When *"finishing school"* is not equal: wage gaps in Brazil between youth and adult education and regular upper secondary education

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Resumo: Este artigo examina os efeitos no salários ao concluir o ensino médio por meio do programa Educação de Jovens e Adultos (EJA) em comparação com o ensino regular. Foi utilizado os microdados da PNAD Contínua de 2023, para construir um grupo de controle para os tratados foi utilizado o método de *propensity score matching* e regressão quantílica para estimar o *gap* salarial. Os resultados mostram uma penalidade salarial persistente para os formados pela EJA, em média, eles recebem R$ 204 a menos por mês do que os egressos do ensino médio regular. A análise de regressão quantílica revela que essa diferença salarial não é uniforme ao longo da distribuição, sendo a penalidade mais acentuada nos quantis superiores e inferiores. Esses resultados ressaltam as desvantagens enfrentadas no mercado de trabalho, por indivíduos que concluem o ensino médio por vias alternativas, além de destacar a importância de políticas voltadas à melhoria tanto da qualidade quanto da percepção dos programas de educação de adultos no Brasil.

Palavras-chave: Educação de Jovens e Adultos, Ensino Médio, Desigualdade Salarial

Abstract: This study examines the wage effects of completing upper secondary education through Brazil's Youth and Adult Education (EJA) modality compared to the regular track. Using microdata from the 2023 PNAD Contínua, we apply propensity score matching and quantile regression to estimate wage differentials. Results show a persistent wage penalty for EJA graduates, on average, they earn 204 BRL less per month than regular-track graduates. Quantile regression analysis reveals that this wage gap is not uniform across the distribution, the penalty is more pronounced at the upper and lower quantiles. These findings underscore the enduring labor market disadvantages faced by individuals who complete upper secondary education through alternative pathways and highlight the importance of policies aimed at improving both the quality and the perception of adult education programs in Brazil.

Keywords: Youth and Adult Education, Upper Secondary Education, Wage Inequality, Educação de Jovens e Adultos

Área 11 - Mercado de trabalho, Demografia e Migração

JEL Codes: I26, J24, C21

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1 Introduction

The labor market and its relationship with individual worker characteristics have been widely studied in the economic literature[1]. In his seminal paper, Mincer (1974) sought to associate the understanding of wages with the worker's schooling as a proxy variable for their abilities, in addition to including the worker's experience. However, it is worth noting that a significant part of the empirical studies found have sought to measure schooling in its purest form, to the detriment of delving into its various specifications and subjectivity. Reis (2020) investigated whether the probability of a worker being overeducated is higher among students from public upper secondarys. For the author, this phenomenon may occur due to educational disparities between public and private schools, so public school students tend to seek additional training to match workers from private upper secondarys.

The so-called diploma effect is a phenomenon related to the presence of employment returns, as well as wage returns, when the worker reaches certain thresholds related to the completion of an educational cycle, acting as a kind of signal to the labor market. Crespo e Reis (2006) analyze whether there is significant evidence in the relationship between the completion of educational levels and earnings. For individuals who completed elementary school, the authors estimated an increase of 15% in earnings, while for upper secondary, the diploma effect increases to 18%. Finally, for higher education, an even greater effect was observed, with an increase in earnings of 23%.

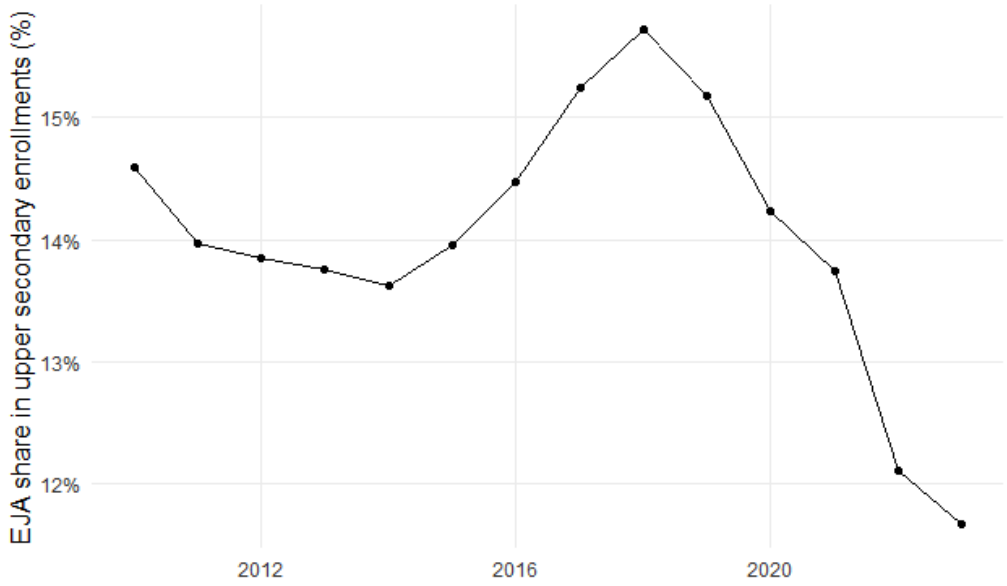
However, the diploma effect is limited to the quantitative analysis related to years of schooling, not aiming to measure the quality of the education provided, as pointed out by Crespo e Reis (2006). Thus, the same number of years of study does not necessarily represent the same amount of knowledge acquired by the student. This phenomenon is also relevant in the Brazilian context, where educational inequality and alternative educational pathways, pose similar questions regarding the signaling value of diplomas in the labor market.

Furthermore, the well-known educational inequality in Brazil leads to the creation of public policies aimed at implementing programs to mitigate this issue. The Youth and Adult Education Program (Educação de Jovens e Adultos - EJA), aims to provide elementary and upper secondary education to people aged 18 or older who have not completed the basic education cycles regularly[2]. Its main goal is to reduce the educational gap through shorter courses, since a student who would complete regular upper secondary education in three years could obtain the diploma in half that time. It should be noted that in 2018, just over 1.4 million EJA upper secondary enrollments were recorded, according to data from the Brazilian School Census (Censo Escolar).

[1] For example, Neal e Johnson (1996) aim to understand the determinants of the wage gap between black and white individuals, while Blau e Kahn (1994) focus on gender wage inequality.

[2] Upper secondary education refers to the final stage of basic education in Brazil, corresponding to *Ensino Médio* in the national system and including both regular and EJA modalities, according to the classification adopted by Brazilian Ministry of Education (*Ministério da Educação* - MEC)

Figura 1 – Relative Share of EJA Enrollments in Upper Secondary Education (2010–2023)



Source: Elaborated by authors using microdata from Censo Escolar (2010–2023). Note: The figure shows the annual proportion of EJA enrollments in relation to total upper secondary enrollments in Brazil between 2010 and 2023. The share is calculated as: EJA Share = EJA enrollments / (EJA enrollments + Regular upper secondary enrollments).

An analysis of enrollment data over the last decade provides important context for the scale and trends of EJA in Brazilian upper secondary education. As shown in Figure 1, the share of EJA enrollments in upper secondary education remained consistently high, exceeding 15% for several years, despite a notable decline since 2018. This downward trend highlights ongoing challenges such as school dropout, insufficient public policies, and the need for more inclusive approaches, especially in rural areas, since 94.5% of EJA enrollments are concentrated in urban zones (Nascimento; Fernandes, 2024).

Even though the creation of public policies aims to reduce the educational gap in the Brazilian population, there are possible negative externalities, according to Tavares, Souza e Ponczek (2014). In addition, another factor that should be a focus is the fact that completing upper secondary education through EJA may send a negative signal to the labor market, since it can be a less costly alternative in terms of effort and time commitment for students. Students participating in EJA programs typically come from low socioeconomic backgrounds, with a history of repeated school failure. This failure is often perceived as an individual responsibility, despite the fact that it results from multiple external and internal factors, including structural inequalities and adverse living conditions (Brazoto, 2024).

Concerning the socio-economic context, Figure 2 presents the share of EJA enrollments by region in 2023, highlighting significant spatial heterogeneity. The North, Northeast and Midwest regions show the highest relative shares of EJA students in upper secondary education, while the South and Southeast lag significantly

Figura 2 – Share of EJA Enrollments in Upper Secondary Education by Region (2023)

Source: Elaborated by authors using microdata from Censo Escolar (2023). Note: The figure presents the share of EJA enrollments in upper secondary education by region in Brazil for the year 2023. The darker the green, the higher the percentage of EJA students among all upper secondary enrollments in the region.

behind. These differences suggest that EJA plays a distinct role in the educational trajectories of students depending on the region, reflecting broader inequalities in access, socioeconomic conditions, and local policy emphasis. Therefore, regional context must be taken into account when evaluating the labor market consequences of obtaining an upper secondary diploma completed in the youth and adult education program.

When analyzing workers who completed upper secondary education through equivalency programs in the United States, Heckman e Rubinstein (2001) noted the presence of a negative signal, the mechanism behind this phenomenon being the presence of non-cognitive skills. This happens because this type of education is intended for students who left regular schooling, in addition to being associated with characteristics such as commitment, instability, among other factors, leading to a negative effect on the perception of employers.

Empirical evidence also from the US highlights the relationship between adult education and labor market outcomes; individuals who obtain a General Educational Development[3] (GED) tend to earn significantly less than regular graduates, in large part due to deficits in non-cognitive skills and employer skepticism toward alternative diplomas (Heckman; Humphries; Mader, 2010). Similarly, Cao, Stromsdorfer e Weeks

[3] The GED certificate is an alternative diploma in the United States that certifies that an individual possesses upper secondary-level academic skills, typically obtained by passing a standardized set of tests. The GED is designed for individuals who did not complete the regular modality.

(1996) finds that the human capital gains associated with the GED do not translate into labor market returns equivalent to those for regular upper secondary diplomas, further reinforcing concerns about limited signaling power.

However, Brough, Phillips e Turner (2022) suggests that more comprehensive adult upper secondary programs can lead to substantial earnings growth for participants, with graduates closing a significant portion of the wage gap relative to non-graduates, indicating the potential value of alternative pathways that provide both formal qualifications and broader skill development. Taken together, these findings underscore the need to evaluate not only the attainment of diplomas, but also the qualitative aspects of adult education programs and their broader impact on worker earnings.

Therefore, based on what has already been presented, the aim of this study is to examine how completing upper secondary education by the youth and adult education modality impacts workers' earnings. To this end, we employ propensity score matching (PSM) to pair individuals with similar observable characteristics, minimizing selection bias between EJA graduates and those from the regular education modality . Subsequently, we apply quantile regression to investigate how the EJA pathway affects wages across different points of the earnings distribution. The analysis uses data from the 2023 National Household Sample Survey (*Pesquisa Nacional por Amostra de Domicílios Contínua* – PNADC).

This study aims to contribute to the understanding of how alternative educational pathways, such as the youth and adult education modality , shape labor market outcomes in a context of persistent educational inequality. By applying statistical methods to recent national survey data, we seek to provide evidence on the wage effects associated with EJA completion, and to clarify the extent to which these effects differ from those of regular upper secondary education. A further contribution of this paper is the analysis of regional differences in EJA's impact, in addition to exploring heterogeneity across the earnings distribution through quantile regression. The remainder of this paper is structured as follows: the next section details the empirical strategy and data sources; section three presents and discusses the main results; and the final section offers concluding remarks, with a particular focus on implications for educational policy.

2 Methodology

2.1 Causal Inference and Identification Strategy

In the context of social sciences and education, it is extremely difficult to conduct randomized controlled trials (RCTs) that would randomly assign individuals to complete upper secondary education via the regular pathway or through the Youth and Adult Education program. Such an experiment, if feasible, would provide clear evidence of the causal impact of educational modality on wages.

In reality, students self-select into EJA or regular based on a array of factors, some observable, for example, age, region, family background, others unobservable like motivation and non-cognitive skills. This self-selection gives rise to selection

bias: direct comparisons between groups are likely to reflect both the effect of the educational trajectory and pre-existing differences between the students who choose them. The problem is that we do not observe the same individual under both treatments and thus cannot directly measure the counterfactual (Angrist; Pischke, 2009).

A particular concern in the literature, emphasized by Heckman e Rubinstein (2001) and Heckman, Humphries e Mader (2010), is the role of unobserved non-cognitive skills. Individuals who choose alternative educational pathways such as EJA may, on average, possess lower levels of persistence or commitment, potentially biasing the estimated effect of EJA if these traits also influence labor market outcomes. While propensity score matching (PSM) cannot directly control for unobserved factors, it does allow for the balancing of observed characteristics between groups. The observed variables included in the matching process serve either as proxies for, or at least help to minimize, potential biases stemming from unobserved attributes by ensuring comparability across groups.

2.2 Propensity Score Matching

To address selection bias on observables, we apply Propensity Score Matching (PSM). The central idea of PSM is to construct a control group of regular upper secondary graduates who are statistically similar to EJA graduates with respect to observed characteristics. The propensity score for each individual is defined as the probability of having completed upper secondary education via EJA, conditional on the vector of covariates:

$$P(T_i = 1 \mid X_i) = \frac{\exp(X_i'\beta)}{1 + \exp(X_i'\beta)} \tag{1}$$

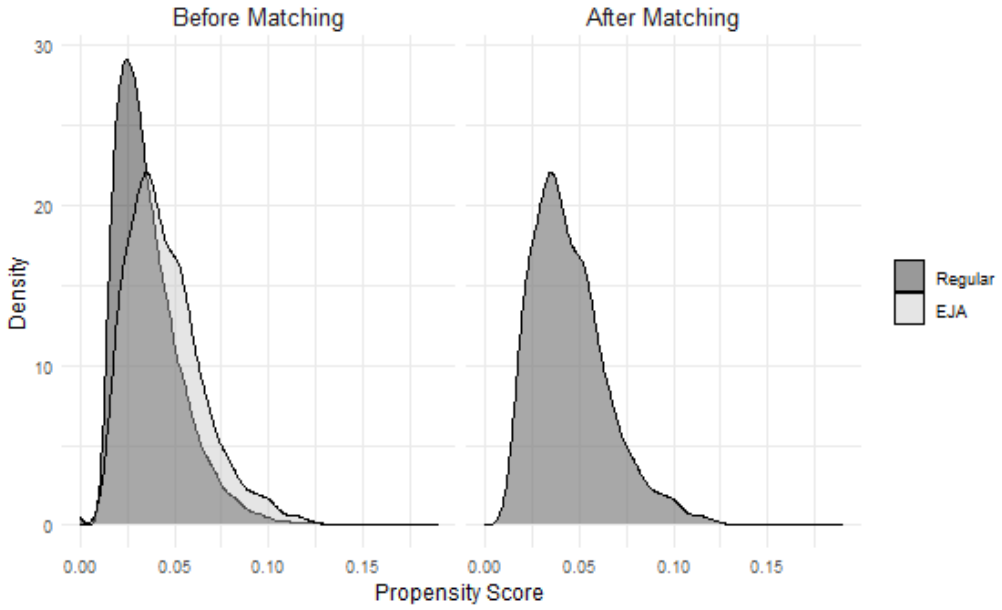
Where $T_i = 1$ for EJA graduates and 0 otherwise, and X_i includes age, gender, race, region, urban/rural status, and household characteristics.

Propensity scores are estimated using logistic regression, where each EJA graduate is matched to a regular graduate with a similar propensity score using Optimal Pair Matching algorithm[4], forming pairs of one treated and one control unit.

The figure 3 shows the overlap in the distribution of propensity scores before and after matching, the estimated overlap coefficient between treated and control units increased from 0.79 before matching to 0.999 after matching, indicating a common support in the matched sample. Despite the good match between individuals, it is important to note that there are limitations, if there are unobservable characteristics that affect both selection into EJA and labor market outcomes such as non-cognitive skills, some residual bias may remain, as we discussed before. Nevertheless, by controlling by a wide array of covariates, PSM brings the analysis more closer to a causal effect than naïve comparisons.

[4] For details on Optimal Pair Matching, see Ho et al. (2011).

Figura 3 – Propensity Score Distribution Before and After Matching



Source: Elaborated by authors. Note: The figure compares the distribution of propensity scores for EJA and regular graduates before and after matching. Overlap indicates better covariate balance after matching.

2.3 Quantile Regression

After matching, we estimate the effect of EJA completion on wages using quantile regression weighted by the PSM matching weights[5]. Unlike ordinary least squares (OLS), which estimates average treatment effects, quantile regression allows us to analyze how the impact of EJA varies across the wage distribution, in this way identifying whether wage penalties or premiums differ at the bottom, middle, or top of the income distribution. The quantile regression model can be specified as:

$$Q_Y(\tau \mid X) = \beta_0(\tau) + \beta_1(\tau) \cdot \text{EJA}_i + \gamma'(\tau) X_i \tag{2}$$

Where $Q_Y(\tau \mid X)$ is the conditional quantile of log wages at the quantile level (τ), EJA_i is the treatment indicator, and X_i is the vector of covariates. The models are estimated for key quantiles, 10th, 25th, 50th, 75th, and 90th percentiles to provide a comprehensive picture of wage heterogeneity.

2.4 Robustness

To ensure the reliability and credibility of our findings, we perform a robustness checks that evaluate whether our main results are sensitive to alternative methodological choices, We estimate treatment effects using alternative matching

[5] In optimal pair matching, the matching weights are equal to one for all matched observations. We present weighted estimates here for consistency with the robustness analysis using 1:k matching, where weights may differ.

algorithms, including Nearest Neighbor and Generalized Full Matching, in addition to the main Optimal Pair Matching approach.

These methods use different criteria for selecting control units for each treated observation and can help address potential biases that may arise from the specific choice of matching procedure. By comparing results across these different matching methods, we assess the stability and consistency of the estimated wage effects of EJA completion.

2.5 Data

The analysis draws on microdata from the 2023 wave of the Continuous National Household Sample Survey (PNAD Contínua), conducted by the Brazilian Institute of Geography and Statistics (IBGE). PNAD Contínua is the main household survey in Brazil and is nationally representative, covering urban and rural areas across all country. The survey provides detailed information on education, labor market participation, demographic profiles, income, and household conditions for millions of individuals.

Its methodology consists of making five consecutive visits to the same household, and its results are published in three forms[6]: quarterly, annual by quarter, and annual by visit. In this study, we opted for the use of the first annual visit of the quarter due to the supplementary survey modules on education, as well as information and communication technologies, in addition to household characteristics. This approach ensures both comprehensive information and comparability across respondents.

To construct our sample, we restrict the data to individuals aged 18 or older who report having completed upper secondary education, either through regular or EJA. Since the EJA program is legally intended for those aged 18 and above, this age threshold ensures proper alignment with program eligibility. Furthermore, we focus on individuals who are actively employed during the survey's reference week, as our primary interest is in labor market outcomes, particularly wages.

The resulting dataset includes all key variables required for propensity score matching: age, gender, race, region, urban or rural location, household assets, and outcome analysis: employment/wage information. By combining the microdata of PNAD Contínua with matching methodology, we are able to compare wage distributions between EJA and regular upper secondary graduate.

3 Results

3.1 Descriptive Statistics

Descriptive statistics allow for a more accurate assessment of the sample. Table 1 presents an overview of the occupational distribution among individuals who completed upper secondary in both educational modalities, EJA graduates are

[6] Further details about the PNAD Contínua data dissemination formats, see Osorio (2022).

approximately 3 percentage points less likely to be employed in the private sector compared to their peers from the regular track. indicating a greater concentration in lower-status occupations The proportion of EJA graduates who are self-employed is also slightly higher, which may reflect a combination of necessity-driven entrepreneurship and limited access to formal employment opportunities. Public sector employment is very similar across groups, which may reflect the potential equalizing effect of public entrance examinations. Since access to these positions is determined by standardized selection processes, both groups seem to have similar opportunities.

Tabela 1 – Occupational Distribution by Upper Secondary Type

Upper Secondary Type	Private Sector	Domestic Worker	Public Sector	Self-employed
EJA	53.20%	9.10%	9.30%	28.40%
Regular	56.80%	6.20%	9.80%	27.20%

Source: Elaborated by authors using microdata from PNAD Contínua (2023).. Notes: Domestic workers include individuals employed in private households (e.g.: cleaning, child/elder care). Self-employed refers to individuals working on their own, without formal employment contract.

The demographic and socio-economic profiles presented in Table 2 reinforce that, while EJA and regular graduates are broadly similar im several observable characteristics, some small but meaningful differences persist. Racial composition shows that EJA graduates are marginally more likely to identify as Black when comparing regular graduates and slightly less likely to be Brown. These patterns are consistent with broader evidence that adult education programs in Brazil tend to attract people from historically disadvantaged backgrounds, reflecting persistent educational and labor market inequalities along racial lines.

Tabela 2 – Demographic Characteristics by Upper Secondary Type (%)

Upper Secondary Type	Female	Black	White	Brown	Urban	Vehicle	Bathroom
EJA	45.98	13.07	39.00	46.81	82.33	68.03	98.67
Regular	44.33	11.83	37.96	49.03	83.22	70.13	98.72

Source: Elaborated by authors using microdata from PNAD Contínua (2023).. Notes: Self-declared race categories based on PNAD (2023), where Black includes *Pretos* and Brown refers to *Pardos*. Vehicle indicates ownership of at least one car or motorcycle. Bathroom refers to domiciles with at least one exclusive-use bathroom (with shower or bathtub and toilet), including those on the property grounds.

Regarding living conditions, both groups report high rates of urban residency and almost universal access to basic infrastructure, measured by the presence of

a bathroom. When comparing vehicle ownership, 68.0% of EJA graduates report owning a car or motorcycle, compared to 70.1% among regular-track graduates. Although this difference is not large, usually vehicle ownership is often considered an indicator of income, suggesting a slightly lower socio-economic status among EJA graduates.

Tabela 3 – Distribution of Upper Secondary Graduates by Region

Region	EJA (%)	Regular (%)
MidWest	4.75	95.25
North	2.59	97.41
Northeast	2.61	97.39
South	5.46	94.54
Southeast	3.68	96.32

Source: Elaborated by authors using microdata from PNAD Contínua (2023).. Notes: Percentages are calculated within each region, shares sum to 100% per row.

When we analyze the regional distribution of upper secondary graduates, the overall proportions are relatively low, this spatial pattern likely reflects both regional differences in educational infrastructure and variations in access to regular upper secondary education during youth. The higher presence of EJA graduates in the South and Midwest may indicate either greater outreach of EJA programs or a higher prevalence of interrupted educational trajectories in these regions. It is important to note that Table 3 concerns to the distribution of graduates, not current enrollments as illustrated in Figure 2, the regional distribution of graduates may differ substantially from enrollment statistics, which often report higher shares of EJA students in certain regions. This discrepancy arises because the composition of graduates reflects not only current participation but also historical access and completion patterns over time.

Tabela 4 – Wage Statistics by Upper Secondary Type

Upper Secondary Type	Mean Wage (BRL)	Median Wage (BRL)
EJA	1,879.38	1,550
Regular	1,958.03	1,500

Source: Elaborated by authors using microdata from PNAD Contínua (2023).. Notes: Monthly wages in Brazilian Reais (BRL).

Wage statistics in Table 4 reveal a wage disadvantage for EJA graduates when observes the average monthly wage for EJA graduates, which is about 4% lower than earned by regular-track graduates. Interestingly, the median wage for

EJA graduatesis actually higher than that of regular graduates, suggesting a more compressed wage distribution for EJA graduates. While, EJA graduates tend to earn less on average, the wage gap is not uniform across the distribution. The following section investigates this pattern further using quantile regression.

3.2 Wage Effects Across the Distribution

The estimates reveal a persistent and statistically significant wage penalty for individuals who complete upper secondary education through the EJA modality . In the specification that controls for both individual and geographic characteristics, the wage gap is approximately 6.1% at the median of the wage distribution. However, this penalty is not uniform, being more pronounced at the lower (10th quantile: -11.1%) and upper (90th quantile: -13.7%) tails, while it is somewhat attenuated near the median, suggesting that the disadvantage associated with EJA completion is particularly acute among lowest and highest earners, pointing to a heterogeneity in how alternative educational pathways are valued in the labor market.

Tabela 5 – Quantile Treatment Effects of EJA on Wages

	Quantile (τ)				
	0.10	0.25	0.50	0.75	0.90
Model 1	-0.1035	0.000	-0.0317	-0.0619*	-0.1542***
(Baseline)	(0.0731)	(0.0096)	(0.0248)	(0.0324)	(0.0511)
Model 2	-0.1152*	-0.033	-0.0407**	-0.0607***	-0.123***
(+ Individual)	(0.0650)	(0.0203)	(0.0164)	(0.0230)	(0.0318)
Model 3	-0.1105***	-0.0626***	-0.0608***	-0.0746***	-0.1365***
(+ Geographic)	(0.0389)	(0.0206)	(0.0168)	(0.0197)	(0.0356)
Observations			3,607		

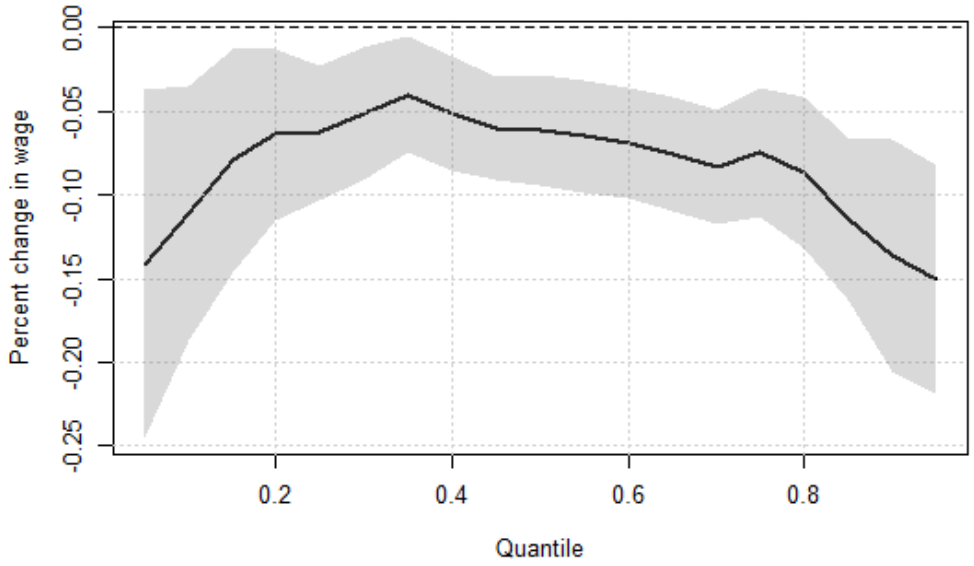
Source: Elaborated by authors. Notes: Table presents quantile regression estimates of the treatment effect of EJA certification on log wages. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. Model 1 includes only the treatment indicator; Model 2 adds individual characteristics (age, age squared, race dummies, and gender); Model 3 further adds geographic controls (urban status, capital city dummy, and region fixed effects).

Table 5 compares the estimated wage gap across different model specifications. Model 1, which includes only the treatment indicator, already suggests a wage penalty for EJA graduates at the upper end of the wage distribution. Adding individual characteristics controls in Model 2, such as age, gender, and race, , results in the wage penalty becoming statistically significant not only at the upper end of the distribution, but also at lower ($\tau = 0.1$) and median ($\tau = 0.5$) quantiles. In Model 3, which includes controls for both individual characteristics and geographic factors, specifically urban status, capital city dummy and region fixed effects, wage penalty is statistically significant at the 1% level across all quantiles.

Figure 4 offers a more granular view, plotting the estimated percent wage penalty for EJA graduates across the entire wage distribution, from the 5th to the

95th quantile. The figure illustrates that the wage penalty is relatively modest at the center of the distribution but tends to increase toward both extremes. The 95% confidence intervals remain narrow throughout, indicating the statistical significance. The non-linear shape of the penalty curve suggests that labor market returns to EJA completion is more pronounced for individuals at both the lower and upper tails of wage distribution as reported before.

Figura 4 – Estimated Wage Penalty for EJA Graduates Across the Wage Distribution



Source: Elaborated by authors. Note: The solid line depicts the estimated percent change in wage for EJA graduates relative to regular upper secondary graduates across wage quantiles. The shaded region indicates 95% confidence intervals. Estimates were computed for quantiles τ ranging from 0.05 to 0.95, in increments of 0.05.

In absolute terms, the average treatment effect on the treated (ATT) of EJA completion is estimated at approximately 204 BRL per month. Annualized, this amounts to a difference of about 2,448 BRL per year, putting this in perspective, the monthly minimum wage in Brazil in 2023 was 1,320 BRL, so this penalty represents nearly two full months of minimum wage earnings over a year. This comparison emphasizes the gap and underscores how alternative certification pathways can have a substantial and persistent impact on workers' living standards.

Some mechanisms may help explain these results. At the lower end of the distribution, EJA graduates are likely to be overrepresented in informal or low-paying occupations, where educational signaling is less weight, and employer skepticism toward alternative diplomas may be heightened (Cano-Urbina, 2015; Park; Qu, 2013; Nordin; Persson; Rooth, 2010). At the upper tail, the earnings ceiling for EJA graduates may reflect limited access to higher-skilled positions or promotions, potentially due to a gap in non-cognitive skills, which are increasingly valued by employers and have been shown to significantly influence access to skilled jobs (Deming, 2017; Lindqvist; Vestman, 2011). Furthermore, disparities in professional

networks can further disadvantage holders of alternative credentials, restricting their opportunities for advancement and access to promotions (Calvo-Armengol; Jackson, 2004). The evidence thus suggests that the labor market continues to treat EJA and regular upper secondary credentials as distinct, even when controlling for a set of observed characteristics.

The persistence of the wage penalty after adjusting for observable characteristics and across the wage distribution underscores structural challenges in the Brazilian labor market. Not only does this reinforce concerns about the limited signaling value of alternative educational credentials but it also reveals that these pathways may be least effective in promoting social mobility for those already facing significant barriers.

3.3 Regional Heterogeneity

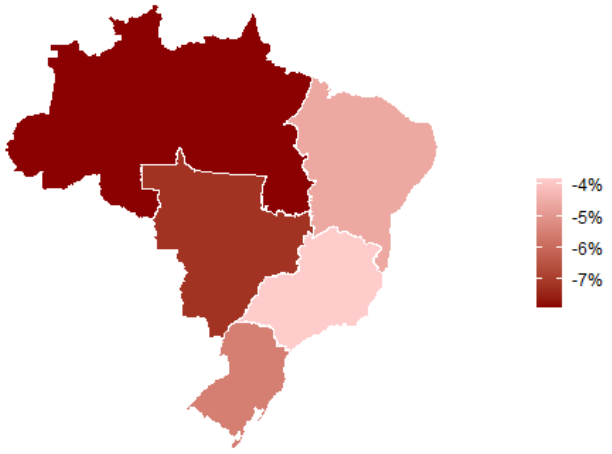
Thus, while the wage penalty associated with EJA certification persists throughout the entire wage distribution as previously reported, the results demonstrate that its magnitude has a strong regional component. To illustrate this, Figure 5 shows the estimated median wage penalty by region, highlighting the presence of spatial variation in income for EJA graduates across Brazil.

The wage gap is most severe in the North and Midwest, where the penalty for EJA reaches as high as 7% at the median. In contrast, the Southeast and South regions exhibit considerably smaller wage penalties, suggesting that the labor market disadvantage associated with EJA certification is less pronounced in these areas. This spatial heterogeneity reflects a confluence of structural, institutional, and social factors.

Regions such as the North and Midwest are characterized by historically higher educational inequality, weaker labor market institutions, and more limited access to high-quality formal employment. In these contexts, EJA may carry less value in the eyes of employers, either due to a perceived lack of commitment, reduced familiarity with the program or persistent stigma attached to non-traditional educational pathways. Futhermore, these regions tend to have higher shares of informal work and lower overall wage levels, which can overestimate the challenges faced by EJA graduates in converting educational attainment into better labor market outcomes (Bourguignon; Ferreira; Menéndez, 2007; Engbom et al., 2022).

In contrast, the Southeast and South, present a different scenario. In those regions the lower wage penalty for second-chance graduates may be attributable to a combination of higher labor demand, more developed education systems, and greater diversity in the recognition of educational credentials (Brambilla; Sartori; Fonseca, 2024; Almeida; Packard, 2018). Employers in these regions may be more accustomed to hiring individuals with a range of educational backgrounds, or there may be more robust mechanisms in place to ensure the quality and equivalence of alternative diplomas (Silva; Almeida; Strokova, 2015). Furthermore, higher overall wage levels and more formalized labor markets may reduce the extent to which educational trajectory alone determines earning potential (Argue; Velema, 2022; Cantalini; Guetto; Panichella, 2023).

Figura 5 – Regional Variation in Wage Penalty for EJA Graduates (%)



Source: Elaborated by authors. The map displays the estimated wage penalty (in percent) for EJA graduates relative to regular upper secondary graduates by region. Darker shades indicate a larger wage penalty. Estimates are based on the median ($\tau = 0.5$) wage differential.

These regional differences underscore that the effectiveness and social acceptance of EJA as a pathway to economic mobility are not uniform across the country. The results suggest that policy interventions aimed at reducing the stigma and improving the quality of EJA programs may need to be tailored to local contexts, with particular attention to the structural disadvantages faced by workers in less developed regions.

3.4 Robustness Checks

To assess the sensitivity and validity of our main findings, we conducted a robustness checks by re-estimating the quantile treatment effects of EJA certification using alternative matching algorithms. As summarized in Table 6, the primary analysis based on Optimal Pair Matching was complemented by results from Generalized Full Matching and Nearest Neighbor Matching. All approaches use the same set of covariates for adjustment and employ propensity score weighting.

Across the three matching procedures[7] and wage quantiles, the estimated wage penalty for EJA graduates remains consistently negative and statistically significant. While there are variations in the magnitude of the effects, the pattern is unchanged, EJA completion is associated with lower wages relative to regular upper secondary graduates at every point in the wage distribution, reinforcing the conclusion that the observed wage penalty is not a particular matching specification.

4 Concluding Remarks and Policy Implications

This study provides the persistent wage penalties associated with completing upper secondary education through Brazil's Youth and Adult Education (EJA)

[7] The full set of quantile regression results for all matching methods are provided in Appendix.

Tabela 6 – Quantile Treatment Effects of EJA Certification on Wages by Matching Method

	Quantile (τ)				
	0.10	0.25	0.50	0.75	0.90
Optimal Pair Matching	-0.1106***	-0.0626***	-0.0608***	-0.0747***	-0.1365***
	(0.0389)	(0.0206)	(0.0168)	(0.0197)	(0.0356)
Generalized Full Matching	-0.1591***	-0.0674***	-0.0533***	-0.0937***	-0.1173***
	(0.0342)	(0.0205)	(0.0130)	(0.0154)	(0.0233)
Nearest Neighbor	-0.1676***	-0.0790***	-0.0695***	-0.0894***	-0.1117***
	(0.0398)	(0.0213)	(0.0161)	(0.0181)	(0.0346)
Observations	3,607				

Source: Elaborated by authors. Notes: Table presents quantile regression estimates of the treatment effect of EJA certification on log wages using three matching methods. Standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. All models used same controls for Individual and Geographic characteristics from Table 5. Weights are based on propensity scores from each matching method.

pathway. After adjusting for observable characteristics, EJA graduates systematically earn less than their peers from the regular track. This penalty is most pronounced at the extremes of the wage distribution, underscoring not only a general disadvantage but also pronounced heterogeneity in labor market outcomes. These results confirm that, despite policies intended to foster educational inclusion and second-chance pathways, the labor market continues to differentiate between traditional and alternative educational credentials.

It is worth noting that our findings also reveal considerable regional variation in the wage penalty associated with EJA certification. The disadvantage is greatest in regions with historically weaker educational infrastructure and less developed labor markets, suggesting that local conditions significantly impact of alternative certification pathways on wages. These regional disparities point out the need for context-specific policy responses and further research into the mechanisms behind such heterogeneity.

The evidence presented here has direct policy implications, it suggests that expanding access to education alone is insufficient to guarantee equitable labor market outcomes. Improving the quality, recognition, and social perception of EJA programs is essential for reducing stigma and leveling the playing field for adult learners. Policymakers should prioritize investments not only in curriculum development and teacher training for EJA, but also in public awareness campaigns and employer engagement to enhance credibility of alternative diplomas. Moreover, targeted support may be warranted in regions with the largest penalties, including partnerships with local employers, tailored job placement programs, and monitoring of educational

standards. Ensuring that EJA serves as a real instrument of social mobility requires concerted efforts to address both the supply and demand sides of the labor market.

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Appendix

Covariate Balance

Tabela 7 – Covariate Balance Before and After Propensity Score Matching

Covariate	Before Matching			After Matching		
	Mean Treated	Mean Control	Std. Diff.	Mean Treated	Mean Control	Std. Diff.
Propensity Score	0.0456	0.0365	0.4299	0.0456	0.0456	0.0000
Age	41.28	37.25	0.3326	41.28	42.73	-0.1198
Female (%)	45.98	44.33	0.0331	45.98	44.88	0.0222
Black (%)	13.07	11.83	0.0369	13.07	13.80	-0.0214
White (%)	39.00	37.96	0.0215	39.00	36.51	0.0511
Brown (%)	46.81	49.03	-0.0444	46.81	48.53	-0.0344
Urban (%)	82.33	83.22	-0.0233	82.33	81.39	0.0247
Capital City (%)	21.72	26.12	-0.1067	21.72	23.60	-0.0457
Midwest Region (%)	13.52	10.35	0.0927	13.52	8.86	0.1361
North Region (%)	9.25	13.27	-0.1388	9.25	11.47	-0.0765
Northeast Region (%)	19.94	28.44	-0.2125	19.94	22.94	-0.0749
South Region (%)	27.48	18.14	0.2092	27.48	23.66	0.0856
Southeast Region (%)	29.81	29.80	0.0000	29.81	33.07	-0.0715
Own House (%)	100.00	99.80	0.0455	100.00	100.00	0.0000
Rented (%)	0.00	0.20	-0.0455	0.00	0.00	0.0000
Granted (%)	0.00	0.00	0.0000	0.00	0.00	0.0000
$\leq$ 3 Rooms (%)	6.26	6.14	0.0048	6.26	7.09	-0.0343
4 Rooms (%)	13.35	13.80	-0.0132	13.35	12.80	0.0163
5 Rooms (%)	33.41	32.07	0.0284	33.41	35.35	-0.0411
6 Rooms (%)	22.05	22.95	-0.0218	22.05	21.83	0.0053
7 Rooms (%)	12.96	12.80	0.0048	12.96	11.36	0.0478
$\geq$ 8 Rooms (%)	11.97	12.23	-0.0081	11.97	11.58	0.0119
Owns Car (%)	68.03	70.13	-0.0450	68.03	64.99	0.0653
Bathroom (%)	98.67	98.72	-0.0044	98.67	97.73	0.0822

Source: Elaborated by authors. Notes: Means refer to the share or mean for each group (Treated = EJA graduates; Control = regular upper secondary graduates). Std. Diff. is the standardized mean difference.

Quantile Regression Results by Matching Method

Tabela 8 – Complete Quantile Regression Results by Matching Method

	Optimal Pair Matching			Generalized Full Matching			Nearest Neighbor		
Variable	Coef.	S.E.	Sig.	Coef.	S.E.	Sig.	Coef.	S.E.	Sig.
τ = 0.10									
EJA	-0.111	0.039	***	-0.159	0.034	***	-0.168	0.040	***
Age	0.054	0.011	***	0.048	0.006	***	0.046	0.011	***
Age²	-0.001	0.000	***	-0.001	0.000	***	-0.001	0.000	***
Black	-0.286	0.098	***	-0.134	0.024	***	-0.214	0.082	**
Brown	-0.075	0.046	*	-0.103	0.022	***	-0.097	0.041	**
Gender (Female)	-0.569	0.050	***	-0.478	0.025	***	-0.569	0.047	***
Urban	0.365	0.080	***	0.398	0.032	***	0.307	0.061	***
Capital	0.111	0.046	**	0.072	0.022	***	0.103	0.046	**
Region: North	-0.699	0.160	***	-0.553	0.037	***	-0.576	0.121	***
Region: Northeast	-1.070	0.085	***	-0.825	0.032	***	-0.972	0.076	***
Region: South	0.102	0.057	*	0.104	0.031	***	0.113	0.050	**
Region: Southeast	-0.116	0.042	***	-0.070	0.022	***	-0.077	0.042	*
τ = 0.25									
EJA	-0.063	0.021	***	-0.067	0.021	***	-0.079	0.021	***
Age	0.049	0.008	***	0.031	0.002	***	0.043	0.006	***
Age²	-0.001	0.000	***	-0.000	0.000	***	-0.001	0.000	***
Black	-0.121	0.051	**	-0.109	0.016	***	-0.079	0.040	*
Brown	-0.086	0.022	***	-0.065	0.010	***	-0.080	0.023	***
Gender (Female)	-0.314	0.023	***	-0.262	0.009	***	-0.283	0.021	***
Urban	0.268	0.049	***	0.219	0.014	***	0.164	0.027	***
Capital	0.105	0.022	***	0.051	0.011	***	0.062	0.026	**
Region: North	-0.405	0.070	***	-0.278	0.015	***	-0.374	0.065	***
Region: Northeast	-0.695	0.073	***	-0.485	0.025	***	-0.669	0.067	***
Region: South	0.092	0.022	***	0.102	0.013	***	0.089	0.026	***
Region: Southeast	-0.081	0.030	***	-0.050	0.011	***	-0.061	0.027	**
τ = 0.50									
EJA	-0.061	0.017	***	-0.053	0.013	***	-0.069	0.016	***
Age	0.032	0.005	***	0.025	0.002	***	0.028	0.004	***
Age²	-0.000	0.000	***	-0.000	0.000	***	-0.000	0.000	***
Black	-0.052	0.026	**	-0.093	0.013	***	-0.055	0.030	*
Brown	-0.087	0.019	***	-0.071	0.008	***	-0.086	0.018	***
Gender (Female)	-0.288	0.017	***	-0.247	0.007	***	-0.297	0.016	***
Urban	0.121	0.034	***	0.082	0.012	***	0.049	0.028	*
Capital	0.098	0.020	***	0.042	0.008	***	0.064	0.022	***
Region: North	-0.223	0.041	***	-0.250	0.015	***	-0.232	0.044	***
Region: Northeast	-0.353	0.038	***	-0.311	0.013	***	-0.350	0.035	***
Region: South	0.164	0.036	***	0.104	0.014	***	0.157	0.031	***
Region: Southeast	-0.054	0.033	*	-0.089	0.014	***	-0.056	0.029	*
τ = 0.75									
EJA	-0.075	0.020	***	-0.094	0.015	***	-0.075	0.020	***
Age	0.029	0.005	***	0.030	0.003	***	0.029	0.005	***
Age²	-0.000	0.000	***	-0.000	0.000	***	-0.000	0.000	***
Black	-0.102	0.027	***	-0.123	0.015	***	-0.102	0.027	***
Brown	-0.134	0.024	***	-0.117	0.012	***	-0.134	0.024	***
Gender (Female)	-0.317	0.020	***	-0.308	0.010	***	-0.317	0.020	***
Urban	0.030	0.028		0.048	0.014	***	0.030	0.028	
Capital	0.097	0.031	**	0.041	0.012	***	0.097	0.031	**
Region: North	-0.275	0.051	***	-0.225	0.024	***	-0.275	0.051	***
Region: Northeast	-0.406	0.036	***	-0.376	0.019	***	-0.406	0.036	***
Region: South	0.099	0.036	**	0.076	0.020	***	0.099	0.036	**
Region: Southeast	-0.100	0.036	***	-0.077	0.019	***	-0.100	0.036	***

	Optimal			Quick			Neighbor		
Variable	Coef.	S.E.	Sig.	Coef.	S.E.	Sig.	Coef.	S.E.	Sig.
τ = **0.90**									
EJA	-0.137	0.036	***	-0.117	0.023	***	-0.137	0.036	***
Age	0.027	0.009	***	0.035	0.004	***	0.027	0.009	***
Age^2	-0.000	0.000		-0.000	0.000	***	-0.000	0.000	
Black	-0.077	0.070		-0.158	0.025	***	-0.077	0.070	
Brown	-0.105	0.041	**	-0.130	0.017	***	-0.105	0.041	**
Gender (Female)	-0.365	0.035	***	-0.366	0.014	***	-0.365	0.035	***
Urban	-0.004	0.056		0.000	0.024		-0.004	0.056	
Capital	0.115	0.041	**	0.059	0.017	***	0.115	0.041	**
Region: North	-0.288	0.063	***	-0.221	0.029	***	-0.288	0.063	***
Region: Northeast	-0.427	0.056	***	-0.417	0.021	***	-0.427	0.056	***
Region: South	0.080	0.064		0.040	0.026		0.080	0.064	
Region: Southeast	-0.162	0.053	**	-0.126	0.022	***	-0.162	0.053	**

Source: Elaborated by authors. Notes: Complete quantile regression results for three matching methods (optimal, quick, and nearest neighbor). Standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. All models include identical controls: age (linear and quadratic terms), race dummies (Black, Brown), gender, urban status, capital city dummy, and region fixed effects. The treatment variable (EJA) indicates certification through adult education programs.