust optimization for stock market investment decisions. Abdallah (2025) illustrates how Bayesian inference and probabilistic graphical models support decision-making in artificial intelligence systems. However, Bayesian reasoning is not intuitive: Talboy and Schneider (2016) demonstrate that even professionals make systematic errors when updating probabilities, and that brief training significantly improves their performance. This last point connects the argument to education: if probabilistic reasoning is a professional skill, then it must be taught deliberately.

Materials and methods

The study adopts a quantitative approach, with an aim that is both illustrative and demonstrative: rather than providing an exhaustive explanation of the labor market, it seeks to show how Bayesian reasoning allows us to formulate professional questions and answer them using open data. Transparency and reproducibility were therefore prioritized.

Open data from the World Bank (World Development Indicators, WDI) were used, which in turn are based on modeled estimates from the International Labor Organization (ILO). Three unemployment rate indicators by educational level were used for Ecuador: basic education (SL.UEM.BASC.ZS), intermediate education (SL.UEM.INTM.ZS), and advanced education (SL.UEM.ADVN.ZS), each expressed as a percentage of the economically active population with the corresponding educational level. The time series covers the period from 2005 to 2024; data for 2020 are not available in the source, so the final dataset comprises 57 observations (19 per level). The data are publicly available and can be downloaded from the World Bank's open data portal (https://data.worldbank.org), allowing any reader to replicate the analysis. Since these are modeled estimates, the results should be interpreted as a description of trends, not as a labor force census.

Two models were specified. The first compares the average unemployment rate across educational levels. Let the observed rate for level g in year t be; we assume the model in Equation (1), with a mean and standard deviation specific to each level, and weakly informative priors defined in Equation (2), consistent with the percentage scale of the phenomenon and deliberately uncommitted to any particular outcome.

$$y_{g,t} \sim Normal(\mu_g, \sigma_g) \quad (1)$$

$$\mu_g \sim Normal(4.5, 5), \; \sigma_g \sim HalfNormal(3) \quad (2)$$

The differences in means across educational levels were calculated as derived quantities, along with the posterior probability that each difference would be positive.

The second model estimates the temporal trend in unemployment among those with advanced education using a Bayesian linear regression (Equation 3), where b represents the annual change in percentage points and the covariate is centered on the temporal mean. The priors are defined in Equation (4); the prior for b is centered on the absence of a trend. The posterior probability that the slope is positive was reported.

$$y_t \sim Normal(a + b \cdot x_t, \sigma), \; con \;\; x_t = t - \bar{t} \qquad (3)$$

$$a \sim Normal(5,5), \; b \sim Normal(0,1), \; \sigma \sim HalfNormal(3) \;\; (4)$$

The estimation was performed using Hamiltonian Monte Carlo sampling, via the NUTS algorithm implemented in the PyMC library (4 chains, 2,000 warm-up iterations, and 4,000 sampling iterations per chain; target_accept = 0.95). Convergence was assessed using the $\hat{R}$ statistic and the effective sample size (ESS). Credibility intervals are reported as 94% highest posterior density (HDI) intervals. The analysis, random seeds, and derived datasets are preserved to ensure reproducibility; the choice of the Bayesian framework follows the reasoning presented by Zellner (1995) and Reilly (1976).

Results

Figure 1 shows the evolution of the three unemployment rates. At first glance, a persistent pattern is evident: unemployment is systematically higher among those with intermediate education, followed by those with advanced education, and significantly lower among those with only basic education. Table 1 summarizes these characteristics.

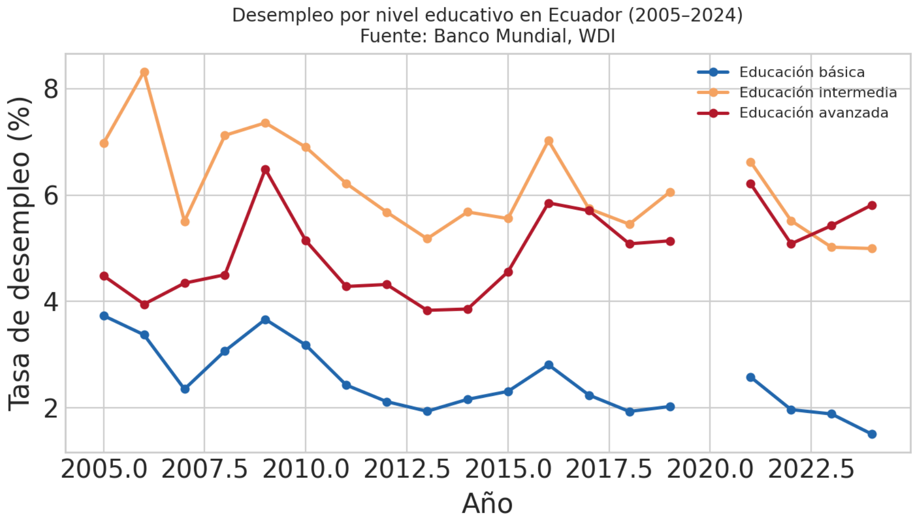

Figure 1. Unemployment rates by educational level in Ecuador (2005–2024).

Note: Prepared by the authors using data from the World Bank (WDI). Data for 2020 are not available in the source.

Table 1

Descriptive statistics on the unemployment rate by educational level (2005–2024)

Educational level	n	Mean (%)	SD	Min.	Max.
Basic	19	2.49	0.64	1.51	3.73
Intermediate	19	6.15	0.92	5.00	8.32
Advanced	19	4.95	0.80	3.83	6.49

Note: SD = standard deviation. Author's own calculations based on World Bank (WDI) data.

Bayesian comparison of levels

The comparison model converges without issues ($\hat{R}$ = 1.00 and ESS greater than 10,000 for all parameters). Figure 2 presents the posterior distributions of the average unemployment rate by level, and Table 2 summarizes the main results. The posterior mean was 2.49% for basic education (HDI 94%: [2.20, 2.80]), 6.15% for intermediate education ([5.73, 6.59]), and 4.95% for advanced education ([4.57, 5.34]).

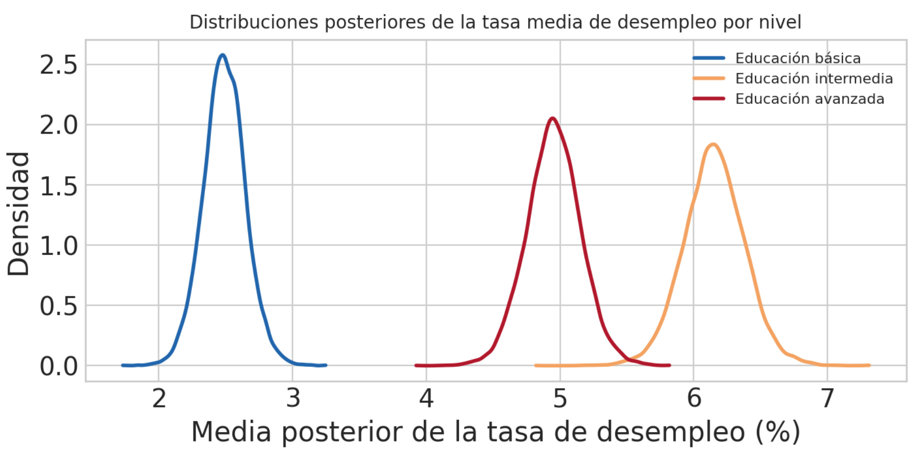

Figure 2. Posterior distributions of the average unemployment rate by educational level.

Note: Each curve summarizes the uncertainty surrounding the mean for the respective level.

The differences are clear. The gap between advanced and basic education is estimated at 2.46 percentage points (94% HDI: [1.98, 2.95]), with a posterior probability of 1.00 that it is positive (Figure 3). The difference between intermediate and basic education is even greater: 3.66 points ([3.10, 4.17]), also with a probability of 1.00. Between advanced and intermediate education, the difference is −1.20 points ([−1.79, −0.63]): the probability that unemployment among those with intermediate education exceeds that among those with advanced education is 0.9998. In other words, the data are practically conclusive in a way that, at first glance, seems counterintuitive: in Ecuador, having more education is associated with a higher—not lower—open unemployment rate.

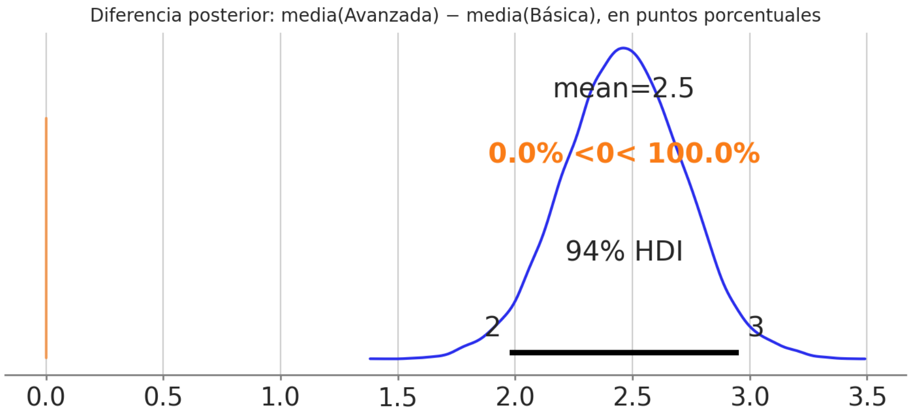

Figure 3. Post-estimation difference between the mean for advanced education and that for basic education.

Note. The lower band indicates the 94th percentile of the HDI; the vertical line marks the zero value.

Table 2

Posterior summary of Bayesian models

Parameter	Mean	94% HDI	P(> 0)
Basic μ (%)	2.49	[2.20, 2.80]	—

Parameter	Mean	94% HDI	P(> 0)
Intermediate μ (%)	6.15	[5.73, 6.59]	—
μ Advanced (%)	4.95	[4.57, 5.34]	—
Advanced − Basic (pp)	2.46	[1.98, 2.95]	1.00
Intermediate − Basic (pp)	3.66	[3.10, 4.17]	1.00
Advanced − Intermediate (pp)	−1.20	[−1.79, −0.63]	0.0002
Trend b (pp/year)	0.068	[0.009, 0.128]	0.98

Note: pp = percentage points; HDI = upper posterior density interval; P(> 0) = posterior probability that the parameter or difference is positive. $\hat{R}$ = 1.00 in all cases.

Unemployment Trend Among Those with Advanced Education

The second model estimates that unemployment among those with advanced education is rising at a rate of 0.068 percentage points per year (94% HDI: [0.009, 0.128]), with a posterior probability of 0.98 that the trend is indeed upward (Figure 4). Although the pace is moderate, the signal is consistent: over two decades, labor market participation among the most highly educated has not improved in terms of open unemployment—quite the opposite.

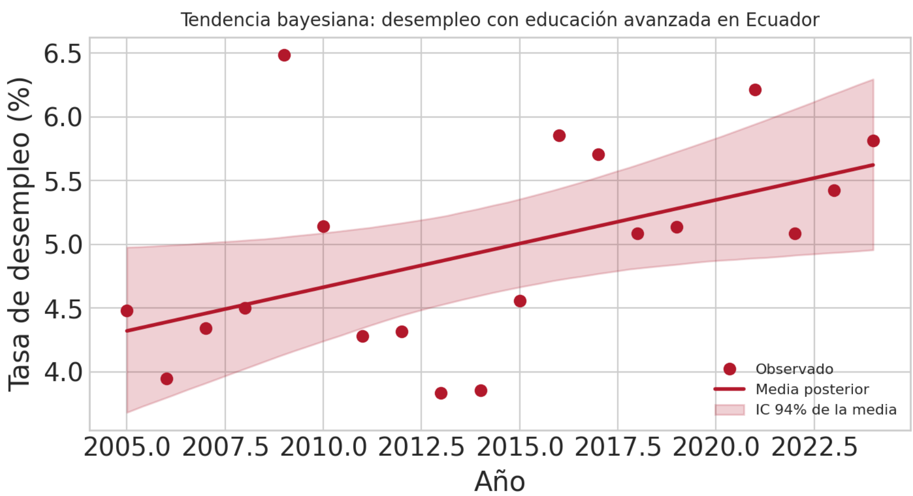

Figure 4. Bayesian trend in unemployment among those with advanced education in Ecuador.

Note. The band represents the 94% credibility interval for the mean; the points are the observed values.

Discussion

How should we interpret the fact that, in Ecuador, more education is associated with higher open unemployment? This is where the careful quantitative reasoning that this article advocates as a professional skill becomes indispensable. A naive interpretation would conclude that studying "is pointless"—an inference as tempting as it is mistaken. The most plausible explanation is that offered by the literature on dual labor markets in economies with high levels of informality: those with less education cannot afford to be unemployed and accept almost any job—often in the informal sector—so their measured unemployment rate is low even though their precariousness is high; in contrast, those with more credentials tend to wait and search longer for formal employment commensurate with their training, which raises their open unemployment rate without implying lower well-being. This "queueing" mechanism for formal employment is consistent with the evidence from Ecuador: Rivera Ávalos (2026) shows that higher education increases the probability of formal employment, and MacIsaac and Rama (1997) document the role of regulations in determining income. The open unemployment rate, on its own, does not capture the quality of employment; interpreting it without this nuance leads to error.

The professional lesson is twofold. First, the numbers do not speak for themselves: they require a model and an interpretation. Bayesian inference helps precisely because it forces us to make assumptions explicit (the priors) and provides conclusions in the form of manageable probabilities—"there is a 98% probability that the trend is upward"—rather than binary verdicts. Talboy and Schneider (2016) point out that this type of reasoning does not come naturally and must be learned ; Berry (2006), Etzioni and Kadane (1995), and Kostoulas and Doi (2024) demonstrate its usefulness in medicine, while Takramah et al. (2022), Akhavan Niaki and Fallah Nezhad (2007), Ferrara et al. (2017), and Abdallah (2025) do so in public health, manufacturing, finance, and artificial intelligence. Ecuadorian professionals who master these tools will be better positioned to make decisions.

Second, this finding raises questions for education and economic policy. The fact that returns on education exist—as confirmed by Lee and Wie (2017)—but do not translate seamlessly into better labor market outcomes suggests that the problem lies not only in the supply of skills but also in the structure that absorbs them. Ontaneda Jiménez and Mendieta Muñoz (2022) emphasize the role of institutional factors in subnational growth; Reinoso Avecillas (2023) and Acosta and Stefos (2021) point to relevance and quality assurance; Jiménez Cabrera (2021) and Jameson (1997) remind us that university governance is a long-term factor. Training good professionals is necessary, but it is not enough if the productive sector does not generate sufficient formal employment. And here, the gaps in origin documented by Gamboa and Waltenberg (2012), Gamboa and Krüger (2016), Guerra et al. (2026), and Martins and Veiga (2010), along with the gender inequalities identified by Beekman and Ober (2015) and Martínez et al. (2023), and the influence of attitudes described by Lim and Chapman (2015), determine who ends up competing for those jobs.

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